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The Information in Industry-Neutral Self-Financed Trades

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Abstract

We identify Industry-Neutral Self-Financed Informed Trading (INSFIT) as stock trades financed by offsetting, equivalent dollar-denominated stock trades in the same industry. Approximately 37% of short-term mutual fund trading profits can be attributed to these trade pairs. Consistent with informed trading, INSFIT precedes unusually high media coverage for the underlying stocks. The trades underlying INSFIT are also larger as the release of stock-level news becomes more imminent. Both relative valuation and the hedging of industry exposure motivate INSFIT's industry neutrality. While INSFIT positively impacts fund performance, active fund managers who execute INSFIT more aggressively obtain smaller trading profits per execution.

I. 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. Most empirical

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methodologies in the existing literature identify informed trading by examining who placed orders or how the orders are placed. Based on the conventional wisdom that institutional investors are likely to be informed, a large literature examines the trading and performance of active fund managers. However, this literature has yet to reach a consensus on whether the trading activities of institutional investors generate a significant alpha.[1] Alternatively, a large strand of the market microstructure literature infers informed trading from order submission strategies. However, this literature usually focuses on a single asset.[2]

In contrast, we identify a specific type of informed trading; Industry-Neutral Self-Financed Informed Trading (INSFIT) by conditioning on institutional trades in a multiple-asset setting. Akepanidtaworn, Di Mascio, Imas, and Schmidt (2021) 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." For example, consider a fund manager who acquires a positive private signal regarding a firm and immediately wants to buy its stock. The urgent need to execute INSFIT reflects the imminent expected release of public information related to the fund manager's signal. By simultaneously selling stock in the same industry, the fund manager mitigates industry exposure while also financing the informed stock purchases. The same intuition applies to a fund manager who acquires a negative firm-specific private signal and wants to preserve their industry exposure while also avoiding the opportunity cost of holding cash. Put differently, the pairing of institutional buy trades with sell trades in the same industry indicates firm-level trade informativeness provided the investor does not also possess industry-level information that would induce a cross-industry reallocation.

The extant literature highlights several motivations for informed managers to execute industry-neutral self-financed trades. First, private signals often contain information regarding a firm's performance relative to its industry peers. This motivation is consistent with relative valuation techniques that rank firms in the same industry (Purnanandam and Swaminathan (2004), Da and Schaumburg (2011)). For example, discounted cash flow models typically condition on valuation multiples within the same industry. Second, industry neutrality allows fund managers to hedge industry risk and therefore isolate the firm-specific implications of their private signals. For investors capable of short selling, Huang, O'Hara, and Zhong (2021) document the use of industry exchange traded funds to hedge industry risk.[3] Third, fund managers may strive to maintain industry-specific allocations to minimize tracking error (Cohen, Gompers, and Vuolteenaho (2002)).[4] Although industry neutrality implies that stock purchases are mechanically self-financed by stock sales in the same industry, cash constraints provide another motivation to self-finance informed stock purchases.

[1]This literature includes contributions discussed later that focus on specific institutional investor trades.

[2]This literature includes methodologies that infer informed trading from order imbalances such as Kyle (1985) and other extensions discussed later that focus on a single asset.

[3]Although hedge funds are able to short sell, the number of hedge funds in our sample is negligible. Additional details regarding the impact of short selling on our results are provided later.

[4]We thank Pingle Wang for providing us with empirical evidence that tracking error in the fund management industry has been decreasing during the past two decades.

We examine institutional investor trades in the ANcerno database that primarily 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.[5] Thus, our classification of manager-industry trades enables us to infer INSFIT by individual fund managers in individual stocks on individual days. Figure 1 illustrates the refinements involved in identifying INSFIT, while Figure 2 summarizes the respective cumulative abnormal return (CAR) of buy trades underlying INSFIT for each refinement.

In terms of economic significance, INSFIT accounts for over 37% of the risk-adjusted trading profits of fund managers in the short-term, despite comprising less than 3% of their trading activity. Short-term is defined by the 10 trading days following INSFIT. For a subset of funds in which ANcerno data are matched with Center for Research in Securities Prices (CRSP) Mutual Fund data, INSFIT predicts abnormally high monthly fund alphas of 0.16%. Thus, we link informed trading with improved fund performance. However, as INSFIT is infrequent for the majority of fund managers, our results are also consistent with the lack of persistence in fund performance.

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 pair trades that define INSFIT.

Empirically, the vast majority of pair trades underlying INSFIT involve one firm being purchased and another sold. For these one-to-one balanced intra-industry pair trades, the CAR over the subsequent 10 trading days for the long position is 0.952%, compared to 0.786% without the one-to-one restriction. Besides limited attention on the part of fund managers when selling (Akepanidtaworn et al. (2021)), fund managers appear to hedge industry risk since the industry betas of both the long and short positions underlying INSFIT are large (significantly above 1) and identical.[6] This evidence indicates that institutional investors avoid deviating from market indices.

The CAR spreads following cross-industry pair trades (not industry neutral) and unbalanced intra-industry pair trades (not self-financed) are both insignificant. Therefore, our 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

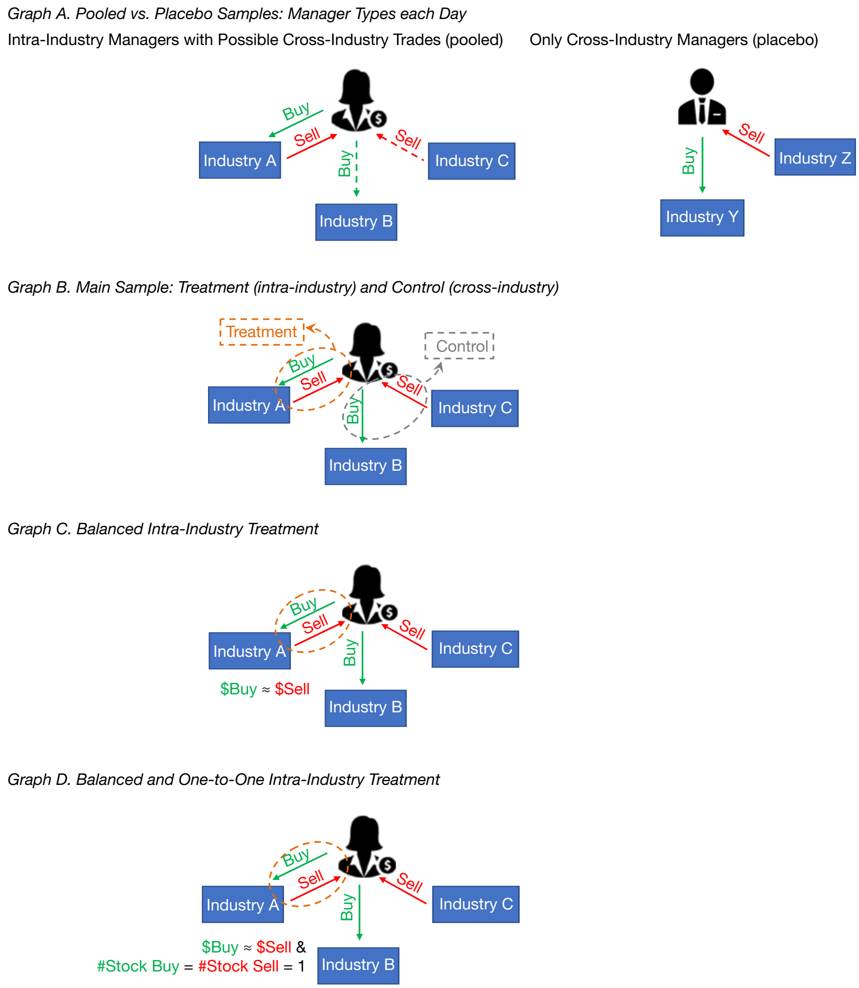
[5]Our analysis does not condition on intraday trade execution times. While ANcerno provides such timestamps, the literature finds these timestamps to be unreliable since they often reflect client *choices* to disclose placement as well as execution times (Eisele, Nefedova, Parise, and Peijnenburg (2020)).

[6]Transactions involving industry or sector ETFs are not included in our study. As their industry betas are close to 1 by construction, ETFs are less effective at offsetting the industry risk of the long positions underlying INSFIT compared to sales of individual stocks.

FIGURE 1

Identification of INSFIT

Figure 1 illustrates our sample construction and the refinement process underlying the identification of INSFIT. Graph 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 (pooled sample); (b) cross-industry managers only buy and sell stocks in distinct industries (placebo sample). Graph B illustrates our main sample that contains both a treatment and control group at the manager-day level. Graphs C and D illustrate the balanced and one-to-one refinements of the treatment group.



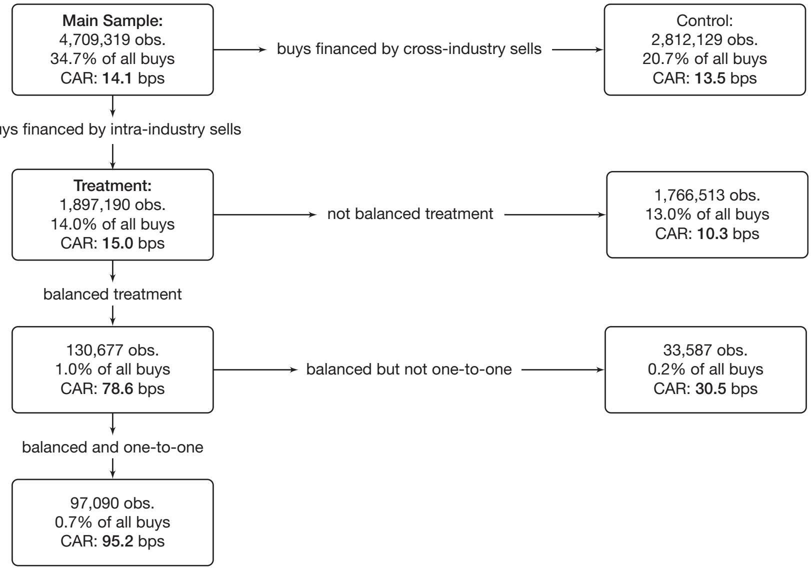
fund managers, their study does not impose either of these two properties on fund manager trades. INSFIT is also distinct from the reinvestment motive in Frydman, Hartzmark, and Solomon (2018)). Furthermore, in contrast to Chen, Chen, Chen, and Li's (2019) identification of pair trades using historical return correlations, we study the actual trades of institutional investors.[7]

[7]Gatev, Goetzmann, and Rouwenhorst (2006) examine pair trades determined by a normalized price criterion instead of the actual pair trades executed by institutional investors.

FIGURE 2

INSFIT Refinement Process and the Abnormal Returns of Buys

Figure 2 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 Graph 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.



We also find that fund managers with tighter cash constraints are more likely to execute INSFIT. Specifically, INSFIT decreases with a fund manager's cash holdings and increases with their prior outflows.[8] Thus, fund managers do not appear to accumulate cash in anticipation of acquiring a private signal. Furthermore, while fund managers with high turnover are more likely to execute INSFIT (Binsbergen, Han, Ruan, and Xing (2021)), cash constraints are as important as turnover to INSFIT.

Consistent with the heterogeneity in manager skills documented by Kacperczyk and Seru (2007), the execution of INSFIT varies across fund managers, with 2.6% of fund managers accounting for almost a quarter of all INSFIT executions and associated trading profits. This small subset of active managers use larger dollar-denominated trades when executing INSFIT and execute INSFIT within more industries. These managers also hold less cash and unwind the positions underlying INSFIT more rapidly compared to managers who execute INSFIT less frequently. This evidence supports Kadan, Michaely, and Moulton's (2018) conclusion that mutual funds exhibit different profit-taking patterns. Moreover, aggregate trading profits attributable to INSFIT are similar across fund managers as those who execute INSFIT more frequently earn lower trading profits per execution.

[8]Alexander, Cici, and Gibson (2007) report that the returns of active fund managers increase when their funds are experiencing outflows.

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The private signals that motivate INSFIT can originate from a local information advantage (Coval and Moskowitz (2001), Christoffersen and Sarkissian (2009)), political (Cohen, Frazzini, and Malloy (2008)) and insider networks (Hwang, Titman, and Wang (2018), Ahern (2020)), proprietary and big data (Zhu (2019), Mukherjee, Panayotov, and Shon (2021)), in-house information processing (Dugast and Foucault (2018)), or other nonpublic information sources. The ability of institutional investors to trade immediately before the release of public information supports prior evidence (Irvine, Lipson, and Puckett (2007), Baker, Litov, Wachter, and Wurgler (2010), Hendershott, Livdan, and Schürhoff (2015), Bernile, Hu, and Tang (2016), and Ben-Rephael, Da, Easton, and Israelsen (2022)). More recently, Bolandnazar, Jackson, Jiang, and Mitts (2020) document informed trading after corporate events that have yet to be disclosed. Consistent with the theoretical predictions and empirical evidence in Caldentey and Stacchetti (2010) and Foucault, Hombert, and Rosu (2016), the dollar-denominated trades involved in executing INSFIT increase in magnitude when media coverage for the underlying stocks is more imminent. To clarify, the buy and sell trades underlying INSFIT are typically executed by a single fund manager. Therefore, INSFIT is not a response to the release of public information that induces correlated trading across multiple fund managers (Pomorski (2009)). Instead, INSFIT precedes the release of public information.

As further evidence that INSFIT captures informed trading, the buy trades underlying INSFIT are associated with the imminent arrival of intense positive media coverage. In addition, both the buy and sell trades underlying INSFIT predict news sentiment correctly. Therefore, our media coverage analysis indicates that INSFIT is motivated by short-horizon private signals. As these results are unrelated to scheduled corporate events, fund managers cannot be expected to increase their cash holdings in anticipation of informed trading opportunities.

The buy and sell trades underlying INSFIT occur in stocks that are indistinguishable in terms of their size, BM, past return, liquidity, and beta characteristics. Moreover, BM, past return, and liquidity characteristics cannot explain the likelihood a trade is attributable to INSFIT, while industry momentum cannot explain its profitability. In general, the cross-sectional return spread from INSFIT appears to be unrelated to persistent firm characteristics, risk factors, and industry returns.

INSFIT builds on the literature concerning the profitability of specific institutional investor trades (Cohen et al. (2002), Pomorski (2009), Massa, Reuter, and Zitzewitz (2010), and Antón, Cohen, and Polk (2021)). 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 (such as the underreaction of individual investors to positive cash flow news), INSFIT identifies trades executed by fund managers who possess private firm-specific signals. Puckett and Yan (2011) study interim "round-trip" trades that are unwound within the same quarter. 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. Intuitively, post-INSFIT abnormal returns can persist if the market is slow to impound private information into prices.

Da, Gao, and Jagannathan (2011) along with Binsbergen et al. (2021) report that fund managers profit from long-horizon private signals.[9] Informed purchases reflecting such signals rely less on cash constraints since future inflows provide an alternative source of financing. Nevertheless, as firm-specific information does not induce industry reallocations, industry neutrality continues to motivate the self-financing property of INSFIT.

Our study also complements a related literature on the value of active fund management. Evans, Gomez, Ma, and Tang (2022) report that fund managers with relative performance incentives deviate from market indices. Busse, Green, and Baks (2006) as well as Cremers and Petajisto (2009) link such deviations with active management and superior performance, while Chen et al. (2000) report that widely held stocks do not outperform. Furthermore, Kacperczyk, Sialm, and Zheng (2005) link superior performance with greater industry concentration, which further motivates the industry-neutral property of INSFIT, while Wermers (2000) links superior performance with higher turnover. We contribute to the active fund management literature by reporting that INSFIT is an infrequent yet profitable occurrence for most fund managers that improves their fund's short-term performance.

Finally, our article contributes to the empirical identification of informed trading. This challenging task has led most empirical methodologies to focus on a single asset. Inferences regarding informed trading are then drawn by examining how orders were placed or who placed the orders.[10] In contrast, our methodology identifies informed trading across multiple assets in the same industry.[11]

II. Identification of INSFIT

This section details the construction of our sample and the refinements that identify INSFIT.

A. 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

[9]Cohen et al. (2008) report that fund manager performance benefits from having long-term relationships with corporate board members.

[10]This literature has been extended to allow for multiple agents, time-varying liquidity, liquidity timing, optimal execution, and multiple trading venues (Admati and Pfliederer (1988), Holden and Sumbrahmanyam (1992), Foster and Viswanathan (1996), Back, Cao, and Willard (2002), Zhu (2013), Collin-Dufresne and Fos (2016), and Choi, Larsen, and Seppi (2019)). Methodologies that examine "unusual" trading patterns by insiders include Cohen, Malloy, and Pomorski (2012), Kelly (2018), and Shkilko (2018). Empirical studies such as Collin-Dufresne and Fos (2015) use insider trades as proxies for informed trading to study liquidity timing.

[11]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)).

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.[12] 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.[13] Using variables "CUSIP," "SYMBOL," and "STOCKKEY," we 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."[14] 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.

As informed trading in our study focuses on private firm-level signals, our analysis examines trades motivated by the imminent arrival of firm-level information arrival, the mitigation of industry risk exposure, and cash constraints as well as tracking error constraints. 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 CARs over subsequent trading days using "CUSIP." These abnormal returns are computed by estimating 4-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

[12]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.

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

[14]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.

stock-manager-day trade observations with daily abnormal returns. We use parameter estimates and concurrent daily factor returns to construct the post-trade 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.[15] 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.[16] 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.[17] We also calculate volume-weighted same-day returns, CARs, 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 that day in an industry. A later robustness test obtains 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 Wharton Research Data Services (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-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 industry neutral and self-financing.

Media coverage data are obtained from RavenPack Analytics, which conducts a textual analysis of news stories covered by *Dow Jones Newswires* and other news aggregators.[18] Following Bushman, Williams, and Wittenberg-Moerman (2017), we focus on full news articles with "relevance" scores of 75 and higher, where relevance scores are scaled from 0 to 100. We classify media coverage as low or high intensity according to the median number of daily news stories featuring the firm (on days with media coverage) in the preceding month.[19] Using the daily average Composite Sentiment Score (CSS) provided by RavenPack Analytics' proprietary news sentiment algorithm, we also classify the sentiment of media

[15]Constructing same-day risk-adjusted returns is challenging because ANcerno trade time stamps are unreliable (Hu et al. (2018)).

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

[17]We obtain industry definitions and monthly returns to systematic risk factors from Professor Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[18]These include *Alliance News*, *Benzinga Pro*, *The Fly*, *MoreOver News*, and social media.

[19]Days without media coverage in the previous month are excluded.

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coverage as negative, neutral, or positive. As CSS is between −1.00 and 1.00, negative, zero, and positive values reflect negative, neutral, and positive sentiment, respectively.[20] We merge RavenPack Analytics with CRSP using DATE and CUSIP.

We use CRSP Mutual Fund data 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.[21] Using the link tables provided by the CRSP Mutual Fund database, we merge fund cash holdings and flows with the managing fund family identified by Thomson Reuters' 13F institutional holdings. Based on the managing-institution (fund family) identity file *ManagerXref* provided by ANcerno, we manually link the identifier from ANcerno to the identifier "`mgrno`" from 13F holdings. Similar to Eisele et al. (2020), we successfully match 263 managing fund families from 1,029 valid ANcerno codes across the databases.[22] We then calculate average end-of-quarter cash holdings and quarterly fund flows at the fund family level, weighting observations across the different funds by their respective total net assets (TNAs). We measure the asset size of each fund family as the sum of TNAs across all constituent funds and also calculate two measures of asset (fund) concentration for each fund family: i) the inverse of the number of funds under management, and ii) the Herfindahl index of fund-level TNAs. This Herfindahl index equals 1 for a fund family that manages one fund, and approaches 0 as the number of funds increases and the fund family's TNA becomes more evenly distributed across funds.[23]

Merging databases using the Eisele et al. (2020) methodology requires information to be aggregated within fund families. An alternative algorithm that avoids this aggregation is implemented by Agarwal et al. (2014), Busse, Chordia, Jiang, and Tang (2021), as well as Binsbergen et al. (2021). This approach matches trading activity in ANcerno with quarterly portfolio holding changes in Thompson Reuters.[24] The resulting links, in conjunction with MFLINKS (Wermers (2000)), allow us to identify monthly fund returns and flows for 988 individual fund managers. Consistent with Busse et al. (2021), 525 individual fund managers are then matched across the ANcerno, Thompson Reuters S12, and CRSP Mutual Fund databases. Within this subset, we construct monthly fund flow and TNA measures as well as quarterly measures for cash holdings and turnover ratios.[25]

[20]In older versions of RavenPack Analytics, CSS is scaled from 0 to 100.

[21]Fund flows reflect the change in total net assets adjusted for fund returns and, in rare cases, mergers.

[22]Hu et al. (2018) also discuss this matching procedure.

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

[24]We thank Baozhang Yang for generously sharing a link table for the 2002 to 2011 period.

[25]In cases where an individual fund manager is linked to multiple funds, we construct a TNA-weighted average across funds.

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CRSP and Compustat data underlie 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).[26] A stock's BM characteristic is its most recent book value of equity divided by its market capitalization from the previous month.[27] Past return measures include the previous month's return (MOM_{-1}), the compound return over the preceding 5 months (MOM_{-6}^{-2}), and the prior 6 months (MOM_{-12}^{-7}) preceding MOM_{-6}^{-2}.

Hedge funds, which can finance informed purchases using leverage and the proceeds from short selling, comprise a small fraction of the funds in ANcerno (Jame (2018)). Only six hedge funds are present in our sample, and these hedge funds are only responsible for 10 instances of INSFIT.[28] The exclusion of these informed trades therefore does not alter our results. Chen, Desai, and Krishnamurthy (2013) study a subset of mutual funds able to short sell and conclude that this ability is reserved for skilled mutual fund managers who demonstrate superior performance. Although short sales are not identified in ANcerno, the use of short sale proceeds to finance informed purchases would cause INSFIT to underestimate informed trading.

B. 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. Graph 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). 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. Graph 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

[26]Barardehi, Bernhardt, Ruchti, and Weidenmier (2021) find this modified measure significantly outperforms the original Amihud measure in capturing liquidity and explaining cross-sectional returns.

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

[28]Hedge funds are identified in ANcerno using the CLIENTMGRCODE list available on Russell Jame's website (https://russelljame.com/).

TABLE 1

Main Sample: Treatment, Control, and Refinement

Panel A of Table 1 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 when 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				
No. of obs.	1,897,190	1,897,190	2,741,799	2,812,129
Mean no. 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	–	–

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

$$\text{(1)} \qquad \text{IMB} = \left| \frac{\$-\text{VALUE\_BOUGHT} - \$-\text{VALUE\_SOLD}}{\$-\text{VALUE\_BOUGHT} + \$-\text{VALUE\_SOLD}} \right|.$$

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.[29] This refinement is illustrated by Graph C in Figure 1 and summarized in Table 1. The subsample of balanced intra-industry pair trades contains 130,677 manager-industry-day observations, comprising our treatment group. The subsample of cross-industry pair trades containing 488,113 sell trades and 519,887 buy

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

trades comprises our control group. Of note, certain cross-industry trades in Table 1 may overlap for the balanced and unbalanced intra-industry pair trades since 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 of Table 1 summarizes the number of trades, the average CAR, the average dollar-denominated trade size, and the annual frequency per fund manager of different trade types in the main sample.[30]

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)).

III. Empirical Results

To examine the informativeness of the trades underlying INSFIT, we estimate post-trade CAR spreads for a variety of different trade pairs using the following specification:

$$\text{(2)} \qquad \text{CAR}_{ij}(t,t+s) = \alpha_{0s} + \alpha_{1s} I\left(\text{SIDE}_{ij}^{t}\right) + \text{FEs} + u_{ij}^{t,s} \text{ for } s \in \{1,\ldots,N\},$$

where $\text{CAR}_{ij}(t,t+s)$ denotes the post-trade s-day CAR on manager i's trade in industry j on day t. $I\left(\text{SIDE}_{ij}^{t}\right)$ 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.

A. Preliminary Analysis

We begin our study with the pooled sample consisting of all trades by managers who both buy *and* sell in at least one industry, regardless of the manager's trading across other industries (illustrated on the left in Graph A of Figure 1). INSFIT is defined by the balanced intra-industry pair trades within this pooled sample. We also construct a placebo sample using the trades of managers who *only* buy and sell in distinct industries on a given day (illustrated on the right in Graph A of Figure 1).

[30]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 et al. (2018), CLIENTMGRCODE may change over time. However, as our analysis of INSFIT is based on a relatively short horizon of 10 trading days, variation in CLIENTMGRCODE is irrelevant for our study of informed trading.

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TABLE 2

Preliminary Analysis of Pair Trade Types in the Pooled and Placebo Samples

Table 2 presents average same-day return (R) and cumulative abnormal returns (CAR) following the buy and sell trades underlying balanced intra-industry pair trades in columns 1–3 and unbalanced intra-industry pair trades in columns 4–6 from the pooled sample as well as those following balanced cross-industry pair trades in columns 7–9 from the placebo sample. A manager's trades are included in the pooled sample if the manager both buys and sells in at least one industry on a given day (the illustration on left in Graph A of Figure 1). A manager's trades are included in the placebo sample if all their buy and sell trades take place in distinct industries on a given day (the illustration on right in Graph A of Figure 1). 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). The standard errors reported in parentheses are clustered by fund and date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Balanced Intra-Industry			Unbalanced Intra-Industry			Balanced Cross-Industry		
	Sell	Buy	Spread	Sell	Buy	Spread	Sell	Buy	Spread
	1	2	3	4	5	6	7	8	9
$R(t)$	−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)
No. of obs.	218,819	218,819		1,704,930	1,704,930		424,608	473,105	

According to columns 1–3 of Table 2, INSFIT is followed by a large and significant post-trade CAR spread. This "informed trading profit" remains statistically significant for the subsequent 10 trading days.[31] In contrast, as columns 4–6 of Table 2 indicate, 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 informed. Instead, self-financing is an important determinant of informed trading.

According to columns 7–9 of Table 2, the CAR spreads following the placebo sample's balanced cross-industry pair trades are insignificant. 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 informed. Instead, industry neutrality is an important determinant of self-financed 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

[31]The implicit trading cost for individual buy or sell orders in our sample is approximately 5 bps (Puckett and Yan (2011)), resulting in a round-trip institutional trading cost of 10 bps. Thus, one should adjust for an expected 10 bps round-trip trading cost. For example, the cost-adjusted 7-day CAR associated with balanced intra-industry trades in column 3 of Table 2 is $30.0-10=20$bps, and is associated with an approximate t-statistic of $\frac{30.0-10}{7.2}=2.78$.

us to partition manager-industry-day observations into treatment and control groups, as illustrated by Graph B in Figure 1 and summarized in Table 1. The sample obtained using these selection criteria is referred to as our *main sample* and underlies our analysis of INSFIT for the remainder of the article.

B. Balanced Trades: Treatment Versus Control

To quantify the incremental value of the information motivating INSFIT, we estimate CARs as well as same-day raw returns using equation (2) for balanced intra-industry pair trades in the main sample. According to column 3 of 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.

Section A of the Supplementary Material demonstrates the robustness of INSFIT's profitability to alternative industry classifications. Section B of the Supplementary Material establishes that INSFIT's profitability declines for less balanced pair trades but is robust to including pair trades in which the dollar-denominated amounts of stock bought and sold are slightly different (in the same industry on the same day).

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 0. The return reversals following sell trades are consistent with the willingness of fund managers to incur price impacts in order to immediately finance informed buy trades whose expected returns are sufficiently high to justify incurring these price impacts.

TABLE 3

Main Analysis: Treatment and Control Groups

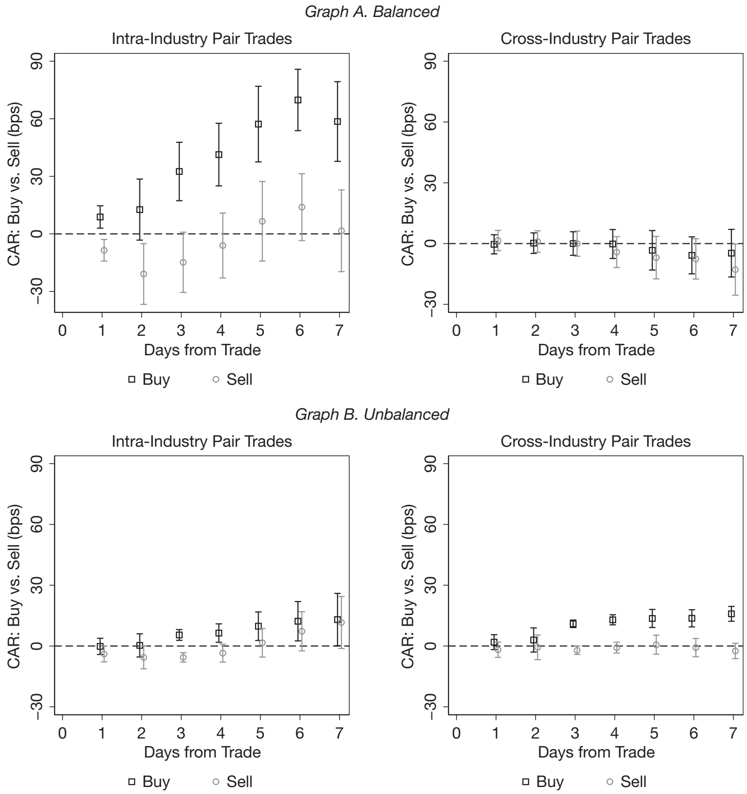
Table 3 reports average same-day return (R) and cumulative abnormal returns (CAR) following buy and sell trades as well as the spread between these trades after 1, 3, 5, 7, and 10 days. The same-day return and CARs are estimated using equation (2) for trades in the treatment (intra-industry pair trades)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

	Balanced									Unbalanced	
	Intra-Industry: All Trades			Intra-Industry: One-to-One			Cross-Industry			Intra-Industry	Cross-Industry
	Sell	Buy	Spread	Sell	Buy	Spread	Sell	Buy	Spread	Spread	Spread
	1	2	3	4	5	6	7	8	9	10	11
$R(t)$	−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)
No. of obs.											
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

FIGURE 3

Balanced Versus Unbalanced: Treatment Versus Control

Figure 3 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) in the main sample 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.



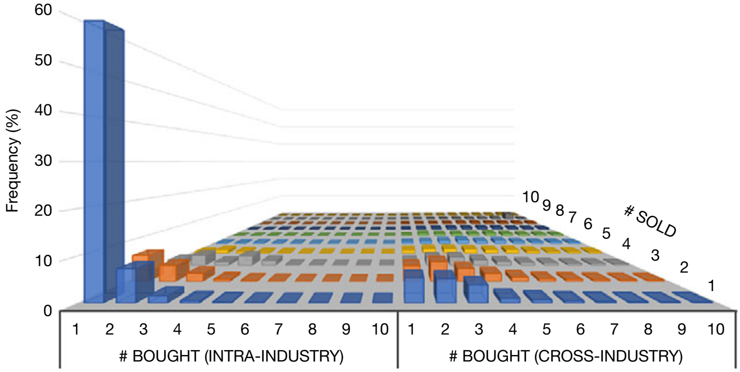
We also estimate equation (2) using observations in the main sample that correspond to unbalanced intra-industry pair trades. Columns 7–9 of Table 3 report that the post-trade CAR spreads for these unbalanced intra-industry pair trades are minimal, often insignificant, and smaller than balanced intra-industry pair trades. Columns 10 and 11 of this table report post-trade CAR spreads associated with cross-industry trades. Although some estimates are positive, none remain positive after accounting for implicit institutional trading costs (except the 7-day CAR spread for "unbalanced cross-industry" trades). Unreported results confirm that the abnormal return spreads remain insignificant for unbalanced intra-industry pair trades regardless of whether the underlying buy trades are larger than sell trades (positive net purchases) or vice versa (positive net sales). This finding highlights the importance of conditioning on balanced pair trades, which are industry neutral, 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. An ordered pair

FIGURE 4

One-to-One Trades and INSFIT

Figure 4 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, with the left (right) area of the plot pertaining to the treatment (control) group.



(number of stocks sold, number of stocks bought) is constructed for each manager-day to compare the relative frequency of intra-industry pair trades and cross-industry pair trades. These relative frequencies are plotted in Figure 4. Observe that over 60% of intra-industry pair trades are one-to-one, while the percentage of one-to-one cross-industry trades is below 10%. Thus, although INSFIT imposes no restriction on the number of stocks traded, one-to-one pair trades are typical for INSFIT but not for cross-industry trades executed by the same manager on the same day.

Column 5 of 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 95 bps over the subsequent 10 trading days, while column 6 of this table reports that the CAR spread itself exceeds 89 bps over this horizon. In contrast, unreported results indicate that the small subset of balanced intra-industry pair trades that are not one-to-one produce negligible post-trade abnormal returns.

Section C of the Supplementary Material reports the results of three additional robustness tests. First, to confirm the importance of firm-specific signals regarding relative industry performance, we examine industry competition using the product market fluidity measures of Hoberg, Philips, and Prabhala (2014). Within competitive industries, post-trade returns following sell trades attributable to INSFIT are negative. Second, to confirm the importance of return volatility, we examine temporal variation in INSFIT. While INSFIT increased significantly during the 2008–2009 global financial crisis, it was profitable in both an early and later subperiod. Third, we confirm that INSFIT is distinct from Puckett and Yan's (2011) study of round-trip interim trades.

C. Execution of INSFIT

Investors possessing private information may execute larger trades and consequently incur greater trade execution costs (Kyle (1985), Easley and O'Hara

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TABLE 4

INSFIT and Trade Execution

Table 4 compares the dollar-denominated trade size and implicit execution cost underlying INSFIT to other trades executed 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 $1,000 s) 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. The number of brokers variable refers to the number of brokers employed to execute the underlying buy and sell orders involving a stock on a given day. All estimates control for date, stock, and fund manager fixed effects. The standard errors reported in parentheses are double-clustered by date and stock. 95% CI denotes a 95% confidence interval for the above coefficient. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Trade Size ($1,000s)			Execution Cost (bps)			Number of Brokers		
	INSFIT	Other	Difference	INSFIT	Other	Difference	INSFIT	Other	Difference
Buy trades	411.6***	313.3***	98.3***	9.0***	7.1***	1.9*	1.85***	1.69***	0.17***
	(10.4)	(1.1)	(11.5)	(1.0)	(0.1)	(1.1)	(0.03)	(0.00)	(0.03)
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]	[1.80, 1.90]	[1.68, 1.69]	[0.10, 0.22]
Sell trades	416.1***	331.0***	85.1***	3.6**	2.2***	1.4	1.89***	1.74***	0.15***
	(10.1)	(1.1)	(11.2)	(1.5)	(0.2)	(1.7)	(0.02)	(0.00)	(0.02)
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]	[1.84, 1.93]	[1.73, 1.74]	[0.10, 0.19]

(1987)). We test these predictions by comparing the buy (sell) trades underlying INSFIT to other buy (sell) trades executed by the same manager on the same day. All comparisons involve date, stock, and manager fixed effects, with standard errors double-clustered by date and stock.

Table 4 reports that the dollar value of buy (sell) trades underlying INSFIT are about 31% (26%) larger than other buy (sell) trades executed by the same manager on the same day.[32] This evidence provides further support that balanced intra-industry pair trades are informed and, in conjunction with INSFIT's profitability, indicates disproportionately large dollar-denominated trading profits per INSFIT execution.[33]

According to Table 4, the implicit execution costs associated with INSFIT are not larger than other trades executed by the same manager on the same day despite INSFIT involving relatively large trades. In particular, the difference in execution costs is insignificant for sell trades. For buy trades, the difference is economically negligible and its statistical significance is marginal. This finding supports Christoffersen, Keim, Musto, and Rzeznik's (2022) conclusion that price impacts alone cannot identify informed trading. Furthermore, Table 4 reports that the number of brokers executing INSFIT is over 10% larger than the number executing other trades by the same fund manager on the same day. This evidence suggests fund managers attempt to conceal their intended trade sizes and reduce their trading costs by routing orders through a larger pool of brokers when executing INSFIT.

Although the buy and sell trades underlying INSFIT are relatively large, they comprise a small fraction of both institutional and overall trading volumes on the same day. The median ratio of INSFIT volume relative to same stock-day's total ANcerno-reported volume is 2%, while this ratio is only 0.02% relative to overall

[32]Provided a subset of non-INSFIT buy trades are also informed, 31% represents a lower bound for the difference in trade size between informed and uninformed buy trades.

[33]Many microstructure models focus on individual transactions, not the institutional "parent" orders in our study. As our empirical results support the predictions of these models, investors appear to execute larger trades within a single day when trades are informed.

CRSP-reported volume.[34] These small ratios are 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.[35] O'Hara (2015) along with Kacperczyk and Pagnotta (2019) also conclude that informed trading is not necessarily associated with higher transaction costs. Our results indicate that investors executing INSFIT accumulate positions within a trading day without incurring significant price impacts since the positions are not large relative to overall trading activity.

There are two explanations for the higher execution costs associated with the buy trades compared to the sell trades underlying INSFIT. Hu (2009) reports that execution costs are larger for buy trades in down markets, and INSFIT is more prevalent in down markets such as the global financial crisis. Second, the majority of INSFIT's profitability is from buy trades, which are more likely to be informed among the long-only funds in our sample.

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. Later results in Section V.A indicate that the individual stocks fund managers select to sell when executing INSFIT hedge the industry risk associated with the accompanying informed purchases. This industry hedging objective offers an explanation for the decision of fund managers to sell a large amount of a single stock with a high industry beta instead of selling smaller amounts of multiple stocks with lower industry betas.

Finally, one may question why the execution of INSFIT does not involve even larger trades. Antón et al. (2021) also question why fund managers do not hold more concentrated portfolios and instead appear reluctant to deviate from market benchmarks (Cohen et al. (2002)). Besides the minimization of tracking error and the potential for higher trading costs, later evidence links larger trades with the more imminent release of public information.

IV. INSFIT and Fund Characteristics

Having established INSFIT's profitability, our next analysis examines whether INSFIT impacts fund performance and is associated with tighter cash constraints.

A. INSFIT and Fund Performance

Our next analysis examines the ability of INSFIT to predict fund performance. As discussed in Section II.A, CRSP Mutual Fund data are matched with ANcerno

[34]These ratios are calculated for trading days with nonzero INSFIT volume. If these ratios were treated as zero on stock-days without INSFIT, the medians would be much smaller. The ratios are highly skewed. With ANcerno-reported volume in the denominator, the average, 75th percentile, and 95th percentile are 12.2%, 12.2%, and 67.1%, respectively. With CRSP volume in the denominator, these statistics are 2.3%, 1.1%, and 8.4%, respectively. This skewness may explain the temporary price impacts (return reversals) following sell trades.

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

data for a subset of 263 fund families. An alternative approach conducts this matching for individual fund managers using trading activity and obtains a match for 988 individual fund managers. By implementing both approaches, we establish the robustness of our results to the trade-off between a larger sample size, which is offered by the first approach, and higher accuracy, which is offered by the second approach.

After determining when INSFIT occurs in one of the constituent funds of an individual fund manager, we construct two indicator variables to identify whether the constituent fund executes INSFIT in the current or previous month. The corresponding panel regression of fund family (individual fund manager) returns on these indicator variables control for fund family fixed effects and double-clusters standard errors by fund family and month.

Table 5 reports that neither fund families nor individual fund managers display a significant overall alpha after adjusting for systematic risk factors. However, we find incremental monthly alphas of 16.4 and 13.4 basis points per month when a constituent fund and an individual fund manager, respectively, execute INSFIT in the previous month. Consequently, we find a positive relation between INSFIT and short-term fund performance. Later results provide a more complete interpretation

TABLE 5

INSFIT and Fund Performance

Panel A of Table 5 presents estimates from a monthly 4-factor model to determine the relation between INSFIT and fund performance (alpha). A panel of monthly TNA-weighted fund family returns, in excess of 1-month T-bill rates, are regressed on monthly risk factors along with interaction variables defined by these risk factors and an indicator variable INSFIT. This indicator variable equals 1 if a constituent fund in the respective fund family executed INSFIT in month m where $m \in \{\text{currentmonth}, \text{previousmonth}\}$. Thus, "previous" and "current" refer to the month in which INSFIT is executed to examine the impact of these pair trades on subsequent and contemporaneous returns, respectively. Panel B presents estimates for individual fund managers instead of fund families. In both specifications, the estimates control for fund family fixed effects and the standard errors (reported in parentheses) are double-clustered by fund family and month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Fund Families			*Panel B. Individual Fund Managers*		
		INSFIT Realization in			INSFIT Realization in	
		Current Month	Previous Month		Current Month	Previous Month
Intercept	5.84 (6.14)	4.49 (6.27)	4.60 (6.19)	2.13 (4.37)	2.41 (4.37)	−0.68 (4.48)
INSFIT		8.94 (6.38)	16.40** (7.31)		−1.68 (5.19)	13.40** (5.66)
$(R_m - r_f)$	0.91*** (0.02)	0.91*** (0.02)	0.91*** (0.03)	1.01*** (0.02)	1.01*** (0.02)	1.01*** (0.02)
$(R_m - r_f) \times$ INSFIT		0.026 (0.03)	0.034 (0.03)		−0.011 (0.02)	−0.0079 (0.02)
HML	0.060** (0.03)	0.071** (0.03)	0.070** (0.03)	−0.059* (0.03)	−0.063** (0.03)	−0.071** (0.03)
HML × INSFIT		−0.082** (0.03)	−0.098*** (0.03)		0.019 (0.03)	0.060*** (0.02)
SMB	0.15*** (0.03)	0.16*** (0.03)	0.16*** (0.03)	0.17*** (0.03)	0.18*** (0.03)	0.18*** (0.03)
SMB × INSFIT		−0.057* (0.03)	−0.064** (0.03)		−0.060** (0.03)	−0.083*** (0.03)
UMD	0.0083 (0.01)	0.0094 (0.01)	0.0075 (0.01)	0.0088 (0.02)	0.0087 (0.02)	0.0070 (0.02)
UMD × INSFIT		−0.0076 (0.01)	0.011 (0.01)		−0.00071 (0.01)	0.0028 (0.01)

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of INSFIT's ability to predict fund manager returns since the horizon underlying this return predictability varies across fund managers.

Furthermore, we examine the interaction between risk factors (market, HML, SMB, and UMB) and the INSFIT indicator variables. The often insignificant or negative coefficients for these interactions indicate that INSFIT does not increase fund returns through exposure to risk. Instead, this finding is consistent with INSFIT arising from firm-specific private information. Observe that, with the exception of HML and its interaction with INSFIT, the coefficients in Table 5 are consistent across the fund family and individual fund manager subsets.

The impact of INSFIT on fund performance is unlikely to persist and signify fund manager skill since the pair trades underlying INSFIT are infrequent. After estimating 4-factor alphas for the 233 fund managers in this subset that have a return time-series of at least 30 observations, unreported results reveal no statistical difference between the average alpha of fund managers that execute INSFIT at least once versus those that never executes INSFIT. Thus, INSFIT does not translate into improved long-term fund performance.

In summary, despite comprising a relatively small fraction of trading activity, INSFIT is a major contributor to institutional trading profits and also predicts fund performance. Specifically, of the 9,348,308 manager-industry-day trades in our sample, 261,534 (130,677 pairs) or 2.9% are classified as INSFIT. Back-of-the-envelope calculations involving the corresponding 10-day risk-adjusted trading profits indicate that INSFIT produces $99.05 million in trading profits, out of a total 10-day risk-adjusted trading profit of $266.7 million.[36] Thus, INSFIT constitutes over 37% of fund manager short-term trading profits (over a post-INSFIT horizon of 10 trading days), despite representing less than 3% of their trading activity.[37]

B. INSFIT and Cash Constraints

Self-financing stock purchases by selling stock are 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, higher 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 TNAs held in cash and fund flows. Building on samples constructed in Section IV.A, we first measure quarterly cash holdings and fund flows at the fund family level, and then match

[36]We multiply the signed dollar value of each buy and sell trade by the corresponding 10-day risk-adjusted return to obtain 10-day risk-adjusted trading profits at the manager-day-industry level. We then aggregate these trading profits across the trades of all managers. The $99.05 million amount represents the total trading profit from all INSFIT trades, while $266.7 represents the total trading profit from all trades by managers who executed INSFIT on the same day.

[37]INSFIT's profitability extends over longer horizons. For example, in unreported results over a 20-day horizon, INSFIT's profitability continues although other trades executed by the same manager produce a loss. Figure C.3 in the Supplementary Material illustrates INSFIT's profitability over a 40-day horizon.

these quantities with fund managers underlying each fund family in the ANcerno data (i.e., a fund family's constituent fund managers). We estimate the likelihood of INSFIT using a logistic regression whose dependent variable is an indicator function that equals 1 if a constituent fund manager in fund family executes a balanced intra-industry trade in a particular quarter. This analysis controls for quarter fixed effects and clusters standard errors by quarter. Independent variables are defined at the fund family level and reflect quantities from the previous quarter. For each institution, we measure cash constraints using average cash holdings and fund flows, weighting fund-family level observations by each constituent fund's TNAs.

Furthermore, motivated by Binsbergen et al. (2021), we control for the TNA-weighted average turnover ratios of fund families. These authors find evidence that fund manager skill is horizon dependent as high turnover is associated with fund managers whose selection ability involves short-lived signals, while low turnover is associated with selection ability involving long-horizon signals. We also account for the natural logarithm of TNA (sum of fund-level TNAs) to control for fund size.

To clarify, the same cash constraint measure is assumed to be identical for all funds within a fund family. To account for this assumption's accuracy, we condition on a fund family's asset concentration measured as i) the inverse number of funds in the institution, and ii) the Herfindahl index of fund-level TNAs. With higher asset concentration signifying greater cash constraint accuracy, we interact each fund family characteristic with an indicator variable that identifies high versus low asset concentration defined by the quarterly cross-sectional median of the respective asset concentration measure.

The above analysis is also conducted for the 525 individual fund managers whose trades in ANcerno are matched with CRSP Mutual Fund data and Thompson Reuters S12 data. A different set of fund characteristics are compiled at the individual fund manager level to estimate the probability of executing INSFIT in a given month. The cash, turnover, and TNA measures are from the previous calendar quarter, while fund flows are from the preceding month to capture variation in this proxy for cash constraints. Once again, the dependent indicator variable equals 1 if a fund manager executes INSFIT in month m, and 0 otherwise. To maintain consistency across specifications, this analysis controls for month fixed effects and clusters standard errors by month.

Table 6 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. We calculate the marginal effects of each relevant independent variable in the logistic regressions using the sample means and standard deviations reported in Table 6. Our calculations highlight the economic significance of cash constraints on INSFIT.[38] At the fund family level (Panel A),

[38]With a single independent variable x that loads with an estimated coefficient of $\widehat{\beta}$ in the logistic regression that has an estimated intercept of $\widehat{C}$, the marginal effect of a 1-standard-deviation increase in x on the success likelihood is calculated as follows. Let $\overline{x}$ and S_x denote x's sample mean and standard deviation, respectively. The effect of a 1-standard-deviation increase in x on the success rate (i.e., execution of INSFIT in our context) is given by $\left(\frac{\exp\left\{\widehat{C}+\widehat{\beta}(\overline{x}+S_x)\right\}}{\exp\left\{\widehat{C}+\widehat{\beta}\overline{x}\right\}}-1\right)\times 100.$

TABLE 6

INSFIT and Cash Constraints

Panel A of Table 6 presents logistic regression estimates for the likelihood of INSFIT. The dependent indicator variable equals 1 if a fund manager performs at least one INSFIT in quarter q. CASH is a fund family's average cash holding in quarter $q-1$ weighted by constituent funds' total net assets (TNAs). FLOW is a fund family's average fund flow in quarter $q-1$ weighted by constituent funds' TNAs. Similarly, TURN is a fund family's average turnover ratio in quarter $q-1$ and ln(TNA) is the natural logarithm of a fund family's TNA. The estimation is conditioned on one of two asset concentration measures (higher measure, higher concentration): i) inverse number of funds in the fund family, and ii) Herfindahl index constructed from fund-level TNAs. For each measure, the indicator variable CON equals 1 if the respective asset concentration measure for a fund family is above the cross-sectional median. Panel B presents estimates for individual fund managers whose trades in ANcerno are matched with CRSP Mutual Fund data and Thompson Reuters data. The dependent indicator variable equals 1 if a manager executes INSFIT in month m, and 0 otherwise. FLOW is constructed in the previous month, $m-1$, while CASH, TURN, and TNA are constructed in the previous quarter. Quarter (Panel A) and month (Panel B) fixed effects are included and standard errors, reported in parentheses, are clustered by quarter (Panel A) and month (Panel B). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The bottom rows report sample means and standard deviations.

	Panel A. Fund Family			*Panel B. Individual Manager*		
		Asset Concentration Measures				
	Unconditional Estimates	1/(# of Funds)	Herfindahl	1	2	3
CASH	−6.72***	1.68	0.90	−2.10**	−2.13**	
	(1.53)	(1.56)	(1.63)	(0.91)	(0.91)	
CASH × CON		−7.61***	−8.27***			
		(1.55)	(1.49)			
FLOW	−5.12***	−2.20**	−2.99**	−0.95*		−0.98*
	(1.64)	(1.06)	(1.16)	(0.54)		(0.53)
FLOW × CON		−3.33**	−3.12**			
		(1.35)	(1.43)			
TURN	0.71***	1.11***	1.40***	0.25***	0.26***	0.23***
	(0.19)	(0.28)	(0.29)	(0.03)	(0.03)	(0.03)
TURN × CON		−0.04	−0.14			
		(0.17)	(0.19)			
ln(TNA)	0.26***	0.15**	0.20***	0.026*	0.028*	0.027*
	(0.03)	(0.07)	(0.07)	(0.01)	(0.01)	(0.01)
ln(TNA) × CON		−0.10***	−0.08***			
		(0.04)	(0.04)			
Intercept	−15.9***	−15.3***	−15.6***	−1.42*	−1.44*	−1.55*
	(1.06)	(1.26)	(1.39)	(0.13)	(0.13)	(0.11)
Sample summary statistics		Mean	Std. Dev.		Mean	Std. Dev.
	CASH	0.037	0.046	CASH	0.025	0.050
	FLOW	0.014	0.064	FLOW	0.770	0.660
	TURN	0.650	0.360	TURN	0.008	0.074
	ln(TNA)	8.64	2.16	ln(TNA)	6.33	2.13

a 1-standard-deviation decrease and increase in these metrics are associated with a 31% and 38% increase in the likelihood of executing INSFIT, respectively. In the analysis of individual fund managers (Panel B), these increases in INSFIT are 11.1% and 7.3%, respectively.

Consistent with Binsbergen et al. (2021), fund managers with high turnover are more likely to execute INSFIT. However, cash constraints are as important to INSFIT as turnover. Specifically, a 1-standard-deviation increase in past turnover increases the likelihood of INSFIT by 29.1% at the fund family level and 18% at the individual manager level.

Intuitively, as INSFIT's alpha persists over time (Section C of the Supplementary Material documents persistence over 40 trading days), INSFIT appears to originate from information that tends to be processed slowly by market participants. Consistent with this interpretation, the results in Section C of the Supplementary Material indicate that only 40% of buy trades attributable to INSFIT are fully unwound after two years. In addition, INSFIT is positively related to an institution's total assets, which indicates that larger institutions with more resources trade on more private signals. Our conditional estimates also highlight the importance of estimating fund characteristics accurately. In particular, the negative impact of cash constraints on INSFIT is more salient for fund families with higher asset concentrations.

C. INSFIT and Fund (Manager) Characteristics

Our analysis sorts fund managers into four groups according to the frequency with which they execute INSFIT. Denote the number of INSFIT executions per year as N. Groups 1, 2, 3, and 4 correspond to fund managers with $N=1$, $N \in [2,3]$, $N \in [4,10]$, and $N \geq 11$, respectively. Table 7 reports that groups 1, 2, 3, and 4 comprise 26.5%, 26.0%, 24.8%, and 22.7% of all INSFIT executions but 61.0%, 26.1%, 10.3%, and 2.6% of manager-year observations. Thus, each group contains a similar

TABLE 7

Fund Manager Characteristics and INSFIT Profitability

Table 7 presents fund manager and INSFIT characteristics conditional on the frequency of INSFIT executions by fund managers. Each year, fund managers are sorted into four groups based on the frequency of executing INSFIT, N: (1) $N=1$, (2) $N \in [2,3]$, (3) $N \in [4,10]$, and (4) $N \geq 11$. The following characteristics are reported for each group: (a) number and share of individual managers as well as INSFIT pairs; (b) industry concentration of trades and time until the buy trades underlying INSFIT are unwound; (c) fund characteristics for the subset of funds in Panel B of Table 6; and (d) average $-size, $-profit, and alpha of INSFIT trades. Standard errors, reported in parentheses, are double-clustered by fund and date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Outcome Variable	1	2	3	4
Manager-INSFIT Distributions				
Number of managers	34,650	14,821	5,874	1,450
Share of managers (%)	61.0	26.1	10.3	2.6
Number of INSFIT pairs	34,650	33,980	32,351	29,696
Share of INSFIT pairs (%)	26.5	26.0	24.8	22.7
Institutional Trading Behavior				
Industry trade concentration (HHI)	10.7%	7.6%	6.9%	6.0%
Quarters until INSFIT buys unwound	7.8	7.3	6.5	5.5
Mutual-Fund Characteristics				
ln(TNA)	6.94	7.77	7.87	7.02
Turnover ratio	0.69	0.73	0.80	1.03
Industry holding concentration	5.21%	5.13%	5.06%	4.97%
Churn ratio	0.163	0.156	0.163	0.191
Cash holdings (% of TNA)	1.32	0.86	0.80	0.58
INSFIT Characteristics				
Average trade $-value				
Sell	216,484	385,019	756,367	940,973
Buy	216,541	385,150	757,801	944,936
Profit ($)				
All INSFIT trades	176,323,841	133,491,449	55,160,174	111,401,453
Average INSFIT trade	5,089	3,929	1,705	3,751
Average manager/year	5,089	9,007	9,391	76,829
Post-INSFIT alpha				
5 trading days	98.6**	51.3**	20.0***	27.3***
	(41.31)	(24.40)	(7.27)	(4.50)
10 trading days	157.4**	45.3	22.5*	39.7***
	(70.75)	(31.05)	(12.28)	(7.46)
20 trading days	253.0**	105.1*	54.3	38.7***
	(98.84)	(54.65)	(36.66)	(9.60)
30 trading days	230.5***	102.4**	36.4	32.6***
	(62.49)	(51.82)	(28.35)	(11.65)
40 trading days	218.0***	95.1*	39.2	25.4*
	(54.57)	(52.37)	(39.48)	(13.34)

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number of INSFIT executions but a distinct number of fund managers since INSFIT is executed very frequently for the small subset of fund managers in group 4.

As shown by Table 7, fund managers who execute INSFIT more frequently unwind their long positions over a shorter horizon. On average, group 1 managers unwind the long positions underlying INSFIT in 7.8 quarters, compared to 5.5 quarters for group 4 managers. This pattern indicates that fund managers who execute INSFIT more frequently also realize their associated risk-adjusted trading profit over shorter horizons. Specifically, group 1 managers realize their highest post-INSFIT alpha after 20 trading days, whereas group 4 managers realize their highest alpha of 39.7 bps after 10 trading days.

INSFIT appears to represent an endogenous fund manager characteristic. Using fund characteristics constructed from the previous quarter's 13F statement, we find that INSFIT is executed more frequently for funds with higher turnover, shorter holding horizons, and lower cash holdings.[39] To construct the churn ratios in Table 7, we follow Gaspar, Massa, and Matos (2005) and Cella, Ellul, and Giannetti (2013); and quarterly churn ratios are the inverse of holding horizons.

In addition, managers who execute INSFIT more frequently do so with larger trades as the average dollar-denominated trade in group 4 are nearly five times larger than those in group 1. Reflective of their active trading style, despite displaying a similar *holding* concentration (measured by the Herfindahl index) across industries, fund managers in group 4 actively trade across many different industries. This industry diversity leads to a low *trade* concentration index for their portfolio holdings. However, the active managers in group 4 realize significantly smaller alphas per INSFIT execution.

Overall, we find significant variation across fund managers in their propensity to execute INSFIT. Relative to managers that execute INSFIT less frequently, managers who frequently execute INSFIT: i) execute INSFIT in more industries; ii) unwind the long positions underlying INSFIT over shorter horizons; iii) manage funds with higher turnover ratios, shorter holding horizons, and lower cash holdings; iv) execute INSFIT with significantly larger dollar-denominated trades; and v) realize smaller trading profits per execution of INSFIT over shorter post-INSFIT horizons.

V. INSFIT, Stock Characteristics, and Media Coverage

This section examines the stock characteristics and trading behavior underlying INSFIT to shed light on the relevance of industry neutrality and short-horizon private signals, respectively.

A. Comparison Between Buys and Sells

Panel A of Table 8 compares the characteristics of the stocks bought and sold through INSFIT. Our analysis controls for both month and industry fixed effects to account for temporal and cross-industry variation in the stock characteristics, with standard errors clustered by month and industry. The bottom rows in Panel A

[39]Recall that these characteristics are only observable for a subset of managers underlying the results in Panel B of Table 6.

TABLE 8

Comparison of Buy Versus Sell Trades Underlying INSFIT

Panel A of Table 8 compares the stock characteristics of buy trades and sell trades underlying INSFIT. SIZE is the natural logarithm 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 logarithm of the open-to-close Amihud's measure of liquidity (Barardehi et al. (2021)) 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, are estimated using weekly observations from the 104-week period ending in the previous month, requiring at least 52 weeks of observations. Industry betas, denoted $BETA^{I}$, are estimated by regressing individual daily firm returns on their respective equally weighted industry returns using daily observations from the preceding calendar year. For each characteristic, 95% confidence intervals of characteristic of stocks being bought and sold by INSFIT are reported along with those of the respective differences. INDRET denotes the equally weighted average industry return in the previous month. Panel B compares mean industry betas of stocks being bought and sold by INSFIT within INDRET terciles. The difference-in-mean tests and interval estimates include both month and industry fixed effects, with standard errors double-clustered by month and industry. These standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Stock Characteristics

	Trade		
	Sell	Buy	Difference
SIZE	[9.141, 9.551]	[8.921, 9.347]	[−0.630, 0.206]
BM	[0.515, 0.576]	[0.479, 0.541]	[−0.097, 0.026]
OCAM	[−8.823, −8.396]	[−8.590, −8.144]	[−0.194, 0.678]
SDRET	[2.644, 2.892]	[2.633, 2.953]	[−0.229, 0.309]
MOM_{-1}	[0.005, 0.026]	[0.017, 0.037]	[−0.009, 0.033]
MOM_{-6}^{-2}	[0.007, 0.055]	[0.088, 0.042]	[−0.014, 0.080]
6–10MOM_{-12}^{-7}	[−0.070, 0.176]	[0.041, 0.085]	[−0.031, 0.050]
BETA	[1.072, 1.191]	[1.077, 1.201]	[−0.114, 0.129]
$BETA^{I}$	[1.090, 1.141]	[1.100, 1.153]	[−0.041, 0.063]

Panel B. Returns to Industry Momentum

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

indicate that the stocks traded through INSFIT have higher-than-average but equal exposures to market and industry risk. This finding reinforces our identification strategy's focus on industry-neutral pair trades that do not restrict industry risk but requires the within-industry counter trades to have equal dollar-denominated values. Consistent with an industry hedging objective, fund managers appear to select stocks to sell with similar market *and* industry risk exposures. This buy–sell matching greatly limits the subset of stocks available to execute the pair trade underlying INSFIT, thereby justifying the empirical regularity that balanced intra-industry pair trades are typically one-to-one.

According to Panel B of Table 8, industry momentum also cannot explain INSFIT's abnormal returns. For industries with high past returns (high INDRET), stocks sold by INSFIT have higher industry betas than those bought by INSFIT, 1.20 compared to 1.12. Thus, INSFIT's 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.

To complement our earlier finding that INSFIT's profitability is unrelated to common risk factors (SMB, HML, and UMD), our next analysis examines the

TABLE 9

Stock Characteristics of the Buy Trades Underlying INSFIT

Table 9 presents logistic regression estimates where the dependent variable is an indicator variable equaling 1 if a fund manager's buy trades are attributable to INSFIT. SIZE is the natural logarithm 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. (2021)) 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, are estimated using weekly observations from the 104-week period ending in the previous month provided at least 52 weeks of observations are available. Industry betas, denoted $BETA^{I}$, are estimated by regressing individual firm daily returns on their respective equally weighted industry returns using daily observations from the preceding calendar year. Month fixed effects are included. Standard errors, reported in parentheses, are clustered by stock. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The last two columns report sample mean and standard deviation for each stock characteristic.

	Likelihood of INSFIT Buy/Sell				Sample Statistics	
	1	2	3	4	Mean	Std. Dev.
SIZE	0.14***	0.14***	0.13***	0.13***	8.904	1.703
	(0.03)	(0.03)	(0.03)	(0.03)		
BM	0.091	0.093	0.099	0.10*	0.504	0.503
	(0.06)	(0.06)	(0.06)	(0.06)		
OCAM	0.20	0.27	0.48***	0.50***	0.004	0.044
	(0.13)	(0.17)	(0.14)	(0.14)		
SDRET	0.14***	0.14***			2.577	1.332
	(0.04)	(0.04)				
BETA			0.15	0.14	1.091	0.530
			(0.09)	(0.09)		
$BETA^{I}$			0.20**	0.20**	1.089	0.507
			(0.08)	(0.08)		
MOM_{-1}		0.52		0.58	0.014	0.118
		(0.38)		(0.39)		
MOM_{-6}^{-2}		−0.052		−0.045	0.054	0.274
		(0.14)		(0.15)		
MOM_{-12}^{-7}		−0.096		−0.11	0.101	0.332
		(0.11)		(0.12)		
Intercept	−3.72***	−3.69***	−3.59***	−3.58***		
	(0.38)	(0.38)	(0.35)	(0.35)		

likelihood a stock trade attributable to INSFIT is related to specific firm characteristics. Building on our previous analysis, which finds no difference between the characteristics of bought and sold stocks underlying INSFIT, we compare the characteristics of any stock traded through INSFIT to those of the wider cross section of stocks. Specifically, a logistic regression estimates how the likelihood that a stock trade underlying INSFIT is related to stock characteristics. To account for the temporal variation in INSFIT, month fixed effects are included.

Table 9 reports that BM, liquidity, and past return characteristics are unrelated to stock purchases attributable to INSFIT.[40] Instead, larger stocks have a higher likelihood of being traded through INSFIT, likely reflecting greater attention from institutional investors. In terms of its economic magnitude, reflected by the marginal effects in logistic regressions discussed in Section IV.B, a 1-standard-deviation increase in firm size is associated with a 39.2% increase in the likelihood that a stock's trade is attributable to INSFIT. Furthermore, a stock's return volatility and its industry beta have positive relations with INSFIT likelihood. A 1-standard-deviation

[40]The statistical significance of Amihud illiquidity measure is attributable to the absence of return volatility. Despite its significant coefficient, a 1standard-deviation change in illiquidity only alters the likelihood of a stock trade being attributable to INSFIT by 2.2%.

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increase in a firm's return volatility and industry beta increase the likelihood that a stock's trade is attributable to INSFIT by 32.2% and 10.7%, respectively. However, due to the high correlation between return volatility and betas, which exceed 0.50, the respective impacts of these firm characteristics are not jointly significant.

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

B. INSFIT and the Arrival of Media Coverage

Our next analysis, motivated by Bolandnazar et al. (2020), examines whether fund managers trade more aggressively when the public release of information regarding the stocks underlying INSFIT is more imminent.

We define Distance as the time interval between the date at which INSFIT is executed and the subsequent date at which the underlying stocks receive media coverage. Trade sizes at the stock-date level are measured in dollars, and the distance is measured in days for the subsequent 7 post-INSFIT trading days. We then regress the natural logarithms of trade sizes on distance, controlling for trade sign (buy versus sell) as well as date and manager fixed effects. Recall from Table 7 that managers who execute INSFIT more frequently tend to realize their INSFIT profits over shorter horizons, which suggests these active managers are more likely to trade on relatively shorter-horizon signals. Therefore, we condition our analysis on the frequency of executing INSFIT at the manager level.

Panel A of Table 10 reports that the trade sizes underlying INSFIT are unrelated to distance for fund managers who execute INSFIT infrequently. In contrast, for fund managers that frequently execute INSFIT, the average stock-level INSFIT trade size decreases by nearly 4% per additional day of distance. This finding is consistent with informed fund managers possessing trading more aggressively when the release of public information is more imminent, supporting the theoretical predictions and empirical evidence in Caldentey and Stacchetti (2010) as well as Foucault et al. (2016).[41]

Our next analysis establishes that the buy trades underlying INSFIT are more strongly associated with the imminent arrival of media coverage than the sell trades. Specifically, long positions are more strongly associated with the arrival of intense media coverage (high number of news articles) that is also positive. These findings are consistent with the positive abnormal post-trade returns of the long positions underlying INSFIT, and reinforce our interpretation that stock purchases underlying INSFIT are disproportionately more likely to be motivated by positive short-horizon signals. In contrast, the sell trades underlying INSFIT may more often reflect non-informational motives such as maintaining industry exposure, which is consistent with their negligible post-trade abnormal returns.

The existing literature has documented the ability of institutional investors to trade before the release of public information. For example, Irvine et al. (2007)

[41]While the estimates control for manager and date fixed effects, our findings are also robust to including industry fixed effects or removing all the fixed effects.

TABLE 10

INSFIT and Post-Trade Media Coverage

Table 10 reports on the relationship between INSFIT and post-trade media coverage. Stock-date media coverage reflects "highly relevant" full news articles on the stocks underlying INSFIT according to RavenPack Analytics. Panel A presents the association between stock-level natural logarithm of \$-trade sizes (re-scaled by 100), underlying INSFIT and the distance, measured in days, between the trade date and the subsequent media coverage date for the following 7 trading days. Estimates control for trade sign (buy versus sell) and include date and manager fixed effects. Standard errors are double-clustered by fund and date. The impact of distance on trade size is estimated separately for fund managers in the four INSFIT frequency groups in Table 7. Panel B presents our results for media intensity, which reflects the odds ratios of media coverage within k trading days following INSFIT relative to k days prior to INSFIT. For any stock in at least one long (short) position underlying INSFIT, event windows from k days before to k days after INSFIT excluding the respective INSFIT date are constructed. News intensity is low if there is exactly 1 article or fewer articles than the previous month's median number of articles per media-coverage day. News intensity is high if there are multiple news articles or at least as many as the previous month's median. Intensity categories are quantified by indicator variables that equal 1 if a stock-day is in the respective category, and 0 otherwise. News type refers to odds ratios after classifying news according to textual characteristics described in Table D.1 in Section D of the Supplementary Material as either positive or other. News sentiment refers to odds ratios of news articles bearing negative, neutral, or positive sentiment, reflecting news articles with negative, zero, or positive average Composite Sentiment Scores, respectively. Estimates control for quarter and industry fixed effects, with standard errors clustered by firm. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. ln(Trade \$-Value) and Distance Until News Release

	Fund Manager INSFIT Group			
Trade Size	1	2	3	4
Distance	−2.54 (1.67)	−2.07*** (0.53)	−3.82*** (0.74)	−3.69*** (0.76)
No. of obs.	51,899	51,386	46,580	42,570

Panel B. Predictive Power of INSFIT for News Release

		News Intensity		News Type			News Sentiment		
	k	Any	Low	High	Positive	Other	Negative	Neutral	Positive
Buys	3	1.10*** (0.01)	1.05*** (0.01)	1.08*** (0.01)	1.09*** (0.01)	1.10*** (0.01)	0.86** (0.06)	0.86** (0.05)	1.16** (0.09)
	5	1.15*** (0.02)	1.06*** (0.01)	1.14*** (0.02)	1.14*** (0.02)	1.16*** (0.02)	0.82** (0.07)	0.83*** (0.04)	1.22** (0.10)
	7	1.21*** (0.02)	1.09*** (0.01)	1.19*** (0.02)	1.19*** (0.02)	1.21*** (0.02)	0.69*** (0.05)	0.73*** (0.04)	1.45*** (0.10)
Sells	3	0.99 (0.01)	1.01 (0.01)	0.98* (0.01)	0.98* (0.01)	0.99 (0.01)	1.05* (0.03)	1.01 (0.05)	0.95* (0.03)
	5	1.00 (0.01)	1.01 (0.01)	0.99 (0.01)	0.99 (0.01)	0.99 (0.01)	1.09*** (0.03)	1.05 (0.06)	0.92*** (0.02)
	7	1.01 (0.01)	1.01 (0.01)	1.01 (0.01)	0.99 (0.01)	1.01 (0.01)	0.95** (0.02)	1.04 (0.05)	1.05** (0.02)

document that analysts "tip" their institutional clients before releasing stock recommendations. Baker et al. (2010) find institutions trade profitably before earnings announcements, while Hendershott et al. (2015) report that institutional order flow predicts the sentiment of news and market reactions to news. Bernile et al. (2016) document informed trading during embargoes of Federal Open Market Committee (FOMC) scheduled announcements. More recently, Bolandnazar et al. (2020) document informed trading after corporate events that have yet to be disclosed.

As INSFIT can identify informed trading based on short-horizon private signals, we examine the characteristics of news articles that immediately follow the buy trades and sell trades underlying INSFIT. Our analysis focuses on "highly relevant" full news articles referenced by RavenPack Analytics. First, using logistic regressions, we examine the likelihood of media coverage in the $k \in \{3,5,7\}$ days following INSFIT relative to the previous k days.

Second, we classify stock-days with media coverage according to their news intensity, accounting for cross-sectional variation in media coverage across firms.

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Media coverage on a specific day is classified as low intensity if the number of news article related to the stock is below the stock's median number of daily news articles in the prior month. Similarly, high media coverage intensity refers to the number of news article being greater than or equal to previous month's median. In cases where the stock's median number of daily news articles is 0 or 1 in the prior month, a single news article is classified as high news intensity.

Third, we examine the content of news articles. Specifically, we examine news articles whose text contains positive keywords listed in Table D.1 in Section D of the Supplementary Material to determine whether INSFIT is associated with news articles that have positive stock price implications. In addition, using the CSS compiled by RavenPack's proprietary news sentiment algorithm, we classify media coverage as negative, neutral, or positive.[42] We then estimate the likelihood of each sentiment type post-INSFIT relative to pre-INSFIT.

Panel B of Table 10 summarizes the odds ratios for different outcomes k days post-INSFIT relative to k days pre-INSFIT. An odds ratio equaling 1.00 indicates equally likely outcomes before and after INSFIT. Observe that while media coverage is 10–21% more likely to occur in 3–7 days after a buy trade attributable to INSFIT than before, it is equally likely for a sell trade attributable to INSFIT. Moreover, the increased odds of media coverage following buy trades is largely due to high (intense) media coverage. Conversely, high media coverage within 3 days is 2% less likely for the sell trades underlying INSFIT compared to before, which confirms their non-informational origin. These findings are consistent with the tendency of fund managers to execute more informed stock purchases than informed stock sales. Additional findings confirm the robustness of these findings to the type of news. Regardless of news type, media coverage is more likely for buy trades underlying INSFIT and marginally less likely for the sell trades.

Panel B of Table 10 reports that media coverage with negative or neutral sentiment is 14–31% less likely for the long positions underlying INSFIT compared to before this pair trade was executed. Furthermore, media coverage with positive sentiment is 16–45% more likely for the long positions underlying INSFIT compared to before. This combined evidence indicates that the buy trades attributable to INSFIT are associated with the imminent release of positive information by the media. Unlike the intensity of media coverage, sell trades predict news sentiment, albeit with less strength and persistence than buy trades predict positive sentiment. We find negative sentiment becomes 5–9% more likely in the 5 trading days following sell trades attributable to INSFIT. Conversely, positive sentiment becomes 5–8% less likely in the 5 trading days following sell trades attributable to INSFIT. These findings are consistent with the interpretation that some INSFIT executions are motivated by negative private signals.

To clarify, while INSFIT precedes high media-coverage with positive sentiment, its post-trade abnormal returns are not attributable to information that induces correlated trading (Pomorski (2009)). To examine whether INSFIT's profitability arises from correlated trading across fund managers, an untabulated analysis

[42]The Composite Sentiment Score combines various sentiment metrics to identify short-term share price impacts. These metrics are constructed ex ante based on words and phrases that have previously been identified as having positive price impacts.

examines stock-days with at least one balanced intra-industry pair trade.[43] Within this subset of stock-days, we then count the number of fund managers who buy the same underlying stock on the same day and within 3-, 5-, and 7-day windows around that day. This analysis finds that the trades underlying INSFIT are largely independent across fund managers. Specifically, 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 windows spanning 3 to 7 days, indicating that correlated trading across fund managers cannot explain the abnormal returns of INSFIT. This finding also indicates that INSFIT is unlikely to spillover across fund managers in the same fund family. Instead, the private signals of fund managers could originate from a local informational advantage (Coval and Moskowitz (2001), Christoffersen and Sarkissian (2009)), political (Cohen et al. (2008)) and insider networks (Hwang et al. (2018), Ahern (2020)), proprietary and big data (Zhu (2019), Mukherjee et al. (2021)), in-house information processing (Dugast and Foucault (2018)), or other nonpublic information sources.

VI. Conclusion

We identify a specific type of informed trading; INSFIT, by conditioning on how long-only investors in possession of private signals are likely to execute trades in a multi-asset setting. Specifically, we hypothesize that informed long-only fund managers buy and sell equivalent dollar amounts of stock in the same industry on the same day. Self-financing in this way is consistent with fund managers being cash constrained, while industry neutrality is consistent with their use of relative valuation techniques and their hedging of industry risk.

In terms of its economic significance, approximately 37% of fund manager short-term trading profits are attributable to INSFIT, although these pair trades constitute less than 3% of such trades. The execution of INSFIT varies across fund managers, with 2.6% of fund managers accounting for almost a quarter of all INSFIT executions and associated trading profits. Active fund managers who execute INSFIT more aggressively obtain smaller trading profits per execution. Nevertheless, despite INSFIT's profitability and ability to predict a fund manager's alpha, its infrequent occurrence is consistent with the lack of persistence in individual fund manager performance.

We find empirical support for both the self-financing and industry neutrality properties that define INSFIT. As the random arrival of private signals prevents fund managers from accumulating cash to finance informed buy trades, fund managers with lower cash holdings and larger outflows are more likely to execute INSFIT. Consistent with industry risk-hedging, we find the key characteristics of stocks bought and sold through INSFIT to be identical. In support of INSFIT being partially motivated by private signals, INSFIT precedes the release of media coverage regarding the firms, and its trade size increases as news becomes more imminent.

[43]The theoretical literature on informed trading allows for correlated signals across multiple traders in a single asset (Holden and Sumbrahmanyam (1992), Foster and Viswanathan (1996), and Back et al. (2002)).

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000091.

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