The Information in Industry-Neutral Self-Financed Trades*

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Abstract

We identify *Industry-Neutral Self-Financed Informed Trading* (INSFIT) by long only fund managers who possess a positive short-lived private signal and self finance informed stock purchases by selling an equivalent dollar amount of stock in the same industry. INSFIT, which constitutes less than 1% of trading, produces a cumulative abnormal return spread of nearly 0.90% over the subsequent ten days. INSFIT also precedes the release of positive public information. The prevalence of relative valuation as well as the need to maintain industry allocations and hedge industry exposure motivate INSFIT's industry neutrality. Furthermore, INSFIT occurs more frequently among cash-constrained managers but is uncorrelated across fund managers. Although INSFIT involves relatively large dollar-denominated trades, transaction costs cannot account for its profitability.

Keywords: Informed Trading, Self Financing, Industry Neutral

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1 Introduction

Informed trading is central to many important theories in finance. For example, informed trading has implications for the price efficiency of markets, the ability of firms to raise capital, and the performance of fund managers. Nevertheless, the empirical identification of informed trading is challenging. Most empirical methodologies in the existing literature identify informed trading by examining how orders were placed or who placed orders in a single asset.[1]

In contrast, we identify a specific type of informed trading; *Industry-Neutral Self-Financed Informed Trading*, denoted INSFIT by conditioning on how trades are financed in a multiple asset setting. Akepanidtaworn, Di Mascio, Imas, and Schmidt (2019) conduct extensive interviews with fund managers and conclude that they *"appear to focus primarily on finding the next great idea to add to their portfolio and view selling largely as a way to raise cash for purchases"*. Therefore, consider a long-only fund manager who acquires a short-lived positive signal regarding a stock and wants to immediately begin buying the stock. To self finance the informed buy trades, the manager sells a portion of their existing portfolio holdings. The stronger the short-lived positive signal, the more selling is required to finance the informed buying. Conversely, uninformed buying can be financed using periodic cash inflows. Put differently, how a trade is financed indicates its informativeness.[2]

The preference of fund managers to self finance informed stock purchases through the sale of stock in the same industry, and therefore be industry neutral, has several motivations.

[1]For example, methodologies that infer informed trading from order imbalances include Kyle (1985) and Easley, Kiefer, O'Hara, and Paperman (1996). This literature has been extended to allow for multiple agents, time-varying liquidity, liquidity timing, optimal execution, and multiple trading venues (Admati and Pfliederer 1989; Holden and Subrahmanyam 1992; Foster and Viswanathan 1996; Back, Cao, and Willard 2002; Zhu 2013; Collin-Dufresne and Fos 2016; Choi, Larsen, and Seppi 2018). Methodologies that examine "unusual" trading patterns by insiders include Cohen, Malloy, and Pomorski (2012), Kelly (2018), and Shkilko (2018). Empirical studies such as Collin-Duresne and Fos (2015) exploit insider trades reported to the SEC as instances of informed trading to study liquidity timing.

[2]Theoretical models of informed trading across multiple assets typically examine long-lived information and the correlation of signals across assets to obtain portfolio-level implications for volatility and order flow dynamics (Bernhardt and Taub 2008; Boulatov, Hendershott, and Livdan 2013).

First, private signals may be obtained using relative valuation techniques that rank firms in the same industry (Da and Schaumburg 2011). For example, discounted cash flow models typically condition on valuation multiples within the same industry. Thus, private signals may contain information regarding a firm's relative industry performance. Second, selling within the same industry hedges industry risk and therefore isolates the firm-specific implications of private signals. For investors capable of short selling, Huang, O'Hara, and Zhong (2020) document the use of industry exchange traded funds to hedge industry risk. Third, fund managers may strive to maintain specific industry allocations to minimize tracking error.

We examine institutional investor trades in the ANcerno database that mostly contains long-only unlevered fund managers. Sifting through over 160 million actual institutional trades from 1999 to 2011, we identify INSFIT using balanced intra-industry pair trades in which the dollar amount of stock bought approximately equals the dollar amount of stock sold in the same industry on the same day. Thus, our classification of manager-industry trades enables us to infer INSFIT by individual fund managers in individual stocks on individual days. While the buy trades underlying INSFIT constitute less than 1% of all buy trades executed by fund managers, these buy trades are extremely profitable. Figure 1 illustrates the refinements involved in identifying INSFIT, while Figure 2 summarizes the respective cumulative abnormal return of buy trades underlying INSFIT for each refinement.

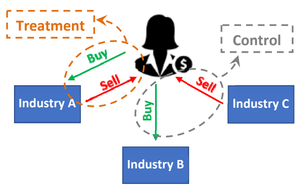
Our analysis is primarily conducted at the manager-day level to control for variation across fund managers and over time. Specifically, our empirical design classifies each manager's buy and sell trades as being either within the same industry (intra-industry pair trades) or across different industries (cross-industry pair trades) on the same day. Therefore, an intra-industry treatment sample and a cross-industry control sample are both available at the manager-day level. We further classify intra-industry pair trades as balanced if the dollar amount of stock bought approximately equals the dollar amount of stock sold, thereby imposing a self-financing property on the intra-industry pair trades that define INSFIT.

Figure 1: **Identification of INSFIT.**
This figure illustrates our sample construction and the refinement process underlying the identification of INSFIT. Panel A displays two relevant manager types on each day; (a) intra-industry managers buy and sell stocks in at least one industry on the same day and may also buy and/or sell stocks in distinct industries; (b) cross-industry managers only buy and sell stocks in distinct industries (placebo sample). Panel B illustrates our main sample that contains both a treatment and control group at the manager-day level. Panels C and D illustrate the balanced and one-to-one refinements of the treatment group.

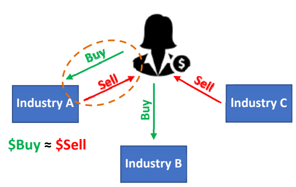
Panel A: manager types each day

intra-industry managers who may execute cross-industry trades | **only** cross-industry managers (placebo)

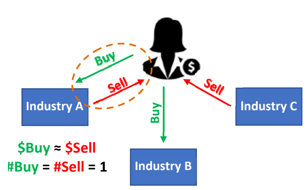
Panel B: main sample: treatment (intra-industry) and control (cross-industry)



Panel C: balanced intra-industry treatment

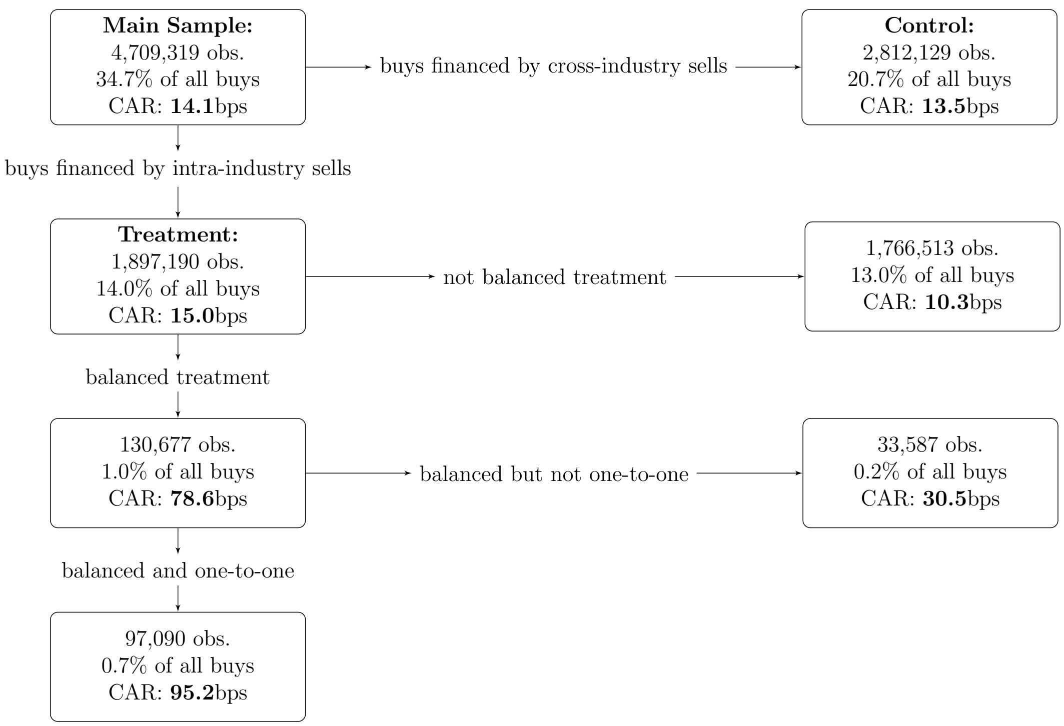


Panel D: balanced and one-to-one intra-industry treatment



To further refine the identification of INSFIT, we focus on one-to-one balanced intra-industry pair trades in which exactly one firm is bought and one firm is sold. While the

Figure 2: **INSFIT Refinement Process and the Abnormal Returns of Buys.**
This flowchart is a companion to Figure 1 and illustrates the sample sizes and cumulative abnormal returns (CARs) over a 10-day horizon for the buy trades underlying INSFIT throughout the refinement process. The main sample described in Panel B of Figure 1 contains both treatment and control groups on the same manager-day. The intra-industry treatment group contains buy trades financed using at least one sell trade in the same industry. The cross-industry control group contains buy trades financed using sell trades in different industries. The treatment group is decomposed into balanced and unbalanced trades. INSFIT is defined by balanced intra-industry pair trades, with a further refinement isolating a subset of one-to-one trades.



majority of balanced intra-industry pair trades are one-to-one, the cumulative abnormal return for buy trades underlying INSFIT increases to 0.952% from 0.786% over the subsequent ten trading days for one-to-one balanced intra-industry pair trades compared to the slightly larger subset of balanced intra-industry pair trades.

Overall, nearly two-thirds of trading activity involves fund managers buying and selling stocks on the same day rather than only buying or only selling stocks. The most stringent definition of INSFIT results from one-to-one balanced intra-industry pair trades that produce a positive cumulative abnormal return spread (nearly 0.90% over the next 10 days). In contrast, the cumulative abnormal return spread following cross-industry pair trades (not industry neutral) and unbalanced intra-industry pair trades (not self financed) are insignificant. Therefore, the identification of informed trading requires pair trades to have both the industry-neutral and self-financing properties. Although Chen, Jegadeesh and Wermers (2000) find that stocks bought by fund managers outperform those sold by fund managers, their study does not impose the industry-neutral and self-financing properties on fund manager trades. Furthermore, in contrast to Chen, Chen, Chen, and Li (2019)'s identification of pair trades using historical return correlations, INSFIT is defined by the actual intra-industry pair trades of institutional investors.

Consistent with short-lived information, balanced intra-industry pair trades portend an increased number of earnings announcements within the industry. Moreover, at the firm level, the buy trades underlying INSFIT precede more positive earnings forecast revisions (Gleason and Lee 2003), higher earnings announcement returns (Baker, Litov, Wachter, and Wurgler 2010), and more frequent positive price jumps. However, INSFIT does not cluster at the stock level since the buy trades underlying INSFIT are typically executed by a single fund manager in a single stock. Therefore, INSFIT does not reflect the arrival of public information capable of inducing correlated trading across multiple fund managers in the same stock. In terms of trade size, the dollar-denominated trades underlying INSFIT are over 30% larger than other trades executed by the same fund manager on the same day. While INSFIT involves relatively large trades, consistent with short-lived private signals, INSFIT is not associated with significantly higher transaction costs. Indeed, INSFIT averages only 1.3% of a stock's daily trading volume. Kacperczyk and Pagnotta (2019) also conclude that informed trading is associated with higher returns but not higher transaction costs.

Intuitively, short-lived private signals prevent fund managers from accumulating cash to finance stock purchases. Consequently, short-lived private signals increase their reliance on using stock sales to self finance informed stock purchases. Ahern (2020) confirms the short-lived nature of private signals that motivate informed trading. The importance of short-lived signals is also consistent with the abnormal returns identified by Puckett and Yan (2011) for interim "round-trip" trades that are unwound within the same quarter.[3] However, only 12% of buy trades and 7% of sell trades underlying INSFIT are unwound by the quarter's end. More important, excluding these unwound trades does not affect the post-trade abnormal returns of INSFIT.

Alexander, Cici, and Gibson (2007) report that the returns of active fund managers increase when their funds are experiencing outflows. In support of the self financing property, INSFIT is more frequent for fund managers with tighter cash constraints. Specifically, INSFIT decreases with a fund manager's cash holdings and increases with their prior outflows. For example, INSFIT increased significantly during the 2008-2009 Global Financial Crisis. Nevertheless, INSFIT is profitable in both the early and later years of our sample period.

The buy and sell trades underlying INSFIT occur in stocks that are indistinguishable in terms of their size, book-to-market, past return, liquidity, and beta characteristics. Moreover, industry momentum cannot explain INSFIT's abnormal returns. Similarly, book-to-market, past return, and liquidity characteristics cannot explain the likelihood a buy trade is attributable to INSFIT. Instead, we find marginal evidence that INSFIT is higher for larger stocks and those with higher return volatility. Besides being consistent with INSFIT's increase during periods of financial turmoil, the positive relation between INSFIT and return volatility is consistent with incentives to acquire and trade on private signals.

The cumulative abnormal return spread associated with INSFIT is mostly attributable to buy trades. Akepanidtaworn, Di Mascio, Imas, and Schmidt (2019) also report that the sell trades of institutional investors are typically driven by heuristics rather than information.

[3] Da, Gao, and Jagannathan (2011) along with Van Binsbergen, Ruan, and Xing (2020) report that fund managers also profit from long-horizon private signals. These buy trades are less reliant on self financing since future inflows provide an alternative source of financing.

Nevertheless, in competitive industries, a positive signal regarding one firm is likely to represent a negative signal for an industry rival. Using the product market fluidity measures of Hoberg, Phillips and Prabhala (2014), we find negative post-trade returns for the sell trades underlying INSFIT in competitive industries. Furthermore, consistent with the importance of relative valuation, the post-trade returns of buy and sell trades underlying INSFIT are more symmetric in competitive industries.

INSFIT builds on the vast literature that examines the profitability of specific institutional investor trades. Cohen, Gompers, and Vuolteenaho (2002), Pomorski (2009), Massa, Reuter, and Zitzewitz (2010) along with Cohen, Polk, and Silli (2010) report that a subset of active fund manager trades are informed. Indeed, Wermers, Yao, and Zhao (2012) provide a methodology capable of predicting stock returns by conditioning on fund holdings. However, instead of attempting to identify trades motivated by the "best ideas" of fund managers or return anomalies attributable to individual investors (such as the underreaction to positive cash flow news), INSFIT identifies trades executed by cash-constrained fund managers who possess short-lived (positive) information.

Complementing the above literature is a related literature that examines the value of active fund management. Evans, Gomez, Ma, and Tang (2020) document the performance incentives of mutual fund managers whose performance is often determined relative to peer funds. Their model predicts that the portfolios of fund managers with relative performance incentives deviate from market indices. Busse, Green, and Baks (2006) as well as Cremers and Petajisto (2009) link portfolio deviations with active management and superior performance, while Chen, Jegadeesh and Wermers (2000) report that widely-held stocks do not outperform.[4] Furthermore, Kacperczyk, Sialm, and Zheng (2005) directly link superior performance with portfolios exhibiting greater industry concentration, which further motivates the industry-neutral property of INSFIT, while Wermers (2002) links superior performance

[4]The ANcerno data in our study contains detailed data on fund manager trades but does not contain portfolio holdings.

with higher turnover. We contribute to the active fund management literature by reporting that, despite its profitability, INSFIT is a rare occurrence for individual fund managers. Nevertheless, whether INSFIT's frequency and profitability are sufficient to cover the cost of active fund management is a question left for future research.

2 Identification of INSFIT

This section details the construction of our sample as well as the refinement process that identifies INSFIT.

2.1 Data

Our study uses ANcerno data from Abel Noser. Institutional investors employ Abel Noser to analyze the execution costs of their trades. Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2012), and Jame (2018) confirm the representativeness of ANcerno trade data. These authors report that Abel Noser institutional investors parallel those identified by the Securities and Exchange Commission's Form 13F in terms of stock holdings and trades. Furthermore, ANcerno data contains institutional trades that are representative in terms of profitability and execution difficulty.[5] Puckett and Yan (2011) compare cumulative quarterly ANcerno trades to changes in quarterly 13F holdings for a subsample of matched institutions. This comparison is able to match more than 80% of quarterly trades with respect to the stock traded and the trade direction.

Our sample of ANcerno data includes U.S.-based common shares listed on the NYSE, AMEX, and NASDAQ between 01/01/1999 and 09/31/2011. We construct daily institutional trades using ANcerno data.[6] Using variables "`cusip`", "`symbol`" and "`stockkey`", we

[5]ANcerno consults exclusively on execution costs and does not analyze investment performance. Thus, investors have no incentive to submit more profitable trades to ANcerno. Furthermore, once an institutional investor subscribes to ANcerno, all trades are routed to ANcerno.

[6]Hu, Jo, Wang, and Xie (2018) estimate that ANcerno data covers 12.3% to 12.6% of CRSP trading volume between January 1999 and September 2011.

match 161,148,431 raw institutional trade observations from ANcerno with common shares reported by CRSP. We aggregate multiple trades (if any) in the same stock by the same manager on the same day using identifying variables "`clientmgrcode`" and "`tradedate`".[7] We classify these stock-specific aggregate trades into buy versus sell orders according to the sign of the net order flow for each fund manager each day. The dollar value of individual trades is calculated as the number of shares traded times the price reported by the client to ANcerno, signed negative (positive) for a sell (buy) trade. Thus, net order flow in a stock reflects a fund manager's sum of signed dollar values in the stock that day. Net sell (buy) trades correspond to negative (positive) total dollar values. This procedure yields 71,036,228 stock-manager-day observations.

Recall that we focus on trades motivated by short-lived private signals. As these trades are likely executed within a single trading day, we exclude a stock-manager-day trade if the manager trades the same stock in the preceding trading day. This filter reduces the number of stock-manager-day observations to 50,217,139. However, our findings are robust to aggregating trades over prior days.

For each institutional trade, we compute cumulative abnormal returns over subsequent trading days using "`cusip`." These abnormal returns are computed by estimating four-factor Fama-French-Carhart models on a daily basis for each stock using Beta Suite by WRDS. Our approach employs rolling windows that span the preceding 252 trading days, requiring a minimum of 126 trading days, to allow for daily variation in the estimated factor loadings. These requirements allow us to match 47,043,935 stock-manager-day trade observations with daily abnormal returns. We use parameter estimates and the concurrent daily factor

[7] We follow Puckett and Yan (2011), Chakrabarty, Moulton, and Trzcinka (2017), and others by relying on "`clientmgrcode`" to identify fund managers. Institutional client types in ANcerno data are identified as investment managers ("`clienttype`=1"), plan sponsors ("`clienttype`=2"), and brokers ("`clienttype`=3"). In studies of institutional trading, it is common to remove broker trades. Our data feature the "`clienttype`" variable for 2006 to 2010. We verify that only 0.7% of the trades in our final sample are from brokers, and that removing these trades does not alter our findings.

portfolio returns to construct the post-trade cumulative abnormal returns (CARs).

In addition to risk-adjusted returns, we calculate each trade's same-day return and implicit trading cost. The same-day return, $R(t)$, measures the difference between the execution price of a trade and the stock's same-day closing price.[8] Following Puckett and Yan (2011), we define the implicit trading cost of a buy trade as the execution price minus the volume-weighted average price (VWAP) on the same day. For a sell trade, the implicit trading cost is defined as VWAP minus the execution price.[9] Both differences are normalized by VWAP.

We then remove stock-year observations if a stock's daily closing price falls below \$5 during the preceding year, leaving 46,575,557 stock-manager-day observations. We assign stocks to the 49 Fama-French industries based on SIC codes from CRSP, and classify trades as either intra-industry or cross-industry.[10] We also calculate volume-weighted same-day returns, cumulative abnormal returns, and trading costs for buy trades and sell trades at the industry-manager-day level. This aggregation results in a manager-industry-day sample that contains 26,898,686 observations. However, 8,804,233 of these observations do not represent pair trades and are discarded from the sample since the manager only buys or only sells stock in a single industry that day. In a later robustness test, we obtain similar results using the 24 industries defined by the Global Industry Classification System (GICS). We obtain the GICS industry codes from Compustat, and use the `permno-gvkey` links from the CRSP-Compustat link table in WRDS to merge these codes with our sample.

We also calculate the number of stocks bought and sold at the manager-day and manager-industry-day levels. In addition, for each manager-day and each manager-industry-day, we construct trade imbalance measures that divide the absolute difference between the dollar-

[8]Constructing same-day risk-adjusted returns is challenging because ANcerno trade time stamps are unreliable (Hu, Jo, Wang, and Xie 2018).

[9]In cases where the same manager executes multiple trades in the same stock, we calculate size-weighted average measures.

[10]Industry definitions are available on Professor Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

value of buy trades minus the dollar-value of sell trades by the total dollar-value traded. A perfectly balanced (unbalanced) trade has an imbalance measure equaling zero (one). Intuitively, a balanced trade arises from a pair trade that is self financing.

Earnings announcement dates are obtained from Compustat. We match the observations in our sample with Compustat using the `permno-gvkey` links from the CRSP-Compustat link table in WRDS. Each earnings announcement's return reflects the average daily return in the three-day window from the day before to the day after an announcement. Quarterly analyst forecasts are obtained from the I/B/E/S Detail History database. To match these forecasts with our sample, we use the `permno-ticker` links from the CRSP-IBES link table in WRDS. At the beginning of each quarter, the consensus earnings per share forecast reflects the average analyst forecast released during the preceding quarter. The consensus forecast is updated whenever a new analyst forecast is released. Forecast revisions then measure the change in the consensus forecast during the quarter before an earnings announcement.

We use the CRSP Mutual Fund database to obtain end-of-quarter cash holdings and to construct quarterly measures of net fund flows. We define monthly net fund flows following the standard approach, as in Barber, Huang, and Odean (2016), and then aggregate these flows to form quarterly observations.[11] Using the link tables provided by the CRSP Mutual Fund database, we merge fund cash holdings and flows with the managing institution identified by Thomson Reuters' 13F institutional holdings. Based on the managing-institution identity file *ManagerXref* provided by ANcerno, we manually link the institution identifier from ANcerno to the identifier "`mgrno`" from 13F holdings. Similar to Eisele, Nefedova, Parise, and Peijnenburg (2020), we successfully match 263 managing institutions from 1,029 valid ANcerno institution codes across the three databases.[12] We then calculate average end-of-quarter cash holdings and quarterly fund flows at the managing-institution level, weighting observations across the different funds by their respective total net assets (TNA).

[11] Fund flows reflect the change in total net assets adjusted for fund returns and, in rare cases, mergers.
[12] Hu, Jo, Wang, and Xie (2018) also discuss this matching procedure.

We measure the asset size of each institution as the sum of TNAs across all constituent funds. We also calculate two measures of asset (fund) concentration for each institution: (i) the inverse of the number of funds under management and (ii) the Herfindahl index of fund-level TNAs. This Herfindahl index equals one for an institution that manages one fund, and approaches zero as the number of funds increases and the institution's TNA becomes more evenly-distributed across funds.[13]

CRSP and Compustat data are used to construct monthly stock characteristics. Using CRSP data, we construct each stock's return volatility using daily observations from the preceding 12 months ($SDRET$). We also use daily open and close prices as well as dollar-denominated volumes from the preceding 12 months to construct a modified version of Amihud's illiquidity measure ($OCAM$).[14] A stock's book-to-market (BM) characteristic is its most recent book value of equity divided by its market capitalization from the previous month.[15] Past return measures include the previous month's return (MOM_{-1}) and the compound return over the preceding 11 months (MOM_{-12}^{-2}).

2.2 Identifying INSFIT

We first classify managers on each day according to one of two possible types. An intra-industry manager executes at least one intra-industry pair trade, and may also buy and/or sell stocks in other industries on the same day. Conversely, a cross-industry manager only buys and sells stocks in different industries on the same day. Panel A in Figure 1 illustrates the difference between these two manager-day observations.

We further refine the sample of intra-industry managers to ensure each manager's intra-industry pair trades (treatment) are matched with their cross-industry pair trades (control).

[13]For example, the index for an institution managing funds A and B with 95% of the fund family's TNA in fund A is $HI = 0.95^2 + 0.05^2 = 0.905$.

[14]Barardehi, Bernhardt, Ruchti, and Weidenmier (2020) find this modified measure significantly outperforms the original Amihud measure in capturing liquidity and explaining cross-sectional returns.

[15]Book value is defined as Compustat's shareholder equity value (`seq`) plus deferred taxes (`txdb`).

Thus, our main sample focuses on manager-days where a fund manager (i) sells and buys within at least one industry, (ii) only sells in (at least) a second industry, and (iii) only buys in (at least) a third industry. These manager-days form our main sample. Panel B of Figure 1 illustrates the manager-days in the main sample, while Table 1 summarizes the sample. Observe that using the daily trades of each fund manager enables our identification to control for variation across fund managers and over time.

We also exclude manager-day-industry observations where a manager trades five or more stocks within an industry on the same day since information regarding a single firm is difficult to isolate on these days. This filter excludes less than 25% of the remaining observations. Table 1 summarizes the intra-industry trades excluded by this filter. A later analysis of one-to-one trades verifies the usefulness of this filter, although our findings are robust to imposing less restrictive filters.

We then classify the imbalance between the dollar value of stock bought and the dollar value of stock sold in the same industry on the same day as

$$IMB = \left| \frac{\text{\$-value bought} - \text{\$-value sold}}{\text{\$-value bought} + \text{\$-value sold}} \right| . \tag{1}$$

We also aggregate manager-industry-day trade imbalances to the manager-day level in order to quantify balanced cross-industry pair trades.

Intra-industry pair trades in the treatment group are divided into a balanced subsample, where IMB is below 0.05, and an unbalanced subsample for the remaining trades.[16] This refinement is illustrated by Panel C in Figure 1 and summarized in Table 1. The subsample of balanced intra-industry pair trades contains 130,677 manager-industry-day observations and comprises our treatment group. The subsample of cross-industry pair trades containing 488,113 sell trades and 519,887 buy trades comprises our control group. Note that certain cross-industry trades in Table 1 may overlap for the balanced and unbalanced intra-industry

[16]Requiring $IMB = 0$ to identify balanced pair trades leaves too few observations due to mechanical effects such as round lot trading, illiquidity, etc.

pair trades because the only restriction is belonging to the same fund manager on the same day.

Unbalanced intra-industry pair trades and cross-industry pair trades enable us to conduct an external validity exercise for INSFIT. Panel B in Table 1 summarizes the number of trades, the average cumulative abnormal return (CAR), the average dollar-denominated trade size, and the annual frequency per fund manager of different trade types in the main sample.[17]

Observe that INSFIT is relatively rare for individual fund managers since the average fund manager executes 4.1 balanced intra-industry pair trades per year, which is far less frequent than the execution of cross-industry pair trades. The paucity of INSFIT is consistent with the lack of persistence in fund manager performance (Barras, Scaillet, and Wermers 2010; Busse, Goyal, and Wahal 2010). However, the relation between INSFIT and fund performance is left for future research.

3 Empirical Results

Our main result is the identification of INSFIT using balanced intra-industry pair trades. Intuitively, such trades are likely to be executed by a cash-constrained long-only investor who acquires a short-lived signal regarding a firm's relative industry performance.

We find that buy trades underlying INSFIT precede positive price jumps and high earnings announcement returns. Furthermore, the dollar-denominated size of these buy trades is relatively large, which is consistent with the need to urgently execute trades motivated by short-lived private signals. Despite involving relatively large trades, INSFIT does not induce larger trading costs than other transactions by the same manager on the same day.

We also find evidence that INSFIT is more frequent for cash-constrained investors and

[17]Trade frequency is normalized by the number of years a fund manager's ID, `clientmgrcode`, is observed in the sample to account for variation across fund manager tenure. According to Hu, Jo, Wang, and Xie (2018), `clientmgrcode` may change over time. However, as our analysis of INSFIT is based on a horizon shorter than 10 days, variation in `clientmgrcode` is irrelevant for the information content of trades.

verify the importance of relative valuation to INSFIT. Furthermore, we establish that less than 15% of the buy trades underlying INSFIT are unwound by the quarter's end. Morever, the returns from INSFIT are robust to excluding these unwound trades. Finally, size and return volatility are positively associated with INSFIT but not book-to-market, liquidity, and past return characteristics.

We estimate post-trade cumulative abnormal return spreads for a variety of different trade pairs using the following specification

$$CAR_{ij}(t, t+s) = \alpha_{0s} + \alpha_{1s} I(Side^t_{ij}) + \text{FEs} + u^{t,s}_{ij} \quad \text{for } s \in \{1, \ldots, N\}, \tag{2}$$

where $CAR_{ij}(t, t+s)$ denotes the post-trade s-day cumulative abnormal return on manager i's trade in industry j on day t. $I(Side^t_{ij})$ is an indicator variable that equals 0 if manager i's trade on day t is a sell and 1 if it is a buy. Hence, α_{0s} captures average post-trade CARs from sell trades, $\alpha_{0s} + \alpha_{1s}$ captures average post-trade CARs from buy trades, and α_{1s} therefore captures the return spread between buy and sell trades. By substituting R_{ij} as the dependent variable, we also analyze same-day raw returns, which are defined as the return between the execution price and closing price on day t. The above specification controls for both fund manager and date fixed effects. This specification also accounts for autocorrelation in the error term and double-clusters the standard errors by fund and date.

3.1 Preliminary Analysis of Pooled Sample

We begin our study with the pooled sample consisting of all available trades in the main sample. INSFIT, defined by balanced intra-industry pair trades, within the pooled sample results in a positive post-trade cumulative abnormal return spread. This return spread is due primarily to the buy trades underlying INSFIT. In contrast, unbalanced intra-industry pair trades and cross-industry pair trades do not result in positive post-trade CAR spreads.

According to Table 2, INSFIT is followed by a large and significant post-trade CAR spread. This "informed trading profit" remains statistically significant for the subsequent ten trading days. In contrast, unbalanced intra-industry pair trades are followed by smaller and often insignificant CAR spreads. The disparity between the CAR spreads following unbalanced intra-industry pair trades versus balanced intra-industry pair trades is difficult to reconcile with intra-industry pair trades generally being motivated by information. Instead, self financing is an important determinant of informed trading.

According to Table 2, the CAR spreads following balanced cross-industry pair trades are insignificant and occasionally negative. The disparity between the CAR spreads following balanced cross-industry pair trades versus balanced intra-industry pair trades is difficult to reconcile with balanced pair trades generally being motivated by information. Instead, relative valuation within an industry is an important determinant of informed trading.

Despite accounting for manager and date fixed effects in the pooled sample, post-trade returns may be attributable to unobserved factors that govern a fund manager's decision to trade within industries or across industries on a given day. Therefore, we focus on manager-industry-days where a manager executes pair trades both within industries and across industries on the same day. This enables us to partition manager-industry-day observations into treatment and control groups, as illustrated by Panel B in Figure 1 and summarized in Table 1.

3.2 Balanced Trades: Treatment versus Control

To quantify the short-lived information motivating INSFIT, we estimate cumulative abnormal returns as well as same-day raw returns using equation (2) for balanced intra-industry pair trades. According to Table 3, the CAR spread defined by these pair trades reaches 68 basis points. In contrast, cross-industry pair trades by the same managers on the same days lead to insignificant post-trade alphas. Figure 3 illustrates these CAR spread differences. Appendix A demonstrates the robustness of these CAR spread differences to using an alternative industry classification.

The CAR spread following INSFIT is primarily attributable to the positive abnormal returns following buy trades. Sell trades temporarily predict negative abnormal returns before reversing to zero. The return reversals following sell trades are consistent with the willingness of fund managers to incur price impacts in order to immediately self finance buy trades whose expected returns are sufficiently high to justify incurring these price impacts.

We also estimate equation (2) using observations in the main sample that correspond to unbalanced intra-industry pair trades. Table 3 reports that the post-trade CAR spreads for these unbalanced intra-industry pair trades are minimal, often insignificant, and smaller than balanced intra-industry pair trades.[18] More important, the CAR spreads following unbalanced pair trades are typically insignificant. This finding highlights the importance of conditioning on balanced pair trades, which are self financing, to identify informed trading.

Our next analysis demonstrates that the majority of INSFIT involves the purchase and sale of individual stocks. Specifically, the sale of exactly one stock to finance the purchase of exactly one stock in the same industry. Consequently, one-to-one balanced intra-industry pair trades drive the post-trade cumulative abnormal return associated with INSFIT.

For each manager-day observation, we produce an ordered pair (# of stocks sold , # of stocks bought) and compare the relative frequency of intra-industry pair trades and cross-industry pair trades. Figure 4 presents these relative frequencies. For each ordered pair (# of stocks sold, # of stocks bought), the relative frequency is plotted for intra-industry pair trades and cross-industry pair trades. Observe that over 60% of intra-industry pair trades are one-to-one, while the percentage for cross-industry trades is at most 10%.

Table 3 reports that the buy trades underlying one-to-one balanced intra-industry pair trades produce an average post-trade abnormal return that exceeds 95bps over the subse-

[18]Implicit trading costs for individual buy or sell orders in our sample is approximately 5bps (Puckett and Yan 2011). As a round-trip institutional trading cost of 10bps is expected, even the largest CAR spread for cross-industry pair trades is unlikely to be profitable after accounting for round-trip trading costs.

quent 10 trading days, while the CAR spread of the pair trades exceeds 89bps over the same horizon. Furthermore, unreported results indicate that balanced intra-industry pair trades that are not one-to-one result in negligible abnormal returns.

3.3 Post-Trade Release of Public Information

Our next analyses establish that the buy trades underlying INSFIT portend the release of positive public information.

We first examine the link between INSFIT and upcoming earnings announcements at the industry level. Specifically, we compare the average industry-level number of earnings announcements following balanced intra-industry pair trades with the average number of earnings announcements following cross-industry pair trades. This industry-level comparison controls for industry fixed effects and is robust to adding industry and date fixed effects. Figure 5 indicates that the average daily number of earnings announcements for industries involved in cross-industry pair trades is approximately 0.9 during the subsequent 5 days. However, the average daily number of earnings announcements increases by 20% for industries involved in balanced intra-industry pair trades.

More important, the increased likelihood of earnings announcements following INSFIT is associated with larger analyst forecast revisions, higher earnings announcement returns, and more frequent price jumps in purchased stocks. To study these outcomes, we construct post-trade windows ranging from 1 to 5 days following an INSFIT-based stock purchase. Three event measures are computed inside and outside of these stock-specific post-trade windows, both of which exclude the purchase date. First, starting with the consensus quarterly earnings forecasts from the preceding quarter, we construct forecast revisions that measure changes in the consensus forecast (Gleason and Lee 2003). We control for quarter fixed effects when comparing revisions inside and outside of the post-trade windows.[19] Second, the aver-

[19]Our results are also robust to the inclusion of stock fixed effects.

age daily return of the underlying stock is computed during three-day intervals surrounding earnings announcements. Third, the daily empirical likelihood of a price jump is computed as a percentage.[20] A positive price jump is defined as a positive daily raw return that exceeds twice the daily return's standard deviation during the preceding three months. Under a normal distribution, the probability of this occurrence is 2.5%. When comparing outcomes inside and outside of the post-trade window, we include date fixed effects when examining price jumps and quarter fixed effects when examining earnings announcement returns.

Table 4 reports that forecast revisions are larger, earnings announcement returns are higher, and price jumps are more frequent following balanced intra-industry pair trades compared to other trading days. These findings are consistent with INSFIT being motivated by positive short-lived private signals.

3.4 INSFIT, Trade Size, and Execution Costs

Classical models of trading predict that investors possessing short-lived firm-specific information execute large trades that may be associated with greater execution costs (Kyle 1985; Easley and O'Hara 1987). Our setting allows us to test these predictions by examining the dollar-denominated values and execution costs of trades underlying INSFIT.

We compare the dollar values and implicit execution costs of buy (sell) trades underlying INSFIT with other buy (sell) trades from the same manager on the same day. This comparison has date, stock, and manager fixed effects as well as standard errors double-clustered by date and stock.

Table 5 reports that the dollar-value of buy (sell) trades underlying INSFIT are between 31% (26%) larger than other buy (sell) trades executed by the same manager on the same day.[21] This evidence provides further support for using balanced intra-industry pair

[20] Stock-months with no INSFIT are excluded from the analysis.

[21] As non-INSFIT trades may contain informed trades, 31% represents a lower bound for the difference in trade size between informed and uninformed buy trades.

trades to identify INSFIT.[22] However, the implicit execution costs associated with INSFIT are not larger than other trades executed by the same manager on the same day. In particular, the difference in execution costs is insignificant for sell trades, which are generally uninformed. For buy trades, the difference is economically negligible and its statistical significance is marginal. The negligible difference in execution costs for INSFIT is consistent with Christoffersen, Keim, Musto, and Rzeznik (2018)'s conclusion that price impacts alone cannot identify informed trading.

Although the trades underlying INSFIT are relatively large, the fraction of a stock's daily dollar-denominated volume attributable to INSFIT averages 1.3% (median equals 0.02%).[23] This small fraction is consistent with INSFIT having similar execution costs as other trades, which complements the growing literature on endogenous liquidity consumption and provision by informed investors. Collin-Dufresne and Fos (2015) find that trades by activist investors, who tend to possess long-lived information, coincide with smaller adverse selection measures but greater price discovery.[24] O'Hara (2015) along with Kacperczyk and Pagnotta (2019) also conclude that informed trading is not necessarily associated with higher transaction costs. We find that informed investors possessing short-lived signals can accumulate positions without incurring significant price impacts as these positions are not large relative to overall trading activity.

There are two explanations for the higher execution costs associated with the buy trades underlying INSFIT compared to the sell trades underlying INSFIT. Hu (2009) reports that execution costs are larger for buy trades in down markets, and later evidence indicates that INSFIT is more prevalent during down markets such as the Global Financial Crisis. Second,

[22]Many microstructure models focus on individual transactions, not the institutional "parent" orders in our study. However, our empirical results support their predictions, suggesting that investors execute larger amounts within one trading day when trades are informed.

[23]The fraction is skewed since the 95th and 99th percentiles of this fraction are 4.2% and 15.3%, respectively. This skewness may explain the temporary price impacts of sell trades (return reversals).

[24]Collin-Dufresne and Fos (2016) develop a theoretical model of endogenous liquidity.

the majority of the return spread attributable to INSFIT is from buy trades. Thus, buy trades are more likely to be informed.

Moreover, consistent with the prevalence of one-to-one balanced intra-industry pair trades, the sale of a single stock to finance an informed stock purchase is justified by the low execution costs induced by sell trades. In conjunction with a fixed per stock trading cost, these low execution costs may lead fund managers to prefer selling a large amount of a single stock than smaller amounts of multiple stocks.

3.5 INSFIT versus Unwound Trades

This section demonstrates that INSFIT is distinct from the profitable interim trades identified by Puckett and Yan (2011) that are unwound before the end of the quarter. Using ANcerno data, Puckett and Yan (2011) report that these unwound trades comprise a quarter of all institutional trades. However, the vast majority of trades underlying INSFIT are not unwound within the same quarter. More important, excluding these unwound trades does not alter the returns associated with INSFIT.

Table 6 reports that 12% of buy trades and 7% of sell trades underlying INSFIT are fully unwound before the end of the quarter. These proportions increase as less restrictive benchmarks define unwound trades by only requiring a fraction $x \in \{0.9, 0.8, 0.7, 0.6, 0.5\}$ of the initial trade to be unwound by the quarter's end. More important, Table 6 indicates that the CAR spreads following INSFIT are unaffected by excluding fully or partially unwound trades.

To clarify, fund managers do not have to unwind buy trades once a stock's undervaluation is corrected. Instead, fund managers may hold the stock position to minimize tracking error or until unwinding the position provides liquidity (Christoffersen, Keim, Musto, and Rzeznik 2018).

3.6 INSFIT Across Fund Managers

We next address the possibility that the post-trade abnormal returns from INSFIT represent a return anomaly based on public information. The theoretical literature on informed trading allows for correlated signals across multiple traders in a single asset (Holden and Subrahmanyam 1992; Foster and Viswanathan 1996; and Back, Cao, and Willard 2002).

To address the possibility that INSFIT is correlated across fund managers due to public information, we examine stock-days with at least one balanced intra-industry pair trade. We then count the number of fund managers in the treatment group who buy the same underlying stock on the same day and within 3-day to 7-day windows around that day. In over 75% of the days with INSFIT, only a single manager executes a balanced intra-industry pair trade in the underlying stock. This evidence extends to clusters that span 3 to 7 days.

Overall, INSFIT is not correlated across fund managers. Thus, correlated trading across fund managers due to public information cannot explain the abnormal returns of INSFIT. Instead, INSFIT arises from the private information of individual fund managers.

3.7 Temporal Variation in INSFIT

Our next analysis finds INSFIT varies during the sample period. Consistent with cash constraints tightening with larger outflows, INSFIT is higher in periods of financial turmoil. Higher INSFIT may also reflect an increase in the number of underpriced stocks, hence greater investment opportunities, during periods of financial turmoil. However, financial turmoil does not necessarily increase the availability of private signals. Instead, widespread undervaluation (due to a reduction in market-wide liquidity for example) reflects public information.

Each year and for each fund manager, we divide the number of buy trades involved in balanced intra-industry pair trades by the manager's total number of buy trades and plot this average fraction each year. Figure 6 illustrates the stability of this fraction, which is often below 1%. However, the fraction of buy trades underlying INSFIT increases to as high as 4% during the Global Financial Crisis in 2008 and 2009.

To address the possibility that our findings are driven by the Global Financial Crisis, we split the sample period into two subperiods. Table 7 reports that while fewer than one-third of INSFIT observations occur in the 1999–2005 subperiod, informed trading produces a positive post-trade CAR spread of 0.466% after 10 days. While this CAR spread is lower compared to the 2006–2011 subperiod, which contains over two-thirds of INSFIT observations, the abnormal returns arising from INSFIT are not driven by the Global Financial Crisis in the later subperiod.

3.8 INSFIT and Cash Constraints

While fund managers often self finance stock purchases by selling stock (Akepanidtaworn, Di Mascio, Imas, and Schmidt 2019), self financing is almost compulsory for fund managers who are cash constrained. This constraint applies to cash holdings that are either at or below their optimal level, a level that is endogenous due to its dependence on market conditions. For example, a higher level of cash holdings may be optimal for fund managers expecting redemptions (outflows) in response to poor market performance.

We provide cross-sectional evidence on the importance of cash constraints to INSFIT using two proxies of cash constraints: the fraction of total net assets held in cash and fund flows. An institution is defined as a family of funds. As described in Section 2.1, CRSP mutual fund data can only be matched with ANcerno trade information for a subset of institutions identified in 13F filings, not the underlying funds (Eisele, Nefedova, Parise, and Peijnenburg 2020). Thus, we measure quarterly cash holdings and fund flows at the institution level, and then match these quantities with fund managers in the ANcerno data.

We estimate the likelihood of INSFIT using a logistic regression whose dependent variable is an indicator function that equals one if a fund manager executes a balanced intra-industry trade in a quarter, and zero otherwise. This analysis controls for quarter fixed effects and clusters standard errors at the quarter level. Independent variables are defined at the institution level and reflect quantities from the previous quarter. For each institution, we measure cash constraints using average cash holdings and fund flows, weighting fund-level observations by each fund's total net assets (TNA). We also account for the natural log of an institution's TNA (sum of fund-level TNAs) to control for its size.

To clarify, the same cash constraint measure is assumed to be identical for all funds within an institution. To account for the accuracy of this assumption, we condition on an institution's asset concentration. Asset concentration is measured as: (i) the inverse number of funds in the institution, (ii) the Herfindahl index of fund-level total net assets. We then split the sample of trades at the median of each asset concentration measure, with higher asset concentration measures indicating greater accuracy.

Table 8 reports that the likelihood of INSFIT increases as cash constraints tighten. Specifically, both cash holdings and fund flow have negative coefficients in the logistic regressions. Thus, INSFIT increases following reductions in cash holdings and larger outflows. In addition, as INSFIT is positively related to an institution's total assets, larger institutions appear to obtain more private signals. Our conditional estimates highlight the importance of estimating fund characteristics accurately. In particular, the negative impact of cash constraints on INSFIT is more salient for institutions whose cash constraints are measured more accurately (higher asset concentrations).

3.9 INSFIT and Industry Competition

The cumulative abnormal return spread associated with INSFIT is mostly attributable to buy trades, while sell trades induce temporary negative returns that likely capture price pressure. Akepanidtaworn, Di Mascio, Imas, and Schmidt (2019) also report that the sell trades of institutional investors are often driven by heuristics rather than information.

Nevertheless, in competitive industries, a positive private signal for one firm is more likely to imply a negative private signal for an industry rival. Therefore, to highlight relative valuation's role in INSFIT, we examine balanced intra-industry pair trades in competitive industries where the underlying sell trades are predicted to have more persistent negative post-trade abnormal returns. Post-trade abnormal returns for buy trades and sell trades underlying INSFIT are also predicted to be more symmetric in competitive industries.

We construct industry-level measures of competition using the average product market fluidity measures of Hoberg, Phillips, and Prabhala (2014).[25] We first sort industries into quartiles of product market fluidity and calculate the proportion of balanced intra-industry pair trades relative to all trades by industry and year. The median proportion of balanced intra-industry trades increases monotonically from 1% in the least competitive industries to over 2% in the most competitive industries. This finding highlights the importance of relative valuation to the identification of INSFIT.

We then divide the sample of balanced intra-industry pair trades into high competition and low competition categories based on the cross-sectional median fluidity measure in each year before fitting equation (2) to both subsamples. Table 9 finds evidence of greater INSFIT as well as greater post-trade abnormal return symmetry between the buy trades and sell trades underlying INSFIT in competitive industries. Specifically, for high-competition industries, sell trades underlying INSFIT produce negative CARs during the subsequent 10 trading days. In contrast, for low-competition industries, these sell trades produce positive CARs over this horizon. Furthermore, while INSFIT occurs less frequently in low-competition industries, the buy trades underlying INSFIT are more profitable. Thus, the profitability of INSFIT is inversely related to its frequency.

[25]This measure captures the extent of competitive threats against a firm in the product market. Data and detailed descriptions are available at http://hobergphillips.tuck.dartmouth.edu/.

3.10 INSFIT and Stock Characteristics

After comparing the characteristics of stocks that comprise the short and long positions underlying INSIT, we first report that these positions have indistinguishable stock characteristics. Second, motivated by the increase in INSFIT during the Global Financial Crisis, we examine the association between stock characteristics and the likelihood of INSFIT by comparing the buy trades underlying INSFIT to other buy trades executed by the same manger on the same day.

Panel A of Table 10 compares the stock characteristics of stocks that are sold versus bought by the pair trades underlying INSFIT. When comparing the average stock characteristics, month and industry fixed effects are both included, with standard errors clustered by month and industry. Across the short and long positions underlying INSFIT, we find no significant difference in the size, book-to-market, past return, return volatility, liquidity, and beta characteristics.

According to Panel B of Table 10, industry momentum also cannot explain the abnormal returns associated with INSFIT. For industries with high past returns (INDRET), stocks sold by INSFIT have higher industry betas than those bought by INSFIT, 1.20 compared to 1.12. Thus, INSFIT abnormal returns cannot be attributed to fund managers simply buying high industry beta stocks and selling low industry beta stocks in industries with high expected returns due to industry momentum.

After finding no difference between the stock characteristics of the short and long positions underlying INSFIT, our next analysis compares the stock characteristics of the long position to the wider cross-section of stocks. Specifically, a logistic regression estimates the likelihood that a buy trade arises from INSFIT based on the stock's characteristics.

Table 11 reports that larger stocks have a marginally higher likelihood of being included in the long position of INSFIT. Furthermore, a stock's return volatility and beta both have a positive relation with INSFIT. However, due to the high correlation between these related stock characteristics, which exceeds 0.50, their respective impacts are not jointly significant. Conversely, book-to-market, liquidity, and past return characteristics are unrelated with INSFIT.

Overall, large stocks with higher return volatility are more likely to be involved in INSFIT. Intuitively, return volatility creates opportunities for institutional investors to acquire private signals and execute informed trades in large stocks.

4 Conclusion

We identify a specific type of informed trading; *Industry Neutral Self Financed Informed Trading* (INSFIT), by conditioning on how an informed purchase is likely to be financed. Specifically, we hypothesize that fund managers self finance informed stock purchases by selling an equivalent dollar amount of stock in the same industry. Although infrequent, INSFIT is extremely profitable.

The self financing of stock purchases by stock sales is consistent with cash-constrained fund managers acquiring short-lived positive signals. Furthermore, the widespread use of relative valuation techniques, constraints on industry allocations, and the hedging of industry exposure all motivate the sale of stock in the same industry.

We find that lower cash holdings and larger outflows increase INSFIT. These results are consistent with short-lived signals preventing fund managers from accumulating cash to finance their buy trades. Additional evidence confirms that INSFIT is motivated by short-lived private signals. Specifically, the buy trades underlying INSFIT precede larger analyst forecast revisions, higher earnings announcement returns, and more frequent positive price jumps. Furthermore, the buy trades underlying INSFIT involve relatively large dollar-denominated transactions but are not associated with higher transaction costs.

Although buy trades are primarily responsible for the cumulative abnormal return associated with INSFIT, negative abnormal returns are detected for offsetting sell trades in competitive industries where a positive signal regarding one firm likely constitutes a negative signal for an industry peer. Indeed, consistent with importance of relative valuation, the abnormal returns following buy trades and sell trades underlying INSFIT are more symmetric in competitive industries.

Finally, despite its profitability, INSFIT is a rare occurrence for individual fund managers. This finding provides a potential explanation for the lack of persistence in individual fund manager performance. However, whether INSFIT is sufficient in terms of its frequency and profitability to cover the cost of active fund management is left for future research.

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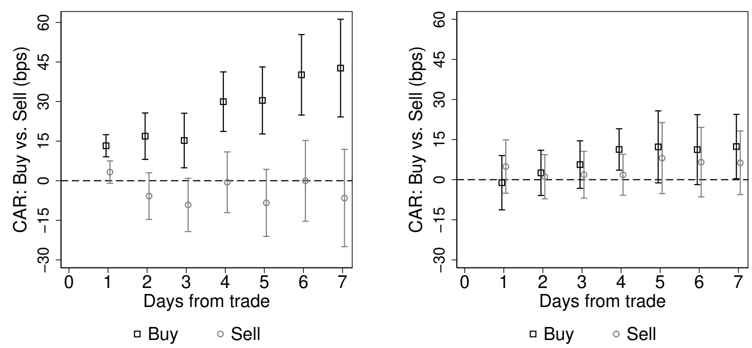
A Appendix: Alternative Industry Classification

This appendix demonstrates the robustness of our main findings to an alternative industry classification. We perform the analysis reported in Section 3.2 using the 24 industries defined by the Global Industry Classification System (GICS) in lieu of the 49 Fama-French industries. Figure A.1 presents similar results as Figure 3 using these more broadly defined industries.

Figure A.1: **GICS Industry Classification**
Balanced versus Unbalanced: Treatment versus Control.
This figure displays average cumulative abnormal returns (CARs) following buy and sell trades in the treatment group (intra-industry pair trades) and control group (cross-industry pair trades) depending on whether the pair trade is balanced or unbalanced. Average post-trade CARs are estimated using equation (2). Point estimates and 95% confidence intervals are plotted each day, with standard errors double-clustered by fund and date.

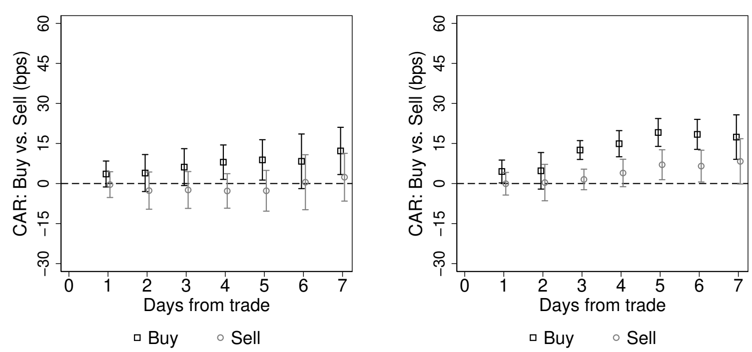
Panel A: Balanced

Intra-industry pair trades | Cross-industry pair trades



Panel B: Unbalanced

Intra-industry pair trades | Cross-industry pair trades



Tables and Figures

Table 1: **Main Sample: Treatment, Control, and Refinement.**
Panel A of this table summarizes the treatment (intra-industry pair trades) and control (cross-industry pair trades) groups. Panel B summarizes the trade characteristics of balanced versus unbalanced pair trades within the treatment and control groups. For each subsample, the number of trades, the post-trade 10-day cumulative abnormal return (CAR), the dollar value per trade, and the frequency of each trade type per fund manager are reported. Excluded trades refer to days where a fund manager trades 5 or more stocks within the same industry. Panel C summarizes the distinction between balanced intra-industry pair trades that are one-to-one versus not one-to-one, where one-to-one pair trades involve the purchase and sale of individual stocks.

		Treatment Intra-industry		**Control** Cross-industry	
		Sell	Buy	Sell	Buy
Panel A: Main sample					
	Observations	1,897,190	1,897,190	2,741,799	2,812,129
	Mean # of industries traded	2.9		8.6	
	Mean $-trade imbalance	0.4		1.0	
Panel B: Main sample decomposition					
Balanced pair trades		130,677	130,677	488,113	519,587
	Mean CAR (bps)	10.5	78.6	−2.6	−11.9
	Mean trade $-value	558,602	559,907	483,102	448,639
	Mean trade frequency/year	4.1	4.1	31.3	34.0
Unbalanced pair trades		1,308,031	1,308,031	2,531,892	2,589,648
	Mean CAR (bps)	18.9	10.3	1.7	15.2
	Mean trade $-value	643,459	613,606	580,616	559,304
	Mean trade frequency/year	39.2	39.2	124.1	128.6
Excluded trades		458,482	458,482	951,249	1,004,368
	Mean CAR (bps)	0.6	10.4	9.0	−3.2
	Mean trade $-value	1,390,793	1,346,932	495,083	466,150
	Mean trade frequency/year	14.2	14.2	64.8	70.2
Panel C: Balanced intra-industry pair trade decomposition					
One-to-one balanced intra-industry pair trades		97,090	97,090	-	-
	Mean CAR (bps)	5.8	95.2	-	-
	Mean trade $-value	438,464	439,963	-	-
	Mean trade frequency/year	3.2	3.2	-	-
Not one-to-one balanced intra-industry pair trades		33,587	33,587	-	-
	Mean CAR (bps)	24.0	30.5	-	-
	Mean trade $-value	905,887	906,631	-	-
	Mean trade frequency/year	0.8	0.8	-	-

Table 2: **Preliminary Analysis of Pair Trade Types in the Pooled Sample.**
This table presents average same-day return (R) and cumulative abnormal returns (CARs) following the buy and sell trades underlying balanced intra-industry pair trades, unbalanced intra-industry pair trades, and balanced cross-industry pair trades. For each type of pair trade, average same-day return and post-trade CARs after 1, 3, 5, 7, and 10 days are estimated using equation (2). Standard errors are clustered by fund and date, and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Balanced Intra-industry			Unbalanced Intra-industry			Balanced Cross-industry		
Dep. Var.	Sell	Buy	Spread	Sell	Buy	Spread	Sell	Buy	Spread
$R(t)$	−2.6	−7.6***	−5.1	−1.5	1.7	3.2	−0.2	−0.7	−0.5
	(2.6)	(2.5)	(5.1)	(1.9)	(2.0)	(3.9)	(2.9)	(2.6)	(5.5)
$CAR(t, t+1)$	−3.2***	4.0***	7.2***	−4.3**	1.9	6.1	0.2	0.1	−0.1
	(0.8)	(1.0)	(1.8)	(1.9)	(2.0)	(3.9)	(5.3)	(4.7)	(10.0)
$CAR(t, t+3)$	−13.1***	12.3***	25.4***	−7.2***	6.9***	14.1***	5.1	−9.5	−14.6
	(4.3)	(3.9)	(8.2)	(1.9)	(1.9)	(3.8)	(7.6)	(6.9)	(14.5)
$CAR(t, t+5)$	−8.4	18.6***	27.0***	−2.5	11.3***	13.8*	−2.1	−0.6	1.5
	(6.1)	(5.3)	(11.4)	(4.1)	(4.0)	(8.1)	(3.5)	(6.2)	(9.8)
$CAR(t, t+7)$	−13.0***	17.1***	30.0***	7.4	16.8**	9.4	4.0	8.3	4.3
	(3.9)	(3.3)	(7.2)	(6.6)	(6.6)	(13.2)	(4.3)	(7.0)	(11.2)
$CAR(t, t+10)$	−5.2	13.0***	18.2**	14.9	15.8	0.8	−4.9	13.6	18.5
	(4.9)	(4.1)	(9.0)	(10.1)	(10.2)	(20.3)	(5.1)	(6.9)	(12.1)
Observations	218,819	218,819		1,704,930	1,704,930		424,608	473,105	

Table 3: **Main Analysis: Treatment and Control Groups.**
This table reports average same-day return (R) and cumulative abnormal returns (CARs) following buy and sell trades as well as the spread between these trades after 1, 3, 5, 7, and 10 days. The same-day return and CARs are estimated using equation (2) for trades in the treatment (intra-industry pair trades) and control (cross-industry pair trades) group as well as the balanced and unbalanced subsamples within the treatment group. Standard errors are double-clustered by fund and date, and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Intra-industry: All trades			Balanced Intra-industry: One-to-one			Cross-industry			Unbalanced Intra-industry	Unbalanced Cross-industry
Dep. Var.	Sell	Buy	Spread	Sell	Buy	Spread	Sell	Buy	Spread	Spread	Spread
$R(t)$	-4.1^{**}	-7.5^{***}	-3.5	-5.7^{**}	-9.7^{***}	-4.0	0.7	-1.6	-2.3	2.1	1.2
	(2.06)	(1.92)	(3.99)	(2.48)	(2.31)	(4.79)	(1.42)	(1.31)	(2.73)	(3.04)	(4.78)
$CAR(t, t+1)$	-8.5^{***}	8.8^{***}	17.4^{***}	-12.6^{***}	7.8^{***}	20.4^{***}	1.5	-0.4	-1.9	3.7	3.7
	(2.87)	(2.97)	(5.84)	(3.68)	(3.78)	(7.46)	(2.55)	(2.41)	(4.95)	(4.02)	(3.80)
$CAR(t, t+3)$	-14.8^{*}	32.5^{***}	47.3^{***}	-22.7^{**}	39.9^{***}	62.6^{***}	0.0	0.0	0.1	11.1^{***}	13.0^{***}
	(7.98)	(7.75)	(15.74)	(9.45)	(9.20)	(18.65)	(3.16)	(2.96)	(6.13)	(2.54)	(2.01)
$CAR(t, t+5)$	6.6	57.2^{***}	50.7^{**}	5.4	69.0^{***}	63.5^{**}	-6.9	-3.3	3.6	8.2	13.0^{***}
	(10.57)	(10.04)	(20.61)	(13.06)	(12.55)	(25.61)	(5.35)	(4.96)	(10.31)	(7.19)	(4.68)
$CAR(t, t+7)$	1.6	58.6^{***}	56.9^{***}	-5.9	67.1^{***}	72.9^{***}	-12.8^{**}	-4.7	8.1	1.4	18.3^{***}
	(10.85)	(10.58)	(21.43)	(14.08)	(13.84)	(27.92)	(6.44)	(5.98)	(12.43)	(13.12)	(3.79)
$CAR(t, t+10)$	10.5	78.6^{***}	68.1^{**}	5.8	95.2^{***}	89.4^{**}	-6.3	-8.5	-2.2	-8.6	17.1^{***}
	(14.09)	(14.06)	(28.15)	(18.39)	(18.43)	(36.83)	(5.69)	(5.33)	(11.02)	(20.94)	(5.70)
Observations:											
Sell		130,677			97,090			488,113		1,308,031	2,531,892
Buy		130,677			97,090			519,587		1,308,031	2,589,648

Table 4: **Analyst Forecast Revisions, Earning Announcement Returns, and Price Jumps.**
This table examines analyst forecast revisions, earnings announcement returns, and the likelihood of a price jump following balanced intra-industry pair trades on day t. Post-trade windows $[t+1, t+s]$ for $s \in \{1, \ldots, 5\}$ are constructed. Earnings forecast revisions, defined as the change in the consensus forecast, are compared inside and outside of these post-trade windows each quarter. Similarly, average earnings announcement returns are compared inside and outside of these post-trade windows. This comparison controls for quarter fixed effects. The frequency of a price jump is also compared inside and outside of these post-trade windows in the same month (excluding day t). This comparison controls for date fixed effects. Standard errors are reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Analyst forecast revisions			Earnings announcement return			Price jump likelihood		
Post-trade window	Inside	Outside	Difference	Inside	Outside	Difference	Inside	Outside	Difference
$[t+1, t+1]$	−0.0220***	−0.0576***	0.0357***	20.7**	2.4***	18.3**	3.5***	2.9***	0.6***
	(0.004)	(0.001)	(0.004)	(8.8)	(0.8)	(8.8)	(0.08)	(0.08)	(0.14)
$[t+1, t+2]$	−0.0229***	−0.0577***	0.0358***	15.1**	2.4***	12.7**	3.3***	3.0***	0.3***
	(0.003)	(0.001)	(0.003)	(6.3)	(0.8)	(6.3)	(0.05)	(0.05)	(0.08)
$[t+1, t+3]$	−0.0212***	−0.0577***	0.0355***	13.0 **	2.4***	10.6**	3.3***	3.0***	0.2***
	(0.002)	(0.001)	(0.002)	(5.2)	(0.8)	(5.3)	(0.04)	(0.04)	(0.06)
$[t+1, t+4]$	−0.0220***	−0.0577***	0.0357***	11.2**	2.4***	8.8*	3.2***	3.1***	0.1**
	(0.002)	(0.001)	(0.002)	(4.6)	(0.8)	(4.7)	(0.04)	(0.04)	(0.06)
$[t+1, t+5]$	−0.0224***	−0.0577***	0.0343***	9.5**	2.4***	7.1*	3.2***	3.1***	0.1***
	(0.002)	(0.001)	(0.002)	(4.2)	(0.8)	(4.2)	(0.03)	(0.03)	(0.05)

Table 5: **INSFIT and Trade Size.**
This table compares the dollar-denominated trade size and implicit execution cost of INSFIT to other trades by the same manager on the same day. The stock-days in this analysis require at least one balanced intra-industry trade to compute dollar values (in $1,000s) for the buy and sell trades underlying INSFIT. For buy trades, implicit execution costs are measured as the respective execution price minus the volume-weighted average price (VWAP). For sell trades, implicit execution costs are measured as the respective VWAP minus the execution price. Both differences are normalized by VWAP. All estimates control for date, stock, and fund manager fixed effects. Standard errors are double-clustered by date and stock, and are reported in parentheses. 95% CI denotes a 95% confidence interval for the above coefficient. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Trade size			Execution cost		
	INSFIT	Other	Difference	INSFIT	Other	Difference
Buy trades	411.6***	313.3***	98.3***	9.0***	7.1***	1.9*
	(10.4)	(1.1)	(11.5)	(1.0)	(0.1)	(1.1)
95% CI	[391.3, 431.9]	[311.1, 315.4]	[75.8, 120.8]	[7.0, 10.9]	[6.8, 7.2]	[−0.2, 4.02]
Sell trades	416.1***	331.0***	85.1***	3.6**	2.2***	1.4
	(10.1)	(1.1)	(11.2)	(1.5)	(0.2)	(1.7)
95% CI	[396.3, 435.9]	[328.8, 333.1]	[63.1, 107.1]	[0.6, 6.5]	[1.8, 2.6]	[−1.9, 4.7]

Table 6: **INSFIT Excluding Round-Trip Trades.**
This table presents the average spread for same-day returns (R) and cumulative abnormal returns (CARs) between sell and buy trades according to equation (2). The sample excludes INSFIT observations whose underlying trades are fully or partially unwound by the quarter's end, where the proportion of unwound trades is denoted $x \in \{1.0, 0.9, 0.8, 0.7, 0.6, 0.5\}$. After excluding unwound trades, the average same-day return spread between buy trades and sell trades underlying INSFIT along with the post-trade CAR spreads after 1, 3, 5, 7, and 10 days are reported. Standard errors are clustered by fund and date, and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Fraction unwound by quarter's end					
	1.0	0.9	0.8	0.7	0.6	0.5
Round-trip trades:						
Sell	7.1%	7.3%	7.6%	7.9%	8.2%	8.7%
Buy	11.9%	12.3%	12.7%	13.2%	13.8%	14.6%
Dep. Var.	INSFIT CAR spreads excluding unwound trades					
$R(t)$	−4.3	−4.2	−4.3	−4.3	−4.4	−4.4
	(4.4)	(4.5)	(4.5)	(4.5)	(4.5)	(4.5)
$CAR(t, t+1)$	19.5***	19.4***	19.5***	19.5***	19.7***	19.8***
	(6.7)	(6.7)	(6.8)	(6.8)	(6.8)	(6.9)
$CAR(t, t+3)$	52.1***	52.1***	52.3***	52.4***	52.5***	52.6***
	(17.7)	(17.8)	(17.9)	(18.0)	(18.2)	(18.2)
$CAR(t, t+5)$	57.4**	57.5**	57.7**	57.8**	57.7**	58.2**
	(25.3)	(25.5)	(25.7)	(26.0)	(26.3)	(26.5)
$CAR(t, t+7)$	65.2**	65.2**	65.4**	65.3**	64.8**	65.2**
	(27.1)	(27.4)	(27.6)	(27.9)	(28.2)	(28.4)
$CAR(t, t+10)$	77.3**	77.5**	77.9**	78.0**	77.4**	78.1**
	(34.6)	(35.0)	(35.3)	(35.8)	(36.3)	(36.9)

Table 7: **INSFIT Over Time.**
This table reports same-day returns (R) and post-trade cumulative abnormal return (CAR) spreads after 1, 3, 5, 7, and 10 days associated with INSFIT in two superiods: 1/1/1999–31/12/2005 and 1/1/2006–30/09/2011. Standard errors are double-clustered by fund and date, and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	1999−2005			2006−2011		
Dep. Var.	Sell	Buy	Difference	Sell	Buy	Difference
$R(t)$	3.4^{***}	7.7^{***}	4.3^{*}	-7.4^{***}	-14.2^{***}	-6.8
	(1.2)	(1.2)	(2.4)	(2.5)	(2.3)	(4.7)
$CAR(t, t+1)$	-3.4^{**}	7.5^{***}	10.9^{***}	-10.8^{***}	9.4^{**}	20.2^{***}
	(1.9)	(2.1)	(4.0)	(3.8)	(3.9)	(7.7)
$CAR(t, t+3)$	-7.0^{***}	14.7^{***}	21.7^{***}	-18.2^{**}	40.3^{***}	58.5^{***}
	(2.6)	(3.1)	(5.7)	(8.8)	(8.3)	(17.2)
$CAR(t, t+5)$	-6.3^{**}	28.1^{***}	34.4^{***}	12.2	70.0^{***}	57.8^{**}
	(2.8)	(3.4)	(6.2)	(13.5)	(12.6)	(26.2)
$CAR(t, t+7)$	-5.5	33.1^{***}	38.6^{***}	4.8	69.7^{***}	65.0^{**}
	(4.4)	(4.9)	(9.3)	(13.5)	(13.0)	(26.6)
$CAR(t, t+10)$	0.3	47.0^{***}	46.6^{***}	14.9	92.5^{***}	77.5^{**}
	(6.0)	(6.4)	(12.4)	(17.8)	(17.8)	(35.6)
Observations	39,813	39,813		90,864	90,864	

Table 8: **INSFIT and Cash Constraints.**

This table presents logistic regression estimates for the likelihood of INSFIT. The dependent variable is an indicator variable that equals one if a fund manager performs at least one balanced intra-industry pair trade during quarter q, and zero otherwise. TNA-weighted cash is a fund family's average fraction of cash holdings, where each fund's cash holding is weighted by its total net assets (TNA) in quarter $q-1$. TNA-weighted flow is a fund family's average fund flow, where each fund's flow is weighted by its total net assets (TNA) in quarter $q-1$. Ln(TNA) is the natural log of a fund family's total net assets. The estimation is also conducted conditional on one of two asset concentration measures: (i) the inverse number of funds in the fund family (higher measure, higher concentration), (ii) Herfindahl index constructed from fund-level total net assets (higher measure, higher concentration). The sample is split at the median of each respective measure to decompose observations into fund families with low versus high asset concentrations. Quarter fixed effects are included and standard errors, reported in parentheses, are clustered by quarter. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		Asset concentration					
		Inverse number of funds			Herfindhal index		
	Full sample	Low	High	Difference	Low	High	Difference
TNA-weighted Cash	-6.01^{***}	4.59^{**}	-8.90^{***}	-13.49^{***}	3.78	-7.60^{***}	-11.38^{***}
	(1.50)	(2.33)	(1.53)	(2.94)	(2.42)	(1.44)	(2.98)
TNA-weighted Flow	-5.46^{***}	-2.75^{*}	-5.52^{***}	-2.77	-1.48	-4.76^{***}	-3.28
	(1.74)	(1.67)	(1.83)	(2.65)	(1.33)	(1.47)	(2.10)
Ln(TNA)	0.21^{**}	0.10^{***}	-0.06	-0.16^{**}	0.04	-0.11^{***}	-0.14^{***}
	(0.03)	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)	(0.07)

Table 9: **INSFIT and Industry Competition.**
This table presents average cumulative abnormal returns (CARs) for the sell trades and buy trades underlying INSFIT. Each year, CARs are computed for these trades in industries with high and low average product market fluidity (Hoberg, Philips, and Prabhala 2014) based on the annual median. For each industry subsample, average post-trade CARs after 1, 3, 5, 7, and 10 days are estimated using equation (2). Standard errors are double-clustered by fund and date, and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Low-competition industries			High-competition industries		
Dep. Var.	Sell	Buy	Spread	Sell	Buy	Spread
$R(t)$	7.3	−9.0	−16.4	−8.8***	−6.9**	1.9
	(7.4)	(7.4)	(14.8)	(3.3)	(3.2)	(6.6)
$CAR(t, t+1)$	0.0	25.1***	25.2*	−12.1**	2.0	14.1
	(7.6)	(7.5)	(15.0)	(4.8)	(5.0)	(9.9)
$CAR(t, t+3)$	4.2	61.6***	57.5*	−22.7***	20.4***	43.1***
	(16.8)	(16.6)	(33.4)	(7.9)	(7.8)	(15.7)
$CAR(t, t+5)$	42.1*	130.8***	88.7*	−8.3*	26.5***	34.8***
	(24.9)	(24.4)	(49.3)	(4.9)	(4.2)	(9.1)
$CAR(t, t+7)$	52.2**	146.9***	94.7*	−19.5***	21.7***	41.2***
	(25.3)	(24.7)	(50.0)	(5.4)	(5.4)	(10.8)
$CAR(t, t+10)$	40.9	205.2***	164.3	−2.2	25.8***	28.0***
	(50.3)	(49.9)	(100.2)	(1.8)	(3.8)	(5.6)
Observations	38,470	38,470		92,207	92,207	

Table 10: **Comparison of Buy Versus Sell Trades Underlying INSFIT.**
Panel A compares the stock characteristics of buy trades and sell trades underlying INSFIT. $SIZE$ is the natural log of the stock's market capitalization at the end of previous month. BM is the stock's most recent book value of equity normalized by its market capitalization from the previous month. $\ln(OCAM)$ is the natural log of the open-to-close Amihud's measure of liquidity (Barardehi et al. 2020) constructed using daily data from the preceding 12 months. $SDRET$ is the stock's daily return volatility based on data from the preceding 12 months. MOM_{-1} denotes the previous month's return, MOM_{-6}^{-2} is the compound return over the preceding 5 months, and MOM_{-12}^{-7} is the compound return over the 6 months preceding MOM_{-6}^{-2}. Monthly market betas, denoted $BETA^{mkt}$, are estimated using weekly observations from the 104-week period ending in the previous month, requiring at least 52 weeks of observations. For each characteristic, the mean characteristic of stocks being bought and sold by INSFIT are reported along with their respective differences. $INDRET$ denotes the equally-weighted average industry return in the previous month. Panel B compares market beta of stocks being bought and sold by INSFIT within $INDRET$ terciles. Industry betas, $BETA^{ind}$, are estimated by fitting stock vs. respective equally-weighted industry returns using daily observations from the preceding calendar year. The difference-in-mean tests include both month and industry fixed effects, with standard errors clustered by month and industry. These standard errors are reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock characteristics of pair trades underlying INSFIT

	Stock Characteristic							
Trade	$SIZE$	BM	$OCAM$	$SDRET$	MOM_{-1}	MOM_{-6}^{-2}	MOM_{-12}^{-7}	$BETA^{mkt}$
Sell	9.35***	0.55***	−8.61***	2.77***	0.016***	0.031***	0.053***	1.132***
	(0.10)	(0.02)	(0.11)	(0.06)	(0.006)	(0.012)	(0.063)	(0.030)
Buy	9.13***	0.51***	−8.37***	2.81***	0.027***	0.065***	0.063***	1.139***
	(0.11)	(0.02)	(0.11)	(0.07)	(0.005)	0.012	(0.011)	(0.032)
Difference	−0.21	−0.04	0.24	0.04	0.012	0.033	0.010	0.008
	(0.21)	(0.03)	(0.22)	(0.14)	(0.011)	(0.024)	(0.021)	(0.062)

Panel B: Industry betas & industry momentum

	$INDRET$		
Trade	Low	Medium	High
Sell	1.15***	1.10***	1.20***
	(0.01)	(0.04)	(0.02)
Buy	1.16***	1.17***	1.12***
	(0.01)	(0.04)	(0.02)
Difference	0.01	0.07	−0.08*
	(0.01)	(0.08)	(0.04)

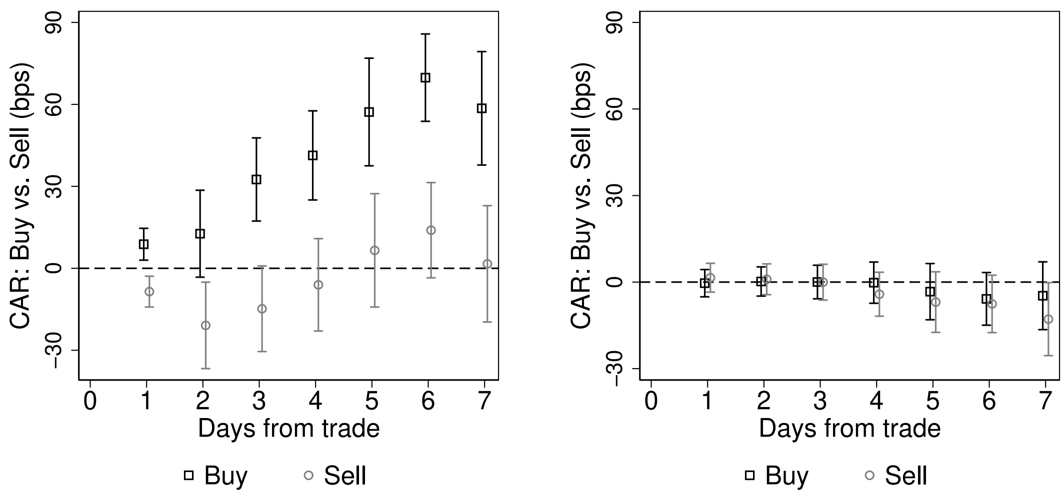
Table 11: **Stock Characteristics of the Buy Trades Underlying INSFIT.**
This table presents logistic regression estimates where the dependent variable is an indicator variable equaling one if a fund manager's buy trade corresponds to INSFIT, and zero otherwise. $SIZE$ is the natural log of the stock's market capitalization at the end of previous month. BM is the stock's most recent book value of equity normalized by its market capitalization from the previous month. $OCAM$ is the open-to-close Amihud's measure of liquidity (Barardehi et al. 2020) constructed using daily data from the preceding 12 months. $SDRET$ is the stock's daily return volatility based on data from the preceding 12 months. MOM_{-1} denotes the previous month's return, MOM_{-6}^{-2} is the compound return over the preceding 5 months, and MOM_{-12}^{-7} is the compound return over the 6 months preceding MOM_{-6}^{-2}. Monthly betas, denoted $BETA^{mkt}$, are estimated using weekly observations from the 104-week period ending in the previous month provided at least 52 weeks of observations are available. $INDRET$ is the equally-weighted average industry return in the previous month. Month and industry fixed effects are included. Standard errors, reported in parentheses, are clustered by stock. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Likelihood of INSFIT				
$SIZE$	0.058*	0.055*		0.055*	0.056*	0.055*
	(0.032)	(0.033)		(0.032)	(0.032)	(0.032)
BM	−0.087	−0.088		−0.076	−0.085	−0.077
	(0.107)	(0.111)		(0.105)	(0.108)	(0.106)
$OCAM$	−0.084	0.011		0.017	−0.134	0.007
	(0.278)	(0.294)		(0.295)	(0.335)	(0.300)
$SDRET$	0.122***	0.078		0.078	0.121***	0.074
	(0.043)	(0.056)		(0.054)	(0.043)	(0.055)
$BETA^{mkt}$		0.137	0.221***	0.148		0.151
		(0.096)	(0.076)	(0.092)		(0.093)
$INDRET$			1.858	1.847		1.787
			(1.307)	(1.232)		(1.230)
$BETA^{mkt} \times INDRET$			−0.435	−0.463		−0.650
			(0.596)	(0.604)		(0.592)
MOM_{-1}					0.467	0.401
					(0.310)	(0.324)
MOM_{-6}^{-2}					−0.004	0.000
					(0.129)	(0.124)
MOM_{-12}^{-7}					-0.093	-0.093
					(0.104)	(0.105)

Figure 3: **Balanced versus Unbalanced: Treatment versus Control.**
This figure displays average cumulative abnormal returns (CARs) following buy and sell trades in the treatment group (intra-industry pair trades) and control group (cross-industry pair trades) depending on whether the pair trade is balanced or unbalanced. For each category, average post-trade CARs are estimated using equation (2). Standard errors are double-clustered by fund and date. Point estimates and 95% confidence intervals are plotted each day.

Panel A: Balanced

Intra-industry pair trades　　Cross-industry pair trades



Panel B: Unbalanced

Intra-industry pair trades　　Cross-industry pair trades

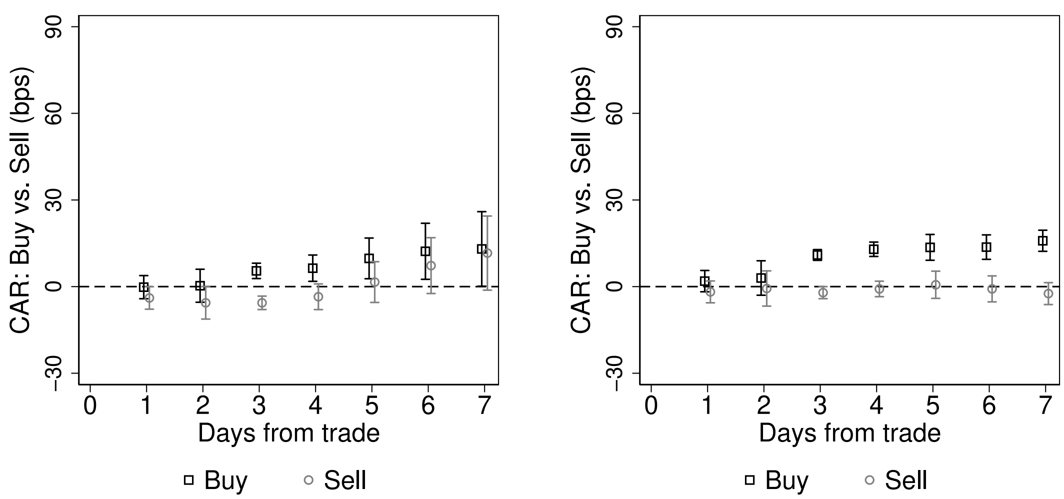


Figure 4: **One-to-One Trades and INSFIT.**
This figure illustrates the relative frequency of one-to-one trades in the treatment (intra-industry pair trades) and control (cross-industry pair trades) groups conditional on the number of stocks bought and sold. The proportion of each [Number of stocks bought, Number of stocks sold] combination is then computed within the treatment (control) group. The solid bars pertain to the control group and the transparent bars pertain to the treatment group.

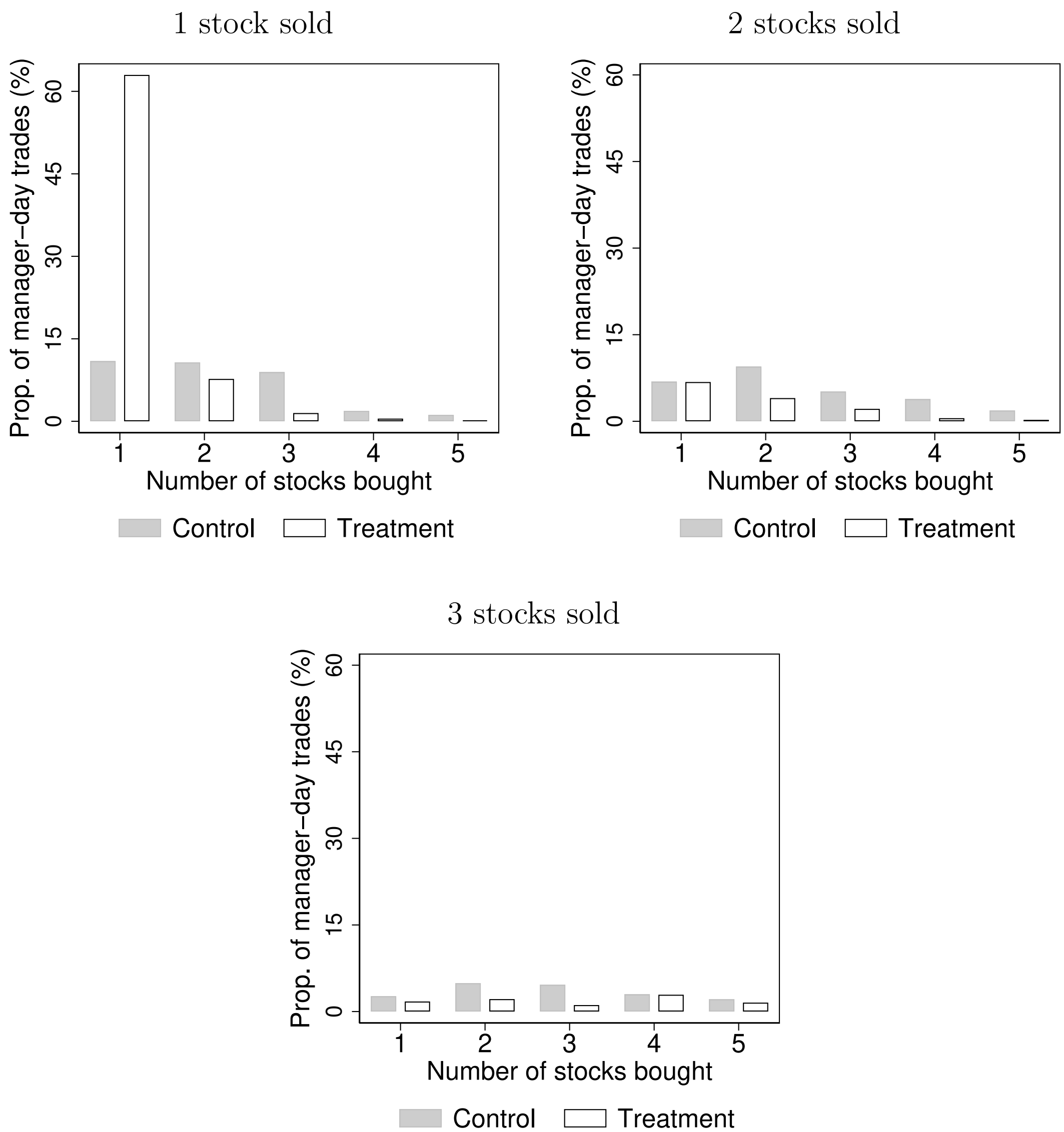


Figure 5: **Buy Trades Underlying INSFIT and Subsequent Earnings Announcements.** This figure compares the number of earnings announcements in the 5 days following balanced intra-industry pair trades versus cross-industry pair trades. Point estimates and 95% confidence intervals are plotted each day. The solid bars denote cross-industry pair trades and the transparent bars denote balanced intra-industry pair trades.

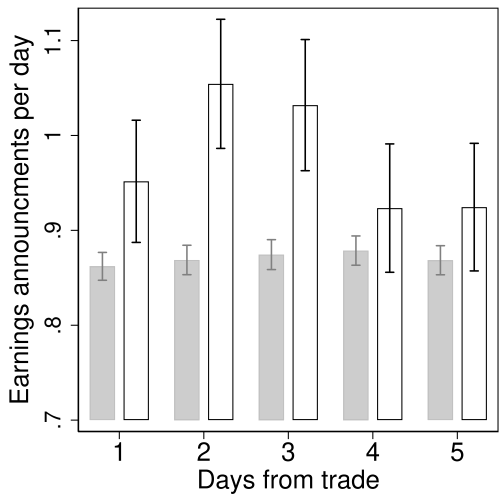


Figure 6: **INSFIT Over Time.**
This figure illustrates the likelihood of INSFIT during our sample period. Each year, the total number of balanced intra-industry pair trades a fund manager executes is divided by the total number of pair trades executed during the year. This annual ratio is then averaged across fund managers, with equal weights, and plotted over time.