Alpha Decay

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ABSTRACT

Stocks purchased by institutional investors earn positive alpha that declines gradually over twelve months following the original trade. Using new transaction-level data, we link this phenomenon to strategic trading behaviour. Fund managers in our sample continue to buy a stock in small increments for as long as the alpha persists, with trade sizes proportional to the remaining mispricing. Greater competition for information is associated with more aggressive trading and lower post-purchase alpha, but only in the first 3-6 months, consistent with the initial "rat race" and subsequent "waiting game" phases of trading first predicted by Foster and Viswanathan (1996).

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How do financial institutions contribute to price formation? Although stocks with higher institutional ownership appear to be more efficiently priced (Boehmer and Kelley (2009)), compelling evidence from the trading performance literature suggests that informational efficiency may still be low in an absolute sense.[1] To wit, abnormal returns on stocks purchased by institutions have been found to accumulate, at a gradually declining rate, for months or even years after the initial trade (e.g. Wermers (1999); Chen, Jegadeesh, and Wermers (2000); Yan and Zhang (2009)).[2] This prolonged pattern of *alpha decay* is troubling because it suggests that the price response to new information may be sluggish despite the presence of informed traders. Considering the real effects of mispricing on firm outcomes, further investigation is warranted.[3]

This article examines strategic trading behaviour as a potential driver of the observed alpha decay. We test the equilibrium predictions of leading theoretical models in the tradition of Kyle (1985), focusing on the dynamics of trading activity and price adjustment, and the effects of competition. In doing so we show that market microstructure can have significant long-run effects on asset prices. We are able to study these issues directly for the first time owing to a comprehensive new dataset provided by Inalytics Ltd., containing not only daily trades but also daily holdings and assets under management (AUM) for over seven hundred institutional portfolios.[4] The sample runs from 2001 to 2013, covers various countries including the US, the UK and Japan, and contains a total of 1.15 million trades ($1.8 trillion in value).

Strategic trading is the subject of a large (and still growing) theoretical literature.[5] A central theme of this literature is that investors who possess private information face conflicting incentives that affect how aggressively they wish to trade. As highlighted by Kyle (1985), less aggressive trading allows an investor to conceal her trades among those of noise traders, reducing

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[1] For a theoretical argument supporting Boehmer and Kelley (2009)'s empirical work, see Edmans (2009).

[2] Other authors have extended this finding to trades by short-sellers (e.g. Desai at al. (2002); Cohen, Diether, and Malloy (2007); Boehmer, Jones, and Zhang (2008)), corporate insiders (Ben-David and Roulstone (2010)), and certain individual investors (e.g. Kaniel, Saar, and Titman (2008); Grinblatt, Keloharju, and Linnainmaa (2010); Kaniel et al. (2012)).

[3] For instance, mispricing can negatively affect firm investment decisions as well as governance (via the likelihood of a takeover). See Bond, Edmans, and Goldstein (2012) for a survey on the real effects of financial markets.

[4] The two most similar datasets currently available—from ANcerno and the Plexus Group—do not include information on portfolio holdings or AUM, and do not cover institutions outside of the US. Moreover, the Plexus Group dataset recycles institution identifiers each month, making it impossible to identify trading by the same institutions over long periods of time (see the discussion in Anand et al. (2012)).

[5] Recent work includes Pasquariello (2007), Chau and Vayanos (2008), Ostrovsky (2012), Boulatov, Hendershott, and Livdan (2013), Buffa (2013), Lambert, Ostrovsky, and Panov (2014), Back and Crotty (2014), and Choi, Larsen, and Seppi (2015).

the amount of private information that can be inferred from aggregate order flow and slowing the rate of price adjustment. On the other hand, if at least one competitor has access to the same information, cautious trading entails a risk that the competitor will act first, moving prices against the investor. Holden and Subrahmanyam (1992) show that the equilibrium strategy in this setting is to trade very aggressively, leading to instantaneous revelation of all information in the continuous time limit.

However, if competitors' information signals are not perfectly correlated, it is unclear whether competition will always increase market efficiency. In Kyle-type models with heterogeneous information, Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) show that a greater number of informed traders leads to faster information revelation only in the short run (the "rat race"). After some time has passed, the market price will have incorporated the common components of the private signals, generating endogenous disagreement. Each investor then has an incentive to make smaller trades while waiting for competitors to move prices away from what she believes to be the true fundamental value of the asset, creating further profit opportunities if her beliefs are correct (the "waiting game").

Despite the abundance of theoretical models, many of their key predictions remain untested. In particular, the relative strengths of the aforementioned incentives and how they change in different competitive environments are open empirical questions. Moreover, this class of models is silent on the length of the trading period, which is an interesting question in its own right.

The results of our investigation are as follows. Using an event study methodology, we first document a correspondence between average *stock-level* Fama-French-Carhart alpha and repeated trading in the same stock over time. Alpha is positive, economically large and statistically significant (37 basis points) in the first month after an initial purchase, declining to effectively zero by month twelve.[6] It does not subsequently turn negative, indicating that the price changes are permanent—cumulative alpha has an increasing, concave shape that levels out in the long run. Over the same year-long period in event time, monthly follow-up purchases (net of follow-up sales) decline from 0.087 percent of AUM to zero, after which the original positions begin to be reversed.[7] Trading frequency (fraction of portfolios with trades on a given day) and trade size

[6] For robustness, we show that the same patterns hold for relative returns (i.e., the difference between the stock returns and the client-specified benchmark return) and for the difference between buys and sells.
[7] The results are similar for gross follow-up purchases, except for the eventual reversal of the position which can only be measured using follow-up sales.

(fraction of AUM) are both proportional to the declining incremental alpha, with the evolution of both variables taking the shape of a power function. In contrast to purchases, sales do not appear to be informed: post-sale alphas are slightly positive (entailing a loss for the manager) and there is no consistent pattern of decay.

Measuring competition as the number of security analysts covering a stock (controlling for market capitalization and other stock characteristics), we then obtain the following results from a *within-portfolio* panel regression setup.[8] A one standard deviation increase in analyst coverage is associated with a 10.9 basis point (bps) decrease in post-purchase alpha in the first month, a 5.8 bps decrease per month in the remainder of the first quarter, and no significant effect thereafter. The same increase in analyst coverage is associated with a 2.4 bps increase in initial order size, as well as follow-up net purchases that are 1.4 bps larger in the first month, 0.9 bps per month larger in the remainder of the first quarter, 0.5 bps larger in the second quarter, and unchanged thereafter. To put the magnitudes into perspective, the decrease in first-month alpha is 26.6% of its unconditional mean, and the increase in initial order size is 27.9% of its unconditional mean. Increased early trading activity also partially displaces later trading activity if the initial increase is associated with competition.

Lastly, we consider the possibility that the observed alpha decay could be driven by risk premia or anomalies that are unrelated to asymmetric information or strategic trading. In a subsample analysis, we rule out momentum trading strategies, liquidity provision, earnings announcement anomalies, and horizon-varying fund manager skill. By reporting round-trip holding period returns calculated using only actual execution prices, we also show that hypothetical market prices (and thus unobserved transaction costs) do not drive the results.[9]

Our findings are broadly consistent with Kyle-type models of strategic trading. More specifically, the concave path of cumulative alpha and the power-function-shaped decline in trading activity are closest to the predictions of the multiple-agent, heterogeneous-information versions of the model (e.g. Foster and Viswanathan (1996), and Back, Cao, and Willard (2000)).

[8] Analyst coverage as a proxy for competition was suggested by Holden and Subrahmanyam (1992), but has also been used to measure information asymmetry, notably by Hong, Lim, and Stein (2000). As we shall argue later, these interpretations are two sides of the same coin.

[9] More generally, we use execution prices whenever possible and always drop stocks from the sample once they are no longer held, to ensure that reported alphas are achievable in practice. In section VI, we also verify that post-purchase alpha is robust to weighting averages by trade size.

The fact that competition has mainly short-run effects is also consistent with the two phases of trading ("rat race" and "waiting game") predicted by these models. Taken as a whole, our results indicate that fund managers act as local monopolists with respect to the unique component of their private information.[10,11] While we do not prove causation, our results are difficult to explain outside of the above theoretical framework, and thus strongly suggest that strategic trading behaviour is responsible for delayed price adjustment (prolonged alpha decay).

This article joins an ongoing effort to bring together the sub-fields of asset pricing and market microstructure. The closest papers to ours are probably those by Pasquariello and Vega (2007, 2013), who test static variations of Foster and Viswanathan's (1996) model. They find that price impact is positively related to information dispersion and negatively related to competition. By contrast, we study the effect of competition on the *long-run dynamics* of price formation and strategic trading at the *individual fund level*. Koudijs (2014) identifies gradual price adjustment consistent with the Kyle model in a historical setting, but does not examine trading behaviour directly. Chan and Lakonishok (1995) and Keim and Madhavan (1995) report that orders are typically split into multiple trades and that larger orders take longer to execute. Our work differs from theirs in that we examine not only how orders are split into multiple trades, but also how multiple orders are used to accumulate positions—over much longer timescales than has previously been appreciated. Chan and Lakonishok (1993, 1995) find that price impact has a larger permanent component for buys than for sells, consistent with our finding that sales are not informed.[12] Hendershott, Livdan, and Schürhoff (2014) show that aggregate institutional order flow anticipates public news and is positively autocorrelated over short horizons, but do not track repeated trading by the same institution or consider the long run.

The previous studies that report slow alpha decay for institutional trades have all relied on changes in quarterly holdings, which at best is a noisy proxy for trades. As such, another of our contributions is to provide a much higher resolution view of the alpha decay phenomenon. Our paper also complements recent *transaction-level* studies of trading skill by showing how traders'

[10] This conclusion also holds if fund managers *believe* that part of their information is unique, whether or not these beliefs are correct.

[11] For the purposes of this paper, we treat as "private" any information that is not widely known or appreciated by the market. In practice it can be difficult to distinguish between strong form and semi-strong form efficiency—information that is technically in the public domain may nonetheless be difficult to find or interpret.

[12] Other related studies include Barclay and Warner (1993), who find that medium-sized trades have the largest price impact, and Chakravarty (2001), who shows that these trades are mostly initiated by institutions. Conrad, Johnson, and Wahal (2001, 2003) study how price impact varies across different types of brokers and trading systems.

profits evolve over extended periods. Existing work in this area (e.g. Puckett and Yan (2011); Anand et al. (2012)) focuses only on the short run.

The organization of this article is as follows. In section I we describe the data and present summary statistics for the main variables of interest. Section II outlines the implications of Kyle-type models, providing hypotheses for our empirical results. In section III we test the models' equilibrium predictions and investigate the effects of competition. Potential alternative explanations for alpha decay are considered in section IV. Section V concludes.

I. Data and Summary Statistics

A. Description of the Data

In this subsection we introduce the dataset, which has not been previously examined in the finance literature. The data are supplied by Inalytics Ltd., a firm whose commercial activities include delegated portfolio monitoring on behalf of institutional asset owners. The asset owners (mostly pension plan sponsors) outsource some or all of their investment decisions to external fund managers, who are also large financial institutions such as banks or traditional asset management houses. Inalytics also analyzes investment decisions for fund manager clients who provide data as part of their internal monitoring efforts, and for asset owners engaged in new manager searches ("beauty contests"). With the exception of searches, the data are ultimately obtained from the fund custodians who are legally obligated to ensure their accuracy. The fund managers and asset owners are anonymized but assigned permanent reference numbers.

The main advantages of our dataset over other transaction-level databases, such as those from ANcerno Ltd. and the Plexus Group, are: (1) daily holdings and assets under management (AUM) in addition to trades; (2) client-specified performance benchmarks; and (3) a global range of institutions and a long sample length, meaning our conclusions are not limited to a particular region or market size.

The sample runs from January 2001 to June 2013 and therefore includes a wide variety of market conditions. Sample lengths of individual portfolios vary. Within the sample, we observe the date of every trade, whether it was a purchase or a sale, the number of shares traded, the execution price, and a code identifying the parent order to which the trade belongs. The dataset covers over 700 long-only institutional portfolios. After discarding portfolios with fewer than 50 orders or less than one year's holdings, we are left with 692 portfolios managed by 206 unique fund management companies. This gives a total of 1,150,494 orders with an aggregate value of 1.8 trillion US dollars. Assets under management of the portfolios range from $9 million to $14 billion.

Table I provides a breakdown of the sample by location of the benchmark (panel A) and location of the fund manager (panel B), as well as by the type of client and the intended purpose of the data (panel C). Panel A indicates that the most frequently-used benchmarks in our sample are global equity indices such as the Morgan Stanley Capital International (MSCI) World Index. However, there are significant numbers of portfolios benchmarked against country-specific indices: 98 for the UK, 64 for the US, 86 for continental Europe, and 36 for Japan. Smaller markets such as Australia (104 portfolios) and South Africa (30 portfolios) are also represented. Unreported robustness checks confirm that our results are unaffected if the smaller and/or emerging markets are excluded from the sample. For non-US portfolios, all prices and returns are converted to US dollars at contemporaneous exchange rates.

The distribution of fund manager locations (shown in table I, panel B) is skewed towards the United Kingdom (275 portfolios, 75 managers) due to the fact that Inalytics is a UK-based firm. Global fund managers, who manage portfolios out of two or more regions, are the second largest group. Almost all of these global companies have offices in the United States, and combined with the pure US managers there are over a hundred with geographical ties to this region.

Panel C of table I indicates that approximately two thirds of the portfolios in our sample are supplied by asset owners, around a quarter by fund managers, and the remainder by managers of managers ("hybrid") and asset owners who manage their own portfolios ("in-house"). The latter two categories are closer to owners than managers. Hybrids supply data from their underlying managers for diagnostic reasons, and in-house managers are concerned only with their own performance rather than with attracting outside investors.

Most of the common sample biases that have been identified in the literature are not major concerns for our dataset. Because asset owners have access to the data in real time, managers do not face incentives to engage in window dressing. And since the sample includes both live and terminated portfolio mandates, the data are not subject to survivorship bias. Back-filling biases are minimized due to the majority of the data (81%) having been collected in real time.

One potential concern is self-selection bias. It may be argued that poorly performing portfolios are unlikely to be shared with a third party for reputational reasons. However, this concern only arises for a minority of the sample: fund manager clients (23%) and asset owners who conduct manager searches (18%). For the remainder there may even be a negative performance bias. Poorly performing portfolios may be *more* likely to be submitted for monitoring in order to diagnose the problem. To some extent, the positive and negative biases should offset each other. In unreported robustness checks we exclude portfolios provided by fund managers or for manager searches. Although average alphas do become smaller, our results remain qualitatively unchanged.

We merge the transaction- and portfolio-level data from Inalytics with security price, market capitalization and benchmark data from Morgan Stanley Capital International, FTSE Group and Russell Investments, as well as analyst coverage and earnings announcement data from I/B/E/S.[13] In order to remove the influence of outliers, we winsorize all stock return and portfolio data at the one percent level.

B. Summary Statistics

Table II presents summary statistics for the variables of interest in our study. Detailed variable definitions can be found in the appendix.

Panel A summarizes performance at the portfolio level. Performance in our sample is above the market average, with mean annualized alphas of between 1.2 and 1.6 percent depending on the risk adjustment. However, only 13-14% of portfolios have alpha that is statistically significant at the 5% level. Market betas are typically close to one, while average Fama-French-Carhart factor loadings show slight tilts towards small, growth, and momentum stocks. Standard deviations are normal for actively managed portfolios (most falling between 19.9% and 28.8%) and median/average tracking errors of 5-6% are in line with standard institutional risk limits.

Panel B of table II summarizes the characteristics of portfolio holdings. The institutions in our sample are highly active, with active shares (see Cremers and Petajisto (2009)) of around 70%. The portfolios are also highly concentrated: on average, 38% of a portfolio's total value is contained in its ten largest holdings, corresponding to a holdings Herfindahl index 4.3 times greater than that of the benchmark. Portfolios are relatively large with a mean AUM of $495 million and a median of $249 million. The mean is inflated by several very large portfolios (up

[13] Analyst coverage data are from the I/B/E/S summary history file, while earnings announcement dates are from the detail actuals file.

to \$14 billion). Median portfolio turnover is around 66% per annum, with a median holding period of 1.5 years, indicating that most institutions in our sample have a medium- to long-term investment focus. Individual portfolio sample lengths range from one to twelve years with a mean of 4.5 years.[14]

Panel C of table II reports execution statistics for buy and sell orders, and selected characteristics of associated stocks. An *order* is defined as a group of one or more *trades* (or *transactions*) that together constitute an investment decision, where each *trade* is a single instruction to a broker to purchase or sell a particular number of shares, and is executed at a single price.

The order execution statistics for our dataset are similar to those reported in Keim and Madhavan (1995) and Chan and Lakonishok (1995). The majority of orders are executed over one or two days, and in one or two separate transactions. It is possible for orders to take several weeks or more than ten transactions to fill, but these instances are rare. Our data differs slightly from that of Keim and Madhavan in showing no significant difference between execution time for buys and sells. Mean buy and sell orders are also of similar sizes, both in dollar terms (\$0.95m and \$0.93m, respectively) and as a fraction of total portfolio value (both 0.11%). Order size as a percentage of total volume in the share is extremely positively skewed, with medians of 0.56% and 0.51% for buys and sells, respectively, but means of 8.25% and 7.99%. The top percentile of orders constitute over 70% of volume.

Also shown in Panel C is the average number of analysts issuing year-end forecasts on the stocks in our sample: 15.79 for purchases and 15.96 for sales. The (untabulated) maximum number of analysts for any stock is 57.[15] Market capitalization has a higher mean (\$25 billion) than that reported by Keim and Madhavan (1995) and Chan and Lakonishok (1995), which can be explained by aggregate equity market growth since the early 1990s. Average share turnover in traded stocks is around 2.3% per day.

[14] The 99th percentile of average holding period exceeds the 99th percentile of sample length because we are reporting the inverse of annual turnover rather than the average *measured* trade duration. The inverse of turnover gives a more accurate picture of the average holding period because the trade lengths that we measure directly (using the method described in section I.*C*) are truncated at the end of each portfolio's sample period.

[15] I/B/E/S does not distinguish between stocks covered by zero analysts and stocks with missing data (which is more often the case for international than US stocks), thus the minimum number of analysts is one.

C. Holding Period Measurement

In this subsection we describe our method of measuring the holding period of a round-trip trade and present additional statistics for various holding period lengths.

A *round-trip trade* (also called a *position*) is comprised of an opening order and any number of closing orders. To match opening and closing orders we use an intuitive *first-in-last-out* (FILO) algorithm. A new round-trip trade begins with every order and ends when the number of shares held in the portfolio (adjusted for corporate actions) returns to its original value at the time of the opening order.[16] The disadvantages of this algorithm are that it (1) generates overlapping trades and (2) sometimes double-counts purchases and sales—for instance, a sale order can constitute the end of a buy position and the beginning of a sell position at the same time. For this reason, we analyse buys and sells separately.[17]

Table III reports summary statistics for the number and size of positions in our sample, divided into holding period buckets of increasing length. For both buys and sells, position size grows monotonically with holding period length. Positions with holding periods of less than one month have an average value of $650,000-$700,000 (or about 0.2% of the portfolio), which increases to $2.1m-$3.4m (or about 0.5% of the portfolio) for holding periods of greater than two years. Total position value is greater above ($1.1trn) than below ($0.7trn) the median holding period, confirming that the institutions in our sample generally have long-term mandates.

II. Predictions of Strategic Trading Models

A. Kyle (1985)

Under the assumption that information is revealed only to a single monopolist investor, the Kyle (1985) model predicts that stock prices will convergence to fundamental values at a constant rate. Despite the fact that prices follow a random walk from the point of view of the market maker, an econometrician able to observe the information sets of all traders would view the expected price path as a straight line (with returns declining over time (t) at rate t^{-1}).

Informed investors trade at every available opportunity for as long as there is a difference between market price and fundamental value. Trading intensity, defined as the coefficient on the

[16] See the appendix for a worked example of how we implement this algorithm.
[17] Since the managers in our sample are not permitted to take short positions, the returns on sold stocks can be interpreted as the opportunity costs of trading. Nonetheless, the majority of our analysis is conducted on purchases only, where the double-counting issue does not arise.

price differential in the optimal trading rule, increases at rate $(1-t)^{-1}$.[18] The increasing trading intensity exactly offsets the declining gap between price and fundamental value, and thus trade size remains constant (in expectation) over the trading period.

B. Holden and Subrahmanyam (1992)

The setup of Holden and Subrahmanyam's (1992) model is identical to that of Kyle (1985), except that at least two traders know the fundamental value of the stock with certainty. Because they internalize the effect of competitors' trades on the market price, each informed trader initially places larger orders with the market maker than would a corresponding monopolist.

Increasing the number of informed traders causes trading activity to be "shifted forward" in time. That is, traders are more aggressive in earlier trading rounds, which causes prices to adjust more rapidly, which in turn lowers trading activity in later rounds. In the limit as the number of informed traders increases to infinity, the market converges to strong form efficiency (i.e. instantaneous price adjustment).

Holding fixed the number of competitors (two or more) and increasing the number of trading rounds also results in convergence to strong form market efficiency. At the same time, perhaps counter-intuitively, trading activity tends to zero. This is because the variance of noise trading is assumed to be proportional to the time between trading rounds (which goes to zero), and a lower intensity of noise trading provides less opportunity for informed traders to conceal their information. Since the number of trading rounds is large in real-world markets, this model provides a natural null hypothesis for our empirical tests.

C. Foster and Viswanathan (1996) and Back, Cao, and Willard (2000)

If, instead, informed traders' signals are imperfectly correlated, several alternative predictions follow. Figure 1, panel A, illustrates these predictions using the method of Foster and Viswanathan (1996, pp.1453-4). We solve the model numerically, setting all variance parameters to 1 and the correlation between information signals to 0.181819, as they do. We then simulate 100,000 trading paths of 252 trading rounds each, and plot the average trade size and cumulative return (analogous to the price) over time.[19] We normalize the starting price to 1 and the true value of the asset to 2.

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[18] Recall that time is defined on the interval $(0,1)$.

[19] We solve the model with 300 trading rounds but only simulate 252 rounds due to discretization errors towards the end of the trading period. 252 is the approximate number of trading days in a calendar year.

We consider the monopolistic case and the imperfectly-competitive case with either 2 or 5 informed traders.

Under imperfect competition, prices start converging to fundamental values at a faster rate than in the monopolistic case (the "rat race"), but the rate of convergence declines until it eventually falls below that of the monopolistic case (the "waiting game"). Thus the expected price path will be concave instead of linear.[20] Trading activity has a similar shape to that in Holden and Subrahmanyam's (1992) model, but does not decline to zero as the number of trading periods increases, due to the "waiting game" effect.

Introducing more informed traders has two effects. First, trading is "shifted forward" in time, but to a greater extent in the "rat race" stage. Second, prices converge more quickly to fundamental values in the "rat race" stage but more slowly in the "waiting game" stage.

While the shape of the price path and associated trading activity can be straightforwardly matched to the data, a complication arises in translating the effects of competition. This is because the theoretical models treat several important parameters—the average difference between prices and fundamental values, the time until private signals are revealed to the public, and the variance of the asset payoff—as exogenous. In reality an increase in the number of informed traders should affect these parameters as well. In particular, a larger number of competitors should result in less available private information *ex-ante*, and thus a lower initial price differential.

Panel B of figure 2 illustrates the potential effect of this endogeneity. We simulate the model as before, but adjust the starting price upward from 1 to 1.2 as the number of competitors increases from 2 to 5. Returns are now reduced to a greater extent in the "rat race" phase because of the smaller initial pricing differential, while the "waiting game" phase is less affected. Correspondingly, more competition leads to lower trading activity overall (via the smaller price differential) but in the short run trade sizes remain larger. Of course, the above predictions depend on the strength of the endogenous response, about which the models are silent. Therefore, in our empirical tests we allow the effect of competition to vary arbitrarily by post-order horizon.

Table IV summarizes the predictions discussed above, in the form of specific testable hypotheses which we will refer to throughout the article.

[20] Returns still decline over time at rate t^{-1}, but with a larger coefficient on t in the denominator.

III. Empirical Analysis

A. Equilibrium Dynamics

In this subsection we make use of a traditional event study to investigate the long-run equilibrium predictions of the various Kyle-type strategic trading models, as described in panel A of table IV.

A.1. Post-Order Alpha

Since the main aim of the article is to improve our understanding of the alpha decay phenomenon, we begin with the models' equilibrium predictions for prices and returns following an information event. We rely on an *ex-post* characterization of information events—that is, buy (sell) orders that are on average followed by positive (negative) stock-level alpha.

The primary method of risk adjustment that we use throughout the paper is the Fama-French-Carhart (FFC) four-factor model (Fama and French (1993); Carhart (1997)), which is standard in the empirical asset pricing literature. However, we show in section IV that the results are robust to the use of alternative risk models.

To compute stock level alphas, we first estimate time-varying FFC factor loadings ($\hat{\beta}_{k,t}$) for each stock i from the following regression:

$$r_{i,\tau} - r_{f,\tau} = \alpha + \beta_{1,t}\left(r_{m,\tau} - r_{f,\tau}\right) + \beta_{2,t}(SMB_\tau) + \beta_{3,t}(HML_\tau) + \beta_{4,t}(UMD_\tau) + \varepsilon_{i,\tau}, \quad (1)$$

using daily data from $\tau = t - 251$ to $\tau = t$ (a one-year rolling window). In equation (1), $r_{i,\tau}$ is the daily return on stock i, $r_{f,\tau}$ is the domestic risk-free rate, $r_{m,\tau}$ is the return on the domestic stock market, SMB_τ is the return on a domestic small minus big market capitalization portfolio, HML_τ is the return on a domestic high minus low book-to-market portfolio, UMD_τ is the return on a domestic portfolio of stocks with high past returns minus stocks with low past returns, and $\varepsilon_{i,\tau}$ is a stock-specific error term.[21] We correct for infrequent trading in small stocks using the method of Dimson (1979), and identify the appropriate domestic market from the client-specified benchmark index.

[21] To construct the factor replicating portfolios we follow the methodology of Kenneth French, as described on his website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The sole exception is our construction of international HML factors, which are computed as the difference between the MSCI Value and MSCI Growth indices for each country. We do this because available accounting data is sparse for some of the markets in our sample.

Once we have the estimated $\hat{\beta}_{k,t}$s, we compute daily alpha estimates $\hat{\alpha}_{i,t}$ by subtracting beta-matched factor portfolio returns from the stock returns, as follows:

$$\hat{\alpha}_{i,t} = r_{i,t} - \left[r_{f,t} + \hat{\beta}_{1,t}\left(r_{m,t} - r_{f,t}\right) + \hat{\beta}_{2,t}(SMB_t) + \hat{\beta}_{3,t}(HML_t) + \hat{\beta}_{4,t}(UMD_t)\right]. \qquad (2)$$

To link stock alphas to trading profits, we match each order j (from portfolio p) to the daily alphas of the corresponding traded stock i, for 18 months (378 trading days) following the date ($\tilde{t}$) of the final transaction in the order:

$$\tilde{\alpha}^{D}_{j,p,d} = \hat{\alpha}_{i,\tilde{t}+d}, \qquad d = 1, \dots, 378. \qquad (3)$$

On day one in event time ($d = 1$), we adjust each alpha for the difference between the volume-weighted average execution price and the market closing price. Thus all first-day alphas we report are based on actual execution prices, though our results remain qualitatively similar if we omit this adjustment. From the daily series we derive the monthly series $\left\{\tilde{\alpha}^{M}_{j,p,m}\right\}_{m=1}^{18}$ by geometrically compounding the alphas every 21 trading days:

$$\tilde{\alpha}^{M}_{j,p,m} = \prod_{d=21(m-1)+1}^{21m} \left(1 + \tilde{\alpha}^{D}_{j,p,d}\right) - 1\,, \qquad m = 1, \dots, 18. \qquad (4)$$

We then compute average alphas across all open positions (i.e., round-trip trades that have not yet been closed out) for each day after the initial order. Taking averages has the effect of netting out, by a law of large numbers argument, future changes in fundamentals that are independent of the information event that motivated the initial order. We include only open trades and use actual first-day execution prices to ensure that the alphas we report are feasible in practice. While we do rely on market closing prices to compute the alphas on subsequent days, we show in section IV that similar patterns emerge if we compare holding period returns using *only* actual execution prices, suggesting that unobserved transaction costs do not drive the results. However, our main focus is the evolution of alpha *within* round-trip trades (which can be thought of as marked-to-market trading performance).

The average alphas are calculated as follows:

$$\bar{\alpha}_d^D = \frac{1}{\sum_{j=1}^{J} 1_{\{d \leq h_j\}}} \sum_{j=1}^{J} \tilde{\alpha}_{j,p,d}^D \, 1_{\{d \leq h_j\}}, \qquad d = 1, \dots, 378, \tag{5}$$

where h_j is the holding period (in number of trading days) of the position originating with order j, and J is the total number of buy or sell orders in the sample (averages for buys and sells are computed separately). Holding periods are measured using the FILO algorithm described in section I.C. The indicator variable $1_{\{d \leq h_j\}}$ equals one when the number of days elapsed since the opening order is less than the measured holding period (i.e., the position is open), and zero otherwise (i.e., the position is closed). Monthly averages $\{\bar{\alpha}_m^M\}_{m=1}^{18}$ are defined analogously, replacing D, d and h_j in equation (5) with M, m and $\lfloor h_j/21 \rfloor$, respectively.[22] For ease of comparison with the theoretical predictions, we also compute cumulative average alpha series $\{\bar{\mathrm{A}}_d^D\}_{d=1}^{378}$ and $\{\bar{\mathrm{A}}_m^M\}_{m=1}^{18}$, which are analogous to the evolution of the average stock price.

Figure 2 displays the cumulative and incremental monthly average alpha series: $\{\bar{\mathrm{A}}_m^M\}_{m=1}^{18}$ and $\{\bar{\alpha}_m^M\}_{m=1}^{18}$, respectively. Cumulative alpha following buy orders is 0.59% after three months, 1.29% after 12 months and 1.41% after 18 months. The twelve-month total is in line with annualized alpha at the portfolio level (see table II, panel A), and the quarterly total is similar to the 0.74% reported by Puckett and Yan (2011).

The price adjustment path is gradual and concave, confirming the predictions of Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) (table IV, panel A, hypothesis H_2^E part 1). Incremental alpha decays nearly monotonically month by month, has the predicted power-function shape, and approaches zero by month twelve.[23] Both the null hypothesis of zero post-purchase alpha (table IV, panel A, hypothesis H_0^E part 1) and the Kyle (1985) model's prediction of linear price adjustment (table IV, panel A, hypothesis H_1^E part 1) are rejected, though the data is closer to Kyle (1985) than to the null (taken from a strict interpretation of Holden and Subrahmanyam (1992)).

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[22] $\lfloor x \rfloor$ is the floor operator.

[23] While a power function provides the best fit for the shape of the post-purchase decay ($R^2 = 0.88$), it is worth noting that the fit of an exponential function is almost as good ($R^2 = 0.80$). This observation is broadly consistent with models of information percolation, which predict exponential convergence of beliefs to a common posterior (see Duffie, Giroux, and Manso (2010)). However, these models are more applicable in over-the-counter markets than in the exchange-based setting of our study.

Figure 2 documents the alpha decay phenomenon in greater detail and for a broader range of portfolios than in previous work, showing that it is a general feature of institutional trading rather than a narrow anomaly within the 13F mutual fund data. The time taken for alpha to decay completely (twelve months) is towards the longer end of estimates in previous studies, underscoring the importance of the phenomenon for real outcomes.

The alpha pattern following sale orders is markedly different. Post-sale alpha is mostly positive (entailing *negative* profits for the fund managers) but does not show the same clear pattern of incremental decay. Total cumulative post-sale alpha is 0.35% after 18 months. We interpret this finding as evidence that institutional sales are not informed, in line with the literature showing that sales have smaller price impact than buys. Indeed, positive alphas following sales may indicate that the long-only fund managers in our sample pay a cost to other informed traders when they wish to sell. This result is consistent with investment opportunity set of a long-only manager.

Of course, it is possible that our choice of risk model omits important factors to which the traded stocks are exposed. If the resulting bias is positive and sufficiently strong, it could mean sales are actually informed while purchases are not. However, omitted factors would presumably be equally relevant whether a stock is purchased or sold, thus any biases should be reduced or eliminated in the difference between post-purchase and post-sale alphas. Post-sale alphas can also be interpreted as a measure of the opportunity costs of trading, because capital for new purchases must first be freed up through sales of existing positions (assuming no capital inflows).[24] The difference between the alphas of buys and sells is therefore a measure of performance net of opportunity costs. As the rightmost panel of figure 2 shows, net-of-opportunity cost performance follows approximately the same path as gross performance, with buys outperforming sells by 1.04% over 18 months.

Table V presents the incremental post-order alphas in numeric form for selected months. In addition to the full-sample results, we also report post-order alphas for a sample of what we call "new" information events, defined as orders with no prior trading activity in the stock for at least 18 months. This subsample rules out potential confounding effects of overlapping trades. For the full sample, standard errors are clustered at the stock level to account for dependency introduced

[24] Consistent with the managed-account nature of our portfolios, the capital flows are infrequent and discontinuous. This is in contrast to mutual fund flows.

by the overlapping trades, while in the new-information-event subsample they are clustered at the portfolio level to account for common investment style.[25]

Incremental alpha patterns are similar in the full sample and the new-information-event subsample. Following buy orders (panel A), incremental alpha declines from a highly significant 37.05 (40.96) basis points in the full sample (subsample) in the first month, to 4.37 (1.20) bps in month eighteen. Incremental alpha becomes insignificant by month 12 for the full sample but remains marginally significant until month 13 for the subsample. Thus the overall level and decay time of post-purchase alpha is slightly higher in the subsample, which is expected given that the subsample captures alpha in earlier stages of decay by construction.

As in figure 2, post-sale alphas (panel B) are mostly positive but also mostly insignificant for both the full sample and the subsample. The difference between buy and sell alphas (panel C) appears to decay more quickly than the buy alphas, and also decays more quickly in the subsample.

A.2. Follow-Up Trading Activity

We now examine the long-run dynamics of trading behaviour by computing average follow-up net purchases in the same stock ($NetSize$) for up to 18 months after each initial order. "Net" means that follow-up purchases and sales are both included in the averages, in order to capture potential reversals of trade direction induced by changes in the market price. $NetSize$ is measured as a fraction of the portfolio's assets under management (AUM), reported in basis points, with net buys having positive signs and net sells having negative signs. Note that follow-up trades are aggregated by day or by month rather than at the order level. To maintain consistency with the measurement of the alphas, we drop additional trades from the averages once the position has been closed.

In the theoretical models considered in section II, speculators wish to participate in every trading round. However, taking into account real-world frictions such as transactions costs (e.g. flat brokerage fees), as well as ambiguity about the true probability distribution of information signals, number of competitors, and time remaining until information becomes public, it is no longer clear that informed fund managers will choose to trade at every opportunity. Thus we

[25] While there may be similarities across portfolios managed by the same fund manager, variation in client specifications (e.g. risk tolerance and benchmark) can result in substantial differences even within the same management company. The results are robust to clustering at the fund manager level (albeit with higher p-values) and also robust to clustering at the calendar quarter level.

decompose the $NetSize$ variable into two components of trading activity: $FracTrading$, the fraction of portfolios for which at least one follow-up trade is observed on a given day, and $NetSizeEx0$, the average trade size excluding zeros, or, in other words, the average size of those trades that *do* take place on a given day.

Figure 3 plots the event-time evolution of daily trading activity for the new-information-event subsample (orders with no prior trading activity for eighteen months) using the above three measures. For trading activity it is more natural to focus on the subsample, since it precludes multiple-counting of the same trade as both a new opening order and part of the follow-up trade sequence from previous orders.

Two observations immediately stand out from figure 3. First, trading activity in a stock does not cease after completion of the initial "package" of transactions that form an order (the focus of previous papers by Chan and Lakonishok (1995) and Keim and Madhavan (1995)). Rather, by all measures, average follow-up trading activity continues seamlessly after the initial order. $NetSize$ and $NetSizeEx0$ are positive for as long as the available alpha is significantly positive: approximately twelve months, corresponding to the alpha decay period in figure 2. Although individual fund managers rarely trade every day (around 8% of portfolios have follow-up trades on a given day in the first week, falling to around 1% per day after twelve months), their propensity to trade and the size of the trades they do make display the same pattern over time. This suggests that long-run strategic trading is lumpy, but the lumps are on average driven by the same information event. As further evidence for the longevity of information signals, even for long breaks between trades, we confirm that average $NetSizeEx0$ still declines following three-month gaps in trading activity. If post-gap trading were in fact motivated by new information events, the observed average trade size would rise, in line with the unconditional average.

The second key observation from figure 3 is that average trading activity *declines* over time and is roughly proportional to the gap between the initial price and the fully-adjusted price (i.e., the price at which incremental alpha reaches zero). This implies that trading activity also declines according to a power function.[26] Net size excluding (including) zeros is approximately 5 bps (0.4 bps) per day in the first week after an initial purchase, falling to zero and then turning negative after 200-250 trading days.

[26] $R^2 = 0.96$.

After an initial sale, net size excluding (including) zeros is approximately -5 bps (-0.4 bps) per day in the first week, and approximately -1 bps (-0.02 bps) per day after one year. It is interesting to note that follow-up selling follows the same pattern of declining intensity as follow-up buying, despite the fact that sales are not informed. This finding can be explained by the liquidity requirements of long-only managers. The portfolios in our sample are managed accounts and thus do not have continuous inflows and outflows as do, say, mutual funds. In order to make new purchases, other stocks in the portfolio must be sold. As such, buying and selling should be mirror images of each other.

Table VI reports the statistical significance as well as the economic magnitudes for $NetSize$ aggregated at the monthly level, for both the full sample and the new-information-event subsample. As with the alphas, standard errors are clustered at the stock level for the full sample and at the manager level for the subsample.

For the subsample, after initial buys, average monthly follow-up net purchases (including zeros) start at a statistically and economically significant 8.69 bps in the first month, and decline to an economically trivial 0.25 bps by month 12, after which they turn negative. For post-sale follow-up trading, net purchases are -10.92 bps in the first month and rise to -0.72 bps by month 18, all statistically significant. The results for the full sample are virtually identical.[27] Magnitudes would be larger if we were to separate follow-up purchases and sales instead of reporting net trading, but none of the conclusions would change.

Overall, the results on follow-up trading behaviour reject the null hypothesis of negligible additional trading based on Holden and Subrahmanyam (1992) (table IV, panel A, hypothesis H_0^E part 2), as well as the alternative hypothesis of constant additional trading, taken from Kyle (1985) (table IV, panel A, hypothesis H_1^E part 2). Instead, the results are consistent with Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) (table IV, panel A, hypothesis H_2^E part 2). If we take the theoretical models seriously, our findings indicate that fund managers behave strategically in response to perceived competition from other investors, whose private information

[27] The fact that there is almost no difference between the full sample and the subsample may run counter to the reader's intuition. The reason for this fact is that repeated trading tends to be highly clustered: some trades are once-off, but when there *are* follow-up trades there tend to be many of them. By eliminating orders with recent prior trading activity we eliminate most of the whole sequence, leaving a greater proportion of once-off trades in the sample. This has a downward effect on average trade size, but is offset by the fact that the remaining trades belonging to sequences tend to be larger because they are, by construction, the earlier trades in the sequence.

is imperfectly correlated with their own. This provides a plausible candidate explanation for the observed delays in price adjustment.

B. Effects of Increased Competition

We now turn our attention to the effects of increased competition on the equilibrium outcomes studied in section III.A. Microstructure theory predicts certain specific responses, outlined in table IV, panel B. If strategic trading is indeed responsible for slow alpha decay, we should be able to confirm at least some of these predictions in the data. Ideally the same models that were rejected in section III.A. should also be rejected here.

To measure the degree of competition among informed traders, we rely on a common empirical proxy: the number of security analysts covering each traded stock ($Analysts$). This proxy was initially suggested by Holden and Subrahmanyam (1992) and has since been used in a similar application by Pasquariello and Vega (2013). Analyst reports are well known to be informative for future stock returns (e.g. Womack (1996); Bradley et al. (2014)) and to incite trading by buy-side investors, both before (e.g. Irvine, Lipson, and Puckett (2007)) and after (e.g. Busse, Green, and Jegadeesh (2012)) the reports are officially released.

In a separate study on the momentum effect, Hong, Lim, and Stein (2000) use analyst coverage as a proxy for information asymmetry. These two interpretations are compatible because greater competition for information about a stock increases the likelihood that a particular piece of information will become public.

Hong, Lim, and Stein (2000) also point out that market capitalization is highly correlated with analyst coverage and should be included as a control variable. We go a step further. The component of market capitalization that is uncorrelated with analyst coverage is itself an indirect proxy for the aggregate attention paid to a stock (through channels other than sell-side research) and thus another proxy for competition. We would therefore expect to see broadly similar results whether we use analyst coverage or market capitalization.

We do not measure the number of competitors using concurrent trading within our sample for two reasons. First, herding in *trades* within our dataset is relatively rare, possibly because the wide coverage of international markets means we observe a smaller fraction of trades in any single market. Second, fund managers in most cases do not observe which of their competitors are active in a given stock in real time, and so should make strategic decisions based on expected competition rather than realized competition. Analyst coverage can be thought of a measure of expected competition and is easily observable to all market participants.

B.1. Effect of Competition on Post-Purchase Alpha

To test the effect of competition on price adjustment, we use a standard panel regression with portfolio fixed effects. We therefore measure the effect of competition *within* portfolios, and also within the same types of trade through event-time (by controlling for trade characteristics). The dependent variable, $\tilde{\alpha}^M_{j,p,m}$, is the same as in equation (4), but now only includes *post-purchase* alphas. We discard post-sale alphas as a consequence of our finding that sales are not informed. $\tilde{\alpha}^M_{j,p,m}$ is indexed along three dimensions: trades (j), portfolios (p), and event-time in months (m). The trade index j is a combination of stock i and calendar time t. As in section III.A., we drop alphas from the regression once positions have been closed.

To allow for arbitrary effects of competition at different points in event time, we use a fairly general piecewise-linear specification: each independent variable is interacted with dummies for particular stretches of event-time. This approach is analogous to running separate regressions for different post-order periods, except that the estimation is done jointly.

Formally, we estimate the coefficients (δ, βs, γs and ϕs) in the following equation, by OLS:

$$\begin{aligned}\tilde{\alpha}^M_{j,p,m} = \delta_p + \beta_0 Analysts_j + \gamma_0{}' Controls_{j,p} \\ + \sum_{\eta \in \{\{1\},\{2,3\},\{4,5,6\}\}} \left[\varphi_\eta + \beta_\eta Analysts_j + \gamma_\eta{}' Controls_{j,p}\right] 1_{\{m \subseteq \eta\}} + \varepsilon_{j,m},\end{aligned} \tag{6}$$

where η identifies either the first month ($\{1\}$), the remainder of the first quarter ($\{2,3\}$), or the second quarter ($\{4,5,6\}$).[28] The indicator variable $1_{\{m \subseteq \eta\}}$ equals one when the monthly alpha on the LHS of the equation is from the post-order period indicated by η, and zero otherwise. $\varepsilon_{j,m}$ is the error term. The coefficients β_0 and γ_0 represent the baseline effects of the explanatory variables, while the $\beta_\eta s$ and γ_ηs capture the incremental effects in the short run (the total effect is the sum of both). The φ_ηs are the incremental intercepts for the post-order horizons specified by η, and can also be thought of as horizon fixed effects.

[28] We choose these groupings for ease of presentation; the results are similar if we use six quarterly dummies or eighteen monthly dummies, though they are quite noisy in the latter case.

$Controls_{j,p}$ is a vector of control variables. As discussed above, the most important of these is the stock's market capitalization ($MarketCap$). We also include the dummy variables $LiqProv$ and $EAWeek$ to capture two other potential sources of decaying alpha: liquidity provision and proximity to earnings announcements, respectively. Nagel (2012) shows that short-term contrarian strategies proxy for the returns generated by liquidity-providing market makers. As such, we consider a purchase to be liquidity providing if the previous day's stock return was negative. The earnings announcement dummy takes a value of one if a trade takes place within one week of an announcement. It is included to control for the post-earnings-announcement drift, which has been found to have a similar decaying pattern (see Bernard and Thomas (1989), fig. 1).

We also include additional stock characteristics that may be correlated with future alphas: one-, three- and six-month past returns; share turnover (total trading volume divided by shares outstanding) on the day of the trade; and a dummy for whether or not the stock was included in the client-specified benchmark index. To account for the possibility that winning and losing positions may differ in likelihood of being closed out (e.g. the disposition effect documented by Shefrin and Statman (1985) and Odean (1998)), we include the position's ex-post holding period (measured as in section I.C.). Finally, because purchases of stocks that are already overweight in the portfolio relative to the benchmark may be less likely to be undertaken for rebalancing reasons, we include the difference between the traded stock's portfolio weight and its benchmark weight at the time of the trade.

While time-invariant portfolio characteristics are captured by the fixed effects regression setup, some important attributes are time-varying. Thus our control variable vector contains the portfolio's AUM, its active share (a measure of the similarity of portfolio holdings to those of the benchmark) and the holdings' Herfindahl index, all measured on the day of the trade.

Lastly, the control variable vector contains three measures of the economic environment in which the trade takes place: the past quarterly return on the benchmark index, the volatility of the benchmark (estimated from daily returns over the preceding quarter), and a dummy for the 2007-2009 financial crisis/recession.

Table VII presents the estimated coefficients for several versions of equation (6) using different sets of control variables. We also estimate the regression using both the full sample of trades and the new-information-event subsample (orders with no prior trading activity for eighteen months). As in section III.A., standard errors are clustered at the stock level for the full sample and at the portfolio level for the subsample. For clarity, we mostly focus on the coefficients that are relevant for the hypotheses outlined in section II. The extended tables are available from the authors on request.

Whether the number of competing informed traders is measured by analyst coverage or simply by the size of the stock, with or without additional control variables, and for both the full sample and the subsample, the overall pattern is the same. In absolute terms, competition decreases post-purchase alpha only in the short run, and to a greater extent in the very short run.

Focusing first on the subsample results with no controls (column 5), the incremental coefficient on analyst coverage in the first month after the initial purchase is a highly significant -1.95, falling to -0.82 (but remaining highly significant) for the remainder of the first quarter, and falling further to an insignificant -0.19 for the second quarter. The baseline coefficient is 0.04 and insignificant, indicating that the effect of competition on post-purchase alpha is confined to the short run. The results for market capitalization alone (column 6) are similar at -0.49 (highly significant) for month one, -0.09 (marginally significant) for months two and three, and insignificant thereafter. The baseline coefficient is also insignificant and economically close to zero. Estimating the effect of analyst coverage and market capitalization together (column 7) reduces the magnitude of the coefficients on both variables but mostly maintains their significance, especially in the very short run. Finally, including a full set of controls (column 8) further reduces the magnitudes and slightly lowers the level of significance, but the overall tenor of the results do not change. With the full set of controls, the incremental effect (compared to an insignificant baseline) of one additional analyst on post-purchase alpha in the first month is -1.27 basis points (highly significant at the 1% level). In months two and three the incremental effect is -0.66 bps (significant at the 5% level), and it is insignificant thereafter. The coefficients are similar though slightly longer-lasting for the full sample (columns 1-4).

The economic magnitudes of these effects are also significant. In the full specification of column 8, a one standard deviation increase in analyst coverage leads to a total decrease in post-purchase alpha of 10.8 bps in the first month (26.6% of the unconditional mean), a total decrease of 5.9 bps per month in the remainder of the first quarter (36.1% of the unconditional mean), and no effect thereafter. For market capitalization the same figure is 14.8 bps in month one (36.2% of the unconditional mean) and zero thereafter.

Column 8 also shows the coefficients for one of the additional control variables, which is worth discussing because its effects are so pronounced: the liquidity provision dummy. Liquidity-providing purchases earn an extra 15.95 bps of alpha in the first month (38.9% of the unconditional mean), but carry no additional premium thereafter. This raises the question: to what extent can the overall alpha decay pattern be attributed to a short-term liquidity-provision effect? We answer this question in section IV.

B.2.1. Effects of Competition on Opening Order Size

In this subsection we examine the effect of competition on opening orders. We consider the effects on follow-up trades in subsection B.2.2.

For the opening orders we use a similar fixed-effects panel regression setup. The dependent variable ($OpeningSize_{j,p}$) is the size of the opening order measured either as a fraction of portfolio AUM or in US dollars, and is indexed by order number j and portfolio number p. Calendar time t is subsumed by the order index. As in section III.B.1, the dependent variable only includes *purchase* orders. It also only includes orders from the new-information-event subsample (orders with no prior trading activity for eighteen months), so as not to conflate opening orders and follow-up trades (which we analyse separately).

The equation we estimate is as follows:

$$OpeningSize_{j,p} = \delta_p + \beta \cdot Analysts_j + \gamma' Controls_{j,p} + \varepsilon_j, \tag{7}$$

where δ_p are the portfolio fixed effects, ε_j is the error term, and $Controls_{j,p}$ is a vector containing the same control variables as used in equation (6). The controls cover cross-sectional stock and trade characteristics, time-varying portfolio characteristics, and the market environment (see the discussion in section III.B.1 for further details). Standard errors are clustered at the portfolio level.

Table VIII presents the estimated coefficients (βs and selected γs). The first result is that analyst coverage is positively related to order size. This basic relationship is consistent across all regression specifications: with or without control variables, and for order size measured as a fraction of AUM or in dollars. For each additional analyst covering the traded stock, the size of the opening order rises by 0.36 basis points, or $12,980 (columns 1 and 5). When control variables are included (columns 4 and 8), the effect falls to 0.29 bps or $9,570 but remains highly significant (at well below the 1% level). Regarding economic significance, for the specification with controls, a one standard deviation increase in analyst coverage increases opening order size by 27.9% relative to its unconditional mean. As expected, the effect of market capitalization goes in the same direction as that of analyst coverage. Stocks that are $1bn larger see opening orders that are on average 0.05 bps ($2,730) larger. Magnitude wise, a one standard deviation increase in market capitalization is associated with an 23.0% increase in order size, which is similar to the magnitude for analyst coverage.

The effects of the additional control variables (columns 4 and 8) go in sensible directions. A 1% increase in share turnover (total trading volume divided by shares outstanding) leads to opening orders that are larger by 0.79 bps or $32,500. Higher share turnover can be interpreted either as greater activity from noise traders, or as a signal of more private information in the stock (see Easley et al. (1996)). Both interpretations should lead to larger trades by informed traders, either because higher levels of noise trading reduce price impact (Kyle (1985), Theorem 3) or because the information signal is stronger. The coefficients on the $HoldingDeviation$ of the traded stock serve to emphasise the importance of portfolio rebalancing to the trading process. $HoldingDeviation$ is the difference between the weight of the traded stock in the portfolio and its weight in the benchmark. A more positive $HoldingDeviation$ therefore indicates a stock that is more overweight in the portfolio relative to the benchmark; it is not surprising that purchases would be smaller when a stock is already overweight. Lastly, the effect of AUM depends on whether order size is measured in dollars or as a fraction of portfolio value. In dollar terms, unsurprisingly, managers of larger portfolios tend to make larger orders. As a fraction of portfolio value, however, order size decreases: each additional $100m added to the portfolio leads to orders that are 0.31 basis points smaller. This finding is consistent with strategic trading: managers of larger portfolios will make proportionately smaller orders if they are concerned about price impact.

B.2.2. Effects of Competition on Follow-Up Net Purchases

Having established the effect of competition on the first order in a sequence, we now examine its effects on the rest of the sequence. Studying these effects separately allows us to include the initial order size as an independent variable in the regressions for follow-up trading activity; thus we are able us to test whether a competition-related increase in initial order size is offset by smaller follow-up net purchases.

We again use a panel regression setup with portfolio fixed effects and an event-time dimension, as in section III.B.1. The dependent variable is $FollowUpSize_{j,p,m}$, defined as the total size (fraction of AUM) of all trades executed in post-order month m in the same stock as order j (from portfolio p). As in the previous regression, we use only the new-information-event subsample to ensure that sequences of trades are uniquely identified. But unlike the previous regression, the dependent variable includes both purchase and sale orders, in order to capture net activity and allow for position reversals.

We estimate variants of the following regression by OLS:

$$FollowUpSize_{j,p,m} = \delta_p + \mathrm{B}_0{}'Z + \sum_{\eta \in \{\{1\},\{2,3\},\{4,5,6\}\}} \left[\varphi_\eta + \mathrm{B}_\eta{}'Z\right] 1_{\{m \subseteq \eta\}} + \varepsilon_{j,m}, \tag{8}$$

where $Z = [Analysts_j, OpeningSize_{j,p}, Analysts_j \times OpeningSize_{j,p}, Controls_{j,p}{}']'$,

and B_0 and B_η are coefficient vectors.

As in section III.B.1, all explanatory variables are interacted with dummies for specific post-order periods: the first month, the remainder of the first quarter, and the second quarter. The elements of the vector Z are the independent variables; in order: the number of analysts covering the traded stock ($Analysts_j$), the size of the opening order ($OpeningSize_{j,p}$), the interaction between analyst coverage and opening order size, and the same set of controls as in equations (6) and (7)—see section III.B.1. for details. To facilitate the interpretation of the coefficients on analyst coverage and opening order size, due to the presence of the interaction term, both variables are demeaned. Thus, the coefficients represent the effect of each variable on follow-up net purchases when the other is equal to its mean.

As noted in section II.C., the models of Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) predict two effects of competition on follow-up trading activity that pull in opposite directions: trading becomes more aggressive, but is also "shifted forward" in time. The interaction between analyst coverage and opening order size allows us to disentangle these effects.

Table IX presents the estimated coefficients from equation (8). The results are similar with or without controls, so we focus here on the full specification (column 2). To begin with, the direct effect of competition of follow-up net purchases is at its largest in the short run: the first month incremental coefficient is 0.158 bps, the second and third month incremental coefficient is 0.095 bps, and the second quarter incremental coefficient is 0.039, all highly significant, compared to an insignificant baseline. The economic magnitudes, for a one standard deviation increase in analyst coverage, are 16.7%, 21.7% and 25.2% of the respective unconditional means.

Holding competition constant, opening order size has a negative relationship with follow-up trading activity, supporting the idea that fund managers choose whether to make the same trade earlier or later. The interaction between analyst coverage and opening order size explicitly links this forward displacement of trades to competition. The results are intuitive and theoretically appealing. The incremental coefficients on the interaction are negative and declining as the horizon increases (-0.363 in the first month, -0.232 in months two and three, -0.031 in months four to six, and insignificant thereafter). Negative signs indicate that when analyst coverage is high at the same time that opening order size is large, follow-up net purchases tend to be smaller. This is what is meant by trades being "shifted forward" in time.

The interaction coefficients are also economically significant: moving from the lower quartile to the upper quartile of analyst coverage shifts the combined effect of a 1% increase in opening order size on follow-up net purchases from 0.98 to -3.05 bps in the first month, from -4.51 to -7.11 bps in the remainder of the first quarter, and from -4.89 to -5.83 in the third quarter.

B.3. Discussion

The relevance of competition for both post-purchase alpha and follow-up trading activity clearly rejects the null hypothesis, implicit in the Kyle (1985) model, of a single informed trader (table IV, panel B, hypothesis H_0^C). Increased attention from security analysts is associated with more aggressive trading and lower trading profits, providing strong evidence that competition contributes to more efficient price formation. These results underscore the importance of security analysts, especially at a time when their presence in the market has been in sharp decline.

The results are also inconsistent with a strict reading of Holden and Subrahmanyam's (1992) model (table IV, panel B, hypothesis H_1^C) because the effects of competition are mostly seen in the short run—beyond six months they disappear completely across all of our empirical specifications. Moreover, while competition reduces the overall level of alpha, the *rate* of decay is not much affected. Instead, these results confirm the "rat race" and "waiting game" phases of trading predicted by the heterogeneous information models of Foster and Viswanathan (1996) and Back, Cao, and Willard (2000), outlined in table IV, panel B, hypothesis H_2^C, parts 1–3.

One finding that is not fully consistent with the heterogeneous information models (and indeed all of the models we consider) is that competition does not reduce trading activity in the long-run "waiting game" phase (part 4 of hypothesis H_2^C); it merely has no effect. Perhaps expecting highly stylized models to match reality precisely is asking too much: the more basic insight that competition should have stronger short run effects is strongly validated. Recall also that hypothesis H_2^C part 2 required the additional assumption that the initial discrepancy between prices and fundamental values is also reduced by the presence of more informed traders. The models treat this difference, and many other clearly endogenous variables, as exogenous.

Taking these factors into account, it is remarkable that our results match the models' predictions as closely as they do. The conclusions drawn from the effects of competition are consistent with the overall equilibrium dynamics reported in section III.A. and thus further strengthen the case for strategic behaviour as a driver of slow price adjustment/alpha decay.

IV. Alternative Explanations

In this section we investigate potential alternative explanations for the alpha decay phenomenon that, if true, would go against the strategic trading hypothesis. Of course, the explanations we rule out do not constitute an exhaustive list, but are in our view the most plausible.

First we verify that the positive post-purchase alphas reported in section III are not simply artefacts of using equally weighted averages or the Fama-French-Carhart risk model. We then conduct a subsample analysis to rule out momentum trading strategies, liquidity provision premia, earnings announcement anomalies, and horizon-varying fund manager skill. Finally, we examine holding period returns using only execution prices to address the potential issue of unobserved transaction costs.

A. Robustness to Average-Weighting Method and Choice of Risk Model

Panel A of Table X reports average incremental post-purchase alphas for selected months using the methodology described in section III.A.1. Averages are weighted equally as in equation (5) or, alternatively, by the size of the opening order. Equal weighting is well-known to inflate portfolio returns, and there may be a concern that trading performance could also be affected in the same way. Weighting by order size alleviates this concern and brings the averages more closely in line with the actual profits earned by the fund managers. The alphas themselves are computed relative to the Fama-French-Carhart (FFC) risk model or, alternatively, relative to the client-specified benchmark. Berk and van Binsbergen (2014) argue that an appropriate benchmark for an active fund is the closest available passive investment because this represents the opportunity costs of the fund's investors. Due to the limitations of their data Berk and van Binsbergen are forced to choose passive benchmarks somewhat arbitrarily, but, fortunately, we observe the client-specified benchmarks directly.

Panel A of table X shows that the overall pattern of gradual alpha decay is preserved regardless of the weighting method or the choice of risk model. For the FFC alphas, order size weighting perhaps accelerates the decay slightly—alphas reach insignificance by month 9 instead of month 12—but the point estimates at nine months are not significantly different from each other.

Average monthly returns relative to the client-specified benchmark decline initially and then flatten out after nine months. However, they do not reach zero. The relative return in month 18 is 15.7 basis points for the equally weighted average and 14.6 for the order-size-weighted average (both significant at the 1% level). The observation that incremental relative returns do not decay completely can be attributed to risk factors not captured by the client-specified benchmarks. While some of these benchmarks have value/growth or size tilts, many do not, and none control for momentum. Exposure to these factors can nonetheless be considered a source of skill if clients cannot obtain the exposure elsewhere.

B. Subsample Analysis

Panel B of Table X reports average incremental post-purchase FFC alphas for various subsamples of the data, constructed as follows. First, even though our risk model corrects for stocks' exposure to a momentum *factor*, momentum is also a trading strategy (Jegadeesh and Titman (1993)). As such, we divide the sample into orders with positive and negative six-month past returns. Comparing the two, momentum orders are clearly have longer-lived post-purchase alpha. However, even though the decay is faster for contrarian orders (reaching insignificance by month 6), it is still gradual in an absolute sense. Momentum strategies may well be part of the story, but they are not all of it.

Second, we consider the effect of liquidity provision/demand on the observed trading alphas, especially in light of the large first-month coefficient on the liquidity provision dummy reported in table VII. Following Nagel's (2012) approach, we divide the sample into purchases following one-day negative returns (liquidity provision) and those following one-day positive returns (liquidity demand). While panel B of table X clearly reveals a short-term discount for liquidity-demanding trades, the overall decay pattern in both subsamples is similar. Figure 4 breaks the first month's post-purchase alpha into daily increments, demonstrating that the effects of liquidity are mostly felt in the first two *days* after the order. The results show that fund managers pay a once-off price concession to obtain liquidity and earn a once-off premium for providing it, but liquidity cannot explain the longer-term pattern of the alphas.

Third, we examine the influence of earnings-announcement-related anomalies. As Bernard and Thomas (1989) show (fig. 1 in their paper), stock prices tend to drift over time in the direction of earnings surprises in a way that resembles the alpha decay we observe. Frazzini and Lamont (2007) also document positive abnormal returns to a strategy that buys stocks just before announcements and sells them afterwards. In order to profit from either of these anomalies, fund managers would need to trade in a narrow window around announcement dates. Figure 5 shows a histogram of the proximity of orders in our dataset to the nearest earnings announcement, indicating that there is indeed increased activity in the week before. Thus, we divide the sample into orders that were executed within one week of an earnings announcement and those that were executed outside of this period. The results are reported in last set of rows in panel B of table X. Orders executed close to earnings announcements are more profitable at all horizons than those that are more distant, but both subsamples experience similar patterns of alpha decay, suggesting that earnings-related effects are not the primary cause of long-lived alphas.

Fourth, in panel C of table X we split the sample into trades by institutions with above- and below-median portfolio turnover (65 percent per annum) to check whether alpha decay is the result of short-term institutions being more informed (Yan and Zhang (2009)). In addition, by dividing the sample into above- and below-median holding periods (9 months), we check whether the decay seen in the averages is simply a consequence of superior performance of short-horizon *trades* (e.g. Puckett and Yan (2011)). Aside from the short-horizon trades' alphas decaying more quickly by construction, the pattern is similar in each of these subsamples.

C. Holding Period Returns

Until this point, we have used execution prices only to compute alphas on the first day after an order.[29] For every other post-order period, the incremental alphas have been calculated using daily market closing prices. This could potentially introduce a positive bias if the stocks traded in our sample have high bid-ask spreads or market impact. Therefore we compute holding period returns for all round-trip trades (positions) using only opening and closing execution prices:

$$r_k^H = \frac{X_{k,t+h}}{X_{k,t}} - 1, \tag{9}$$

where $X_{k,t}$ is the execution price for the order associated with position k at calendar time t (i.e., either the opening or the closing order), and h is the holding period of the position (computed using the FILO algorithm described in section I.C.). We adjust the holding period returns for risk by subtracting the returns of either the client-specified benchmark or a beta-matched Fama-French-Carhart benchmark (using the procedure described by equations (1) and (2), but with the benchmark returns compounded from t to $t + h$).

Table XI reports the *annualized* holding period FFC alphas and returns relative to the client-specified benchmarks, sorted into various holding period buckets as in table III. For purchases, both the alphas and relative returns decline substantially as we move from the shortest (< 1 month; 6.10% FFC alpha; 16.25% relative return) to the longest holding periods (> 2 years; 1.66% FFC alpha; 3.58% relative return). Unlike the incremental average alphas reported previously, annualized holding period alphas following sales are large and negative for short-horizon round-trip trades (-15.83% FFC alpha and -23.18% relative return for holding periods less than one month). All figures are significant at below the 1% level. The discrepancy is due to the fact that annualizing short-term returns is often not practical, as the opportunities themselves may be short-lived, and also because fund managers tend to realize their gains early and hold on to their losses for longer (the disposition effect; see Odean (1998)). Nonetheless, the results clearly refute the potential claim that unobserved trading costs are responsible for higher incremental alphas in the short run, since holding period returns display much the same pattern. In fact, the institutions'

[29] In untabulated results, we verify that all of the results in the paper go through if we use market closing prices rather than execution prices to compute the first days' alphas.

trading desks are consistently able to execute short-run trades at better than market closing prices (consistent with Anand et al. (2012)).

Execution prices include bid-ask spread and price impact, although they do not include brokerage commissions. However, the alphas we report are substantially larger than any reasonable accounting for brokerage fees.

V. Conclusion

We present evidence that institutional fund managers are informed, and that they exploit their information by trading strategically over much longer periods of time than has previously been appreciated. Their strategic behaviour is associated with a slow market price response to new information, which manifests as the gradual decay in post-purchase incremental alpha that we and others have observed.

Post-purchase alpha and follow-up trading activity (in the same stock) both take the shape of a declining power function, reaching zero by the twelfth month after the initial order. Cumulative alpha has an increasing, concave shape that eventually levels out. Greater competition for information, measured by higher analyst coverage, results in lower post-purchase alpha and more intense follow-up trading, but only in the short run (3-6 months after the initial order). We also show that some of the later trading activity is "shifted forward" to earlier periods.

Our findings are relevant for the theoretical market microstructure literature, which has generated many models of strategic trading. The evidence we present is most consistent with the predictions of Foster and Viswanathan (1996) and Back, Cao, and Willard (2000), who study imperfect competition among heterogeneously informed traders. In particular, their models predict two phases of trading: a "rat race" where competition increases trading aggressiveness and accelerates price adjustment, and a "waiting game" where the effect of competition is muted. Our findings provide a link between the empirical phenomenon of alpha decay, which is well known but poorly understood, and a theoretical literature that to date has only been sparsely tested.

Appendix

A. Variable Definitions

Table A.1 provides detailed definitions and formulas for the variables used in the study but not defined explicitly in the main text.

B. Holding Period Measurement Algorithm

Our implementation of the first-in-last-out (FILO) algorithm is illustrated in figure A.1 In this example, the first position (a buy) is initiated on date 1 when the number of shares in the portfolio rises from zero to 200. On date 2 a further 100 shares are purchased, beginning the second buy. The key to the FILO rule is that the second buy must be completed either before or at the same time as the first. In our example, a third buy starts on date 4 and is completed, along with the second buy, on date 5. The first sell position (the fourth position in total) begins simultaneously on date 5 with a sale of 200 shares, and ends on date 7 when the 200 shares are re-bought. The repurchase also begins one final buy position (the fourth). At the end of the example, two positions remain open: the first and last buys.

Given that our sample consists exclusively of long-only managers, this methodology may not seem intuitive when dealing with sales. However, it is appropriate because a long-only active portfolio can always be decomposed into a long position in the benchmark index and a long/short overlay. A sale causes a stock to become more underweight relative to the benchmark, which is analogous to a taking short position.

In figure A.2 we present histograms of holding periods in the cross-section of trades (left panel) and median holding periods in the cross-section of portfolios (right panel).[30] Holding periods in the cross-section of trades have an exponential-shaped distribution, suggesting that opening and closing orders follow a (possibly non-homogenous) Poisson process. The distribution of median holding periods indicates that while some institutions are certainly more short-term-focussed than others, there are very few managers that engage exclusively in short-term or long-term trading.

[30] The distribution shown in figure A.2 includes truncated round-trip trades (i.e., trades that remain open at the end of the sample period), but looks almost identical if the truncated trades are excluded.

C. List of Benchmarks

Table A.2 contains an exhaustive list of all benchmarks that are assigned to fund managers by the clients in our sample, grouped by country or broader economic region.

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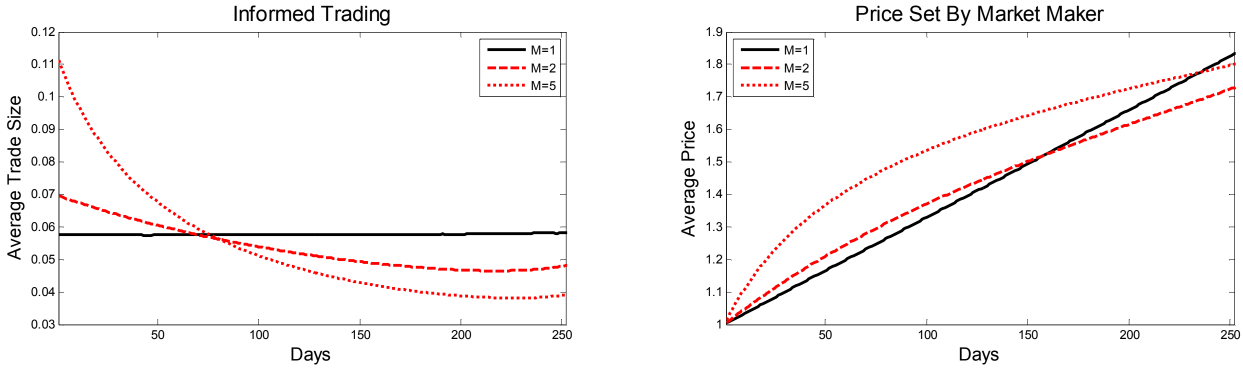
Panel A



Panel B

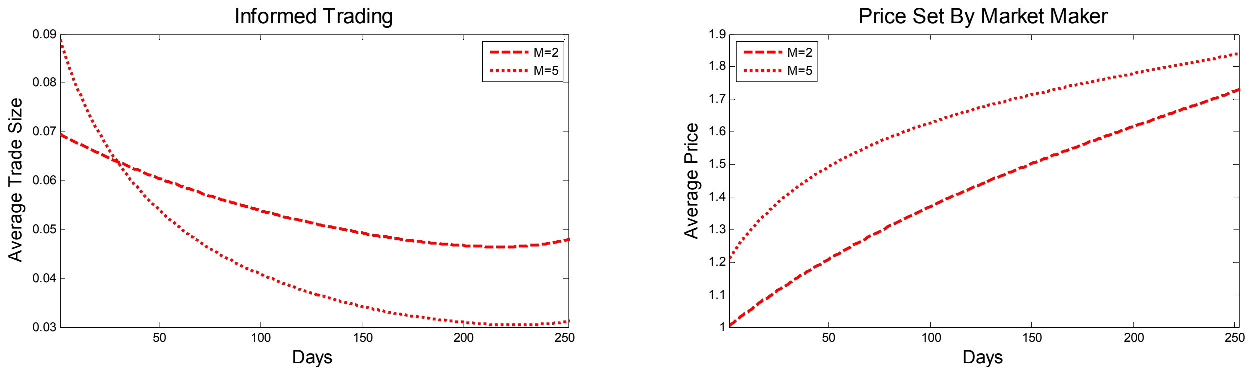


Figure 1. Simulating Foster and Viswanathan's (1996) model. Panel A shows the evolution of trading activity (left panel) and price (right panel) for 252 trading rounds in a numerical simulation of the model. We use Foster and Viswanathan's solution method to generate 100,000 sample paths, then plot the mean of the paths over time. The variance of noise trader demand and the initial variance of the informed traders' signals are both normalized to 1, and the initial correlation in information signals is set to a low value of 0.181819. Starting price is also normalized to 1 and fundamental value is set to 2. The number of informed traders (M) is either 1, 2 or 5. True fundamental value is not known precisely to any individual trader (except when M=1) but is collectively known by all traders. When M=1, the model reduces to that of Kyle (1985). Panel B plots the simulated price and trade size paths for M=2 and M=5 but adjusts the starting price upwards to 1.2 when M=5, to account for endogeneity in the initial difference between prices and fundamental values. As this difference is exogenous in the Foster and Viswanathan model, the plots in panel B are for illustrative purposes only.

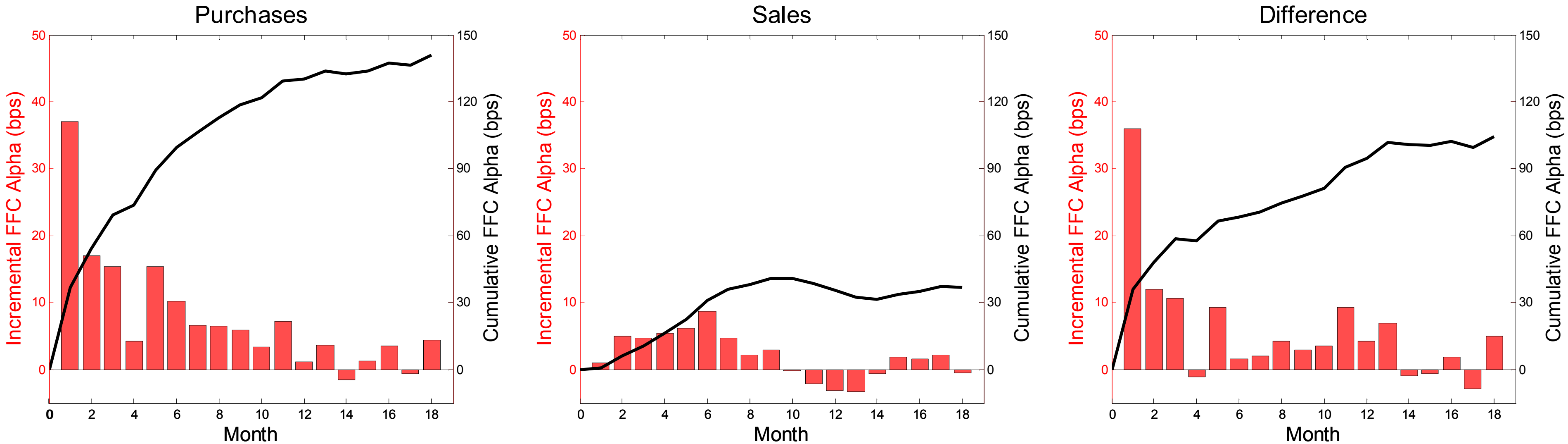


Figure 2. Monthly post-order alphas. This figure plots incremental (red bars, left axes) and cumulative (black lines, right axes) Fama-French-Carhart alphas in basis points for up to eighteen months after an initial order, averaged over all open positions. A position begins with an opening order and is closed when the number of shares held by the fund manager returns to its original level (see the appendix for a worked example). The left panel shows alpha accruing to purchased stocks, the centre panel shows alpha accruing to sold stocks, and the right panel shows the difference between them.

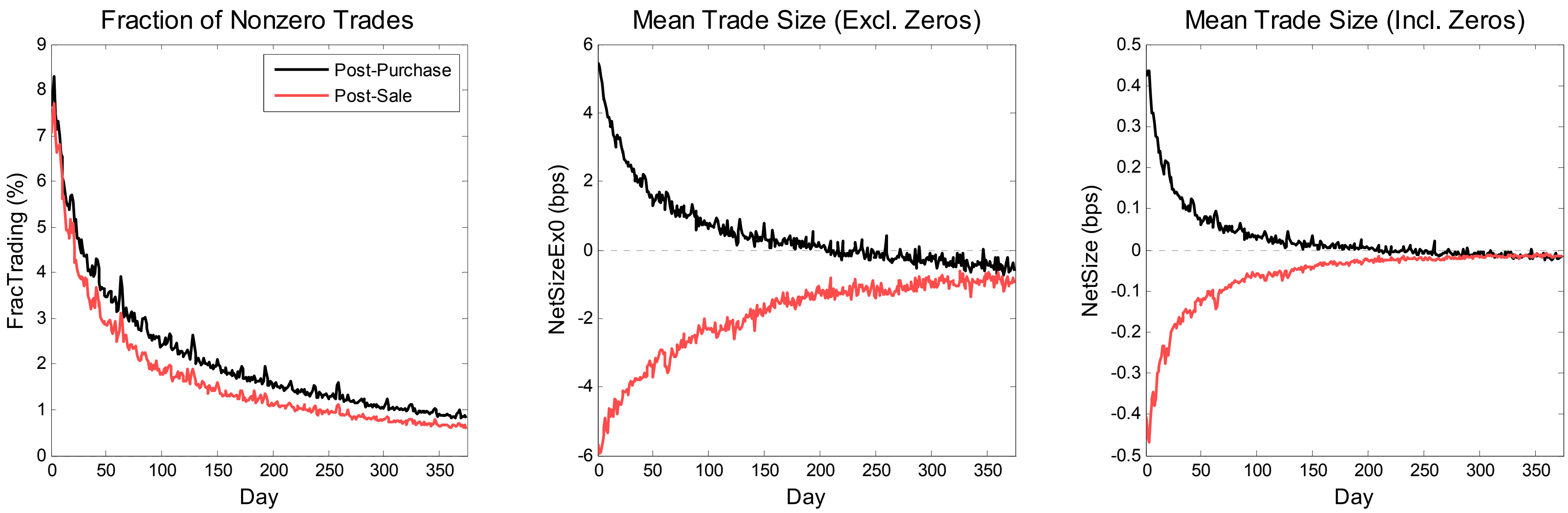
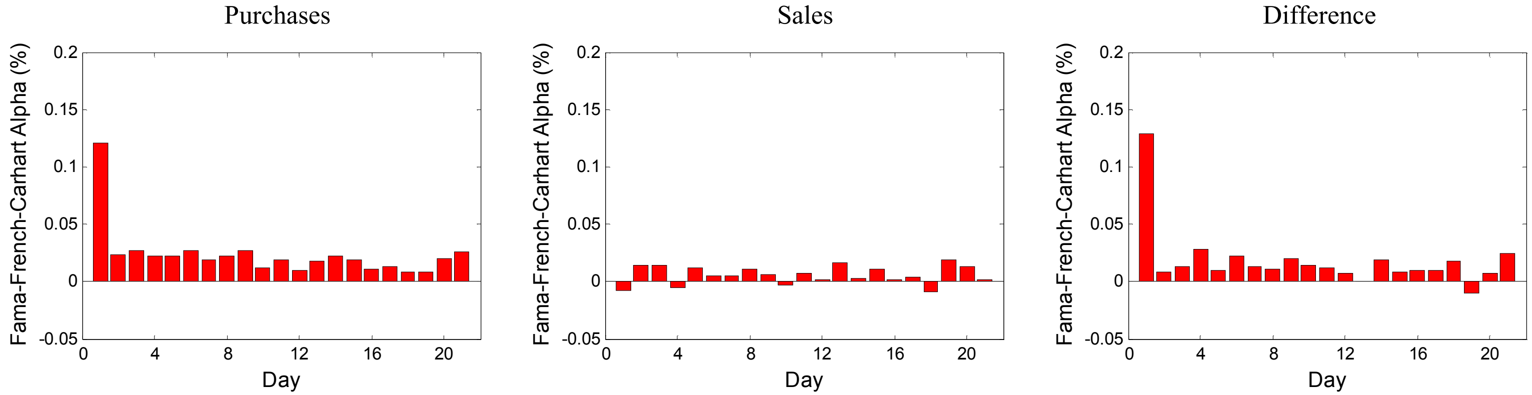


Figure 3. Monthly follow-up net purchases. This figure plots three measures of follow-up trading activity for 378 trading days (18 months) after the initial order. The left panel shows the fraction of portfolios for which there is activity in the same stock (regardless of magnitude or direction) on a given day ($FracTrading$). The centre panel shows the mean size of net purchases (as a fraction of AUM) conditional on trading activity being observed—i.e., average trade size excluding observations where the size is zero ($NetSizeEx0$). The right panel combines these two measures, showing the average size of net purchases including cases of no trading activity/zero trade size ($NetSize$). Negative values of $NetSize$ and $NetSizeEx0$ indicate net sales. The black line shows post-purchase follow-up trading, and the red line shows post-sale follow-up trading. To avoid counting a single trade multiple times, the averages are calculated using the "new information event" subsample (no prior trade in the stock for eighteen months) and only include open positions. A position begins with an opening order and is closed when the number of shares held by the fund manager returns to its original level (see the appendix for a worked example).

Panel A. All Orders



Panel B. Liquidity-Demanding Orders Only

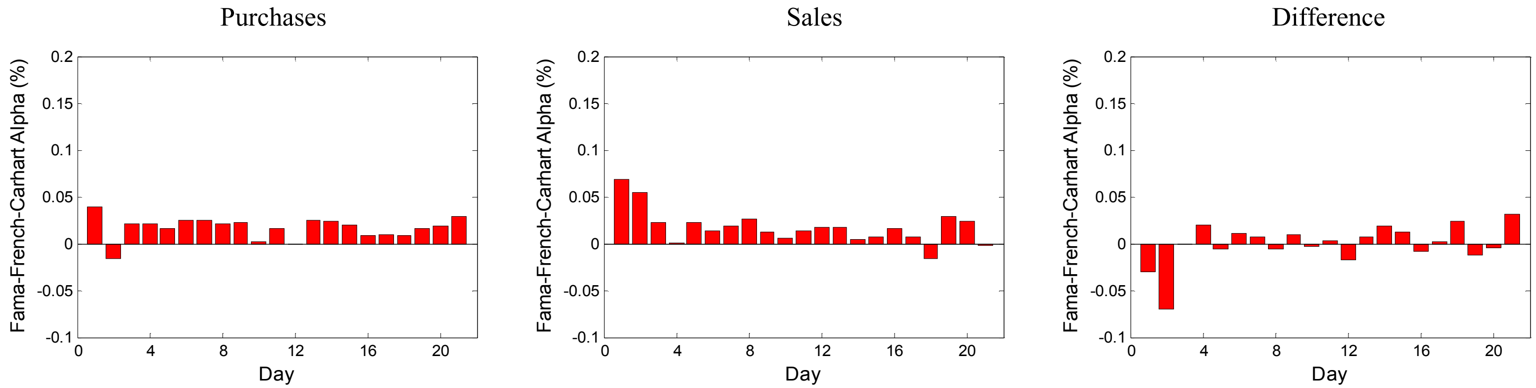


Figure 4. Effect of liquidity provision on daily incremental alphas. Panel A presents daily post-order incremental Fama-French-Carhart alphas for the full sample. Panel B shows the same but for a subsample of liquidity-demanding orders, defined as purchases following one-day positive returns or sales following one-day negative returns. The left panel shows alpha accruing to purchased stocks, the centre panel shows alpha accruing to sold stocks, and the right panel shows the difference between them.

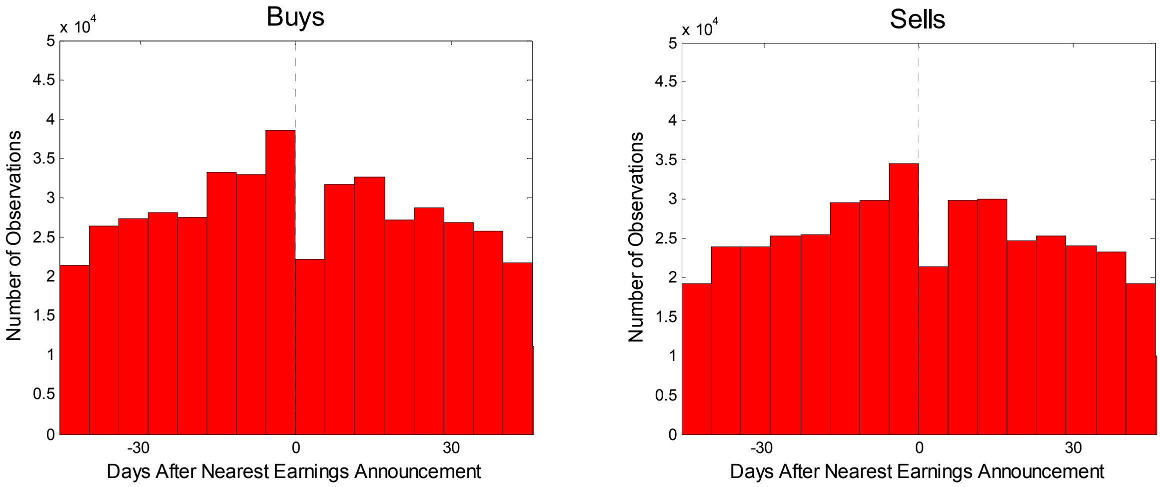


Figure 5. Distribution of trades around earnings announcements. This figure shows histograms of trade execution dates relative to the nearest earnings announcement date, separately for buys (left panel) and sells (right panel). If the trade consists of multiple transactions, the trade date used is that of the first transaction in the order. Negative values on the *x*-axis represent days before the announcement. Each bar of the histogram represents one week.

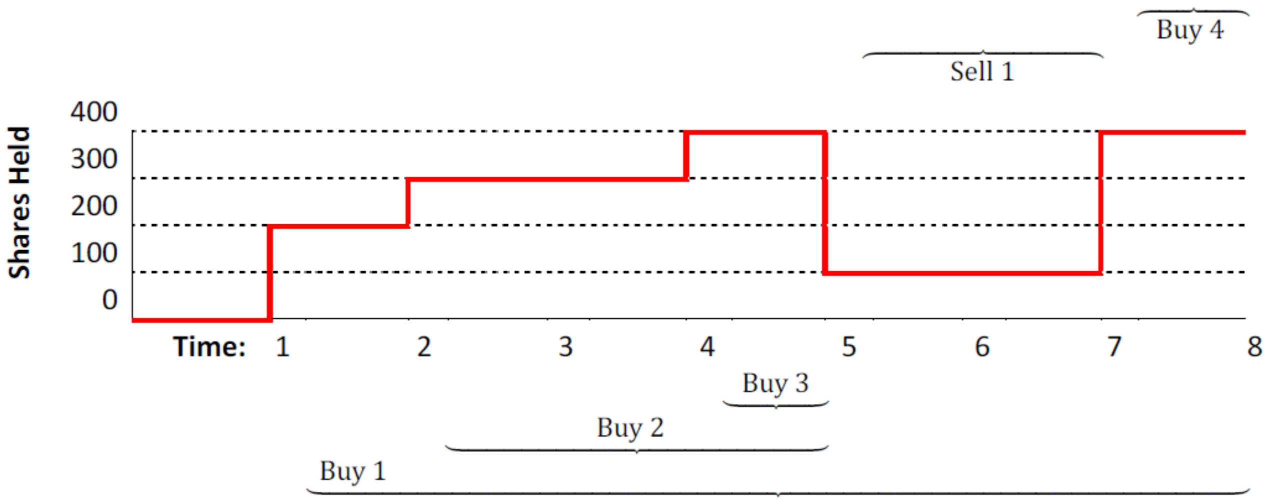


Figure A.1. Holding period measurement. This figure shows an example of the *first-in-last-out* (FILO) algorithm that we use to determine the holding period of each round-trip trade. Every recorded order counts as the beginning of a new round-trip trade, which lasts until the number of shares held (adjusted for corporate actions) returns to its original value at the time of the opening order.

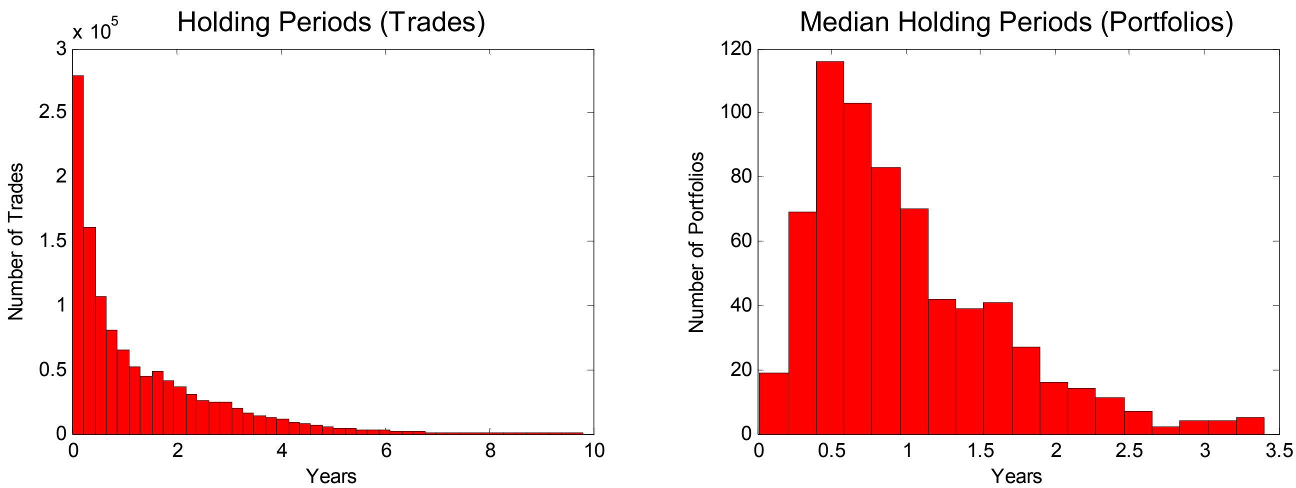


Figure A.2. Distribution of holding periods across trades and portfolios. This figure shows histograms of the distribution of holding periods in the cross-section of trades (left panel) and of median holding periods in the cross-section of portfolios (right panel).

Table I

Data Sources and Geographic Breakdown

This table presents a breakdown of the number of portfolios, unique fund managers and unique clients in our cleaned sample, broken down by location of the benchmark (panel A), location of the fund management company (panel B), and source/purpose of the data (panel C). Totals for the whole sample are shown in the final column of panel A. *Clients* are the parties who supply data to Inalytics, usually the asset owners. In the case of data supplied by fund managers, the client and manager are the same entity. In panel A, *global* refers to benchmarks containing stocks from multiple regions, while in panel B *global* refers to portfolios managed by multi-regional teams. In Panel C, the label *hybrid* refers to "managers of managers" who supply data on their underlying portfolios. The label *in-house* refers to asset owners who directly employ their own fund managers. *Monitoring* portfolio data are provided in real time for the purpose of ongoing diagnostic analysis, while *search* portfolio data are obtained at a single point in time as part of a new manager selection process ("beauty contest"). See the appendix for a full list of benchmarks.

Panel A: Benchmark Location

	Developed Markets							Emerging Markets		Total
	Australia	Asia-Pacific	Europe	Japan	UK	US	Global	South Africa	Global	
Portfolios	104	32	86	36	98	64	190	30	52	692
Unique Managers	46	22	46	23	48	42	71	5	36	206
Unique Clients	11	14	30	18	32	25	50	2	22	94

Panel B: Manager Location

	Australia	Asia-Pacific	Japan	UK	US	South Africa	Global
Portfolios	105	34	36	275	75	30	137
Unique Managers	47	22	23	94	52	5	67
Unique Clients	11	15	18	61	33	2	45

Panel C: Data Sources

	Provider				Purpose	
	Asset Owner	Fund Manager	Hybrid	In-House	Monitoring	Search
Portfolios	458	162	56	16	562	130
Unique Managers	161	72	22	5	178	91
Unique Clients	57	34	7	6	75	19

Table II

Summary Statistics

This table presents annualized descriptive statistics for the 692 portfolios in our cleaned sample. Detailed variable definitions are given in the appendix. Panel A summarizes the distribution of portfolio risk and return. The last two columns, *% Sig+* and *% Sig-,* indicate the percentage of estimates that are positive and significant, and negative and significant (both at the 5% level), respectively; except for the *1F Beta* and *FFC MRP Beta* rows, where they indicate the percentage of estimates significantly greater or less than one. Panel B reports the distribution of various holdings-related characteristics in the cross-section of portfolios. All variables except s*ample length* are first averaged over time. Panel C reports order execution statistics and selected characteristics of the traded stocks (buys and sells shown separately). An order consists of one or more transactions corresponding to a single investment decision.

Panel A: Portfolio Performance and Risk

	Mean	Std. Dev.	Percentiles 1st	25th	50th	75th	99th	% Sig+	% Sig-
Raw Return (%)	6.65	11.06	-26.42	1.48	6.56	12.33	37.56		
Relative Return (%)	1.50	4.28	-9.74	-0.53	1.40	3.62	13.84		
Single-Factor (1F) Alpha (%)	1.58	4.15	-7.52	-0.42	1.44	3.61	13.67	13.87	1.45
Fama-French-Carhart (FFC) Alpha (%)	1.21	3.92	-6.38	-0.52	0.96	3.08	9.96	12.57	1.73
1F Beta	0.97	0.10	0.68	0.93	0.99	1.02	1.19	34.10	49.28
FFC MRP Beta	0.98	0.09	0.67	0.94	1.00	1.03	1.18	38.15	45.09
FFC SMB Beta	0.04	0.18	-0.52	-0.03	0.03	0.11	0.63	50.87	25.58
FFC HML Beta	-0.05	0.18	-0.72	-0.12	-0.03	0.05	0.35	28.18	45.95
FFC UMD Beta	0.01	0.10	-0.22	-0.03	0.01	0.06	0.27	43.21	29.77
Portfolio Standard Deviation (%)	24.76	6.58	12.50	19.93	24.61	28.79	41.87		
Tracking Error Standard Dev. (%)	5.95	3.51	1.22	3.81	5.07	7.38	17.21		

Panel B: Portfolio Holdings Characteristics

	Mean	Std. Dev.	Percentiles 1st	25th	50th	75th	99th
Active Share (%)	70.48	18.40	21.24	57.27	71.94	85.55	99.33
Holdings Herfindahl Index (%)	3.06	2.81	0.37	1.68	2.55	4.09	8.55
Excess Herfindahl Ratio	4.32	6.13	0.69	1.51	2.53	5.06	25.80
Weight in Top 10 Holdings (%)	38.16	15.21	10.10	26.21	35.17	50.77	73.08
Assets Under Management ($m)	495.17	962.63	15.10	120.69	249.01	520.46	4780.15
Annual Portfolio Turnover (%)	108.27	167.25	6.94	39.08	65.61	107.70	1013.86
Mean Holding Period (Years)	2.24	2.52	0.10	0.93	1.52	2.56	14.41
Sample Length (Years)	4.47	2.17	1.00	2.83	4.42	5.73	10.51

Panel C: Order/Stock Characteristics

Buys	Order Completion Time (Days)	1.98	2.61	1	1	1	2	13
	Transactions Per Order	1.88	2.47	1	1	1	2	12
	Order Size ($m)	0.95	1.77	0.004	0.08	0.27	0.89	9.44
	Order Size (% of AUM)	0.25	0.36	0.001	0.04	0.11	0.29	1.74
	Order Size (% of Daily Volume)	8.25	19.78	0.003	0.12	0.56	3.04	71.33
	Number of Analysts	15.79	8.37	1	10	14	21	37
	Market Capitalization ($bn)	25.74	40.06	0.15	2.69	8.86	29.49	204.20
	Daily Share Turnover (%)	2.29	2.27	0.14	0.94	1.58	2.73	13.69
Sells	Order Completion Time (Days)	2.03	2.76	1	1	1	2	14
	Transactions Per Order	1.94	2.56	1	1	1	2	12
	Order Size ($m)	0.93	1.72	0.003	0.07	0.25	0.89	8.73
	Order Size (% of AUM)	0.26	0.38	0.001	0.03	0.11	0.31	1.78
	Order Size (% of Daily Volume)	7.99	19.52	0.003	0.11	0.51	2.84	71.32
	Number of Analysts	15.96	8.38	1	10	15	21	37
	Market Capitalization ($bn)	25.41	39.24	0.15	2.79	8.92	29.41	200.48
	Daily Share Turnover (%)	2.31	2.29	0.15	0.95	1.59	2.75	13.77

Table III
Round-Trip Trade Statistics by Holding Period

This table reports statistics on round-trip trades (positions), grouped into various holding period buckets. Holding periods are measured using a first-in-last-out algorithm, beginning with an opening order and ending when the number of shares held (adjusted for corporate actions) returns to its original value. See the appendix for a worked example of how we implement this algorithm.

	Holding Period					
	<1 Month	1M-3M	3M-6M	6M-1Y	1Y-2Y	>2 Years
Panel A: Purchases						
Number of Trades	75,050	108,908	101,542	110,901	107,999	102,339
Mean Holding Period (Months)	0.52	1.94	4.38	8.69	17.41	39.44
Mean Position Size (% of AUM)	0.20	0.24	0.25	0.27	0.34	0.55
Mean Position Size ($m)	0.70	0.94	1.09	1.25	2.57	3.43
Total Value of Positions ($bn)	52.90	102.05	110.58	138.53	277.22	350.71
Panel B: Sales						
Number of Trades	53,004	67,524	66,467	81,839	110,470	164,451
Mean Holding Period (Months)	0.50	1.92	4.41	8.76	17.90	41.31
Mean Position Size (% of AUM)	0.19	0.27	0.30	0.31	0.33	0.46
Mean Position Size ($m)	0.65	0.87	0.98	1.12	1.26	2.09
Total Value of Positions ($bn)	34.38	58.67	64.98	91.60	139.24	343.70

Table IV

Summary of Hypotheses from Strategic Trading Models

This table summarizes the predictions of several leading theoretical microstructure models. Panel A shows hypotheses about the equilibrium dynamics of informed trading and associated price adjustment, while panel B shows hypotheses about the effects of competition on the aforementioned variables. Part 2 of hypothesis H_2^C makes the additional assumption that greater competition reduces the average differential between prices and fundamental values, which the models treat as exogenous.

	Model	Hypotheses
		Panel A: Equilibrium Dynamics
H_0^E	Holden and Subrahmanyam (1992)	(1) Price adjustment is (almost) immediate (2) Informed trading occurs only in the first few trading rounds
H_1^E	Kyle (1985)	(1) Price adjustment is gradual and linear (2) Informed trade size is constant over time until prices have adjusted
H_2^E	Foster and Viswanathan (1996); Back, Cao, and Willard (2000)	(1) Price adjustment is gradual and concave (2) Informed trade size declines over time proportionally to remaining mispricing
		Panel B: Effects of Competition
H_0^C	Kyle (1985)	No effect on price adjustment or informed trading behaviour (relevant information is known only to one trader)
H_1^C	Holden and Subrahmanyam (1992)	Increased competition is associated with: (1) Faster price adjustment (2) Lower total profits to informed traders at all horizons (3) Trading "shifted forward" at all horizons
H_2^C	Foster and Viswanathan (1996); Back, Cao, and Willard (2000)	Increased competition is associated with: (1) Faster price adjustment initially, but slower adjustment in the long run (2) Lower profits to informed investors, but more so in the short run (3) Trading "shifted forward in time", but more so in the short run (4) More aggressive trading in the short run; less aggressive trading in the long run

Table V

Monthly Post-Order Incremental Alphas

This table reports average alphas, in basis points, for selected months after each initial order. Alphas for the first month are computed using the order execution price and the market closing price one month (21 trading days) later. Subsequent monthly alphas are computed using market closing prices for months m and $m-1$. To adjust for risk, we estimate rolling Fama-French-Carhart factor loadings (betas), and subtract the returns of a "beta-matched" benchmark from the stock returns (see section III.A.1. for more detail). Alphas for purchase and sale orders are shown in panels A and B, respectively, and panel C reports the difference between them. In each panel, results are given for the full sample as well as a restricted "new information event" subsample of orders with no prior trades in the stock for eighteen months. Alphas are dropped from the averages after positions are closed (i.e., once the number of shares held returns to its original level before the initial order). Standard errors are reported in parentheses below the alpha estimates, with the number of open positions in square brackets below the standard errors. Standard errors are clustered at the stock level for the full sample and at the portfolio level for the subsample. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Months After Opening Order (m)					
	1	3	6	9	12	18
			Panel A: Buys			
All Orders	37.05***	15.40***	10.21***	5.81**	1.17	4.37
	(2.56)	(2.55)	(2.60)	(2.72)	(3.02)	(3.10)
	[526,537]	[418,789]	[318,504]	[254,255]	[209,234]	[148,484]
New Information Events Only	40.96***	15.56***	10.05***	6.05	6.63*	1.20
	(4.94)	(3.04)	(3.16)	(3.78)	(3.98)	(4.38)
	[141,836]	[115,590]	[89,698]	[72,700]	[60,447]	[44,028]
			Panel B: Sells			
All Orders	0.82	4.72*	8.86***	2.83	-3.18	-0.33
	(2.64)	(2.62)	(2.60)	(2.67)	(2.82)	(2.87)
	[485,679]	[418,759]	[353,063]	[306,875]	[272,569]	[217,778]
New Information Events Only	3.06	11.12***	12.24***	3.28	3.94	1.66
	(3.66)	(3.23)	(3.26)	(3.78)	(4.70)	(3.42)
	[130,116]	[114,949]	[99,333]	[87,317]	[77,966]	[63,376]
			Panel C: Buys Minus Sells			
All Orders	36.23***	10.69***	1.35	2.98	4.35	4.7
	(2.73)	(2.83)	(3.02)	(3.21)	(3.55)	(3.68)
	[1,012,216]	[837,548]	[671,567]	[561,130]	[481,803]	[366,262]
New Information Events Only	37.90***	4.44	-2.20	2.77	2.69	-0.46
	(7.15)	(4.22)	(4.39)	(4.89)	(6.52)	(5.79)
	[271,952]	[230,539]	[189,031]	[160,017]	[138,413]	[107,404]

Table VI
Monthly Follow-Up Net Purchases

This table documents follow-up trading activity in the same stock for selected months after each initial order ($NetSize$). The numbers reported in the table are total purchases net of total sales during month m, measured as a fraction of assets under management (in basis points). Net purchases following initial buys and sells are shown in panels A and B, respectively. In each panel, results are given for the full sample as well as a restricted "new information event" subsample of orders with no prior trades in the stock for eighteen months. Net purchases are dropped from the averages after positions are closed (i.e., once the number of shares held returns to its original level before the initial order) to avoid double-counting orders and to maintain continuity with the alphas. Standard errors are reported in parentheses below the trade size, with the number of open positions in square brackets below the standard errors. Standard errors are clustered at the stock level for the full sample and at the portfolio level for the subsample. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Months After Opening Order (m)					
	1	3	6	9	12	18
			Panel A: Buys			
All Orders	8.62***	4.07***	2.08***	1.16***	0.70***	-0.12
	(0.15)	(0.22)	(0.18)	(0.16)	(0.16)	(0.16)
	[526,537]	[418,789]	[318,504]	[254,255]	[209,234]	[148,484]
New Information Events Only	8.69***	3.21***	1.31***	0.62**	0.25	-0.29
	(0.65)	(0.36)	(0.31)	(0.27)	(0.21)	(0.19)
	[141,836]	[115,590]	[89,698]	[72,700]	[60,447]	[44,028]
			Panel B: Sells			
All Orders	-10.76***	-5.67***	-2.93***	-1.70***	-1.31***	-0.84***
	(0.23)	(0.16)	(0.11)	(0.11)	(0.09)	(0.08)
	[485,679]	[418,759]	[353,063]	[306,875]	[272,569]	[217,778]
New Information Events Only	-10.92***	-5.09***	-2.51***	-1.56***	-1.11***	-0.72***
	(0.93)	(0.41)	(0.21)	(0.17)	(0.14)	(0.13)
	[130,116]	[114,949]	[99,333]	[87,317]	[77,966]	[63,376]

Table VII
Effect of Competition on Post-Purchase Alpha

This table reports the estimated coefficients from a panel regression of monthly post-purchase alpha (in basis points) on the number of security analysts covering the stock (our proxy for competition) and control variables. Controls include the market capitalization of the stock at the time of the order (in billions USD), a dummy variable indicating whether the purchase was liquidity providing (following a one-day negative return) or liquidity demanding (following a one-day positive return), as well as additional portfolio, stock and order characteristics (see section III.B.1. for details). Only alphas from positions that have not yet been closed (fully sold) are included in the regression, up to eighteen months after the initial order. All independent variables are interacted with horizon dummies, as shown in the regression equation:

$$\tilde{\alpha}^M_{j,p,m} = \delta_p + \beta_0 Analysts_j + \gamma_0{}' Controls_{j,p} + \sum_{\eta \in \{\{1\},\{2,3\},\{4,5,6\}\}} \left[\varphi_\eta + \beta_\eta Analysts_j + \gamma_\eta{}' Controls_{j,p}\right] 1_{\{m \subseteq \eta\}} + \varepsilon_{j,m},$$

where $\tilde{\alpha}^M_{j,p,m}$ is the month-m alpha following the jth opening order (from portfolio p), δ_p is the portfolio-specific component of the intercept, φ_η is the horizon-specific component of the intercept, and $1_{\{m \subseteq \eta\}}$ is an indicator variable that equals one when the number of months elapsed after the opening order is a subset of η. Thus each coefficient is split into one baseline and three incremental coefficients: for the first month, the remainder of the first quarter, and the second quarter. Results are shown for the full sample and the "new information event" subsample (no prior trades in the stock for eighteen months). Standard errors are clustered at the stock level for the full sample and at the portfolio level for the subsample, and are reported in parentheses below the coefficients. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	All Purchases				No Prior Trades for Eighteen Months			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Analysts$	0.12		0.15	0.05	0.04		0.01	-0.03
	(0.26)		(0.28)	(0.29)	(0.20)		(0.22)	(0.23)
$Analysts \times 1_{\{m=\{1\}\}}$	-1.43***		-0.81***	-0.77**	-1.95***		-1.36***	-1.27***
	(0.28)		(0.30)	(0.32)	(0.40)		(0.39)	(0.41)
$Analysts \times 1_{\{m\subset\{2,3\}\}}$	-0.58**		-0.45*	-0.47*	-0.82***		-0.78**	-0.66**
	(0.23)		(0.26)	(0.26)	(0.28)		(0.31)	(0.30)
$Analysts \times 1_{\{m\subset\{4,5,6\}\}}$	-0.53**		-0.46*	-0.42*	-0.19		-0.18	-0.04
	(0.21)		(0.24)	(0.24)	(0.30)		(0.32)	(0.33)
$MarketCap$ ($\$bn$)		-0.09	-0.01	-0.01		-0.06	0.02	0.00
		(0.06)	(0.06)	(0.06)		(0.04)	(0.04)	(0.04)
$MarketCap \times 1_{\{m=\{1\}\}}$		-0.35***	-0.31***	-0.22***		-0.49***	-0.40***	-0.37***
		(0.05)	(0.06)	(0.06)		(0.08)	(0.08)	(0.08)
$MarketCap \times 1_{\{m\subset\{2,3\}\}}$		-0.07*	-0.06	-0.05		-0.09*	-0.03	-0.03
		(0.04)	(0.05)	(0.05)		(0.05)	(0.05)	(0.06)
$MarketCap \times 1_{\{m\subset\{4,5,6\}\}}$		-0.04	-0.03	-0.03		0.00	-0.01	-0.04
		(0.04)	(0.04)	(0.04)		(0.05)	(0.05)	(0.05)
$LiqProv$				2.37				1.27
				(1.3)				(2.00)
$LiqProv \times 1_{\{m=\{1\}\}}$				22.19***				14.68***
				(3.51)				(5.31)
$LiqProv \times 1_{\{m\subset\{2,3\}\}}$				-6.09				-3.05
				(2.66)				(3.96)
$LiqProv \times 1_{\{m\subset\{4,5,6\}\}}$				-5.62				-5.00
				(2.51)				(3.62)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	No	Yes	No	No	No	Yes
Horizon Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-square (%)	0.12	0.13	0.13	0.18	0.13	0.13	0.13	0.17
Observations	4,662,028	5,023,883	4,633,036	4,348,392	1,418,000	1,540,775	1,417,821	1,321,007

Table VIII
Effect of Competition on Opening Order Size

This table reports the estimated coefficients from a panel regression of opening order size (either fraction of AUM or dollar value) on the number of analysts covering the purchased stock (our proxy for competition) and assorted control variables. Controls include the stock's market capitalization (in billions USD), the total share turnover during the order (volume divided by shares outstanding), the deviation of the stock's weight in the portfolio from its weight in the benchmark (*holding deviation*), the assets under management in the portfolio (in hundreds of millions USD), and additional portfolio, stock and order characteristics (see section III.B.1. for details). The equation estimated is as follows:

$$OpeningSize_{j,p} = \delta_p + \beta \cdot Analysts_j + \gamma' Controls_{j,p} + \varepsilon_j,$$

where $OpeningSize_{j,p}$ is the size of opening order j in portfolio p and δ_p is a portfolio-specific intercept. The results shown are for the "new information event" subsample (orders with no prior trades in the stock for eighteen months) to prevent multiple-counting of the same order when we examine follow-up trading activity in table IX. Standard errors are clustered at the portfolio level and are reported in parentheses below the coefficients. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Dependent variable:	Fraction AUM (bps)				Dollar Value ('000s)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Analysts$	0.36***		0.25***	0.29***	12.98***		7.66***	9.57***
	(0.04)		(0.04)	(0.04)	(1.63)		(1.65)	(1.48)
$MarketCap$ ($\$bn$)		0.09***	0.08***	0.05***		4.10***	3.65***	2.73***
		(0.01)	(0.01)	(0.01)		(0.46)	(0.47)	(0.50)
$ShareTurnover$ (%)				0.79***				32.50***
				(0.08)				(4.43)
$HoldingDeviation$ (%)				-9.82***				-249.00***
				(0.77)				(27.86)
AUM ($\$100m$)				-0.31***				77.79***
				(0.07)				(9.19)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	No	Yes	No	No	No	Yes
Portfolio Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-square (%)	38.25	38.43	38.59	46.29	46.96	46.63	47.27	51.98
Observations	1,418,000	1,540,775	1,417,821	1,321,007	1,418,000	1,540,775	1,417,821	1,321,007

Table IX
Effect of Competition on Follow-Up Net Purchases

This table reports the estimated coefficients from a panel regression of monthly follow-up net purchases, measured as a fraction of AUM (in basis points), on the number of analysts covering the purchased stock (our proxy for competition). Follow-up net purchases are defined as the sum of all buys and sells in the same stock for each month after the opening order, for up to eighteen months. Also included in the regression is the size of the opening order (now in *percentage* points), the interaction between analyst coverage and opening order size, and additional portfolio, stock and order characteristics (see section III.B.1. for details). Analyst coverage and opening order size are demeaned. Each independent variable is further interacted with horizon dummies. The equation we estimate is as follows:

$$FollowUpSize_{j,p,m} = \delta_p + \beta_0 Analysts_j + \theta_0 OpeningSize_{j,p} + \xi_0(Analysts_j \times OpeningSize_j) + \gamma_0 Controls_{j,p} + \sum_{\eta \in \{\{1\},\{2,3\},\{4,5,6\}\}} [\varphi_\eta + \beta_\eta Analysts_j + \theta_\eta OpeningSize_{j,p} + \xi_\eta(Analysts_j \times OpeningSize_j) + \gamma_\eta Controls_{j,p}]\, 1_{\{m \subseteq \eta\}} + \varepsilon_{j,m},$$

where $FollowUpSize_{j,p,m}$ is the total size of net purchases in month m following opening order j in portfolio p, δ_p is the portfolio-specific component of the intercept, φ_η is the horizon-specific component of the intercept, and $1_{\{m \subseteq \eta\}}$ is an indicator variable that takes the value one when the number of months elapsed after the opening order is η. Thus each coefficient is split into a baseline coefficient and three incremental coefficients: one for the first month, one for the remainder of the first quarter, and one for the second quarter. Results shown are for the "new information event" subsample (orders with no prior trades in the stock for eighteen months), to prevent multiple-counting of the opening orders examined in table VIII. Standard errors are clustered at the portfolio level and are reported in parentheses below the coefficients. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)
$Analysts$	0.040***	0.015
	(0.012)	(0.009)
$Analysts \times 1_{\{m=\{1\}\}}$	0.127***	0.158***
	(0.044)	(0.040)
$Analysts \times 1_{\{m \subset \{2,3\}\}}$	0.110***	0.095***
	(0.020)	(0.017)
$Analysts \times 1_{\{m \subset \{4,5,6\}\}}$	0.045***	0.039***
	(0.012)	(0.012)
$OpeningSize$ (%)	-2.858***	-2.830***
	(0.265)	(0.257)
$OpeningSize \times 1_{\{m=\{1\}\}}$	5.379***	1.659
	(1.502)	(1.312)
$OpeningSize \times 1_{\{m \subset \{2,3\}\}}$	-0.754	-3.071***
	(0.786)	(0.747)
$OpeningSize \times 1_{\{m \subset \{4,5,6\}\}}$	-1.513***	-2.564***
	(0.364)	(0.357)
$Analysts \times OpeningSize$	0.012	-0.004
	(0.027)	(0.027)
$Analysts \times OpeningSize \times 1_{\{m=\{1\}\}}$	-0.366**	-0.363**
	(0.171)	(0.175)
$Analysts \times OpeningSize \times 1_{\{m \subset \{2,3\}\}}$	-0.263***	-0.232***
	(0.069)	(0.067)
$Analysts \times OpeningSize \times 1_{\{m \subset \{4,5,6\}\}}$	-0.094***	-0.081***
	(0.029)	(0.030)
Constant	Yes	Yes
Controls	No	Yes
Horizon Fixed Effects	Yes	Yes
Portfolio Fixed Effects	Yes	Yes
Adjusted R-square (%)	4.93	5.68
Observations	1,418,000	1,321,007

Table X

Post-Purchase Alphas: Alternative Explanations

This table reports average alphas (in basis points) for selected months after each opening order, using the same methodology as in table V, but with the following differences. Panel A shows alternative average-weighting schemes (equal vs. order size) and risk adjustments (Fama-French-Carhart alpha vs. return in excess of the client-specified benchmark (*relative return*)). Panel B divides the sample into orders with high and low medium-term past returns (momentum vs. contrarian), orders with positive and negative one-day past returns (liquidity demand vs. liquidity provision), and orders taking place further than one week from an earnings announcement and within one week of an announcement. Panel C divides the sample into orders by long- and short-term institutions (below or above median portfolio turnover) and long- or short-term positions (above or below median holding period). Standard errors are clustered at the stock level and are reported in parentheses below the alpha estimates, with the number of open positions in square brackets below the standard errors. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Months After Opening Order (m)					
	1	3	6	9	12	18
			Panel A			
FFC Alpha (Equal Weights)	37.05***	15.40***	10.21***	5.81**	1.17	4.37
	(2.56)	(2.55)	(2.60)	(2.72)	(3.02)	(3.10)
	[526,537]	[418,789]	[318,504]	[254,255]	[209,234]	[148,484]
FFC Alpha (Order Size Weights)	34.42***	19.84***	19.51***	4.33	3.38	2.08
	(3.55)	(3.61)	(3.68)	(3.97)	(4.28)	(4.64)
	[526,537]	[418,789]	[318,504]	[254,255]	[209,234]	[148,484]
Relative Return (Equal Weights)	52.63***	26.40***	19.33***	14.92***	12.24***	15.72***
	(2.86)	(2.79)	(2.84)	(2.92)	(3.31)	(3.41)
	[526,537]	[418,789]	[318,504]	[254,255]	[209,234]	[148,484]
Relative Return (Order Size Weights)	48.58***	29.20***	19.66***	10.79**	12.55***	14.60***
	(4.12)	(4.14)	(4.13)	(4.37)	(4.80)	(4.94)
	[526,537]	[418,789]	[318,504]	[254,255]	[209,234]	[148,484]
			Panel B			
Momentum Orders	32.50***	16.47***	20.00***	7.71**	6.67*	6.37
	(2.91)	(2.98)	(3.06)	(3.37)	(3.75)	(4.03)
	[312,391]	[249,169]	[190,229]	[152,363]	[125,500]	[88,892]
Contrarian Orders	50.01***	18.45***	1.25	7.03	-1.04	1.07
	(4.46)	(4.36)	(4.43)	(4.67)	(5.16)	(5.14)
	[219,298]	[173,612]	[131,257]	[104,302]	[85,668]	[60,918]
Liquidity-Demanding Orders	20.85***	19.32***	11.74***	4.88	1.09	1.63
	(2.85)	(2.93)	(3.04)	(3.25)	(3.64)	(3.84)
	[269,849]	[214,320]	[162,632]	[129,788]	[107,045]	[76,042]
Liquidity-Providing Orders	54.16***	11.30***	8.54**	6.76	1.41	4.51
	(3.11)	(3.05)	(3.29)	(3.41)	(3.77)	(4.17)
	[256,688]	[204,469]	[155,872]	[124,437]	[102,189]	[72,442]
Orders Outside Week of EA	36.63***	16.60***	9.37***	4.88	-3.13	3.16
	(2.77)	(2.72)	(2.87)	(3.01)	(3.27)	(3.37)
	[416,366]	[330,624]	[250,548]	[199,537]	[163,888]	[115,917]
Orders Within Week of EA	45.49***	20.35***	15.57***	14.17**	23.25***	16.11**
	(5.02)	(5.40)	(5.70)	(6.19)	(6.73)	(6.95)
	[77,746]	[61,832]	[47,410]	[37,800]	[31,109]	[22,094]

Table X—*Continued*

	Months After Opening Order (m)					
	1	3	6	9	12	18
			Panel C			
Long-Term Institutions	38.77***	12.97***	5.12	8.95**	0.70	3.78
	(3.60)	(3.44)	(3.61)	(3.74)	(4.15)	(4.43)
	[174,974]	[152,677]	[125,753]	[102,687]	[89,038]	[64,802]
Short-Term Institutions	37.14***	17.88***	14.66***	4.80	3.27	4.96
	(2.82)	(2.94)	(3.05)	(3.21)	(3.68)	(3.91)
	[351,563]	[266,112]	[192,751]	[151,568]	[120,196]	[83,682]
Long-Term Positions	39.79***	21.39***	16.59***	5.81**	1.17	4.37
	(3.02)	(2.88)	(2.81)	(2.72)	(3.02)	(3.10)
	[254,255]	[254,255]	[254,255]	[254,255]	[209,234]	[148,484]
Short-Term Positions	37.81***	10.35***	-6.53			
	(3.11)	(3.53)	(4.75)			
	[272,282]	[164,534]	[64,249]			

Table XI
Holding Period Returns for Round-Trip Trades

This table reports annualized, risk-adjusted holding period returns for round-trip trades, identified using the first-in-last-out algorithm described in section I.C. and table III. Returns are calculated using the volume-weighted average execution prices of the opening and closing orders, then adjusted for risk either by subtracting the client-specified benchmark return (*relative return*) or using the Fama-French-Carhart risk model (*FFC alpha*). Panel A shows holding period returns for buy positions, panel B shows returns for sell positions, and panel C shows the difference between them. In each panel, the returns are reported separately for various holding period buckets matching those in table III. All returns/alphas are expressed in percentage points. Standard errors are clustered at the stock level and are reported in parentheses below the estimates. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Holding Period					
	<1M	1M-3M	3M-6M	6M-1Y	1Y-2Y	>2Y
			Panel A: Buys			
Relative Return (%)	16.25***	6.67***	4.29***	3.21***	2.49***	3.58***
	(1.91)	(0.31)	(0.18)	(0.12)	(0.08)	(0.06)
FFC Alpha (%)	6.10***	2.89***	0.64***	0.74***	1.16***	1.66***
	(1.85)	(0.28)	(0.16)	(0.10)	(0.07)	(0.05)
			Panel B: Sells			
Relative Return (%)	-23.81***	-6.02***	-0.69***	1.48***	2.23***	3.31***
	(2.33)	(0.39)	(0.22)	(0.14)	(0.09)	(0.06)
FFC Alpha (%)	-15.83***	-6.31***	-1.81***	-0.73***	0.22***	1.49***
	(2.26)	(0.36)	(0.20)	(0.12)	(0.08)	(0.05)
			Panel C: Buys Minus Sells			
Relative Return (%)	40.06***	12.69***	4.97***	1.73***	0.26**	0.26***
	(3.01)	(0.50)	(0.29)	(0.19)	(0.12)	(0.08)
FFC Alpha (%)	21.93***	9.20***	2.45***	1.48***	0.93***	0.17**
	(2.92)	(0.46)	(0.25)	(0.16)	(0.11)	(0.07)

Table A.1
Variable Definitions

This table provides definitions and formulas for the variables used in the study but not defined explicitly in the main text or in the other tables. Variables appear in alphabetical order.

Variable Name	Definition	Formula
1F Alpha and Beta	The estimated intercept and slope, respectively, from a regression of portfolio excess returns on client-specified benchmark excess returns.	$r_t^p - r_t^f = \alpha + \beta(r_t^B - r_t^f) + \varepsilon_{p,t}$
Active Share	The sum of absolute deviations of the portfolio weights from the benchmark weights, scaled by 1/2 to give a value between 0 and 1 (see Cremers and Petajisto (2009)). An active share of 1 describes a portfolio that is identical to its benchmark, while an active share of 0 describes a portfolio that has none of its holdings in common with the benchmark. Active share is computed daily.	$\frac{1}{2}\sum_{i=1}^{N}\lvert w_{i,t}^P - w_{i,t}^B\rvert$
Excess Herfindahl Ratio	The ratio of the Herfindahl Index of the portfolio holdings to that of the benchmark holdings.	$\frac{Portfolio\ Herfindahl}{Benchmark\ Herfindahl}$
FFC Alpha and Betas	The estimated intercept and factor loadings, respectively, from a regression of portfolio excess returns on four factor portfolios: the market risk premium (MRP), a small-minus-big market cap factor (SMB), a high-minus-low book-to-market-ratio factor (HML), and an up-minus-down momentum factor (UMD).	$r_t^p - r_t^f = \alpha + \sum_{k=1}^{4}\beta^k F_t^k + \varepsilon_{p,t}$
Holdings Herfindahl Index	The sum of squared portfolio weights on date t.	$\sum_{i=1}^{N}(w_{i,t}^P)^2$
Portfolio Standard Deviation	The sample standard deviation of daily portfolio return. The formula given here is annualized in the main text/tables.	$\frac{1}{T-1}\sum_{t=1}^{T}(r_t^P - \bar{r}_t^P)^2$
Portfolio Turnover	Portfolio turnover is calculated as the minimum of turnover from buy trades and turnover from sell trades (which must be equal in the absence of capital flows). Buy turnover is the sum of {shares purchased (S_j^b) times execution price (X_j), divided by contemporaneous portfolio value (V_t^P)}. Sell turnover is defined analogously for shares sold.	$\min\left\{\frac{1}{J_b}\sum_{j=1}^{J_b}\frac{S_j^b X_j}{V_t^P}, \frac{1}{J_s}\sum_{j=1}^{J_s}\frac{S_j^s X_j}{V_t^P}\right\}$
Relative Return (r_t^R)	The portfolio return minus the client-specified benchmark return.	$r_t^P - r_t^B$
Share Turnover (Daily)	The total number of shares of a particular stock traded on a given day, divided by the total number of shares outstanding.	$\frac{Volume_t}{SharesOutstanding_t}$
Tracking Error Standard Deviation	The sample standard deviation of the daily relative return (as defined above). The formula given here is annualized in the main text/tables.	$\frac{1}{T-1}\sum_{t=1}^{T}(r_t^R - \bar{r}_t^R)^2$

Table A.2
List of Client-Specified Benchmarks

This table presents the full list of benchmarks linked with the portfolios in our sample. These benchmarks are specified in advance by the asset owners and form an explicit part of the contract between the owners and the fund managers. The benchmarks are grouped by country or economic region.

United States	**Japan**
S&P 500	MSCI Japan
RUSSELL 1000	FTSE Japan
RUSSELL 1000 Growth	TOPIX - Tokyo 1st Section
RUSSELL 1000 Value	
RUSSELL 2000	**Asia Pacific**
RUSSELL 2000 Growth	MSCI AC Asia Pacific ex Japan
RUSSELL 2000 Value	MSCI Pacific ex Japan
RUSSELL 3000	FTSE World Asia Pacific
MSCI USA	MSCI AC Far East ex Japan
United Kingdom	**Australia**
FTSE All-Share	S&P/ASX 200
FTSE 350	S&P/ASX 300
FTSE Small Cap	S&P/ASX 300 ex REIT
	S&P/ASX Small Ordinaries
Europe	
MSCI Europe	**Emerging Markets**
MSCI Europe ex UK	MSCI EM (Emerging Markets)
FTSE Europe	FTSE Emerging
FTSE Europe ex UK	
	South Africa
Global	JSE All Share
MSCI World	FTSE/JSE Shareholder Weighted
MSCI ACWI	JSE Top40 (Tradable)
MSCI World ex Australia	FTSE/JSE Capped All Share
MSCI ACWI ex Australia	
FTSE All-World	**Other**
FTSE All-World ex Japan	MSCI Canada
FTSE All-World ex UK	MSCI Hong Kong
FTSE World	
MSCI WRLD/Energy	