Alpha Decay*

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Using a novel sample of professional asset managers, we document positive incremental alpha on newly purchased stocks that decays over twelve months. While managers are successful forecasters at these short-to-medium horizons, their average holding period is substantially longer (2.2 years). Both slow alpha decay and the horizon mismatch can be explained by strategic trading behavior. Managers accumulate positions gradually and unwind gradually once the alpha has run out; they trade more aggressively when the number of competitors and/or correlation among information signals is high, and do not increase trade size after unexpected capital flows. Alphas are lower when competition/correlation increases.

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1. Introduction

Despite the prominence of institutional asset managers in global equity markets,[1] a complete picture of their trading behaviour and their skill in predicting stock returns remains elusive.[2] We introduce a novel dataset of over seven hundred long-only institutional portfolios, made available by Inalytics Ltd, a provider of delegated portfolio monitoring services. For each portfolio in the sample, we observe every individual trade, all holdings on a daily basis, and the investor-specified performance benchmark.[3] Using these data we examine the forecasting ability of managers over both short and long horizons, how their forecasts influence their trading activity, and the role they play in price formation. Our analysis is the most extensive investigation of institutional trading in the literature to date.

The investigation centres around a robust stylized fact that emerges from a simple event study: alpha on new trades decays over twelve months on average. When fund managers in our sample purchase a stock, it tends to earn positive four-factor (Fama-French-Carhart) risk-adjusted returns that accumulate at a gradually declining rate—starting from an average of 36 basis points in the first month and reaching zero one year later, with no subsequent reversal.[4] The shape of the decay resembles a power or exponential function with a half-life of about four months.

This length of time is either surprisingly short or surprisingly long depending on one's perspective. From a practitioner's point of view it is surprisingly short. Traditional fund managers generally emphasize longer-term investing, consistent with an average holding period of 2.24 years in our sample.[5] In other words, the horizon over which these managers are able to forecast stock returns is shorter than the horizon over which they actually invest. From an academician's point of view, on the other hand, an alpha half-life of four months is surprisingly long. In a competitive market we would expect information advantages to be rapidly competed away. That they persist for many months requires further explanation.

We proceed first by verifying that the fund managers in our sample are able to forecast returns beyond what could be inferred from common "public alpha" signals. Public signals

[1] For example, institutional asset managers hold approximately 33% of listed equity in the United States (see Lines, 2016, figure 1).
[2] Existing transaction-level datasets do not include persistent institution identifiers (Plexus), holdings or portfolio values (Plexus and Ancerno), or all trading activity in each portfolio (Plexus and Ancerno). Prominent studies making use of these datasets include Keim and Madhavan (1995,1997), Chiyachantana et at. (2004), Puckett and Yan (2011), Anand et al. (2011, 2013), and Henry and Koski (2017). Existing trade datasets also do not contain information on benchmarks.
[3] The sample runs from 2001 to 2013, includes a wide range of countries (notably the US, UK and Japan) and contains a total of 1.15 million orders ($1.8 trillion). Assets under management range from $9M to $14Bn.
[4] The same is not true for sales, for which alpha is slightly positive and does not exhibit the same decay pattern.
[5] To measure holding periods we use a first-in-last-out (FILO) algorithm, but the results do not change materially under the alternative first-in-first-out rule.

based on stock characteristics are also thought to decay over time, similarly to the decay we observe in our event study (e.g. Gârleanu and Pedersen, 2013), and have been shown empirically to be predictive even of future *risk-adjusted* returns (Brennan, Chordia, and Subrahmanyam, 1998). However, while we find that our fund managers do exhibit some preference for certain characteristics—particularly small firms, high stock prices, high volatility, high dividend yields, and low/negative past returns/alphas—these preferences do not explain their ability to outperform a four-factor model when buying stocks. A panel regression of stock alpha in month $t+k$ on in-sample purchases in month t (the cross-sectional dimension being all stocks in the manager's benchmark) reveals essentially the same pattern as the event study, even when including stock characteristics as controls.

How do these fund managers translate their private information into profitable trades? Since we observe only trades and not information signals directly, we must make an assumption about the timing of signal arrival. Specifically, we assume that a manager's first trade after (at least) eighteen months of no activity in a particular stock marks the arrival of new stock-specific private information.[6] Subsequent activity in that stock is assumed to be associated with the same information event until the next eighteen-month break.[7]

Classifying trades in this way allows us to study how fund managers build positions when they become informed. Upon receiving a signal they begin to accumulate shares gradually, in increments that are small relative to the final position size. The absolute size of each trade declines over time, following the same shape as the alpha decay. Trading continues for about the same amount of time that the alpha remains positive (approximately twelve months). On average, a third of the total position has been accumulated by the end of the first month, half by the end of the second month, and 90% by the end of month eight. Managers begin to unwind their positions after month twelve in the same gradual fashion. This slow rate of trading can account for much of the discrepancy between forecasting horizon and average holding period.

A plausible hypothesis for why such gradual trading occurs can be derived from theoretical models of informed trading. When an informed agent faces imperfect competition from other speculators with different information signals (Foster and Viswanathan, 1996; Back, Cao, and Willard, 2000; Bernhardt and Miao, 2004), her best response is to trade slowly with declining order size over time, just as we observe empirically. To test this hypothesis more formally we note that the optimal trading strategy in these models is more

[6] The results are not sensitive to the precise number of months without activity.
[7] This may appear to be a strong assumption, but as long as any additional signals are uncorrelated their average will approach zero in a large sample.

aggressive when the number of competitors is greater or information signals are more highly correlated. Intuitively, fund managers should trade more aggressively the more likely it is that another manager might "beat them to the punch". We construct empirical proxies for these variables using analyst coverage data: the number of analysts covering a stock (controlling for firm size) proxies for the number of potential competitors, and dispersion in their price targets proxies for the (inverse of) signal correlation.[8]

We find that order size is positively related to analyst coverage in the short run (i.e., first quarter after information arrival) but negatively related at longer horizons, consistent with trading activity being shifted forward in time (i.e., becoming more aggressive) in response to increased competition. Order size is negatively related to price target dispersion (primarily in the first quarter), consistent with trading becoming more aggressive in response to higher signal correlation. The first-quarter magnitudes of the effects of one-standard-deviation changes in analyst coverage and price target dispersion are, respectively, 25% and 5% of the unconditional mean order size. We also examine the effects of these variables on alpha. We find that more analysts and lower price target dispersion are associated with lower alpha (again concentrated in the first quarter), consistent with erosion of profits as informed investors trade more aggressively.[9] The first-quarter magnitudes of the alpha responses are both close to 40% for one-standard-deviation changes in the explanatory variables. Overall, we reject the null hypothesis that the strategic trading environment has no effect on fund manager behaviour and trade profitability. We cannot definitively rule out arrival of multiple *correlated* signals over time as the explanation for persistent trading activity. However, we note that this hypothesis would not predict the responses to competition and signal correlation that we observe in the data.

Finally, we document that unexpected capital flows do not lead to increases in order size, which is consistent with strategic trading but inconsistent with alternative explanations based on limited arbitrage capital. The alternative argument is that fund managers who are required to remain fully invested may not be able to sell existing positions quickly enough to take immediate advantage of new opportunities. To test this hypothesis, we compute total monthly and quarterly percentage flows for each portfolio, fit an AR(1) model to each series, and

[8] The use of security analysts as a proxy for informed competitors was first suggested by Holden and Subrahmanyam (1992). Similar applications can also be found in Pasquariello and Vega (2007, 2013).

[9] In the theory there is a causal relationship between trading and returns; however, a naïve regression of one on the other suffers from an identification problem. Fund managers may trade more aggressively because they are concerned about strategic competitors, or because investment opportunities are greater. Since we do not observe the manager's opportunity set, the two are observationally equivalent. For this reason we rely on cross-sectional comparative statics.

interpret the residual as a measure of unexpected or unanticipated flows.[10] We find no effect of unexpected flows on order size, and the coefficients on the analyst coverage variables are unchanged.

In our interpretation these results tell a consistent story. The managers in our sample take views on the prospects of certain stocks that differ from the market consensus. Fundamental (public) information arrives over the medium term, typically proving them correct. When trading on their views the managers strategically limit their order flow to avoid immediately revealing their private information to the market, allowing prices to adjust at their own pace.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes our dataset in more detail. Section 4 reports the main stylized facts on alpha decay and fund managers' private information/forecasting ability. Section 5 reports the evidence on trading behaviour and managers' investment horizon. Section 6 examines the effects of the strategic environment and capital flows. Section 7 provides an important discussion of the results viewed as a whole, and section 8 concludes.

2. Literature

This paper is situated at the intersection of asset pricing, market microstructure, and institutional trading. There is, accordingly, a large body of related work. We will focus on clarifying our contribution relative to a few of the most similar empirical studies, and on the theoretical literature from which some of our empirical hypotheses are derived.

The observation that alpha decays gradually is not new per se. In fact, it appears to be a robust characteristic of informed trading. The earliest documentation of this result, as far as we are aware, can be found in Wermers (1999) who identifies informed trades by examining herding among mutual funds. Chen, Jegadeesh, and Wermers (2000) find a similar result in a wider sample of mutual funds. Yan and Zhang (2009) find alpha decay in the trades of a still wider set of institutions (those required to file form 13F) with a short-term focus—i.e., those in the top tercile of turnover. Chen, Da, and Huang (2017) find slow alpha decay in hedge fund arbitrage trading. There are also similar findings for trades by dedicated short-sellers (e.g. Desai, Ramesh, Thiagarajan, and Balachandran, 2002; Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008), corporate insiders (Ben-David and Roulstone, 2010), and even certain individual investors (e.g. Kaniel, Saar, and Titman, 2008; Grinblatt, Keloharju, and Linnainmaa, 2010; Kaniel, Liu, Saar, and Titman, 2012).

[10] As most of our data come from pension investors, flows are largely independent of past performance.

Our contribution relative to these papers is first and foremost to treat gradual alpha decay as central rather than incidental—the phenomenon is not specifically discussed in prior work—and to examine its causes and implications. Second, because the existing literature relies on changes in quarterly holdings as a noisy proxy for trades, the shape and rate of the decay has been recorded imprecisely.[11] Using daily transaction-level data, we are able to report more accurate and definitive measurements.

Many of our hypothesis tests are derived from models of strategic trading in the tradition of Kyle (1985). Kyle's original paper studies optimal trading by a single informed speculator facing a rational price-setting market maker, showing that the speculator's best strategy is to trade continuously over the trading period. Prices adjust at a linear rate. Holden and Subrahmanyam (1992) extend Kyle's model to the case of multiple speculators. In their setting competition drives each speculator to trade instantaneously, resulting in immediate price adjustment. Here markets are strong-form efficient. Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) then study the more realistic case of multiple speculators with different information signals, showing that imperfect competition causes speculators to trade at a gradually decaying rate determined by the number of competitors they face and the similarity of their information. Prices adjust over time with a concave shape. Incremental returns exhibit power decay. Bernhardt and Miao (2004) extend the realism of the setting still further, allowing for information signals to arrive at different times for different speculators, and for some probability that private information will become public in each period. These additional complications, however, do not qualitatively change the cross-sectional predictions of Foster and Viswanathan (1996) and Back et al. (2000).

Certain implications of these models have been examined empirically. Using analyst coverage proxies similar to ours, Pasquariello and Vega (2007) test a static version of Foster and Viswanathan's (1996) model and find that price impact is positively related to belief dispersion in the US treasury market. For NYSE and NASDAQ stocks, Pasquariello and Vega (2013) find that price impact is positively related to analyst belief dispersion and negatively related to analyst coverage. Using Trade and Quote (TAQ) data, Barclay and Warner (1993) find that medium-sized trades have the largest price impact, and Chakravarty (2001) shows that these trades are mostly initiated by institutions. While these papers examine short-run price impact in detail, they do not study price adjustment over time nor do they examine fund-level trading or the effect of strategic competition on this behaviour.

[11] One notable exception to this methodology can be found in Campbell, Ramadorai, and Schwartz (2009). The authors use a sophisticated algorithm to infer institutional trades from the TAQ database. However, they find a different pattern in post-trade alphas: that they are are initially low before rising in the long run.

Koudijs (2014) identifies slow price adjustment consistent with Kyle-type models in a historical setting but does not observe trades. Chan and Lakonishok (1995) and Keim and Madhavan (1995) report that institutional orders are typically split into multiple trades over several days. However, in their datasets institution identifiers are recycled each month, preventing an examination of long-run behaviour. We confirm their finding that individual orders are typically split into multiple trades. Our work differs in that we document the use of multiple orders to build larger positions over much longer horizons than previously appreciated. Collin-Dufresne and Fos (2015) use 13D filings by activist investors to show that price-based empirical measures of adverse selection—many derived from the Kyle (1985) model—cannot detect the presence of informed traders. They argue that classical strategic trading models "fail" because informed, strategic agents use limit instead of market orders and choose to trade when noise trader activity (and thus liquidity) is high. We directly test the classical models' predictions for trading activity, and show that their broad insights remain relevant even under very general circumstances.

Finally, our paper complements recent transaction-level studies of trading skill by showing how traders' profits evolve over extended periods, and by examining the strategic determinants of these profits. Existing work (e.g. Puckett and Yan, 2011; Anand et al., 2012) focuses only on the short run, and does not explore the strategic environment. Our investigation fills this gap in the literature.

3. Data

3.1 Data Description

In this subsection we introduce our dataset, which has not been examined previously 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.[12] The data are ultimately obtained from the fund custodians who are legally obligated to ensure their accuracy.[13] Fund managers and asset owners are anonymized but assigned permanent reference numbers.

[12] 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"). These constitute a minority of the sample and do not change the results if they are excluded.
[13] With the exception of manager searches (see footnote 15).

The main advantages of our dataset over other transaction-level databases, such as those from ANcerno and the Plexus Group, are: (1) complete information on all trading activity, whereas the other datasets contain only a subset of trades submitted by clients for transaction cost analysis; (2) daily holdings and assets under management (AUM) in addition to trades; (3) client-specified performance benchmarks; and (4) a global range of institutions and a long time series, 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 from one to twelve years with a mean of 4.5 years. 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 1 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. For non-US portfolios, all currencies are converted to US dollars at contemporaneous exchange rates. For the analysis in subsequent sections, in light of concerns that the factor structure of returns is more difficult to identify for international markets, we restrict the sample to the set of developed markets where the four-factor structure of returns has been clearly established (e.g. Fama and French (2012); Asness, Moskowitz, and Pedersen (2013)): the UK, developed European countries, Japan, Australia and the remaining developed markets in the Asia-Pacific region. This procedure results in a sample of 610 portfolios.

The distribution of fund manager locations (shown in table 1, 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 managers with geographical ties to this region.

Panel C of table 1 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. Since 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 by asset owners 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 our transaction- and portfolio-level data with security price, market capitalization and benchmark data from Morgan Stanley Capital International, FTSE Group and Russell Investments, trading volume and accounting information from CRSP and COMPUSTAT, and analyst coverage and earnings announcement data from I/B/E/S.[14]

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

3.2. Summary Statistics

Table 2 presents summary statistics for the variables of interest in our study. 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 2 summarizes the characteristics of portfolio holdings. The institutions in our sample are quite active, with active shares (see Cremers and Petajisto, 2009) of around 70%, which is in line with the average active shares for all institutional US asset mangers computed from 13F filings (Lines, 2016). 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 that is 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.

Panel C of table 2 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. 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.[15] Our data differs slightly from that of Keim and Madhavan (1995) 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, and means of 8.25% and 7.99%.

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.[16] Market capitalization of

[15] It is possible for orders to take several weeks or more than ten transactions to fill, but these instances are rare.
[16] 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. The maximum number of analysts for any stock is 57.

traded stocks has a mean of $25 billion. Average share turnover (i.e., trading volume divided by shares outstanding) in traded stocks is around 2.3% per day.

4. Alpha decay and private information

4.1. Event study

If the correct model is used to adjust for risk, price adjustment to new private information is equivalent to incremental alpha decaying to zero. By computing alphas we remove the component of returns attributable to discount rate variation (which is captured by the risk model) and all that remains are changes in expected future cash flows. Positive, decaying alpha in a fund manager's trades therefore indicates that she was in possession of information of about future cash flows that was unknown to the market at the time of the trade. It also suggests that this information was subsequently revealed publicly.

To investigate the accumulation of alpha after institutional purchases and sales we employ a traditional event study methodology. 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.[17] 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:

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

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, $UM\quad_\tau$ 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.[18] 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.

[17] We show in the appendix (section A.4.1) that the results are robust to the use of alternative risk models.
[18] 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 month 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 positions and use actual execution prices to ensure that the alphas we report are feasible in practice.[19]

Average alphas are calculated as follows:[20]

$$\bar{\alpha}^{M}_{m} = \frac{1}{\sum_{j=1}^{J} 1_{\{m \le \lfloor h_j/21 \rfloor\}}} \sum_{j=1}^{J} \tilde{\alpha}^{M}_{j,p,m}\, 1_{\{m \le \lfloor h_j/21 \rfloor\}}, \qquad d = 1, \dots, 378, \qquad (5)$$

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

[19] While we rely on market closing prices to compute the alphas on subsequent days, we show in the appendix 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.
[20] $\lfloor x \rfloor$ is the floor operator.

sells are computed separately). The indicator variable $1_{\{m \leq \lfloor h_j/21 \rfloor\}}$ equals one when the number of months 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). We also compute cumulative average alpha series $\{\overline{\mathrm{A}}_d^D\}_{d=1}^{378}$ and $\{\overline{\mathrm{A}}_m^M\}_{m=1}^{18}$, which are analogous to the evolution of the average stock price.

Holding periods are determined using an intuitive *first-in-last-out* (FILO) algorithm. A new *round-trip trade* (or *position*) begins with an opening 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.[21]

Because orders typically occur in sequences, we must take a stand on which orders come "first" in order to avoid counting orders multiple times. We consider an order to be the beginning of a new sequence if there have been no prior trades by the fund manager in that stock for the past eighteen months. Together with our 18-month post-event window, this ensures that no order will be counted more than once. We interpret orders that begin new sequences as "new information events". This interpretation is necessarily noisy since not every order would be motivated by information—other motives may include rebalancing, profit-taking, and capital recycling.

Figure 1 displays the cumulative and incremental monthly average alpha series: $\{\overline{\mathrm{A}}_m^M\}_{m=1}^{18}$ and $\{\bar{\alpha}_m^M\}_{m=1}^{18}$, respectively. We start by focusing on purchase orders (left panel). Cumulative alpha following initial 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 average annualized alpha at the portfolio level (see table 2, panel A), and the quarterly total is similar to the 0.74% reported by Puckett and Yan (2011). Average incremental alpha is 36 basis points in the first month after the initial order, declining by about half the following month, and continuing to decline towards zero approximately according to a power function.[22] Half of the total alpha accrues by month four (i.e., the half-life of the alpha decay is four months). The fact that incremental alpha decays to zero and does not reverse argues against a misspecified risk model. For comparison, omitting any one of the FFC factors results in alpha that decays to a positive

[21] See the appendix (section A.1) for a worked example of how we implement this algorithm. For the sake of robustness, we find qualitatively similar results using an alternative first-in-first-out algorithm.

[22] 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.

constant rather than zero. This permits the interpretation that prices fully adjust to new private information (as embodied in new trades) over the span of twelve months on average.

One potential weakness of our dataset is that risk factors are more difficult to identify for international markets, and emerging markets in particular. To mitigate these concerns, table 3 reports average incremental FFC alphas (along with standard errors) for the subset of stocks listed in developed markets in the North American, European and Asia-Pacific regions only, following Fama and French (2012) and Asness, Moskowitz, and Pedersen (2013). Averages are computed for the full sample of orders, as well as the "new information event" subsample.

The results are robust to the above modifications, with the alpha remaining around 35-40 basis points in the first month and decaying to zero by month 12, approximately according to a power function. These results show the alpha decay phenomenon in much greater detail and for a broader range of portfolios than in the existing literature, suggesting that it is a robust feature of institutional trading. The time taken for alpha to decay completely is towards the long end of estimates in previous studies, underscoring the importance of the phenomenon.

The alpha pattern following sale orders (right panel of figure 1) is quite 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. For the full sample of orders, total cumulative post-sale alpha is 0.35% after 18 months. The results vary somewhat depending on the subsample (table 3) but display the same overall pattern. We interpret these findings as evidence that institutional sales are not informed, in line with the literature showing that sales have smaller price impact than buys (Chan and Lakonishok, 1993, 1995). 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.

4.2. Private information or public alpha?

If stock returns are predictable using variables other than their risk exposures, then alphas might not represent private information. In this case, decaying alpha would not necessarily correspond to price adjustment and could rather be the result of return predictability. Indeed, Brennan, Chordia, and Subrahmanyam (1998) show that even after adjusting for risk factor exposures, returns are predictable using stock characteristics. In particular, the momentum effect (Jegadeesh and Titman, 1993) strongly resembles the decaying pattern in alphas shown in figure 1. From table 2, panel C, we also know that the average trade size is fairly small, which may mean our results are related to the small-stock effect.

If the fund managers in our sample are in fact trading on the predictability of alpha arising from these publicly-observable stock characteristics ("public alpha"), this would undermine our claim that the managers possess private information. To address this concern, we examine whether trading behaviour can be explained by stock characteristics, and whether these characteristics subsume the information content of institutional purchases when used to forecast future alpha.

We construct each fund's investment opportunity set by taking the union of the stocks in its performance benchmark and any non-benchmark stocks that are traded at least once by the fund during the sample. The ability to identify a valid control group of non-traded stocks is a major advantage of our dataset. Without such a control group, there will not be sufficient variation to identify the differential effect of stock characteristics if the managers only trade stocks with those characteristics.

For each date on which at least one trade is executed, we construct an indicator variable, $Purchase_{i,t}$, that takes a value of one for all stocks purchased on that day and zero for the remainder of the investment opportunity set for that fund. We then estimate the following logit regression by maximum likelihood (separately for each fund):

$$\Pr\left(Purchase_{i,t} \middle| X_{i,t}\right) = \frac{1}{1 + \exp\left\{-\left(\delta + \beta' X_{i,t} + \varepsilon_{i,t}\right)\right\}},$$
$$\text{where } X_{i,t} = \begin{bmatrix} StockChars_{i,t} \\ HoldingDeviation_{i,t} \end{bmatrix}. \tag{6}$$

The vector $StockChar_{\ i,t}$ contains the following variables, constructed for each stock i and date t according to the methodology of Brennan, Chordia, and Subrahmanyam (BCS, 1998): (i) the log of the stock's market capitalization (firm size) one month prior; (ii) the book-to-market ratio as of the firm's most recent annual financial report; (iii) the dividend yield, computed as the sum of all dividends over the year leading up to the month before, divided by the stock price one month before; (iv) the log of dollar volume during the second-to-last month; (v) the stock price one month before; and (vi) the stock return over twelve months leading up to the month before (-12,-1). Going beyond BCS, we include (vii) the long-horizon past stock return, measured over the twenty-four months prior to the twelve-month period just described (-36,-13); and (viii) the stock's annualized volatility, computed from daily returns in the second-to-last month. We also test a specification replacing past returns with past Fama-French-Carhart alphas computed over the same horizons. $HoldingDeviati_{i,t}$ is the difference between the stock's weight in the portfolio and its weight in the benchmark (as of the day before); it is included to capture rebalancing motives. All purchase orders are included in the regression whether they constitute the beginning of a new information event or not.

Table 4 reports the cross-sectional distribution of estimated coefficients across the 610 portfolios that remain after excluding emerging market benchmarks, along with the percentage of portfolios for which the coefficients are significant and negative (% sig-), and significant and positive (% sig+).[23] Panel A reports the specification with past returns, and panel B reports the specification with past alphas. As one might expect, there is a large variety in investment styles, with every characteristic having some portfolios with positive and some with negative coefficients.

We examine the central tendency across all portfolios by looking at the mean and median, and the fractions that are significant in either direction. The overall effects of firm size, volume, and long-horizon past returns/alphas (-36,-13) are negative across all three metrics (i.e., means and medians are negative, and % sig- is greater than % sig+). The magnitudes have a fairly wide range: in panel A, % sig- is between 1.27 times (firm size) and 2.52 times (long-horizon past returns) larger than % sig+. Thus, the institutions in our sample generally exhibit a preference for small stocks and stocks with negative long-run past returns/alphas. The latter result is consistent with institutions avoiding stocks for which momentum has run out or, equivalently, trading on the reversal effect. The effect of one-year past returns/alphas is slightly more ambiguous (mean and median disagree), but overall the effect also seems to be negative, decreasing the likelihood that momentum trading can account for the facts in section 4.1. Positive overall effects can be seen for the dividend yield, stock price and stock volatility. In panel A, % sig+ is between 1.98 times (volatility) and 4.31 times (dividend yield) larger than % sig-. The effect of the book-to-market ratio is also positive but economically small (% sig+ is only 1.09 times larger than % sig- in panel A). The effect of trading volume is negative, suggesting that fund managers generally prefer stocks that trade in smaller quantities, perhaps because these stocks are more likely to be mispriced.

The closest we get to unanimity in the cross-sectional distribution of coefficients is not for any stock-related characteristic but rather for the deviation of portfolio holdings from the corresponding benchmark weights. The negative effect of holding deviation on the likelihood

[23] We do not estimate a joint specification across all portfolios because the number of observations would be prohibitively large (due to the number of non-traded stocks).

of a purchase is consistent with strong motives to rebalance positions when managers stray too far from the benchmark weights. Stocks that are already more overweight in the portfolio are less likely to be purchased again.

Clearly stock characteristics do have some influence on the decision to purchase a stock for the average manager in our sample. If any of these characteristics also forecast future alpha with decaying strength (as assumed in Gârleanu and Pedersen, 2013) this could drive out the predictive value of institutional purchases. To address this possibility we run a series of regressions of FFC alpha in calendar month $t+k$ on the number of fund managers in our sample who purchase that stock in month t, and the set of stock characteristics measured as of month t:

$$\hat{\alpha}_{i,t+k} = \delta + \beta Purchases_{i,t} + \gamma' StockChars_{i,t} + \varepsilon_{i,t+k}, \tag{7}$$

where $\hat{\alpha}_{i,t+k}$ is the alpha for stock i compounded over calendar month $t+k$; and $\varepsilon_{i,t+k}$ is the error term. The number of funds purchasing a stock ($Purchases$) serves as a proxy for the strength of the private information signal. To control for public alpha, we use the BCS set of stock characteristics as in table 4. The universe of stocks included in the regression is identified using the union of benchmarks from the US, UK, Europe, and (developed-market) Asia-Pacific regions, as well as non-benchmark traded stocks. Emerging markets are excluded. Standard errors are clustered at the stock level to account for serial correlation and heteroscedasticity among different stocks.

The results are presented in table 5. Panel A shows results using past returns and panel B shows results using past alphas. Only the coefficients for the number of purchases, size, book-to-market and past returns/alphas are reported for brevity. Arguing in favour of the private information hypothesis and against the public alpha hypothesis, the number of institutional purchases remains a strong predictor of future alpha for 11-12 months after the month in which the purchases took place, even with characteristics included in the regressions. In panel A, each additional purchase is associated with an increase in alpha of about 6 basis points in the first month, declining almost monotonically to about 2 basis points in month eleven, after which the effect becomes insignificant.

The distribution of the number of purchases conditional on at least one purchase is shown in table 6. The mean number of purchases is 2.2, implying that the average effect of institutional purchases is approximately a 13 basis point increase in alpha in the first month, and a 71 basis point increase over twelve months. This magnitude is somewhat lower than the 36 bps first-month effect found in the event study in section 4.1 (figure 1 and table 3).

However, this discrepancy can be partially accounted for by the fact that the calendar-month frequency used in this test misses the alpha that accumulates in the first few days/weeks after the purchase, which can be substantial.

The effects of stock characteristics on alpha are in line with the results in Brennan, Chordia, and Subrahmanyam (1998). The coefficient on firm size is uniformly positive and significant. This may seem to contradict the small-stock premium, but it is the result of also including dollar trading volume in the regression, which is highly correlated with size and has a negative and significant coefficient (not reported in the table for brevity). The effect of book-to-market ratio on future alpha is positive, in line with the well-known value premium, but the effect decays quickly. Similarly, past returns are positively related to future returns, in line with the momentum premium, but the effect also decays quickly. Past alphas, on the other hand, are negatively-related to future alphas after a delay of two months, suggesting a degree of mean-reversion among the set of stocks we include in the regression.

The results in this section indicate that institutional purchases contain additional information about future alpha that is not captured by stock characteristics, and that the institutions' motives for trading are not driven solely by these characteristics. From the results in this and the previous subsection, we conclude that the fund managers in our sample are able to forecast future risk-adjusted returns using information not widely appreciated by the rest of the market. Their trades are associated with gradual subsequent adjustment in the stock price that cannot be accounted for by exposure to known risk factors or characteristics.

5. Investment horizon and position-building

5.1 Average holding period

In a frictionless market, fund managers should overweight a stock only when its expected alpha is positive, which implies that the average holding period on round-trip trades should equal the life of the alpha.[24] To examine whether this is the case, we compute the holding period for each round-trip trade using a first-in-last-out (FILO) algorithm—the holding period begins with the initial information event and lasts until the number of shares held in the portfolio returns to its original level. The appendix describes this method in more detail.

Table 7, panel A, reports statistics on number of orders and order size for several holding period ranges: less than one month, one to three months, three to six months, 6 months to one year, one to two years, and greater than two years. The number of orders in each range is roughly equal (varying from 101,542 to 110,901) except for the first month (75,050).

[24] Note that the prior holding does not need to be zero when a new information event occurs.

However, order size grows monotonically with holding period length. Orders with holding periods of less than one month have an average value of $700,000 (or 0.2% of the portfolio), which increases to $3.4m (or 0.6% 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, indicating that the institutions in our sample generally have longer-term horizons.

Panel B reports the grand average across all holding periods. When computed using the FILO algorithm, the overall average holding period is 1.66 years. However, this method leads to downwardly-biased estimates because only completed round-trip trades are included in the average—holding periods that exceed the end of the sample period (which cannot be computed using the FILO algorithm) are likely to be longer. Thus we also report the average holding period computed as the inverse of annual portfolio turnover, which is 2.24 years. This method is less direct but does not suffer from a downward bias.

The average holding period in our sample is therefore about double the average lifespan of the alpha, indicating a horizon mismatch between managers' information and their actions. There are at least three possible explanations for this fact. First, managers may be less than fully rational, estimating the alpha lifespan with a negative bias. Second, institutional constraints may prevent managers from unwinding positions at the optimal time—pension sponsors have an explicitly long-term mandate, and may put pressure on fund managers if their portfolio turnover is too high. Third, fund managers may tolerate some degree of portfolio inefficiency from the horizon mismatch because it is too expensive to sell quickly. We will return to these potential explanations in the following sections.

5.2. Position building and unwinding over time

Recall that we define an information event as a new trade following no activity by the fund manager in that particular stock for the past eighteen months. We then refer to any trading activity—*in the same stock by the same manager*—over the next eighteen months as "follow-up" trading. Such activity provides a picture of how fund managers build new positions, and unwind them, following an information event.

We compute three measures of follow-up trading activity: (i) the daily fraction of portfolios with at least one trade on that day (*FracTrading*); (ii) daily average net trade size conditional on a trade taking place (*NetSizeEx0*—i.e., average net trade size excluding zeros); and (iii) net trade size summed at the monthly level, where months with no trades are recorded as zeros (*NetSize*). As such, measure (iii) is a combination of measures (i) and (ii), aggregated monthly. Net trade size means purchases minus sales, each measured as a fraction of portfolio AUM. The AUM scaling is used to render trades comparable across portfolios of different sizes. Positive values of *NetSizeEx0* and *NetSize* represent buying and negative values represent selling.

Figure 2 plots *FracTrading* and *NetSizeEx0* over 378 trading days (18 months) following each information event. To maintain consistency with the measurement of alphas, we drop observations from the averages once each position has been closed. The first point that stands out from figure 2 is that trading activity does not cease after completion of the initial "package" of transactions that constitutes an order, as examined by Chan and Lakonishok (1995) and Keim and Madhavan (1995). Rather, trading activity in the same stock continues for many months after the initial order. Although individual fund managers rarely trade every single day, 8% trade again on a given day in the first week, 4% in the tenth week, around 2% in week 30, and about 1% in week 52 (one year out). Thus new positions are accumulated over much longer periods of time than previously appreciated in the literature.

The second key observation from figure 2 is that average trade size declines over time, with roughly the same power-function shape as the post-purchase alpha.[25] After an initial purchase, net trade size excluding zeros is approximately 5 basis points per day in the first week, falling to zero and then turning negative after around 200-250 trading days. That is, follow-up trades have the same sign as the initial purchase order and remain positive for about as long as the alpha is significantly positive—twelve months—after which they begin to be unwound. The pattern is similar when the initial event is a sale except that the follow-up trades have the opposite sign, which does not reverse in the long run, consistent with non-information-driven selling. $NetSizeEx0$ is approximately -5 bps per day in the first week, and approximately -1 bps per day after one year.

Table 8 reports the aggregated monthly *NetSize* in three forms: month-by-month, cumulative, and as a percentage of the peak position size. To maintain consistency with the alphas in table 3, table 8 also omits emerging markets. The peak position size is the maximum (for initial buys) or minimum (for initial sells) values for cumulative *NetSize*. After initial buys, average monthly follow-up net purchases start at a statistically and economically significant 9.22 bps in the first month, and decline to an economically trivial 0.47 bps by month 12, after which they become insignificant. The result of excluding emerging markets is that the unwinding of positions begins later—in month 16—but otherwise the pattern is identical to that shown in figure 2. For post-sale follow-up trading, net purchases are -11.82

[25] $R^2 = 0.96$.

bps in the first month and fall (in magnitude) to -0.87 bps by month 18, all statistically significant.

Cumulative *NetSize* reveals clearly that the daily trades shown in figure 2 are small relative to the eventual maximum position size. Only 32.6% of the final position has been accumulated by the end of the first month of trading, and only 51.3% by the end of the second month. After the eighth month, individual trades are so small/infrequent that it takes almost the same amount of time for the fund manager to reach the maximum position size as it does to accumulate the first 90%.

Another important observation is that the fund managers in our sample unwind their positions as gradually as they accumulate them. Gradual selling after alpha has "run out" can account for much of the discrepancy between forecasting ability and holding period. It indicates that managers may well be aware that a stock is no longer outperforming (since they do begin to sell at the right time) but the time it takes to unwind a position inflates the measured holding period. As such, we consider the first explanation for the horizon mismatch proposed in section 5.1 above—that managers have a biased estimation of their own forecast horizon—unlikely. Due to data limitations, we are unable to evaluate the second proposed explanation—that managers are constrained by institutional norms in favour of longer horizons. However, in section 6 we examine the third potential explanation—that rapid trading is too costly—in more detail.

6. Strategic informed trading

6.1. Characterizing the strategic environment

Trading large blocks of stock at once can be expensive due to price impact. When informed traders submit orders to the market, they reveal a portion of their private information and move prices against themselves (Kyle, 1985). The larger the trade, the more information is potentially revealed and the greater the price impact. In equilibrium, rational traders know that trading a large block of stock, even when they are uninformed, will result in adverse price movements because the market cannot differentiate between informed and uninformed orders.[26] Counterparties simply know that, on average, larger orders convey information. This consideration leads fund managers to split their orders into multiple smaller trades over several days (e.g. Keim and Madhavan, 1995; Chan and Lakonishok, 1995). But can concerns over price impact explain gradual buying and selling over longer horizons?

[26] While Kyle (1985) does not allow for strategic liquidity trading, subsequent authors have done so in a Kyle-type setting; e.g. Mendelson and Tunca (2003).

Is strategic behaviour, intended to limit information leakage, a major factor leading to the trading behaviour reported in figure 2? Does this behaviour prevent more rapid price adjustment, reflected in the prolonged alphas of figure 1? Whether private information is eventually revealed through trading by informed agents or by gradual arrival of public signals over time, the question of why information advantages are not rapidly competed away is closely linked to fund managers' trading behaviour.

Figures 1 and 2 are at least *consistent* with Kyle-type models of informed strategic trading that allow for multiple speculators and heterogeneous information signals (Foster and Viswanathan, 1996; Back, Cao, and Willard, 2000; Bernhardt and Miao, 2004).[27] However, the strategic trading hypothesis is difficult to test directly because trading activity and prices are determined simultaneously and endogenously in equilibrium. Thus a regression of trades on returns, or vice versa, is not identified. Empirically, prices may adjust to a greater extent because informed agents are trading more aggressively, or informed agents may trade more aggressively because prices are expected to move more. Moreover, alternative explanations such as positively correlated information signals arriving over time, naïve cost-minimization algorithms, and other mechanical trading rules, may also consistent with figures 1 and 2.

To get around the identification problem described above, and to develop hypotheses that are inconsistent with other potential explanations, we turn to the cross-sectional predictions of the models. Theoretically, the two key exogenous parameters that determine trade size are the number of informed traders and the correlation among their information signals.[28] More competitors and greater correlation among information signals lead to more aggressive trading: total order size over the trading period is increased and trading activity is also shifted earlier in time. Intuitively, this is because both variables increase the likelihood that another agent has access to the same information. In the limiting case where another agent has an identical signal, Holden and Subrahmanyam (1992) show that the two speculators immediately compete away the profitability of their information (assuming continuous trading)—the expectation that one competitor will trade more aggressively leads the other to trade more aggressively in response, which in turn induces the first competitor to trade more aggressively, and so on—and prices adjust instantaneously.

[27] Since these models are purely theoretical, they do not state their results in terms of observable trading behavior or price movements because these quantities depend on realizations of noise trader demand, which is stochastic. In the appendix, we simulate the most numerically tractable version of this framework—Foster and Viswanathan (1996)—to illustrate the models' consistency with figures 1 and 2.

[28] For empirical tractability, we follow Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) in assuming that all correlations are equal.

As we do not observe fund managers' information sets directly, we must rely on proxies for these variables. Following other papers in the literature, we use data on security analysts. Analyst reports are well known to be informative for future stock returns (e.g. Womack (1996); Bradley, Clarke, Lee, and Ornthanalai (2014)) and to incite trading by buy-side investors, both before (Irvine, Lipson, and Puckett (2007)) and after (Busse, Green, and Jegadeesh (2012)) the reports are officially released.

For the number of competitors, we use the number of analysts covering each traded stock, as originally suggested by Holden and Subrahmanyam (1992). Since analyst coverage is highly correlated with firm size, we always control for market capitalization in the regressions. For the (inverse of) signal correlation, we use the dispersion in analyst price targets, computed as the cross-sectional standard deviation divided by the mean (conditional on at least two available forecasts). Pasquariello and Vega (2007, 2013) use similar proxies for these variables to study their effects on price impact. In a separate investigation of the momentum effect, Hong, Lim, and Stein (2000) use analyst coverage as a proxy for information asymmetry. Their interpretation is compatible with ours because greater competition for information about a stock increases the likelihood that a particular piece of information will become public, thus lowering information asymmetry. We do not measure the number of competitors using concurrent trading within our sample because fund managers do not observe which of their competitors are active in a given stock in real time. As such, they 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.

6.2. Trading after information events as a function of the strategic environment

To examine the relationship between the strategic variables (competition and correlation) and trade aggressiveness after the initial information event, we run the following panel regression:

$$NetPurchases_{j,p,m} = \delta_p + \sum_{q \in \eta} \left[\varphi_q + \beta_q Analysts_j + \theta_q Dispersion_{j,p} + \gamma_q{}' Controls_{j,p}\right] 1_{\{m \subseteq q\}} + \varepsilon_{j,m}, \tag{8}$$

where $\eta = \{\{1\},\{2\},\{3\},\{4,5,6\}\}$; $NetPurchases_{j,p,m}$ is the sum of purchases minus the sum of sales, measured as a fraction of AUM (in basis points), in month m after event j from portfolio p;[29] δ_p are portfolio fixed effects; φ_q are post-event fixed effects for each quarter; $1_{\{m \subseteq q\}}$ is an indicator variable that takes a value of one when the post-event month falls in the quarter denoted by q; and $\varepsilon_{j,m}$ is the regression error. In other words, within the 18-month post-event period, separate coefficients are estimated for each of the first three quarters separately, and for the last three quarters combined. As in previous sections, standard errors are clustered at the portfolio level.

The $Controls$ vector contains the stock characteristics discussed in section 4.2 (size, book-to-market, dividend yield, price, dollar volume, volatility, and past returns/alphas over one- and three-year horizons), the deviation of the traded stock's portfolio weight from that of the benchmark, as well as time-varying portfolio characteristics not captured by the fixed effects (AUM, active share, and the holdings Herfindahl index). We also include dummy variables to capture two other potential sources of alpha: liquidity provision and proximity to earnings announcements. 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 (see Bernard and Thomas (1989), fig. 1) and the earnings announcement premium (Frazzini and Lamont (2007)). As in section 4.2, these variables are include to control for predictability in returns that is unrelated to private information.

The estimated coefficients are reported in table 9. In the first quarter after the information event, trading aggressiveness increases substantially when the number of analysts covering the stock is high. One additional analyst raises net purchases by between 0.33 and 0.53 basis points, depending on the control variables included in the regression. To appreciate the magnitude of this increase, consider that a one-standard-deviation increase in analyst coverage increases first-quarter net purchases by between 15.9% and 24.9% relative to the unconditional mean. In subsequent quarters, the sign of the relationship turns negative, with one additional analyst reducing net purchases by between 0.035 and 0.069 bps depending on the quarter and on which control variables are included. This finding is consistent with trades being shifted forward in time due to an increased risk of being "beaten to the punch" by competitors. Measured over the full 18-month post-event horizon, the net effect on trade size is positive.

[29] *NetPurchases* includes the initial purchase order that identifies the information event in month 1. A value of zero is assigned to any subsequent months where there are no trades.

Higher price target dispersion (i.e., lower correlation) leads to smaller net purchases in the first two quarters, with the effect being strongest in the first quarter. The statistical significance of this result varies somewhat depending on which control variables are included in the regression. While including past alphas instead of past returns in specifications (3) and (5) weakens significance, the signs and magnitudes remain consistent, suggesting that the test is simply lacking power in these cases. There is likely to be substantial measurement error in our proxy for signal correlation because the standard deviation and mean of analyst price targets must be estimated, and in many cases these estimates are derived from a very small sample. Thus we anticipate that the estimated coefficients will be biased towards zero. Indeed, the coefficients are smaller in magnitude than for analyst coverage: a one-standard-deviation increase in dispersion leads to net purchases that are between 1.4% and 4.9% lower in the first post-event quarter.

If strategic considerations are the key binding constraint on trade size and not, say, limited investment capital, we should not expect fund managers to increase trade size when they receive unanticipated cash inflows to the portfolio. However, if limited capital is the relevant binding constraint, fund managers should increase (decrease) trade size in months or quarters with unanticipated flows into (out of) the portfolio.

Because the portfolios in our sample are almost entirely owned by pension sponsors, capital flows will be a function of the demographic profile of the firm/organization underlying each pension plan, rather than a function of past performance (as is the case for mutual funds, e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Growing firms with younger workforces will experience inflows on average (i.e., they are “cash-positive”), as their employees contribute more than they draw in pensions. On the other hand, mature firms with older workforces will experience outflows on average (“cash-negative”). To the extent that these flows are predictable, fund managers may choose to hold securities with liquidity characteristics that are appropriate for the anticipated constraints of the portfolio. For instance, persistent net inflows may allow fund managers to hold less liquid stocks.

Thus if we wish to study the effects of constraints on trading activity, we must use *unanticipated* capital flows. To this end, for each portfolio we fit an AR(1) model for flows and treat the residuals as the unanticipated component. The equation we estimate is:

$$Flow_t = \delta + \rho Flow_{t-1} + u_t, \tag{9}$$

where $Flow_t$ is the sum of all purchases minus the sum of all sales, computed as a percentage of AUM, in each calendar month or calendar quarter (t); and u_t is the residual.

Table 10 reports the cross-sectional distribution of the time-series mean of monthly (panel A) and quarterly (panel B) flows, and the distribution of AR(1) coefficients (ρ), across portfolios. Monthly flows are positive on average through the time-series and cross-section, at 1.57% per month. Quarterly flows are commensurately larger at 4.29%. Relative to the average order size of 0.25%, these flows are large enough in magnitude to have an effect on order size if capital constraints are responsible for gradual trading behaviour. The mean and median AR(1) coefficients are close to zero, while around 11% (5%) of monthly (quarterly) coefficients are positive and significant, compared to 4% (2%) negative and significant. Although flows are not very persistent for the average portfolio, the AR(1) adjustment is meaningful in the tails of the distribution.

After computing the estimated residuals $\hat{u}_t$ from equation 9, we examine whether they are related to post-event trading activity and, if so, whether they drive out the effects of the strategic variables. Formally, we re-estimate equation 8 with $\hat{u}_t$ and its horizon-dummy interactions as additional explanatory variables:

$$\begin{aligned} &NetPurchases_{j,p,m} \\ &= \delta_p + \sum_{q\in\eta}\left[\varphi_q + \omega_q\hat{u}_t + \beta_q Analysts_j + \theta_q Dispersion_{j,p} + \gamma_q{}'Controls_{j,p}\right]1_{\{m\subseteq q\}} \\ &\quad + \varepsilon_{j,m}. \end{aligned} \tag{10}$$

The results are reported in table 11. Whether we use monthly (columns 1-3) or quarterly (columns 4-6) flows, and whether we control for past performance using raw returns (columns 2 and 5) or risk-adjusted returns (columns 3 and 6), unanticipated flows do not significantly affect trading activity at any post-event horizon. Thus we cannot reject the null hypothesis that purchases are unconstrained by available capital. The large number of observations (0.8 to 1.3 million) indicates that statistical power is high. Unexpected flows also do not drive out strategic variables as determinants of trading activity. The estimated coefficients on the number of analysts and price target dispersion in columns 2, 3, 5, and 6 are almost identical to those in columns 4 and 5 from table 9.

6.3. Post-information-event alpha as a function of the strategic environment

We use a similar framework to examine the effect of competition and signal correlation on post-purchase alpha:

$$\tilde{\alpha}^{M}_{j,p,m} = \delta_p + \sum_{q \in \eta} \left[\varphi_q + \beta_q Analysts_j + \theta_q Dispersion_{j,p} + \gamma_q{}' Controls_{j,p} \right] 1_{\{m \subseteq q\}} + \varepsilon_{j,m}. \quad (11)$$

where $\eta = \{\{1\},\{2\},\{3\},\{4,5,6\}\}$. Equation 11 is identical to equation 8 except that the dependent variable is now the month-m Fama-French-Carhart alpha associated with purchase event j from portfolio p (defined previously in equation 4).

Table 12 reports the results. The effects on post-purchase alpha for both the number of analysts and price target dispersion are significant only in the short run, decaying in both economic magnitude and statistical significance as time since the initial event increases. One additional analyst decreases post-purchase alpha by between 1.1 and 1.5 basis points in the first quarter after the initial purchase order, by between 0.5 and 0.7 basis points in the second quarter (though some estimates are statistically insignificant, depending on which control variables are included), and has no significant effect thereafter. In terms of economic magnitude, a one-standard-deviation increase in the number of analysts translates to a decrease in alpha of between 30.4% and 40.0% of its unconditional mean in the first post-event quarter, and a decrease of between 23.8% and 33.5% in the second post-event quarter.

The effect of price target dispersion has the opposite sign but similar economic magnitude, indicating that higher signal correlation leads to lower post-purchase alpha. A one-standard deviation increase in dispersion leads to an increase in alpha of between 30.7% and 38.2% of its unconditional mean in the first quarter, and has no significant effect thereafter.

7. Discussion

We have shown in sections 6.2 and 6.3 that fund managers increase trade aggressiveness in response to greater competition (more analysts) and higher signal correlation (lower price target dispersion), while the profitability of their trades (as measured by four-factor alpha) falls in response to the same increases in these variables.

There are at least two possible interpretations of these results. The first is that analyst coverage and price target dispersion proxy for the competitive environment, as we posit. A less competitive environment leads to more aggressive trading, lower trade profitability (in risk-adjusted terms), and thus more rapid price adjustment. Relatively low average levels of correlation and competition in the economy prevent private information from being revealed rapidly through trading, allowing prices to adjust at the normal rate of public information arrival and/or as private information gradually leaks through trading.[30]

The second possibility is that fewer analysts and higher price target dispersion indicate greater potential investment opportunities. This poses an identification problem similar to the one that invalidates a regression of alpha on order size. We cannot rule out the possibility that changes in investment opportunities explain some of the above results on post-purchase alphas. However, the results on trading behaviour argue against this possibility, because increased investment opportunities (fewer analysts and higher dispersion) should lead to larger trades, not smaller trades as we observe.

The story consistent with both sets of facts is that fund managers trade strategically when facing competition for (heterogeneously distributed) information about the same stocks. If investment opportunities do play a role in the results, they must inflate the magnitude of the estimated effects on alpha, and deflate the magnitude of estimated effects on trade size. Therefore we are most confident in the results on trading behaviour. While the identification is still not perfectly clean—analyst coverage and price target dispersion could theoretically be correlated with some other unobserved variable that affects trade aggressiveness and alpha with opposite signs—we do not think a plausible alternative explanation remains.

Some further discussion is warranted regarding the shape of the responses of trade size and alpha at different points in time following the initial information event. Trade size increases in the first quarter and decreases in the remaining quarters in response to analyst coverage, consistent with trading being shifted forward in time as predicted by the theoretical literature (see appendix, section A.2). However, we do not observe the same consistent sign reversal over time for price target dispersion, even though the models predict similar responses to changes in competition and signal correlation. What we do observe is that the response to price target dispersion is much lower in magnitude and significance in later quarters, and there is a small (but not significant) sign reversal in the final three quarters in some specifications. Thus the discrepancy between empirics and theory appears to be primarily a level effect, which could be explained by the high measurement error in our proxy for signal correlation. An overall increase (decrease) in trade size in response to signal correlation (price target dispersion) can still reasonably be interpreted as an increase in trade aggressiveness.

[30] Our data do not allow us to measure the relative importance of public information arrival versus private information leakage.

The fact that the magnitude of the alpha response (to both strategic variables) declines in over time is consistent with the transition from a "rat race" to a "waiting game", as predicted by Foster and Viswanathan (1996) and Back, Cao, and Willard (2000). In the models, signal correlation falls endogenously as the price comes to reflect the common component of different traders' signals. Once the price moves between traders' valuations, each trader has an incentive to wait for the other group to move first. Thus, over time, the initial strategic environment becomes less salient and both the number of competitors and the initial signal correlation have less of an effect on alpha and trading behaviour. The empirical responses of trading behaviour in later quarters is also much smaller in magnitude, even when there is a sign reversal.

Finally, the fact that follow-up selling displays the same declining intensity as follow-up buying (section 5.2 and figure 2) despite sales not being informed requires some additional commentary. Although the canonical models of strategic trading do not allow strategic agents to trade for liquidity reasons, their predictions for trading behaviour should be the same when traders are informed and when they are uninformed, provided market makers know that some traders are informed and only observe the total order flow.[31]

The discussion in this section notwithstanding, we do not think the interpretation of our empirical results ought to be bound too tightly to the theory, as the models are extremely stylized and many of their assumptions in the service of tractability depart substantially from empirical reality. However, the models are a useful aid to ensure that we have the correct intuition in setting up our empirical hypothesis tests, and their broad insights are validated by the data.

8. Conclusion

This paper investigates the role played by institutional investors in price formation over various horizons. Using a broad sample of daily trades by sophisticated fund managers, we show that these managers are highly successful at forecasting risk-adjusted (Fama-French-Carhart) stock returns over the short and medium term—but not the long term. Their information decays over the course of a year, roughly according to a power function with a half-life of about four months. Publicly-observable non-risk stock characteristics, known to forecast future risk-adjusted returns, cannot account for the information contained in the trades. These facts indicate that the fund managers in our sample possess private information

[31] Although this conjecture is intuitive, a formal proof is beyond the scope of the current paper.

that is gradually revealed to the market over time. Their forecasting ability is restricted to undervalued stocks, and they pay a liquidity cost when selling.

We then examine how our fund managers trade on their information and ask how this might affect prices. We first note that their average holding period is more than double the horizon over which they are able to forecast returns. However, the timing of their trades indicates that they start selling at about the right time, but that it takes a long time to unwind positions. In contrast to previous studies documenting order-splitting over several days, we document long-run position accumulation and unwinding over the course of twelve months or more. Following an initial information event, fund managers trade repeatedly in small, declining increments.

Out of several potential explanations for this behaviour, we provide evidence that fund managers trade strategically to limit information leakage and reduce price impact. Using analyst coverage data, we form proxies for (i) the expected number of competitors for information about a particular stock and (ii) the average correlation among their information signals. We then show that a more competitive environment leads to more aggressive trading and lower trade profitability (indicating greater price adjustment). Fund managers do not increase trade size following unanticipated inflows to the portfolio, suggesting that limited investment capital is not the relevant binding constraint on their behaviour. We conclude that competition and information signal correlation among market participants is sufficiently low to prevent private information from being revealed rapidly through trading, allowing alpha to decay (prices to adjust) gradually over time.

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Figure 1. Post-order alpha. In this figure we plot incremental (grey bars, left axes) and cumulative (black lines, right axes) Fama-French-Carhart alphas in basis points for up to eighteen months after each order. The left panel shows alpha accruing to purchased stocks, and the right panel shows alpha accruing to sold stocks. Averages are computed over all open positions. Positions are closed when the number of shares held by the fund manager returns to its original level before the order.

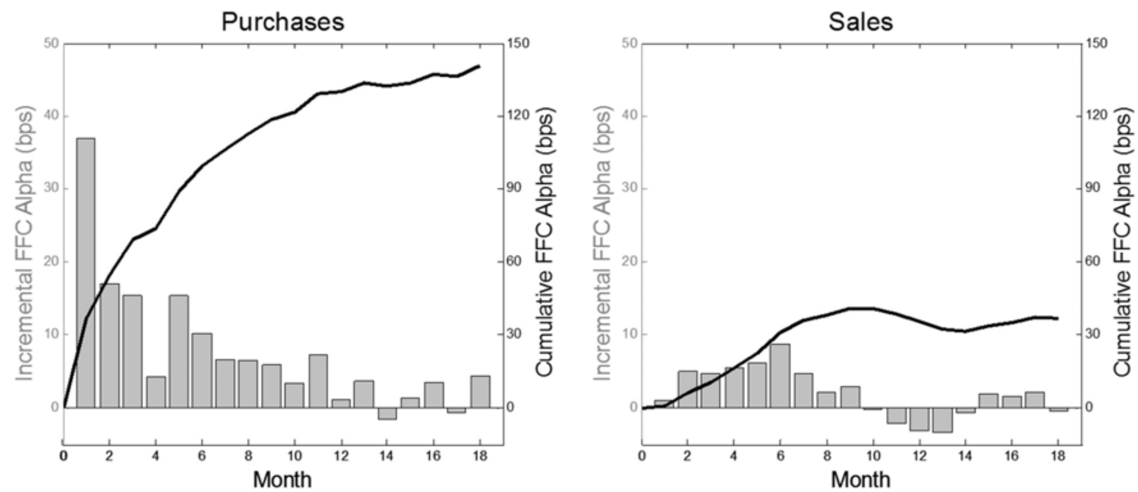


Figure 2. Follow-up trading activity. This figure shows daily follow-up trading activity for 378 trading days (18 months) after each order. The left panel shows the fraction of portfolios for which there is activity in the same stock on a given day, regardless of magnitude or direction ($FracTrading$), and the right 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 ($NetSizeEx0$). Negative values of $NetSizeEx0$ indicate net sales. The black lines show post-purchase activity and the grey lines show post-sale activity. We classify an order as the start of a new sequence if there are no prior trades for eighteen months, and as a follow-up order otherwise. Averages are computed over all open positions. Positions are closed when the number of shares held by the fund manager returns to its original level before the event.

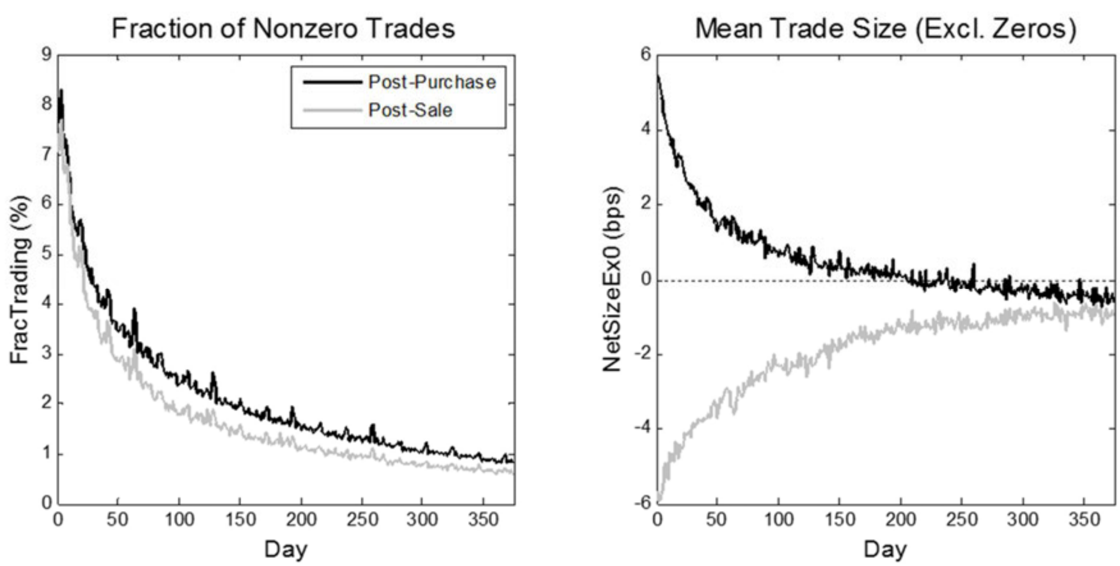


Table 1

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 table A.1 in 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 2
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			% Sig+	% Sig-
			25th	50th	75th		
Raw Return (%)	6.65	11.06	1.48	6.56	12.33		
Relative Return (%)	1.50	4.28	-0.53	1.40	3.62		
Single-Factor (1F) Alpha (%)	1.58	4.15	-0.42	1.44	3.61	13.87	1.45
Fama-French-Carhart (FFC) Alpha (%)	1.21	3.92	-0.52	0.96	3.08	12.57	1.73
1F Beta	0.97	0.10	0.93	0.99	1.02	34.10	49.28
FFC MRP Beta	0.98	0.09	0.94	1.00	1.03	38.15	45.09
FFC SMB Beta	0.04	0.18	-0.03	0.03	0.11	50.87	25.58
FFC HML Beta	-0.05	0.18	-0.12	-0.03	0.05	28.18	45.95
FFC UMD Beta	0.01	0.10	-0.03	0.01	0.06	43.21	29.77
Portfolio Standard Deviation (%)	24.76	6.58	19.93	24.61	28.79		
Tracking Error Standard Dev. (%)	5.95	3.51	3.81	5.07	7.38		

Panel B: Portfolio Holdings Characteristics

	Mean	Std. Dev.	Percentiles		
			25th	50th	75th
Active Share (%)	70.48	18.40	57.27	71.94	85.55
Holdings Herfindahl Index (%)	3.06	2.81	1.68	2.55	4.09
Excess Herfindahl Ratio	4.32	6.13	1.51	2.53	5.06
Weight in Top 10 Holdings (%)	38.16	15.21	26.21	35.17	50.77
Assets Under Management ($m)	495.17	962.63	120.69	249.01	520.46
Sample Length (Years)	4.47	2.17	2.83	4.42	5.73

Panel C: Order/Stock Characteristics

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

Table 3
Monthly post-order alpha in developed markets

This table reports average alphas (in basis points) for eighteen months (m) 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. Averages are taken over all orders as well as a subsample of "new information events"—orders with no prior activity 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). Emerging market stocks are excluded from the sample. Standard errors are reported in parentheses next to the alpha estimates. Standard errors are clustered at the stock level for all order and at the portfolio level for new events. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Purchases				Sales			
m	All Orders		New Events		All Orders		New Events	
1	36.37***	(2.51)	37.17***	(3.58)	4.47*	(2.61)	-5.04	(3.13)
2	16.62***	(2.56)	18.55***	(2.48)	5.70**	(2.54)	4.11	(2.56)
3	14.21***	(2.57)	13.46***	(2.34)	6.34**	(2.60)	5.29**	(2.38)
4	6.66***	(2.56)	6.01**	(2.56)	7.56***	(2.68)	7.71***	(2.40)
5	14.62***	(2.60)	14.50***	(2.56)	6.31**	(2.71)	8.44***	(2.45)
6	11.89***	(2.61)	13.11***	(2.44)	8.87***	(2.64)	8.85***	(2.51)
7	8.38***	(2.69)	8.57***	(2.38)	4.52*	(2.66)	7.96***	(2.60)
8	7.87***	(2.78)	8.73***	(2.45)	6.33**	(2.74)	7.79***	(2.69)
9	6.35**	(2.77)	5.84**	(3.04)	5.36**	(2.70)	8.41***	(3.12)
10	5.54*	(2.93)	6.91***	(2.66)	2.58	(2.66)	6.22**	(2.97)
11	9.47***	(2.94)	12.01***	(2.67)	-0.23	(2.76)	1.39	(2.69)
12	1.35	(3.11)	-1.06	(2.79)	0.14	(2.88)	-0.79	(3.38)
13	4.52	(3.04)	5.06*	(3.02)	-3.49	(2.94)	-1.63	(3.21)
14	-1.15	(3.12)	0.24	(2.72)	1.10	(2.98)	7.75***	(2.94)
15	-0.66	(3.23)	-3.30	(2.91)	3.13	(2.94)	6.46**	(3.04)
16	4.74	(3.21)	2.16	(2.75)	0.72	(2.98)	5.89*	(3.11)
17	0.61	(3.36)	-0.04	(3.22)	2.93	(2.95)	1.93	(3.01)
18	4.11	(3.30)	3.77	(3.16)	1.12	(3.03)	1.82	(2.83)

Table 4
Determinants of purchase decision

This table reports the distribution of estimated coefficients from a series of logit regressions relating purchase decisions to stock characteristics and holding deviation (the difference between a stock's weight in the portfolio and its weight in the benchmark). For each portfolio, on each day with at least one purchase, the dependent variable is a dummy that takes a value of one for purchased stocks and zero for non-purchased stocks. The non-purchased control group consists of all stocks in the performance benchmark specified by the owner of the assets (client). Emerging market stocks are excluded. Formally, the equation we estimate is as follows:

$$\Pr\left(Purchase_{i,t} \middle| X_{i,t}\right) = \frac{1}{1 + \exp\{-(\delta + \beta' X_{i,t} + \varepsilon_{i,t})\}},$$

$$\text{where } X_{i,t} = \begin{bmatrix} StockChars_{i,t} \\ HoldingDeviat_{i,t} \end{bmatrix}.$$

The coefficients are estimated separately for each portfolio by maximum likelihood. The distribution of coefficients across 607 portfolios is summarized in the table. 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. Panel A measures past performance as returns over (-12,-1) and (-36,-12) month windows, while panel B replaces past returns with past Fama-French-Carhart alphas over the same horizons.

Indep. Var.	Mean	Std. Dev.	Percentiles			% Sig-	% Sig+
			25th	50th	75th		
Panel A							
Log(Size)	-0.04	0.69	-0.37	-0.04	0.28	32.23	25.43
Book-to-Market	0.15	0.53	-0.13	0.05	0.35	22.69	24.86
Return (-12,-1)	0.03	0.87	-0.45	-0.12	0.38	35.40	21.39
Return (-36,-13)	-0.04	0.53	-0.27	-0.10	0.12	39.74	15.75
Dividend Yield	5.66	9.26	-0.32	2.69	9.37	8.09	34.83
Log(Volume)	-0.13	0.51	-0.42	-0.09	0.17	36.71	22.40
Price	0.003	0.014	0.000	0.000	0.003	9.25	21.82
Volatility	0.76	1.88	-0.45	0.45	1.68	18.64	36.99
Holding Deviation	-90.1	137.1	-129.0	-74.9	-37.8	79.34	1.88
Panel B							
Log(Size)	-0.02	0.76	-0.42	-0.02	0.32	30.64	25.43
Book-to-Market	0.16	0.61	-0.13	0.03	0.37	21.24	23.99
Alpha (-12,-1)	0.01	1.04	-0.69	-0.20	0.55	31.65	21.68
Alpha (-36,-12)	-0.07	0.54	-0.38	-0.13	0.15	32.37	15.17
Dividend Yield	6.58	13.44	-0.47	2.86	11.35	7.95	34.54
Log(Volume)	-0.15	0.54	-0.48	-0.13	0.15	36.71	19.36
Price	0.003	0.018	0.000	0.000	0.003	9.10	18.06
Volatility	0.49	1.82	-0.57	0.28	1.29	19.65	30.49
Holding Deviation	-77.9	92.9	-123.9	-69.1	-30.2	72.11	3.03

Table 5
Information content of purchases

This table reports the estimated coefficients from a series of regressions of Fama-French-Carhart alpha in calendar month $t+k$ on the number of fund managers purchasing a stock, as well as various publicly-observable stock characteristics, measured in month t. Stock characteristics displayed in the table are the log of market capitalization (size), the book-to-market ratio, and returns (panel A) or FFC alphas (panel B) compounded over twelve months prior to month t. Characteristics not reported in the table are the dividend yield, log of total dollar trading volume in month t, annualized daily volatility in month t, and the stock price. Adjusted R-square is reported in percentage points. Standard errors, clustered at the stock level, are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A

k	# Purchases		Log(Size)		Book-to-Market		$R_{t-12,t}$		Obs.	Adj.R^2
1	0.056***	(0.009)	0.056**	(0.023)	0.114***	(0.025)	0.130**	(0.052)	293,858	0.13
2	0.040***	(0.009)	0.113***	(0.023)	0.066***	(0.024)	0.070	(0.049)	289,968	0.12
3	0.027***	(0.009)	0.131***	(0.023)	0.027	(0.023)	0.002	(0.049)	285,866	0.11
4	0.027***	(0.009)	0.117***	(0.024)	0.022	(0.024)	0.002	(0.050)	281,499	0.11
5	0.048***	(0.009)	0.102***	(0.024)	0.019	(0.023)	0.024	(0.044)	277,043	0.11
6	0.024***	(0.009)	0.118***	(0.025)	-0.001	(0.023)	0.083	(0.043)	272,583	0.09
7	0.033***	(0.009)	0.106***	(0.025)	-0.020	(0.023)	0.034	(0.042)	268,078	0.11
8	0.024***	(0.009)	0.107***	(0.025)	-0.038	(0.023)	-0.030	(0.043)	263,612	0.10
9	0.028***	(0.009)	0.079***	(0.025)	-0.035	(0.023)	-0.044	(0.044)	259,129	0.09
10	0.031***	(0.009)	0.105***	(0.025)	-0.031	(0.023)	-0.008	(0.045)	254,648	0.11
11	0.024**	(0.009)	0.121***	(0.025)	-0.034	(0.024)	-0.042	(0.046)	250,202	0.09
12	0.015	(0.010)	0.155***	(0.026)	-0.007	(0.024)	-0.004	(0.047)	245,853	0.09
13	0.007	(0.010)	0.165***	(0.026)	-0.008	(0.025)	0.037	(0.046)	241,516	0.10
14	0.010	(0.010)	0.178***	(0.027)	-0.009	(0.026)	0.035	(0.045)	237,189	0.10
15	0.013	(0.009)	0.160***	(0.027)	-0.004	(0.025)	0.018	(0.042)	232,854	0.09
16	0.017	(0.010)	0.155***	(0.027)	-0.004	(0.025)	-0.064	(0.046)	228,538	0.09
17	0.009	(0.010)	0.153***	(0.027)	-0.026	(0.026)	-0.059	(0.045)	224,245	0.09
18	0.012	(0.010)	0.156***	(0.028)	-0.016	(0.026)	-0.061	(0.048)	220,002	0.09

Panel B

k	# Purchases		Log(Size)		Book-to-Market		$\hat{\alpha}_{t-12,t}$		Obs.	Adj.R^2
1	0.058***	(0.009)	0.053**	(0.023)	0.095***	(0.025)	-0.089	(0.069)	293,890	0.13
2	0.041***	(0.009)	0.111***	(0.024)	0.052**	(0.024)	-0.098	(0.068)	290,001	0.12
3	0.029***	(0.010)	0.129***	(0.023)	0.009	(0.024)	-0.255***	(0.069)	285,900	0.12
4	0.030***	(0.010)	0.116***	(0.024)	-0.001	(0.024)	-0.322***	(0.071)	281,534	0.12
5	0.050***	(0.009)	0.101***	(0.025)	-0.006	(0.024)	-0.323***	(0.068)	277,079	0.12
6	0.027***	(0.009)	0.114***	(0.025)	-0.033	(0.023)	-0.333***	(0.068)	272,621	0.11
7	0.035***	(0.009)	0.105***	(0.025)	-0.045	(0.024)	-0.295***	(0.066)	268,117	0.12
8	0.026***	(0.009)	0.106***	(0.025)	-0.058	(0.024)	-0.314***	(0.065)	263,652	0.12
9	0.030***	(0.009)	0.079***	(0.026)	-0.049	(0.024)	-0.262***	(0.066)	259,170	0.10
10	0.032***	(0.010)	0.105***	(0.025)	-0.044	(0.024)	-0.194***	(0.068)	254,690	0.11
11	0.025***	(0.009)	0.121***	(0.025)	-0.047	(0.024)	-0.240***	(0.068)	250,245	0.10
12	0.016*	(0.010)	0.154***	(0.026)	-0.021	(0.025)	-0.201***	(0.068)	245,897	0.10
13	0.008	(0.010)	0.163***	(0.026)	-0.028	(0.026)	-0.229***	(0.071)	241,560	0.10
14	0.012	(0.010)	0.176***	(0.027)	-0.029	(0.026)	-0.230***	(0.070)	237,233	0.11
15	0.015	(0.009)	0.158***	(0.027)	-0.023	(0.026)	-0.249***	(0.068)	232,898	0.10
16	0.018	(0.010)	0.155***	(0.027)	-0.017	(0.025)	-0.268***	(0.072)	228,582	0.10
17	0.010	(0.010)	0.153***	(0.027)	-0.036	(0.027)	-0.230***	(0.069)	224,290	0.09
18	0.014	(0.010	0.156***	(0.028)	-0.030	(0.027)	-0.284***	(0.070)	220,047	0.10

Table 6
Distribution of monthly institutional purchases

This table reports summary statistics on the distribution of institutional purchases per stock/month observation, conditional on at least one purchase taking place. The universe of stocks is constructed using the union of all developed-market benchmarks from the US, UK, Europe and Asia-Pacific regions, as well as any non-benchmark stock that is traded at some point in our sample.

Mean	St. Dev.	Min.	Max.
2.22	2.18	1	31

Percentiles				
1st	25th	50th	75th	99th
1	1	1	3	11

Table 7
Holding Periods

This table reports statistics on the distribution of holding periods. Panel A reports the number of orders, mean order size (in US dollars and as a percentage of AUM), and total dollar value of orders for several holding period ranges. The mean order size within each range is also reported. Holding periods are determined using a first-in-last-out (FILO) 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 an example of how we implement this algorithm. Panel B reports the grand average holding period in the sample (in months or years) according to two methods. The first is a weighted average of actual measured holding periods according to the FILO algorithm, where orders are weighted by their dollar value. The second is the inverse of portfolio turnover.

Panel A: Order Statistics by Holding Period

	<1 Month	1M-3M	3M-6M	6M-1Y	1Y-2Y	>2 Years
Number of Purchases	75,050	108,908	101,542	110,901	107,999	102,339
Mean Order Size ($m)	0.70	0.94	1.09	1.25	2.57	3.43
Mean Order Size (% of AUM)	0.20	0.24	0.25	0.27	0.34	0.55
Total Value of Orders ($bn)	52.90	102.05	110.58	138.53	277.22	350.71
Mean Holding Period (Months)	0.52	1.94	4.38	8.69	17.41	39.44

Panel B: Average Holding Period

	Months	Years
Mean Holding Period (FILO)	19.93	1.66
Mean Holding Period (Inverse Turnover)	26.88	2.24

Table 8
Monthly Follow-Up Net Purchases

This table reports average *NetSize* (monthly purchases net of sales), measured as a fraction of AUM (in basis points), for eighteen months (m) after each new information event. New events are defined as new orders with no prior activity in the stock for eighteen months. Emerging market stocks are excluded from the sample. Averages are taken over all open positions—positions where the number of shares held has not yet returned to its original level before the event. Standard errors are reported in parentheses next to the estimates. Standard errors are clustered at the portfolio level. Statistical significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively. The columns labelled *Cuml.* show cumulative *NetSize*, and the columns labelled *% of Peak* show cumulative *NetSize* as a percentage of its maximum (for buys) or minimum (for sells) value.

	Post-Purchase				Post-Sale			
m	*NetSize*	Std. Err.	Cuml.	% of Peak	*NetSize*	Std. Err.	Cuml.	% of Peak
1	9.22***	(0.53)	9.22	32.6	-11.82***	(0.70)	-11.82	23.0
2	5.28***	(0.47)	14.50	51.3	-7.32***	(0.43)	-19.14	37.2
3	3.29***	(0.40)	17.79	63.0	-5.22***	(0.32)	-24.36	47.4
4	2.31***	(0.40)	20.10	71.1	-4.37***	(0.30)	-28.73	55.9
5	2.07***	(0.40)	22.17	78.5	-3.14***	(0.23)	-31.87	62.0
6	1.47***	(0.36)	23.64	83.7	-2.66***	(0.22)	-34.53	67.2
7	1.25***	(0.41)	24.89	88.1	-2.38***	(0.19)	-36.91	71.8
8	0.83**	(0.33)	25.72	91.0	-2.12***	(0.20)	-39.03	75.9
9	0.77**	(0.31)	26.49	93.7	-1.69***	(0.17)	-40.72	79.2
10	0.54**	(0.25)	27.03	95.6	-1.66***	(0.18)	-42.38	82.4
11	0.39	(0.24)	27.42	97.0	-1.46***	(0.19)	-43.84	85.3
12	0.47*	(0.25)	27.89	98.7	-1.18***	(0.13)	-45.02	87.6
13	0.16	(0.23)	28.05	99.3	-1.24***	(0.15)	-46.26	90.0
14	0.16	(0.25)	28.21	99.8	-1.34***	(0.31)	-47.60	92.6
15	0.04	(0.20)	28.25	100.0	-1.06***	(0.14)	-48.66	94.7
16	-0.07	(0.20)	28.18	99.7	-0.87***	(0.10)	-49.53	96.3
17	0.08	(0.20)	28.26	100.0	-1.01***	(0.13)	-50.54	98.3
18	-0.16	(0.18)	28.10	99.4	-0.87***	(0.20)	-51.41	100.0

Table 9
Post-Event Trading and the Strategic Environment

This table reports the estimated coefficients from a panel regression of monthly net purchases (following an information event) on the number of analysts covering the stock (our proxy for competition) and the dispersion in analyst price targets (our proxy for the inverse of signal correlation). The equation we estimate is as follows:

$$NetPurchases_{j,p,m} = \sum_{q\in\{\{1\},\{2\},\{3\},\{4,5,6\}\}} \left[\varphi_q + \beta_q Analysts_j + \theta_q Dispersio\ _{j,p} + \gamma_q{}' Controls_{j,p}\right] 1_{\{m\subseteq q\}} + \delta_p + \varepsilon_{j,m},$$

where $NetPurchases_{j,p,m}$ are recorded (in basis points) in month m following event j from portfolio p; δ_p is the portfolio-specific component of the intercept, φ_q is the horizon-specific component of the intercept, and $1_{\{m\subseteq q\}}$ is an indicator variable that takes the value one when the number of months elapsed since the event falls within the quarter denoted by q. Thus the coefficient for each independent variable is split into four: one each for the first three quarters, and one for the remaining three. An information "event" is a new purchase order after no activity in the stock for eighteen months (same as the post-event window to prevent multiple-counting of orders). Net purchases are defined as the aggregate value of buys minus sells, divided by portfolio AUM, for trades by the same fund manager in the same stock in each month after (and including) the opening purchase. Observations are dropped after the initial position is closed. Control variables are stock characteristics (size, book-to-market ratio, dividend yield, price, dollar volume, volatility), past returns/alphas over one- and three-year horizons, portfolio characteristics (current deviation from the benchmark weight in the stock, assets under management, active share (Cremers and Petajisto (2009), holdings Herfindahl index), a liquidity-provision dummy (Nagel (2012)), and an earnings announcement dummy (one week either side). Emerging market stocks are excluded from the sample. 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: Net Purchases, Fraction of AUM (bps)				
	(1)	(2)	(3)	(4)	(5)
Analysts					
Quarter 1	0.525***	0.394***	0.408***	0.334***	0.334***
	(0.045)	(0.043)	(0.043)	(0.039)	(0.039)
Quarter 2	-0.035**	-0.047***	-0.049***	-0.041***	-0.041***
	(0.016)	(0.017)	(0.017)	(0.015)	(0.016)
Quarter 3	-0.048***	-0.060***	-0.069***	-0.051***	-0.057***
	(0.017)	(0.017)	(0.018)	(0.016)	(0.017)
Quarters 4, 5 and 6	-0.047***	-0.057***	-0.064***	-0.048***	-0.051***
	(0.014)	(0.014)	(0.015)	(0.013)	(0.014)
Dispersion					
Quarter 1	-9.377***	-4.899**	-2.642	-5.527***	-3.831*
	(2.554)	(2.223)	(2.484)	(1.896)	(1.990)
Quarter 2	-3.060***	-2.286**	-2.489**	-1.061	-0.883
	(1.127)	(1.074)	(1.151)	(1.145)	(1.217)
Quarter 3	-2.110*	-1.368	-1.612	-0.377	-0.423
	(1.148)	(1.019)	(1.169)	(0.883)	(0.965)
Quarters 4, 5 and 6	-0.130	0.148	-0.133	0.232	-0.130
	(0.943)	(0.745)	(0.890)	(0.619)	(0.693)
Stock Characteristics	No	Yes	Yes	Yes	Yes
Past Returns	No	Yes	No	Yes	No
Past Alphas	No	No	Yes	No	Yes
Portfolio Characteristics	No	No	No	Yes	Yes
EAWeek Dummy	No	No	No	Yes	Yes
Liquidity Provision Dummy	No	No	No	Yes	Yes
Portfolio Fixed Effects	Yes	Yes	Yes	Yes	Yes
Horizon Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,275,811	1,013,728	841,041	1,013,728	841,041
Adjusted R-Squared (%)	9.57	9.70	9.94	11.27	11.56

Table 10
Capital Flows

This table reports the cross-sectional distribution of (i) the time-series means of monthly and quarterly capital flows for each portfolio, and (ii) the coefficients on lagged flows from an AR(1) model estimated for each portfolio. Monthly flows are shown in panel A and quarterly flows in panel B. Flows are expressed as a percentage of portfolio AUM, and are computed by summing purchases in all stocks for the month/quarter and subtracting the sum of all sales (under the assumption that cash positions are small and stable over time).

	Mean	Std. Dev.	Percentiles			% Sig-	% Sig+
			25th	50th	75th		
Panel A: Monthly Flows (% AUM)							
Mean	1.57	9.76	-0.31	0.43	2.33		
AR(1) Coeff.	0.02	0.20	-0.07	-0.01	0.10	3.90	10.69
Panel B: Quarterly Flows (% AUM)							
Mean	4.29	27.06	-0.90	1.08	6.83		
AR(1) Coeff.	-0.02	0.30	-0.18	-0.02	0.13	1.59	4.62

Table 11

Capital Constraints

This table reports the estimated coefficients from a panel regression of monthly net purchases (following an information event) on lagged unanticipated capital flows (monthly or quarterly). Flows are estimated by adding all purchases and subtracting all sales in a given month/quarter, as a fraction of AUM. Unanticipated flows are then estimated as the residual from an AR(1) model for flows. The regression specification and control variables (including strategic variables) are the same as in table 9. 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: Net Purchases, Fraction of AUM (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Unanticipated Flows						
Quarter 1	0.136	2.478	3.140	-0.542	0.108	0.067
	(1.719)	(1.902)	(1.986)	(0.752)	(0.768)	(0.762)
Quarter 2	-0.879	-0.975	-0.962	-0.237	-0.479	-0.460
	(0.665)	(0.785)	(0.767)	(0.333)	(0.354)	(0.357)
Quarter 3	-1.132	-0.928	-1.066	0.071	-0.201	-0.156
	(0.780)	(0.794)	(0.796)	(0.236)	(0.273)	(0.305)
Quarters 4, 5 and 6	-0.225	-0.146	-0.293	0.064	-0.392	-0.400
	(0.608)	(0.605)	(0.615)	(0.217)	(0.232)	(0.250)
Analysts						
Quarter 1		0.333***	0.333***		0.330***	0.332***
		(0.039)	(0.039)		(0.040)	(0.040)
Quarter 2		-0.041***	-0.040***		-0.040***	-0.040***
		(0.016)	(0.016)		(0.016)	(0.016)
Quarter 3		-0.051***	-0.056***		-0.054***	-0.063***
		(0.016)	(0.017)		(0.016)	(0.017)
Quarters 4, 5 and 6		-0.048***	-0.051***		-0.046***	-0.047***
		(0.013)	(0.014)		(0.013)	(0.014)
Dispersion						
Quarter 1		-5.589***	-3.899*		-5.395***	-3.814*
		(1.893)	(1.986)		(1.897)	(1.994)
Quarter 2		-1.030	-0.874		-1.217	-0.851
		(1.144)	(1.218)		(1.161)	(1.234)
Quarter 3		-0.363	-0.409		-0.301	-0.438
		(0.879)	(0.961)		(0.889)	(0.965)
Quarters 4, 5 and 6		0.236	-0.124		0.337	-0.025
		(0.619)	(0.693)		(0.628)	(0.700)
Monthly/Quarterly Flows	Monthly	Monthly	Monthly	Quarterly	Quarterly	Quarterly
Past Alphas/Returns	N/A	Returns	Alphas	N/A	Returns	Alphas
Other Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,275,811	1,013,728	841,041	1,275,811	1,013,728	841,041
Adjusted R-Squared (%)	9.03	11.28	11.57	8.95	11.38	11.64

Table 12
Post-Event Alpha and the Strategic Environment

This table reports the estimated coefficients from a panel regression of monthly Fama-French-Carhart alpha (for eighteen months following an information event) on the number of analysts covering the stock (our proxy for competition) and the dispersion in analyst price targets (our proxy for the inverse of signal correlation). The equation we estimate is as follows:

$$\tilde{\alpha}^{M}_{j,p,m} = \sum_{q\in\{\{1\},\{2\},\{3\},\{4,5,6\}\}} \left[\varphi_q + \beta_q Analysts_j + \theta_q Dispersion_{j,p} + \gamma_q Controls_{j,p}\right] 1_{\{m\subseteq q\}} + \delta_p + \varepsilon_{j,m},$$

where $\tilde{\alpha}^{M}_{j,p,m}$ is the month-m alpha following the jth opening purchase associated with portfolio p (measured in basis points); δ_p is the portfolio-specific component of the intercept, φ_q is the horizon-specific component of the intercept, and $1_{\{m\subseteq q\}}$ is an indicator variable that takes the value one when the number of months elapsed since the event falls within the quarter denoted by q. Thus the coefficient for each independent variable is split into four: one each for the first three quarters, and one for the remaining three. An information "event" is defined as a new purchase order after no activity in the stock for eighteen months (same as the post-event window to prevent multiple-counting of orders). Observations are dropped after the initial position is closed. Control variables are stock characteristics (size, book-to-market ratio, dividend yield, price, dollar volume, volatility), past returns/alphas over one- and three-year horizons, portfolio characteristics (current deviation from the benchmark weight in the stock, assets under management, active share (Cremers and Petajisto (2009), holdings Herfindahl index), a liquidity-provision dummy (Nagel (2012)), and an Earnings Announcement Dummy (one week either side). Emerging market stocks are excluded from the sample. 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: Post-Purchase FFC Alpha (bps)				
	(1)	(2)	(3)	(4)	(5)
Analysts					
Quarter 1	-1.401***	-1.448***	-1.153***	-1.396***	-1.101***
	(0.263)	(0.306)	(0.325)	(0.305)	(0.323)
Quarter 2	-0.674**	-0.648*	-0.479	-0.671**	-0.491
	(0.317)	(0.340)	(0.343)	(0.340)	(0.344)
Quarter 3	-0.456	-0.476	-0.651	-0.498	-0.671
	(0.311)	(0.364)	(0.416)	(0.365)	(0.418)
Quarters 4, 5 and 6	-0.023	0.055	-0.039	0.076	-0.011
	(0.252)	(0.289)	(0.319)	(0.292)	(0.323)
Dispersion					
Quarter 1	112.51***	126.52***	105.71***	124.05***	101.78***
	(40.89)	(44.36)	(38.11)	(44.51)	(37.98)
Quarter 2	29.19	23.85	24.64	24.34	22.82
	(30.68)	(30.87)	(32.12)	(30.90)	(32.08)
Quarter 3	2.21	-1.61	28.45	-1.71	27.01
	(30.21)	(32.00)	(32.97)	(31.97)	(32.83)
Quarters 4, 5 and 6	-43.41*	-18.43	-6.58	-18.93	-8.97
	(23.85)	(25.26)	(27.74)	(25.18)	(27.50)
Stock Characteristics	No	Yes	Yes	Yes	Yes
Past Returns	No	Yes	No	Yes	No
Past Alphas	No	No	Yes	No	Yes
Portfolio Characteristics	No	No	No	Yes	Yes
EAWeek Dummy	No	No	No	Yes	Yes
Liquidity Provision Dummy	No	No	No	Yes	Yes
Portfolio Fixed Effects	Yes	Yes	Yes	Yes	Yes
Horizon Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,275,811	1,013,728	841,041	1,013,728	841,041
Adjusted R-Squared (%)	0.09	0.11	0.11	0.11	0.11

Appendix

A.1. 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 a histogram of measured holding periods in the cross-section of trades, which have an exponential-shaped distribution, suggesting that opening and closing orders follow a (possibly non-homogenous) Poisson process.

A.2. Simulating Foster and Viswanathan (1996)

As a pure theory paper, Foster and Viswanathan (1996) is concerned with deterministic equilibrium quantities such as the informed trading intensity β_t and the price impact multiplier λ_t. However, these quantities are not directly observable in the data. Rather, we observe the informed trade size $\beta_t(s_i - E[s_i|y])$—which is the informed trade intensity times the difference between a trader's signal and the market maker's conditional expectation of her signal (given total order flow)—and the realized price change $\lambda_t y_t$, which is the price impact multiplier times total order flow.

Since the quantities of interest to us depend on realizations of noise trader demand, we must take expectations, conditional on the informed traders' information set. We do this by simulating paths for trade size and the price, then averaging over the sample paths. We simulate the model using the numerical solution method described in Foster and Viswanathan (1996, pp. 1453-4), conditional on initial undervaluation of the stock. We set all variance parameters to 1, the number of speculators to 5, and the correlation among information signals to 0.181819, as in the original paper. We normalize the starting price to 1 and the true payoff to 2. We then simulate 100,000 sample paths of 378 trading days (18 months) each, assuming one round of trading per day.

Figure A.3 plots average informed trading activity and the average price path conditional on informed traders' information. The resemblance to our empirical observations is striking: trade size (figure A.3, left panel) exhibits gradual power decay like in the data (figure 2), and the price path (figure A.3, right panel) is concave, like the cumulative post-purchase alpha in the data (figure 1). Returns thus exhibit power decay.[32]

Figure A.4 summarizes the effects of competition and signal correlation on trading behaviour. Using the same parameters as for the simulation in figure A.3, in the left panel we vary the number of competitors (2 vs 5) while holding the correlation constant at 0.181819, and in the right panel we vary the correlation (-0.1 vs 0.3) while holding the number of competitors constant at 3. Increasing the number of competitors from 2 to 5 results in larger trades in the short run and somewhat smaller trades in the long run. Increasing the signal correlation from -0.1 to 0.3 results in much larger trades in the short run, larger trades at a medium horizon, and a less-pronounced reversal at a long horizon. The speed of the transition from rat race to waiting game depends greatly on the choice of parameters. Our empirical specification (described in sections 6.2 and 6.3) is sufficiently general to allow the data to speak to the precise shape of the effects.

A.3. List of Benchmarks

Table A.1 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.

A.4. Additional Robustness

In this section we investigate additional potential explanations for the alpha decay phenomenon that, if true, might argue 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 of those remaining.

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

[32] Note that returns in Foster and Viswanathan's (1996) setup are analogous to alphas in our empirical setting. In the model there is no compensation for risk because agents are risk neutral, and empirically we remove the component of returns due to compensation for risk by computing alphas.

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

Panel A of Table A.2 reports average incremental post-purchase alphas for selected months using the methodology described in section II. Averages are weighted equally 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 (2014) are forced to choose passive benchmarks somewhat arbitrarily. However, we observe the client-specified benchmarks directly.

Panel A of table A.2 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.

A.4.2. Subsample Analysis of Alphas

Table A.2 also reports average incremental post-purchase FFC alphas for various subsamples of the data, constructed as follows. First, we consider the effect of liquidity provision/demand on the observed trading alphas. 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 A.2 clearly reveals a short-term discount for liquidity-demanding trades, the overall decay pattern in both subsamples is similar. Figure A.5 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.

Second, we examine the influence of earnings-announcement-related anomalies. As Bernard and Thomas (1989) show, 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. 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 A.2. 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.

Third, in panel C of table A.2 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.

A.4.3. Holding Period Alphas

Until this point, we have used execution prices only to compute alphas on the first day after an order. 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:

$$r_k^H = \frac{X_{k,t+h}}{X_{k,t}} - 1, \tag{12}$$

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 above). 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.

Table A.3 reports the *annualized* holding period FFC alphas and returns relative to the client-specified benchmarks, sorted into various holding period buckets. 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' 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.

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.

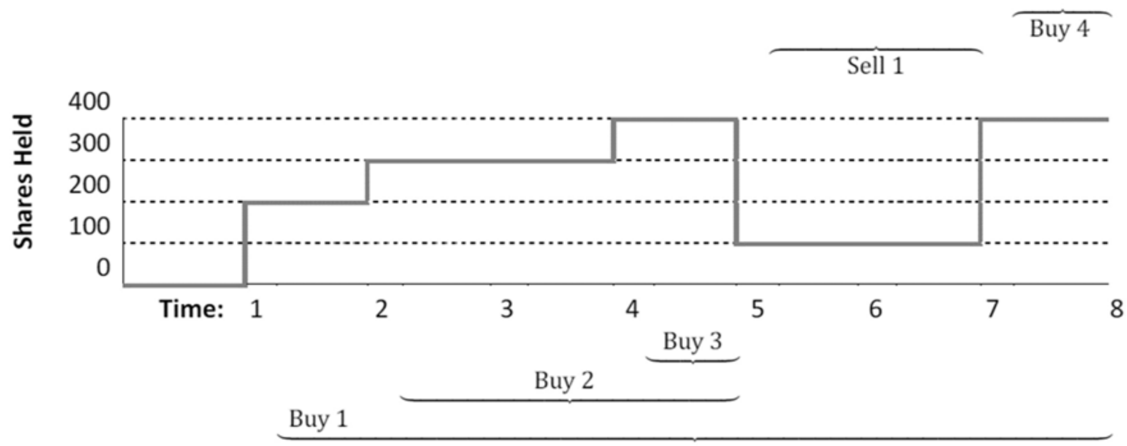


Figure A.2. Distribution of holding periods in the cross-section of trades.

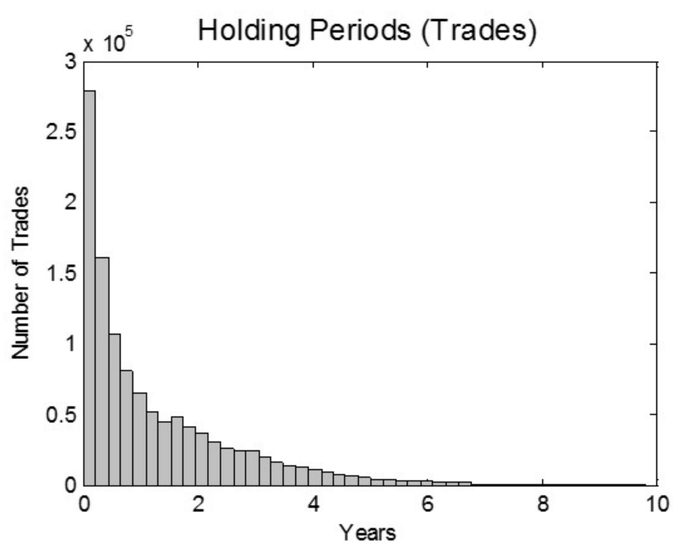


Figure A.3. Simulation of Equilibrium Paths in Foster and Viswanathan (1996). This figure shows simulated average informed trader demand (left panel) and the average stock price (right panel) using FV's numerical solution method. We generate 100,000 sample paths of 378 trading days (18 months) each, then plot the mean of the sample paths for 252 trading days. 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. There are 5 informed traders, and the true fundamental value is equal to the sum of their signals. Starting price is normalized to 1 and fundamental value is set to 2.

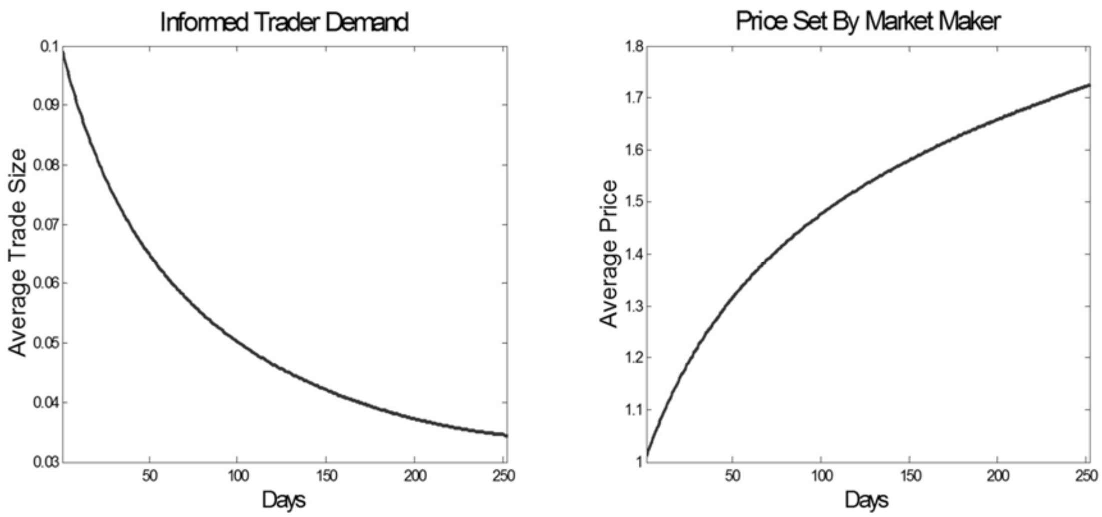


Figure A.4. Effects of competition and signal correlation on trading activity in Foster and Viswanathan (1996). The left panel of this figure shows the effect of varying the number of competitors (M), while holding correlation among information signals (ρ) constant at 0.181819. The right panel shows the effect of varying the correlation, while holding the number of competitors constant at 3. All other parameters are as in figure A.3.

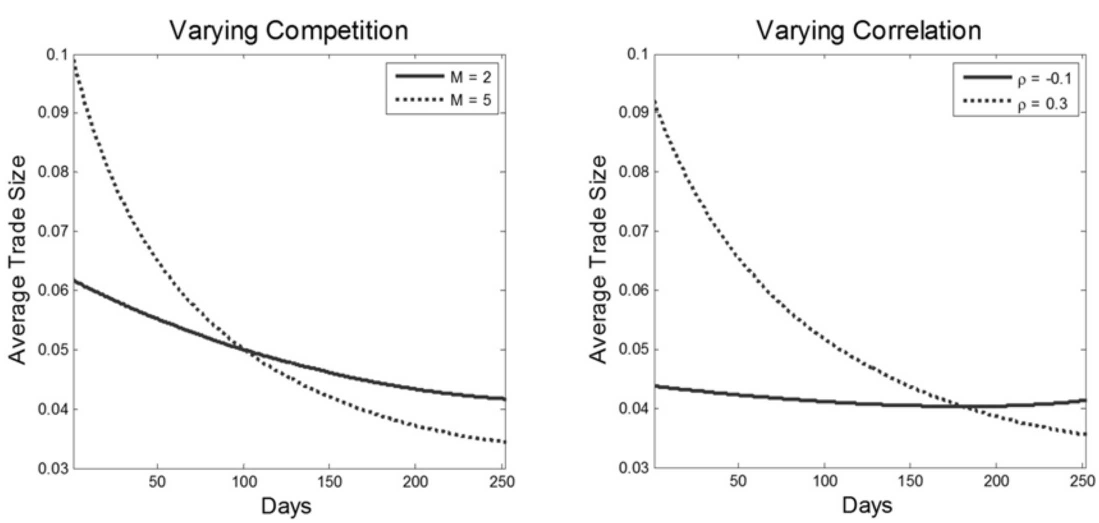
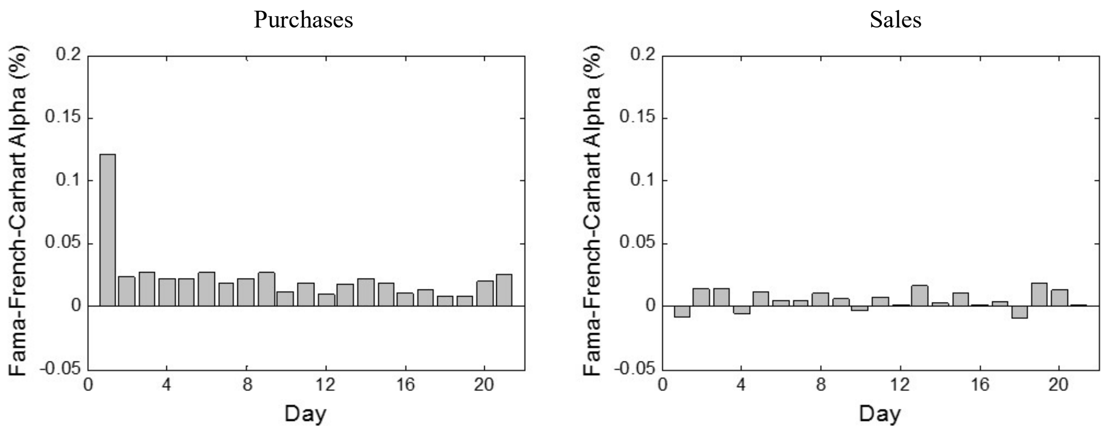


Figure A.5. Effect of liquidity provision on daily incremental alphas. Panel A presents daily post-order incremental Fama-French-Carhart alphas for the full sample. Panel B shows the same but for a subsample of liquidity-demanding orders, defined as purchases following one-day positive returns or sales 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.

Panel A. All Orders



Panel B. Liquidity-Demanding Orders Only

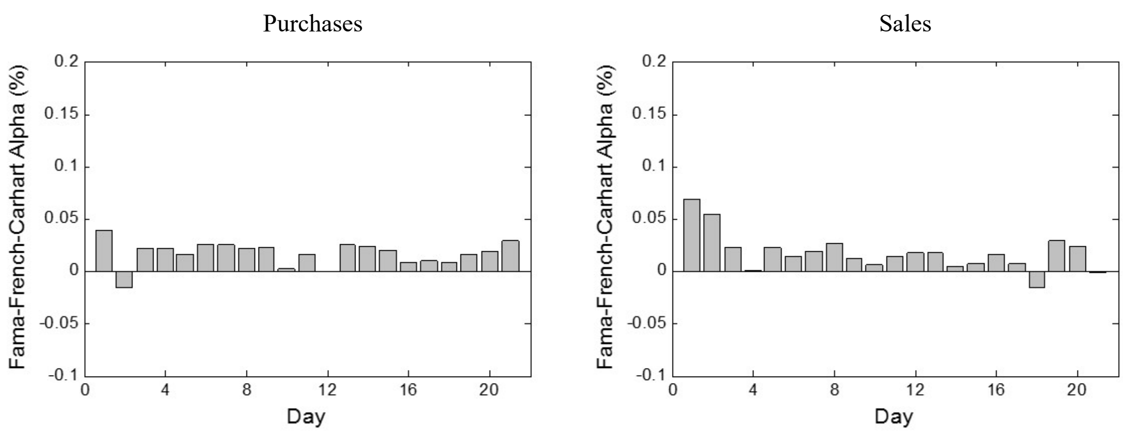


Table A.1

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	

Table A.2
Post-Purchase Alphas: Alternative Explanations

This table reports average alphas (in basis points) for selected months after each opening order. 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						
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]
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 A.3

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)