How Do Hedge Funds Affect Stock Market Quality? Evidence from Hedge Fund Terminations*

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December 6, 2022

Abstract

I examine how hedge funds affect stock market quality by exploiting fund terminations as a quasi-experiment. I find that, following fund terminations, stocks held by defunct hedge funds 1) display less price impact, and 2) underreact more to contemporaneous market movements and earnings surprises. These findings are consistent with hedge funds trading on information, and thereby both exacerbating adverse selection and speeding up the incorporation of information into stock prices. Thus, hedge funds have a mixed effect on the stock market: They harm stock liquidity but improve price efficiency.

JEL Classification: G11, G14, G23

Keywords: Hedge funds, Liquidity, Price efficiency

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*I have greatly benefited from discussions with Olivier Dessaint, Naveen Gondhi, and Joel Peress. I also thank Frederico Belo, Adrian Buss, Dmitry Chebotarev, Winston Wei Dou, Bernard Dumas, Valeria Fedyk (discussant), Sergei Glebkin, Ahmed Guecioueur, Petri Jylhä, Jason Kang, Patrick J. Kelly, Nanying Lin (discussant), Pierre Mabille, Pascal Maenhout, Lin Shen, Shann Turnbull (discussant), Bart Zhou Yueshen, Ziwei Zhao (discussant), Junyuan Zou, and session participants at the 2022 Academy of Finance Conference, the 2022 Financial Markets and Corporate Governance Conference, the 2022 Economics of Financial Technology Conference, the 2022 Trans-Atlantic Doctoral Conference, the 2022 European Financial Management Association Annual Meeting, the 2022 European Economic Association Conference, the 2022 HEC Finance PhD Workshop, and the 2022 Financial Management Association Annual Meeting for helpful comments. The paper was previously entitled "How Do Hedge Funds Affect Stocks That They Trade? Evidence from Hedge Fund Closures". Any errors are solely my own.

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1 Introduction

Hedge funds have grown in importance over the last two decades with assets under management rising from $0.2 trillion in 2000 to $5.1 trillion in 2022.[1] They account nowadays for more than 20% of US equity trading volume.[2] Because their trades are relatively unconstrained – they may lever up, take short positions, use derivatives extensively, and thanks to redemption restrictions, hold illiquid positions – hedge funds may have an outsized impact on the market. Yet, their impact is not well understood. Some studies suggest that hedge funds make markets more efficient by correcting mispricing (e.g., Akbas et al. (2015), Kokkonen and Suominen (2015), and Cao et al. (2018)), while others contend that their impact is destabilizing (e.g., Brunnermeier and Nagel (2004), and the discussion in Stein (2009)). Likewise, some studies report that hedge funds contribute to stock liquidity (e.g., Aragon and Strahan (2012), Jylhä et al. (2014), Çötelioğlu et al. (2021)), although they often have an informational advantage that worries their counterparties (cf. the extensive theoretical literature on adverse selection pioneered by Glosten and Milgrom (1985) and Kyle (1985)).

A likely reason for this divergence of views is that assessing hedge funds' impact is plagued by identification issues. Stock characteristics and hedge fund trading may be driven by common unobserved factors (omitted variable); likewise, hedge funds may be attracted to stocks with certain characteristics (reverse causality). For instance, hedge fund strategies and liquidity might be positively correlated without their relationship being causal if they both depend positively on, say, analyst coverage or earnings volatility, or because hedge funds favour more liquid stocks. An additional issue is data limitation: Quarterly snapshots of hedge fund holdings offer a rather distorted picture of their actual trades (e.g., Huddart et al. (2001), and also Puckett and Yan (2011)).

In this paper, I take on the challenge of measuring hedge funds' causal impact on stock

[1] BarclayHedge: https://www.barclayhedge.com/solutions/assets-under-management/hedge-fund-assets-under-management/hedge-fund-industry

[2] The estimate is obtained by combining traditional hedge funds and quant hedge funds ("Rise of the retail army: The amateur traders transforming markets" Financial Times, March 9, 2021)

market quality by identifying variations in hedge fund ownership that are exogenous to stock characteristics. These variations are generated by hedge fund terminations. Through a rigorous search of the U.S. Securities and Exchange Commission (SEC) filings, media articles and other sources, I hand-collect a sample of 140 hedge funds that terminated soon after filing their last Form 13F. These hedge funds tend to be large, with an average (median) pre-liquidation size of $901 ($336) million.[3] I identify stocks that they held before termination (treated stocks), match them with comparable stocks unaffected by terminations (control stocks), and explore the consequences of hedge fund terminations using a stacked difference-in-differences design.

Using hedge fund terminations as a quasi-natural experiment mitigates endogeneity concerns provided these terminations are not related to the characteristics of treated stocks. Reasons for hedge fund terminations in my sample include personal reasons, poor conditions in the market at large, and investor redemptions combined with long-term underperformance. Supporting the view that these terminations are exogenous to the treated stocks, those stocks' prices display no tendency to decline ahead of terminations and over the longer term after terminations.[4] Moreover, there is no change in the activity of short-sellers in treated stocks, which would have been a sign of their deteriorating prospects. Overall, this evidence is not consistent with hedge fund managers ceasing operations due to the poor realized performance of their portfolio stocks nor in anticipation of these stocks' poor future performance.

I first explore how hedge funds affect stock liquidity. I find a 2% decline in the effective spread in the quarter in which hedge funds liquidate their positions. I then decompose the effective spread into its permanent component (price impact) and temporary complement (realized spread), which capture, respectively, the effect of adverse selection and inventory

[3] The sample includes multi-billion-dollar hedge funds such as Highfields Capital Management, Visium Asset Management, and Galleon Management.

[4] There is temporary price pressure when defunct hedge funds liquidate. They sell on average 0.5% of treated stocks' shares outstanding, depressing treated stocks' prices by 1.6%. Thus, price elasticity of the treated stocks is 3. This is in line with Koijen et al. (2020).

management. The decomposition reveals that price impact component falls by 4% at the time of terminations and stays significantly depressed in the following quarter. In contrast, the realized spread marginally drops in the termination quarter but recovers by the next quarter. The drop of price impact that persists to the next quarter after hedge fund terminations suggests that the hedge funds' disappearance alleviates traders' concerns that they may be trading with a better informed counterparty.

A natural implication of this finding is that treated stocks' information environment is affected. Specifically, their prices may incorporate information less quickly following terminations. I find strong support for this prediction. After terminations, treated stocks' reaction to lagged market movements increases by 5% compared to control stocks. Likewise, treated stocks become by 13% less sensitive to earnings surprises during the first two days of earnings announcements. This implies that less earnings announcement information is incorporated into treated stocks immediately after announcements.

Overall, the results suggest that there is a trade-off between informativeness and liquidity. Specifically, I find that hedge fund trading makes stock prices more informative. However, this benefit comes at a cost of worse liquidity because other investors refrain from trading stocks that attract the attention of hedge funds. These findings are important not only for financial markets but also for the real economy in light of the evidence on the real effects of liquidity (Edmans et al. (2013)) and price efficiency (Edmans et al. (2012), Dessaint et al. (2019), Bennett et al. (2020)).

My results are complementary to those of Aragon and Strahan (2012). Exploiting the 2008 Lehman bankruptcy, these authors establish that stocks held by hedge funds employing Lehman as prime broker suffered greater declines in liquidity following the bankruptcy than did other stocks. My analysis differs in two important ways. First, my focus is on hedge funds as informed traders rather than as market makers. In addition to showing that hedge funds' speculative activities harm liquidity, I find that hedge funds contribute to making stock prices more informative. Second, stakes of hedge funds were frozen following the

Lehman bankruptcy. In my experiment in contrast, treated stocks continue to trade and so terminated hedge funds' holdings are acquired by other traders. As a result, I can measure the impact of hedge funds accounting for the behavior of the traders who take over their stakes; put differently I estimate the impact of hedge funds net of that of their replacements. My findings suggest that those replacements are less informed (i.e., contribute to price impact and informativeness less) than the terminating hedge funds. This finding is crucial for the evaluation of potential consequences of hedge fund regulation.

My findings contribute to several strands of research. First, I add to the literature that examines whether hedge funds are liquidity providers. Jylhä et al. (2014) provide evidence that hedge funds supply liquidity when markets are illiquid, but switch into users of liquidity when markets are liquid. Similarly, Çötelioğlu et al. (2021) show that hedge funds are liquidity providers, but tend to consume liquidity when financial conditions tighten. Consistent with these studies, I find evidence that some hedge funds act as liquidity providers: Hedge funds collectively take on approximately half of the stakes liquidated by terminating hedge funds.[5] In addition, in spite of the liquidity provision by other hedge funds, I find that price impact declines after the disappearance of the large hedge funds studied in the paper.

Second, I contribute to the growing body of literature on how hedge funds affect price efficiency. Akbas et al. (2015) argue that capital flows to hedge funds reduce mispricing. Chen et al. (2020) find that hedge funds scale up information acquisition and trade more aggressively in stocks that have a reduction in coverage by equity analysts. My paper provides evidence that hedge funds help incorporate both market- and firm-specific information into stock prices.

Finally, my paper adds to the broader literature on hedge fund skill. Jagannathan et al. (2010) find significant performance persistence among superior hedge funds. Also, Agarwal et al. (2012) show that confidential holdings of hedge funds are associated with more

[5] The replacing hedge funds keep shares of the treated stocks for one quarter only, suggesting that they likely aim to profit from temporary price pressure. I find no evidence of mutual funds and short-sellers acting as liquidity providers for terminating hedge funds.

information-sensitive events and generate better performance consistent with hedge funds having stock-picking abilities. In addition, von Beschwitz et al. (2021) find that new positions of hedge funds are profitable. I show that the disappearance of hedge funds leads to a delay in incorporation of information into stock prices, implying that hedge funds exert effort on information collection.

The rest of the paper is organized as follows. Section 2 describes the sample of defunct hedge funds; Section 3 covers selection of treated stocks; Section 4 presents the methodology of the study; Section 5 reports the results; Section 6 discusses the findings; and Section 7 concludes.

2 Hedge fund terminations

First, I describe identification of terminated hedge funds. The corresponding filters are summarized in Table 1 Panel A. Next, I present summary statistics on the constructed sample.

2.1 Identification of terminated hedge funds

To identify the defunct hedge funds, I first determine which entities are hedge funds. I apply a modified procedure of Brunnermeier and Nagel (2004) to every entity in Thomson Reuters s34 Master File.[6] To do this, I check whether an entity submitted at least one form ADV.[7]

[6] The main difference between the outlined procedure and the one described in Brunnermeier and Nagel (2004) is the accounting of private funds. SEC demands disclosure of information on private funds following the implementation of the Dodd-Frank Wall Street Reform and Consumer Protections Act (Dodd-Frank Act) in 2011. The modified procedure more accurately identifies hedge funds after 2011 for two reasons: (1) it uses information related to the whole business of an entity (both private and non-private funds are accounted for), and (2) it can be applied to Exempt Reporting Advisers – a group of investment advisers who do not submit information about their advisory businesses in Part 1A, Item 5 of the ADV form.

[7] I find the CIK of an entity by using its name and stock holdings. I compare the latter in Thomson Reuters s34 Master File and either WRDS SEC Analytics Suite 13F Holdings Data (starting from June 2013) or original Form 13F filings (before June 2013). I then manually link CIK to CRD using the entity's name and address on the IAPD website (https://adviserinfo.sec.gov). CRDs are entity identifiers in the ADV form (Part 1A, Item 1, Question E) and the ADV-W form (Item 1, Question C) available at SEC website (https://www.sec.gov/foia/docs/form-adv-archive-data.htm).

If this is the case, then I identify an entity as a hedge fund if it was a hedge fund for at least half of the time based on its forms ADV.[8] Otherwise, I use Google and Factiva to determine whether an entity was called a "hedge fund" by the media.

Form ADV identifies an entity as a hedge fund if at least half of its assets under management (AUM) are identified as being related to hedge fund activity. Total AUM consists of private and non-private funds' assets. A private fund is called a hedge fund if its type is reported as "hedge fund".[9] Non-private funds' assets are considered to be related to hedge fund activity if (a) the majority of an entity's clients consists of high net worth individuals and pooled investment vehicles before November 2011 or more than half of an entity's non-private funds comes from high net worth individuals and pooled investment vehicles starting from November 2011, and (b) an entity charges performance-based fees.[10]

The next step is to identify hedge funds that face serious disruptions of their usual trading activity. I focus on hedge fund terminations as a source of disruption in this paper. I identify hedge funds that are liquidated no later than two quarters after submitting their last Form 13F filings. Liquidations are defined as situations in which hedge funds fully or partially terminate their trading activity.[11] I search for evidence of liquidations in the following

[8] By way of illustration, suppose that an entity submitted its first ADV form on March 1st, 2010, the second ADV form on March 11th, 2010, and an ADV-W form for termination of registration with SEC on March 26th, 2010. Suppose that the first ADV form identifies an entity as a hedge fund, while the second ADV form does not. Then, an entity was a hedge fund for 10 days (between the first and the second ADV forms) and was not a hedge fund for 15 days (between the second ADV form and the ADV-W form) implying that, on average, an entity was not a hedge fund.
If an entity did not submit an ADV-W form, then its latest ADV form is assumed to last for the median number of days between any two consecutive ADV forms submitted by one entity. Moreover, to reduce the impact of outliers, all ADV forms are winsorized to last no longer than 365 days.
I ignore ADV forms before 2011 for all entities with at least three ADV forms filed after 2011 because recent ADV forms are more informative (due to private funds' reporting).

[9] Information about private funds is reported in Schedule D, Section 7.B.(1), Part A. Question 10 asks for the type of a private fund. Question 11 asks to report gross asset value of a private fund.

[10] Information about an entity's advisory business is reported in Part 1A, Item 5. Question D asks about an entity's clients and respective assets under management. This question refers to clients of *non-private* funds after the Dodd-Frank Act was implemented). Question E asks about compensation arrangements. An entity charges performance-based fees if it ticks E(6) or mentions the words "performance," "profit," or "incentive" in E(7). Question F(2) asks to report total AUM. Thus, the size of non-private assets is obtained by subtracting the gross asset value of each private fund from the total AUM.

[11] A hedge fund fully terminates if it liquidates its entire portfolio and stops all job contracts. Examples of partial terminations included in the sample are: (1) a hedge fund returns outside capital and becomes a family office, and (2) an entity manages several hedge funds before liquidating some of them.

sources: (a) media articles (via Google and Factiva),[12] (b) ADV-W forms,[13] (c) notes in Form 13F filings,[14] and (d) LinkedIn.[15] I retain hedge fund liquidations that occurred near the date of the last Form 13F submission to ensure that I have reliable information on stocks that hedge funds traded before termination.

To ensure that disruption of trading activity is serious for partial terminations, the sample includes hedge funds that liquidate at least 75% of their portfolios.[16] This condition filters out partial terminations with small changes in hedge funds' portfolios.[17] I remove such closures because of two concerns related to these cases: (1) operational activity likely remains unaffected, and (2) the assets to be liquidated are chosen by the manager. My focus on the liquidation of the (almost) entire portfolio mitigates concerns that it was driven by unobservable firm-specific factors.

Additionally, I check that at least 50% of control over a terminating hedge fund belongs to its employees.[18] If a closing hedge fund is a subsidiary, then its termination will likely marginally affect the operating activity of a parent firm and traded stocks.[19]

I do not include cases when hedge funds terminate because of mergers and acquisitions. The decision to liquidate stocks can be driven by fundamental reasons in these cases.

[12]This is an example of a media article: *"William Collins is shutting his $300 million hedge-fund firm, Brencourt Advisors, and will begin returning clients' money next month"* (The Wall Street Journal, 27 Sep 2012)

[13]Each entity reports the reason it terminates registration with SEC in Item 2, Question B of the ADV-W form. The reason should be related to the closure of an entity (e.g., *"No longer in business or closing business"*, *"No longer conducting advisory activities"*, or *"Closed funds"*).

[14]This is an example of a relevant note: *"As of October 18, 2013, Karsch Capital Management, LP has stopped all trading and no longer exercises investment discretion over 13(f) securities. This will be the last Form 13F submitted by Karsch Capital Management, LP."* (Form 13F for September 30, 2013)

[15]I count as termination a situation when (i) a hedge fund stops submitting Form 13F filings when it should not stop, (ii) its key employees simultaneously change jobs, and (iii) there is no evidence of a merger as a reason for termination. According to rule 13f-1(a)(1) of the Securities Exchange Act, an institutional investor who files Form 13F can stop filing it only in the third quarter of a year. I use Schedule A of the ADV form as well as media articles to identify key employees (e.g., CEO and CIO) of hedge funds. I then use LinkedIn to track their job changes.

[16]I first search for the fraction of liquidated assets in media articles. If such information is not available, I compare total portfolio values reported in Form 13F filings before and after closure.

[17]For instance, George Soros turned Soros Fund Management into a family office in 2011: *"As part of the change, the fund will return $1 billion to private investors by the end of the year, according to a person familiar with the matter. That translates to about 3% of the $25 billion the fund has under management."* (CNN, July 26, 2011)

[18]I collect this information from Schedule A in ADV forms for entities that are registered with SEC and media articles otherwise.

[19]For example, I exclude terminations of Old Lane Partners (subsidiary of Citigroup) and Opera Trading

The last filter preserves hedge funds with at least four Form 13F filings before termination to identify the stocks that hedge funds traded before liquidation.

2.2 Summary statistics on terminated hedge funds

Figure 1 displays the distribution of the terminated hedge funds over time. The figure shows that hedge fund liquidations are quite uniformly distributed across years (except for spikes in 2012 and 2018).

Table 2 summarizes some properties of the closed hedge funds. An average (median) hedge fund reports 901 (336) $ mln in the last Form 13F filing before closure. The first Form 13F filing was submitted 27 (22) quarters before liquidation, implying that a hedge fund existed for at least 6.5 (5.5) years. It has open positions in 57 (23) stocks that jointly represent 70% (76%) of the reported portfolio based on the last reported Form 13F. 24% of the defunct hedge funds had filed at least one Form 13D during its existence.

3 Treated stocks

I first describe the selection of the treated stocks. The corresponding steps are presented in Table 1 Panel B. Then, I report the summary statistics and describe other data sources used in this paper.

3.1 Identification of treated stocks

I start from all stocks held by terminated hedge funds in the last two Form 13F filings (Table 1, Panel B, Step 0). Appearance of these stocks in the filings shortly before termination indicates recent interest of defunct hedge funds in the stocks. The first filters preserve treated stocks with necessary data for the analysis. I retain stocks that were affected by hedge fund closures between 2000 Q1 and 2019 Q3 to have four quarters of data for the pre-

Capital (subsidiary of BNP Paribas).

termination period and five quarters of data for the post-termination period. I also check that the treated stocks have the required data in the selected event window.

The next filter ensures that terminated hedge funds paid attention to the treated stocks during a year before liquidation. Defining the last quarter when a treated stock appeared in closed hedge fund's portfolio as quarter 0, I require that a treated stock appears in the Form 13F filings submitted at the end of quarters $\{-3, -1\}$, $\{-3, -2\}$, or $\{-4, -2\}$. This condition guarantees that terminated hedge funds paid attention to the treated stocks over a year before liquidation, making this time period a good benchmark for comparison for quarters after liquidation.

The goal of the last set of filters is to increase power of the tests. I remove stocks with market capitalization below the 20^{th} NYSE percentile (micro-cap stocks) for two reasons. First, the reporting of these stocks might be underestimated because of the threshold on inclusion of stocks in Form 13F filings (Chen et al. (2019)). Second, although micro-cap stocks account for 60% of the total number of stocks, their economic significance is small: They constitute only 3% of the market capitalization of the NYSE-Amex-NASDAQ universe (Fama and French (2008)). I also remove stocks with market capitalization above the 10^{th} NYSE percentile since those stocks should be least affected by terminations of hedge funds (Figure 3 shows evidence consistent with the largest stocks having most efficient stock prices).

The penultimate filter identifies treated stocks that likely have the most pronounced effect from hedge fund closures. I use the reduction in aggregate hedge fund trading activity as a measure of impact that hedge fund liquidations have on stocks. In a nutshell, this measure captures the relative contribution of a terminated hedge fund to the aggregate trading dollar volume of all hedge funds that have the treated stock in their investment universe. Details on the construction of the measure are in the Appendix Section 8.1. The filter removes treated stocks with small values of the measure (less than 0.5%).

The last filter preserves 140 closed hedge funds with at least three treated stocks. The threshold for the number of the treated stocks is determined by maximization of the diversification of the resulting sample of the treated stocks.

3.2 Summary statistics on treated stocks

Table 3 shows how closed hedge funds accumulated positions in the treated stocks before termination. Roughly 23% (=100%-77%) of the treated stocks were not reported in the Form 13F filings by closed hedge funds a year before closure. This number drops to 7% (=100%-93%) half a year before closure and stays on this level in the quarter before termination. The size of the position gradually grew until reaching the peak three quarters before closure based both on the mean and the median estimates. The following reduction in the size of the position over the last two quarters before closure was quite modest on average (up to 0.15% of shares outstanding). At the end, closed hedge funds held on average 0.55% of shares outstanding of the treated stocks before liquidation.

Next, there is a sharp drop in holdings during the first quarter after closure. Approximately 91% of treated stocks disappeared from the Form 13F filings of defunct hedge funds, and 96% of stock holdings were liquidated. This evidence suggests that liquidations occur mostly within one quarter.

3.3 Other data sources

Information on stock characteristics related to trading activity is obtained from CRSP. Data on firms' financial statements is sourced from Compustat. Short interest data comes from the Compustat Short Interest File. Stock ownership data from Form 13F filings is obtained from Thomson Reuters s34 Master File (before 2013Q2) and WRDS SEC 13F Holdings Data (starting from 2013Q2).[20] Mutual fund holdings data is sourced from the Thomson Reuters s12 Master File (before 2013Q2) and the CRSP Mutual Fund Database (after 2013Q2). Equity analyst coverage is provided by I/B/E/S. Data on Fama-French factors is collected

[20] Thomson Reuters had issues with several of the latest data updates. For this reason, I switch to alternative data sources for the recent years. The details of the Thomson Reuters data issues are described in the Internet Appendix IA.C. of Ben-David et al. (2021).

from the website of Kenneth R. French.[21] Liquidity measures are constructed in TAQ.[22]

Table 4 summarizes key variables used in the analysis.

4 Methodology

4.1 Matching

Matching procedure is required for identification of suitable control stocks for the treated stocks because the true counterfactual is not observed. I match based on a set of eight characteristics that can affect information production and trading activity of market participants to ensure that treated and control stocks have comparable information environments. I next motivate the need for the inclusion of these controls. Table 4 Panel A describes how these controls are constructed.

General firm controls are: 1) market capitalization (MC_{ann}) and 2) book-to-market ratio (BM_{ann}). These variables proxy for the size of a firm and its growth prospects; they are commonly controlled for in empirical studies (e.g., in Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012)).

Liquidity control is: 3) daily stock turnover ($TrVol_{ann}$). Griffin and Xu (2009) document that hedge funds tend to trade stocks with lower turnover compared to mutual funds.

The noise trading risk control is: 4) idiosyncratic volatility ($IVOL_{ann}$). Idiosyncratic riskiness of a stock should be controlled for since it can deter arbitrageurs (Wurgler and Zhuravskaya (2002), Pontiff (2006)) and so is likely an important factor that hedge fund managers pay attention to.

Information production controls are: 5) hedge fund ownership (HF_{ann}), 6) aggregate short interest ($ShtInt_{ann}$), 7) mutual fund ownership (MF_{ann}), and 8) the number of equity analysts who follow a stock ($Analyst_{ann}$). The first two variables control for hedge fund

[21] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

[22] I am grateful to Joel Peress and Daniel Schmidt for sharing the TAQ liquidity measures used in their paper (Peress and Schmidt (2019)).

trading activity. Kokkonen and Suominen (2015) present evidence of hedge funds reducing mispricing. Short interest proxies for the aggregate position of investors who anticipate a stock price to fall.[23] The activity of short-sellers is associated with more efficient stock prices (Boehmer and Wu (2013)). Equity analysts collect and analyze public information; their presence increases stock price informativeness (Bennett et al. (2020), Chen et al. (2020)).

Except for idiosyncratic volatility, all variables are estimated as medians three or four quarters before hedge fund terminations. This approach mitigates issues related to mean reversion of matched controls, which can be confused with the treatment effect.

There are several restrictions on stocks to be selected in the pool of control stocks. First, a control stock should have data on all matching characteristics. Second, a control stock is excluded from the pool of control stocks in quarter t if any of the terminated hedge funds held more than 0.1% of shares outstanding of the stock or was responsible for at least 0.5% of hedge fund trading activity in any quarter in the window $[t-4, t+9]$. This condition ensures that control firms are exposed to marginal treatment (if any) from terminated hedge funds in the targeted event window.

I construct a counterfactual to every treated stock using an algorithm that is described in Appendix (Section 8.2). The algorithm was inspired by synthetic controls (Abadie et al. (2010), Abadie (2021)) and entropy balancing (Hainmueller (2012)) matching techniques. In a nutshell, each treated stock is paired with a synthetic control stock constructed in a two-layer process. The inner layer selects weights of control stocks that minimizes the distance between a treated stock and the corresponding synthetic control stock under two constraints: (i) weights should sum to 1, and (ii) weights should be non-negative. Better balance is achieved by adding an external optimization layer that attempts to reduce the difference in means of the treated and synthetic control stocks within each closed hedge fund's portfolio. I use this matching procedure because it produced the best balance between treated and control stocks compared to other matching techniques.

[23]Hedge funds accounted for 85% of total shorting volume in 2009 according to the "Hedge Fund Trend Monitor" report by Goldman Sachs.

Table 5 and Figure 2 show that the resulting balance between the treated and the control stocks is good. The mean difference of most characteristics does not exceed 5% of the interquartile range of a characteristic.

4.2 Stacked difference-in-differences approach

I evaluate treatment dynamics using the stacked difference-in-differences approach. Basically, this method stacks event windows for every treated and corresponding control stocks together. I examine the event window spanning from four quarters before to five quarters after hedge fund terminations:

$$Y_{i,c,q} = \sum_{k=-4,\ k\neq 0}^{5} \beta_k \, Treated_{i,c} \, \mathbb{I}(q = k) + \alpha_{i,c} + \gamma_{c,q} + \epsilon_{i,c,q}$$

Here i represents stocks, c is the cohort index (the last calendar quarter before a hedge fund's termination for the treated stocks and the corresponding control stocks), and q is the event quarter that ranges from four quarters before to five quarters after hedge fund terminations. The binary variable $Treated_{i,c}$ equals 1 for treated stocks i in a cohort c and zero otherwise. The binary variable $\mathbb{I}(q = k)$ equals 1 for event quarter $q = k$ and zero otherwise. Event quarter 0 (the last quarter before hedge funds' liquidations) is the benchmark for estimating treatment dynamics. Stock-cohort and cohort-time fixed effects are captured by $\alpha_{i,c}$ and $\gamma_{c,q}$ respectively.

This approach is better than the staggered difference-in-differences approach for two reasons. First, it allows to exclude treated stocks from the pool of control stocks. This correction removes bias from the treatment effect estimates (Baker et al. (2022)). Second, it estimates evolution of the treatment effect over time. Thus, I can assess how quickly stocks recover from the treatment shock (if any effect takes place).

I adjust weights of the treated and the corresponding control stocks to get the average effect from hedge fund terminations. Weight of stocks is adjusted by $1/n$ if a closed hedge fund has n treated stocks. This correction equates the impact of each defunct hedge fund on the estimates and simplifies interpretation of findings.

4.3 Measures of stock price informativeness

I next describe two measures of stock price informativeness used in the paper. The first measure captures the speed of market information incorporation. The second measure is a proxy for the timeliness of firm-specific information incorporation.

4.3.1 Delay of market information incorporation

To illustrate the concept, consider the following model:

$$R_{i,t} = \alpha_i + \beta_0 Mkt_t + \sum_{l=1}^{L} \beta_l Mkt_{t-l} + \epsilon_{i,t}$$

The model estimates sensitivity of daily stock returns $R_{i,t}$ to the contemporaneous market return Mkt_t and its lags. I measure the fraction of market information incorporated from day 1 to day L as

$$mktDelay = \frac{\sum_{l=1}^{L} \beta_l}{\sum_{l=0}^{L} \beta_l}$$

The denominator measures the total sensitivity to market information that is incorporated in stock prices over $L+1$ days: Based on the model, if the market increases by 1% today, then stock prices increase by $\sum_{l=0}^{L} \beta_l$ percent over the next L days. The numerator captures accumulated sensitivity to market information from day 1 to day L – the residual sensitivity to lagged market movements. If stocks incorporate market information immediately, then $\beta_0 > 0$ and $\beta_t = 0$ for $t \geq 1$. In this case $mktDelay$ equals zero. However, if stock prices continue to move in the direction of past market movements, then some of the lagged coefficients become positive. In this case $mktDelay$ becomes positive.

I apply this approach to the difference-in-differences setting in the following way. I estimate the delay measure *mktDelay* for each group of the treated and control stocks separately in each event quarter to get the difference-in-differences estimate. Its standard deviation is constructed using the Delta method.

The main parameter of the method is L – the time period when market information becomes fully reflected in the stock prices. Hou and Moskowitz (2005) choose L to be one month, while Cao et al. (2018) select L equal to one week. Which value is better? If the selected value of L is too large, then the last of the lagged betas add noise to *mktDelay* and reduce power of tests. However, if the selected value of L is too small, then *mktDelay* is undervalued. I analyze the evolution of *mktDelay* over time for stocks from different size groups for different values of L to identify L more accurately. Figure 3 shows two patterns: (1) The largest stocks have no delay while the smallest stocks have the largest delay. (2) Most of the delay is captured by the first week, especially in recent years. The latter finding is consistent with academic studies that show improvement of the efficiency of financial markets over time (Bai et al. (2016), Martineau (2021)). Since most of hedge fund closures have taken place in recent years, in further tests, I choose L equal to four days.

4.3.2 Delay of earnings information incorporation

I use earnings announcements as a laboratory for studying the contribution of hedge funds to stock price informativeness. These events have several beneficial properties. First, earnings announcements are relatively frequent scheduled events when important information might be announced. Second, it is possible to measure the surprise of the market using equity analysts' forecasts. The magnitude of surprises proxies for the importance of information that was revealed to the market on the earnings announcement day. If hedge funds learn new information before earnings announcements, then trading on this information should push prices in the direction of the surprise, leading to a pre-announcement drift.[24] Moreover,

[24] Although managers are not allowed to give privileged access to information to institutional investors, pursuant to the Regulation Fair Disclosure rule, there are other sources of information that can be used for predicting future earnings. For example, satellite images of parking lots can be useful for predicting sales.

hedge funds might help to incorporate information into stock prices immediately after it was announced. In this case, there should be a stronger reaction during earnings announcement days with a smaller post-earnings reaction to the announcement.

I follow Dellavigna and Pollet (2009) and Hirshleifer et al. (2009) in defining earnings announcement dates and constructing analyst earnings surprises. I retain earnings announcements for which the difference in announcement dates between I/B/E/S and COMPUSTAT is not greater than five days. If there is disagreement between the databases, I select the earliest date as the date of an earnings announcement. I define the consensus forecast as the median analyst forecast issued or reviewed in the last 100 calendar days before the earnings announcement (to include revisions after the previous earnings announcements). I keep the latest earnings forecast if an analyst made several forecasts before the announcement. Let $e_{i,t}$ be the earnings per share announced in quarter t for company i and $\hat{e}_{i,t}$ be the consensus forecast for company i for the current quarter. The earnings surprise $S_{i,t}$ is

$$S_{i,t} = \frac{e_{i,t} - \hat{e}_{i,t}}{P_{i,t}}$$

where $P_{i,t}$ is the price of the shares of company i five trading days before the announcement in quarter t. All variables are split-adjusted.

I measure the delay of information incorporation during earnings announcements as the relative residual sensitivity to earnings surprises. That is, I first estimate sensitivity of abnormal stock price reaction to earnings surprises during earnings announcements, as follows:

$$CAR_{i,t}^{[0,1]} = \alpha + \beta_{ea} S_{i,t} + \epsilon_{i,t}$$

Next, I find the full sensitivity of abnormal stock price reaction to earnings surprises assuming that all information is incorporated over $T \geq 2$ days, as follows:

$$CAR_{i,t}^{[0,T]} = \alpha + \beta_{full} S_{i,t} + \epsilon_{i,t}$$

The delay of earnings information incorporation is defined as

$$eaDelay = 1 - \frac{\beta_{ea}}{\beta_{full}}$$

Similar to market information incorporation, the main parameter is the time period of full information incorporation. In light of the existing academic evidence of weakening post-earnings announcement drift over time (Martineau (2021)), I select T to be equal to four days. Hence, I assume that earnings announcement information is fully incorporated within one week.

As with market information incorporation, I estimate the delay measure $eaDelay$ for each group of the treated and control stocks separately in each event quarter to obtain the difference-in-differences estimate. Its standard deviation is constructed using the Delta method.

I use percentiles for both cumulative abnormal stock returns ($CAR_{i,t}^{[0,1]}$ and $CAR_{i,t}^{[0,4]}$) and earnings surprise ($S_{i,t}$) to mitigate the impact of outliers. Percentiles are constructed quarter-by-quarter using all firms with available information on stock returns and earnings surprises.

5 Results

I first present evidence that terminated hedge funds indeed liquidated their holdings in the treated stocks. I then explore what happens with stock liquidity and price informativeness after hedge funds' terminations.

5.1 Evidence of the treatment

I now present direct evidence of the treatment. Because the event window is constructed around the last quarters with reported holdings of closed hedge funds, there should be a noticeable drop in hedge fund ownership when comparing treated and control stocks.

Table 6 shows that this is the case. There is a significant drop in hedge fund ownership (Figure 4) and the total number of hedge funds (Figure 5) in the first quarter after a terminating hedge fund disappeared. Hedge fund ownership of the treated stocks falls on approximately 0.5% of total shares outstanding by the end of the second quarter (roughly 3.7% of the overall hedge fund ownership). The drop in both holdings and the number of hedge funds persists until the end of the event window, implying that there is no evidence of the immediate recovery in hedge fund trading of the treated stocks.

The magnitude of the drop over two quarters coincides with the liquidated holdings by hedge funds (Table 3). However, only half of the drop takes place in the liquidation quarter. This implies that some hedge funds provide liquidity to the terminating hedge funds, but do not stay long in the treated stocks.

The exact timing of hedge fund liquidations becomes clear after examining the behavior of stock prices (Figure 6). Returns of the treated stocks are on average 1.6% smaller by the end of the second month after terminating hedge funds filed their last Form 13F. This suggests that terminating hedge funds liquidate their portfolios within the first two months after submitting their last Form 13F filing.

The figure also shows that the drop in stock prices fully recovers in the next quarter. Thus, the price impact from hedge fund liquidations is temporary. Therefore, it seems unlikely that terminating hedge funds liquidated their holdings because of privately collected negative information about the treated stocks. If this were the case, then stock prices of the treated stocks would have stayed depressed after revelation of the negative information.

5.2 Impact on stock liquidity

I first check what happens with liquidity after hedge fund terminations. I use several liquidity measures constructed in TAQ for the tests. The first measure – effective spread – captures both adverse selection and inventory risk. The second measure – price impact – focuses on adverse selection. The last measure – realized spread – measures inventory costs.

Table 7 shows some evidence supporting the perception of hedge funds as sophisticated investors. There is a significant drop of price impact in the two quarters after hedge fund terminations (Figure 7). At the same time, the drop of the effective spread and the realized spread takes place during the liquidation quarter only.

These results complement findings of Peress and Schmidt (2019). In their paper, the disappearance of noise traders (uninformed investors) leads to worse liquidity. In my setting, the disappearance of hedge funds (informed traders) leads to better liquidity.

5.3 Impact on stock price informativeness

I next explore how hedge funds contribute to information incorporation. I first examine market information incorporation, and then I present results on information incorporation during earnings announcements.

5.3.1 Incorporation of market information

Table 8 and Figure 8 show that the delay of market information incorporation increases on approximately 5% for two quarters after hedge fund liquidations. This finding suggests that hedge funds speed up incorporation of market information in the stock prices.

5.3.2 Incorporation of earnings surprises

I next evaluate whether sensitivity to earnings surprises changes for treated stocks after hedge fund closures. Table 8 and Figure 9 show that this is the case: Approximately 13% of earnings surprise information is incorporated in the treated stocks over three days after the earnings announcement compared to control stocks after hedge fund terminations.

Note that event quarter 0 is highlighted by red in the Figure 9. This reflects an observation that earnings announcements usually take place with a delay of one month, implying that earnings announcements for the event quarter 0 happened when terminating hedge funds either already liquidated their positions or were still in the process of doing it.

6 Discussion

6.1 Comparison with an ideal setting

What is an ideal experiment that allows to estimate the impact of hedge funds on stocks that they trade? Suppose that there are two identical universes with stocks and investors. That is, every hedge fund A that trades shares of firm X in the first universe has an identical copy – hedge fund A' that trades shares of a firm X' in the second universe. In this setting, hedge fund A's impact on firm X can be identified by exogenously closing hedge fund A and comparing changes in the stock characteristics of firm X relative to those of firm X'. The average impact of hedge funds on stocks can be estimated by exogenously terminating a randomly selected subset of hedge funds and taking average of the estimated differences between affected stocks in the first universe and unaffected stocks in the second universe.

Although it is impossible to conduct this experiment, it is helpful for understanding the caveats of using hedge fund terminations as a quasi-natural substitute. The most important threat to identification is that hedge funds *choose* to shut down. Inferences might be biased if hedge fund closures correlate with omitted factors that simultaneously affect variables of interest. For example, an industry-wide negative shock can force a specialized hedge fund to terminate.[25] Suppose that this shock also causes termination of an active mutual fund. If the mutual fund was mainly responsible for information incorporation into stock prices and its closure is not observed, then we might erroneously conclude that it was hedge fund's disappearance that caused stock price informativeness to decline.

To address this concern, I investigate the reasons for hedge fund closures (Section 6.2). As expected, poor performance is one of the main reasons for hedge fund terminations.

[25]The *Deepwater Horizon* oil spill was one of the reasons for the closure of Pool Capital Partners: *"We were a team of 4 people and the two managing partners were approaching retirement age. When the BP oil spill happened energy stocks were hit hard and with us being an energy hedge fund redemptions started pouring in. Once we were under \$50 MM AUM and no one was interested at that time in investing in Energy, it just didn't seem smart to continue."* (Denise Cardozo, Administrator of Pool Capital Partners)

However, as Figure 6 shows, there is no evidence of large drops of the treated stock prices before hedge fund terminations. Moreover, Table 2 shows that terminated hedge funds in my sample were quite diversified before closure. This implies that poor performance that causes termination of some hedge funds in the sample might come from other assets. If this is the case, then liquidation of the equity portfolio is exogenous to stock characteristics. In addition, I look into what happens with other institutional investors after hedge fund terminations to ensure that the effect is driven by hedge fund liquidations (Section 6.3).

Another potential threat is that terminating hedge funds are different from the average hedge fund in terms of skill. It seems reasonable that hedge fund managers with low skills are more likely to close. Although I cannot fully eliminate this concern, there are two reasons that it is not a major issue. First, all closed hedge funds in my sample are large and existed for more than five years on average. It seems unlikely that hedge fund managers with low skills can attain such a scale (Berk and Green (2004)).[26] Second, this bias likely goes against the obtained results: It is unlikely that the disappearance of hedge fund managers with low skills will worsen information incorporation into stock prices.

The next two potential threats are related to short positions. First, I cannot include stocks in which terminated hedge funds had short positions in the set of treated stocks because short positions are not required to be reported in Form 13F filings. The introduced bias has clear direction for the informativeness measures. Short-selling is a costly activity, so I expect hedge funds to use this strategy only if it is backed by thorough research. In this case, the absence of short positions in the set of the treated stocks will likely underestimate the impact of hedge funds on stock price informativeness.

Moreover, it is possible that a treated stock is matched with a control stock that is shorted by a terminating hedge fund. This should also lead to an underestimation of the effect: A difference-in-differences comparison will not detect any impact if both treated and control

[26] Two hedge funds in the sample – Castle Point Capital Management and Peninsula Capital Advisors – terminated because their managers received job offers from Berkshire Hathaway. This suggests that managers of these hedge funds were more likely to have skills than not since they caught Warren Buffett's attention.

stocks are affected by hedge fund terminations in a similar way. However, this issue seems to be small: Only 7.1% of hedge funds (and 6.2% of assets under management) are market-neutral or short bias; the remaining hedge funds are long bias or long/short.[27] Furthermore, I reduce this concern by constructing a diversified portfolio of control stocks as a benchmark.

6.2 Why do hedge funds close?

Two sources are used to measure the reasons for hedge fund closures: 1) media articles (via Google and Factiva), and 2) LinkedIn. I use the latter for contacting former hedge fund employees.

I found at least one reason for closure for 63 hedge funds out of 140 hedge funds in the final sample.[28] Three dominant reasons for terminations are: 1) worsening market conditions,[29] 2) personal reasons,[30] and 3) poor performance.[31] Defunct hedge fund managers mentioned at least one of these reasons in 48%, 40%, and 35% of terminations, respectively.

6.3 Who replaces closed hedge funds?

Given that hedge funds liquidate their holdings before termination, someone should buy shares of the defunct hedge funds. It is important to understand who replaces terminated hedge funds to correctly interpret the results.

Mutual funds do not replace defunct hedge funds, as is shown in Table 9. On average,

[27] The estimate is based on the combination of US-domiciled and non-US-domiciled single-strategy hedge funds (form PF for 2021 Q4, Section "VI. Additional Hedge Fund Industry Information", Subsections C and D). These are available at: https://www.sec.gov/divisions/investment/private-funds-statistics.shtml

[28] So far, I contacted 121 former hedge fund employees from 64 defunct hedge funds for which: (1) I failed to find relevant information in media articles, and (2) I found employees who worked at hedge funds when terminations took place. I got replies from 14 former hedge fund employees (13 defunct hedge funds).

[29] See footnote 25 for an example of a sudden market-wide shock. Another example: *"... financial markets have significantly evolved over the last decade driven by new technologies and the market itself is becoming more difficult to anticipate as traditional participants are imperceptibly replaced by computerized models."* Philippe Jabre from Jabre Capital Partners (Bloomberg, December 13, 2018).

[30] An example: *"My desire to devote more time to my family and other interests runs counter to the obligations of a hedge fund manager who must be immersed in the markets in order to meet client expectations"* Dan Benton from Andor Capital Management (Reuters, August 20, 2008).

[31] For instance, *"Hedge fund Three Bays Capital plans to shutter after years of weak performance"* (Bloomberg, October 31, 2018).

mutual fund holdings do not change when defunct hedge funds liquidate their positions (column 1). Moreover, column 2 shows that changes of mutual fund holdings between event quarters 0 and 1 are not correlated with the size of holdings that terminated hedge funds liquidate.

Similar conclusion applies to short-sellers. There is no evidence of short-sellers closing their short positions when defunct hedge funds liquidate their holdings. Moreover, short-sellers do not change their positions both before and after hedge fund terminations. This implies that hedge fund terminations are both not anticipated by short-sellers and do not convey negative information that short-sellers would trade on.

Interestingly, there is a weak negative relationship between the size of the liquidated position by defunct hedge funds and changes of holdings of both mutual funds and short-sellers some time before liquidation. It suggests that defunct hedge funds increased positions in stocks that had a reduction of interest by mutual funds and short-sellers.

The absence of replacement of terminated hedge funds by institutional investors who submit Form 13F filings implies that these are either small institutional investors or retail investors who get shares of the terminated hedge funds.

7 Conclusion

As Stulz (2007) put it, *"... no analysis has yet reliably quantified the social costs and benefits of hedge funds."* This paper aims to reduce this gap. Using hedge fund terminations as a quasi-natural experiment, I find that both price impact as well as the reaction of stock prices to contemporaneous market movements and earnings surprises decline after defunct hedge funds disappear. The results are consistent with the general perception of hedge funds as sophisticated investors who collect and trade on information, leading to worse stock liquidity but better price efficiency.

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8 Appendix

8.1 Hedge fund trading activity

This section introduces the approach that I use to estimate the trading activity of hedge funds. This approach is useful for the selection of stocks that most likely are affected by hedge fund terminations.

The measure of hedge fund trading activity aims to capture how active terminated hedge funds are in trading treated stocks compared to hedge funds that continue to trade the stocks. Trading activity is estimated by assessing the magnitude of dollar rebalancing of stocks of comparable size by each hedge fund based on stock holdings reported in its past Form 13F filings.

I first determine the investment universe of hedge funds. It is necessary in identifying of stocks that hedge funds pay attention to. Figure 10 shows the distribution of portfolio weight invested in recently reported stocks as a function of the memory size. The figure illustrates that there is decreasing benefit from taking many quarters for the identification of the set of stocks that hedge funds invest in. On average, 81.6% of portfolio weight goes to stocks that were reported in the previous quarter; this number grows to 86.0% (88.9%) when the set of stocks is constructed from the most recent four (12) quarters. The median values are even higher. These numbers are in line with Table 1 of Koijen and Yogo (2019) who estimated investment universe for all institutional investors. Therefore, I define the investment universe of hedge funds as the set of stocks reported in the most recent 12 quarters. However, I estimate trading activity of hedge funds separately for stocks that were last reported in the previous quarter, in quarters $[-4, -2]$, and in the remaining quarters $[-12, -5]$ to capture decreasing interest to stocks that were not traded recently.

Second, I confirm that there is persistence in how hedge funds trade stocks. Table 10 shows that hedge funds tend to reallocate similar fractions of their portfolios between quarters as they did in the past. For example, a hedge fund that reallocated less than 5.7% of its portfolio between the previous and the current quarter will not increase its investment activity much in the future: In the next quarter the fund will reallocate at most 11% of its portfolio with a probability of 77.1%. It is interesting to note that this probability remains larger than 71.7% for each quarter in the following three years. At the same time, a hedge fund that reallocated more than 66.1% of its portfolio between the previous and the current quarter will not decrease its investment activity much in the future: In the next quarter the fund will reallocate at least 52.9% of its portfolio with a probability 79.0%. As above, this probability remains larger than 61.9% for each quarter in the following three years. The obtained probabilities are noticeably larger than the benchmark of 20% – the chance of getting in selected investment boundaries with no persistence in hedge fund investment strategies. The presence of persistence in the investment activity of hedge funds is the foundation of the approach for estimating of hedge fund trading activity, which I will introduce next, as I approximate future hedge fund trading activity using past hedge fund trading activity.

The key part of the approach is the decomposition of hedge fund trading between two consecutive Form 13F filings into three phases. After the number of quarters used to identify a fund's investment universe is determined, the fund manager's investment decisions are decomposed into the expansion of the investment universe (*External investment*), the change of portfolio weights between stocks in the investment universe (*Internal rebalancing*), and the incorporation of capital inflows and outflows (*Capital flows*). Figure 11 shows this decomposition for a hypothetical fund.

The aggregate measure of hedge fund trading activity in a stock is the cumulative dollar value of how much individual hedge funds are able to move in or out of the stock:

$$AggrTrdAct\_dlr = \sum_{i=1}^{N} TrdAct\_dlr_i$$

Aggregation is performed for all hedge funds that have the stock in their investment universe. Individual hedge fund trading activity in dollars is a product of a hedge fund's size and the measure of its trading activity in stocks of comparable size in percentages, as follows:

$$TrdAct\_dlr_i = AvgSize\_dlr_i \cdot StockTrdAct\_pct_i$$

I take the average dollar value of the equity portfolio of a hedge fund over the last four quarters as a proxy for its size ($AvgSize\_dlr_i$).

The second term – $StockTrdAct\_pct_i$ – captures how actively a hedge fund traded stocks of comparable size in the past. Suppose that a hedge fund holds 24% of its equity portfolio in Oracle after the *External investment* phase (Figure 11). What can happen with this position during the *Internal rebalancing* phase? It might increase to 35% or decrease to zero. Or, potentially, it is more likely to grow to 26% or drop to 24% at most. The magnitude of the change depends on the investment approach of the hedge fund. I estimate this magnitude as the standard deviation of an internal rebalancing of stocks with comparable size over the previous five years (if there are at least 20 observations for estimation). Stocks are of a similar size if their market capitalization differs on at most 12 percentile points of the NYSE size distribution.

Finally, after individual measures of hedge fund dollar trading activity $TrdAct\_dlr_i$ are estimated, I find the relative importance of a terminated hedge fund in a treated stock by calculating its contribution to the total trading activity, as follows:

$$RelTrdAct_i = \frac{TrdAct\_dlr_i}{AggrTrdAct\_dlr}$$

8.2 The matching algorithm

I start with the description of preliminary steps for matching. I then introduce the matching algorithm, discuss the choice of its parameters and compare it with other matching techniques.

8.2.1 Preparation before matching

I normalize each matching characteristic by subtracting its median value and dividing by its interquartile range quarter-by-quarter. This procedure makes all matching characteristics comparable with each other and across time. Then, for every treated stock, I rank all suitable control stocks from the nearest to the furthest using the Euclidean distance measure. Overlap in control stocks across treated stocks is allowed. Weights for each matched control stock are determined next.

8.2.2 The optimization problem

Suppose that there are $K \geq 1$ normalized matching characteristics numbered by index k. Also assume that there are $C \geq 1$ available control stocks. Control stocks are numbered by index c from 1 (the closest) to C (the furthest). The treated stock has index $c = 0$.

I determine the following several objects:

$$V = \begin{pmatrix} V_{1,1} - V_{1,0} & ... & V_{1,C} - V_{1,0} \\ ... & V_{k,c} - V_{k,0} & ... \\ V_{K,1} - V_{K,0} & ... & V_{K,C} - V_{K,0} \end{pmatrix}, \quad w = \begin{pmatrix} w_1 \\ ... \\ w_C \end{pmatrix}$$

Here $V_{k,c}$ is the k^{th} characteristic of the stock with index c. Matrix V captures the differences between each control stock and the treated stock. w_c is the weight of the control stock with index c in the synthetic portfolio.

I search for the vector of weights w that solves the following optimization problem:

$$\min \ \frac{1}{2} w^T V^T V w$$
$$\text{s.t.} \ \begin{cases} \mathbf{1}_C^T w = 1 \\ w \geq 0 \end{cases}$$

The objective function is half the squared distance between the synthetic control and the treated stock. Importantly, the sum of the weights of the control stocks should equal 1 and be non-negative. If several synthetic controls exist that solve this optimization problem, then the one with the closest control stocks should be selected.

The formulated problem cannot be solved analytically because of complementary slackness conditions on vector w. However, there exists a closed form solution to the simplified problem in which weights can be negative. Next, I find this solution and explain how it is used for numerical identification of the solution to the entire problem.

Denote $\Omega = V^T V$. Then, the Lagrangian of the simplified problem is:

$$L = \frac{1}{2} w^T \Omega w + \lambda_0 (1 - w^T \mathbf{1}_C)$$

FOC determines w as a function of λ_0, as follows:

$$\frac{\partial L}{\partial w^T} = \Omega w - \lambda_0 \mathbf{1}_C = 0$$
$$w = \lambda_0 \Omega^{-1} \mathbf{1}_C$$

Use the constraint to determine λ_0, as follows:

$$\mathbf{1}_C^T w = \lambda_0 \mathbf{1}_C^T \Omega^{-1} \mathbf{1}_C = 1$$
$$\lambda_0 = \frac{1}{\mathbf{1}_C^T \Omega^{-1} \mathbf{1}_C}$$

Thus, the solution to the simplified problem is

$$w = \frac{1}{\mathbf{1}_C^T \Omega^{-1} \mathbf{1}_C} \Omega^{-1} \mathbf{1}_C$$

The obtained solution might be inappropriate for the full problem because of negative weights. I next explain how I use it for construction of the optimal solution to the full optimization problem.

From a geometrical point of view, each synthetic control is a point that belongs to the K-dimensional convex set $\mathbb{S}$ formed by all possible combinations of control stocks with non-negative weights, the sum of which equals 1. If the treated stock does not belong to $\mathbb{S}$, then the optimal synthetic control is the closest point of $\mathbb{S}$ to the treated stock. In this case, construct a hyperplane that contains the optimal synthetic control and that is orthogonal to the vector that connects the treated stock and the optimal synthetic control. Each control stock will be either on this hyperplane or in the subspace that does not contain the treated stock. This separating feature of the hyperplane suggests a method for how to search for the optimal synthetic control when the treated stock does not belong to $\mathbb{S}$.

The algorithm is the following: 0. Select any control stock as the starting synthetic control. 1. Build the hyperplane that contains the current synthetic control and that is orthogonal to the vector that connects the treated stock with the synthetic control and determine the location of all control stocks relative to this hyperplane.[32] 2. If there are no control stocks in the subspace with the treated stock, then the current synthetic control is optimal; otherwise, add any of the control stocks from the subspace with the treated stock to the synthetic portfolio. 3. Use the solution of the simplified problem to determine the new synthetic control; if all weights in the new synthetic control are positive, then return to Step 1. Otherwise find control stocks that should be removed from the synthetic control so that all remaining control stocks have positive weights and the distance between the new

[32] After subtracting coordinates of the treated stock from all other stocks, the synthetic control has coordinates Vw. All control stocks p for which $w^T V^T p < w^T V^T V w$ belong to the subspace that contains the treated stock.

synthetic control and the treated stock is reduced.

If the treated stock belongs to $\mathbb{S}$, then there exists at least one synthetic control that perfectly matches it. The algorithm described above identifies one of the solutions when the vector between the treated stock and the constructed synthetic control has zero length. If this is the case, then I look for the closest set of control stocks that perfectly matches the treated stock. For example, suppose that the algorithm finds a synthetic control that replicates the treated stock with the furthest control stock in the solution having index $c = 50$. I next check whether there exists another synthetic control that replicates the treated stock by examining the subset of control stocks with index c being at most equal to 49. If there exists a solution, then I repeat this procedure for the new synthetic control. If not, then the control stock with index $c = 50$ is essential for the replication of the treated stock. I next examine the second-furthest control stock. Suppose that it has index $c = 39$. This control stock is also crucial for replication of the treated stock if a set of control stocks with indices $c \in \{1, ..., 38, 50\}$ does not contain a synthetic control that replicates the treated stock. I apply this procedure to each control stock in the synthetic portfolio.

8.2.3 Outer optimization procedure

The algorithm described above identifies the closest synthetic control for each treated stock. However, it ignores the big picture – how the overall set of control stocks approximates the set of treated stocks. For example, if treated stocks are on average larger than control stocks, then the algorithm blindly matches treated stocks with smaller synthetic controls on average. The outer optimization loop is introduced to address this issue.

Correction of the balance is achieved by introducing "phantom" treated stocks. To illustrate the intuition of the approach, suppose that the pool of treated stocks is on average larger than the pool of constructed synthetic controls. In this case, I generate phantom treated stocks that are larger than the actual treated stocks on the mean difference in size between the pools of treated and synthetic control stocks, and then I search for synthetic controls for the phantom treated stocks. Since phantom treated stocks are bigger than the actual treated stocks, the matching algorithm searches for larger synthetic controls, reducing the difference in size between the pools of treated and control stocks. Adjustments to the phantom treated stocks are made until there is no improvement in the mean differences between the pools of actual treated and control stocks.

I apply this correction for every closed hedge fund separately. This makes the pools of treated and control stocks similar in the same points of time.

8.2.4 Choice of the parameters for the matching algorithm

There is only one parameter in the matching algorithm – the number of the closest control stocks that can be used for the formation of synthetic controls (C). I choose the C that produces the most accurate matching w.r.t. the aggregated measure of balance that I describe next.[33]

First, I construct a pooled empirical CDF of the treated stocks for a matching characteristic k, as follows:

$$CDF_k^{treated}(x) = \frac{1}{\sum_{q=q_{min}}^{q_{max}} N_q} \sum_{q=q_{min}}^{q_{max}} \sum_{h=1}^{N_q} \sum_{i=1}^{n_h} \frac{1}{n_h} \mathbb{I}\left(V_{k,i,q} \leq x\right)$$

where index $q \in [q_{min}, q_{max}]$ covers all quarters with hedge fund closures, index h covers closed hedge funds in quarter q (N_q is the total number of closed hedge funds in quarter q), and index i indicates a treated stock in the portfolio of the closed hedge fund (n_h is the total number of treated stocks in the portfolio of the closed hedge fund h). An associated pooled

[33] I literally follow Ho et al. (2007) by searching for the best balance: *"Just as we iteratively evaluate a likelihood function to its optimal parameter values (and ignore any intermediate parameter values on the way to the MLEs), one should try as many matching solutions as possible and choose the one with the best balance as the final preprocessed data set."* Rosenbaum (2020) has a similar suggestion: *"Just as one compares experimental designs before picking a satisfactory design, so too one compares several matched designs for an observational study, selecting a satisfactory design. Because outcomes are not available during this process, the search for a good design neither biases analyses of outcomes nor requires corrections for multiple inference."*

empirical CDF of synthetic controls is

$$CDF_k^{control}(x) = \frac{1}{\sum_{q=q_{min}}^{q_{max}} N_q} \sum_{q=q_{min}}^{q_{max}} \sum_{h=1}^{N_q} \sum_{i=1}^{n_h} \frac{1}{n_h} \sum_{j=1}^{C_q} w_{i,j,q} \mathbb{I}\left(V_{k,j,q} \leq x\right)$$

where $w_{i,j,q}$ is the weight of control stock $j \in \{1, ..., C_q\}$ in a synthetic portfolio matched with a treated stock $i \in \{1, ..., T_q\}$ in quarter q. The maximal distance between the two functions is a measure of balance for a matching characteristic k, as follows:

$$KS_k = \max_x \left(\left|CDF_k^{treated}(x) - CDF_k^{control}(x)\right|\right)$$

The aggregated measure, $KS = \sqrt{\sum_{k=1}^{K} KS_k^2}$, captures the overall balance. I choose $C = 10$ for the final sample since it produces the lowest KS.

8.2.5 Discussion of the matching algorithm

Table 5 compares different matching techniques for the main sample of the treated stocks. In summary, the constructed matching algorithm produces the best balance that I managed to achieve. Compared to 1:1 matching with replacement, it achieves noticeably better balance between treated and control stocks with little sacrifice in distance of control stocks used.

Panel A. Identification of terminated hedge funds

	Filter description	# obs	% change
0.	Initial sample of mgrno from Thomson Reuters s34 Master File	9 899	
1.	An entity is a hedge fund	2 810	-71.6
2.	Serious disruption of hedge fund trading activity		
	(a) Full or partial termination occurs not later than two quarters after the last reported Form 13F	415	-85.2
	(b) At least 75% of assets is liquidated	393	-5.3
	(c) Hedge fund employees control at least 50% of the fund	371	-5.6
3.	There are at least four Form 13F filings before liquidation	342	-7.8

Panel B. Treated mgrno, stock, and quarter triples in the sample

	Filter description	# obs	% change
0.	Initial sample of treated mgrno, stock, and quarter triples	19 073	
1.	Data availability filters		
	(a) Closures take place between 2000 Q1 and 2019 Q3	18 404	-3.5
	(b) There is data for all quarters in the event window	14 481	-21.3
2.	Long-term interest	5 740	-60.4
3.	Stock size filters		
	(a) Remove bottom quintile	5 068	-11.7
	(b) Remove top decile	3 545	-30.1
4.	Total hedge fund trading activity drops at least by 0.5%	1 906	-46.2
5.	Keep closed hedge funds with at least 3 treated stocks	1 787	-6.2

Table 1: Filters for identification of the treated stocks

Panel A shows filters that lead to the final sample of terminated hedge funds. Panel B describes how the final sample of the treated stocks is constructed. *# obs* shows the number of observations left after applying a filter. *% change* shows the percentage of observations removed by a filter from the previous step.

	Mean	St.Dev.	p10	p25	p50	p75	p90
Size	901	1 484	80	153	336	812	2 413
Age	26.9	17.8	9	12	22	37	53
% equity	69.8	24.4	32	55	76	89	96
# stocks	57.0	114	10	16	23	42	121
13D	0.24	0.43	0	0	0	0	1

Table 2: Properties of the final sample of closed hedge funds

The table reports properties of 140 closed hedge funds from the final sample. *Size* is the total portfolio value reported in the last Form 13F filings before closure ($ mln). *Age* is the number of quarters between the first and the last submitted Form 13F filings plus 1. *% equity* represents the percentage of total value that comes from assets with CRSP share codes 10 and 11 in the last Form 13F filings before closure. *# stocks* represents the number of assets with CRSP share codes 10 or 11 in the last Form 13F filings before closure. *13D* is a binary variable that equals 1 if a hedge fund filed form 13D at least once and zero otherwise.

Quarter	% own	Mean	p10	p25	p50	p75	p90
-5	59	0.66	0	0	0.10	0.64	1.65
-4	77	0.75	0	0.02	0.24	0.78	1.78
-3	96	0.81	0.03	0.11	0.32	0.95	1.97
-2	93	0.76	0.02	0.10	0.29	0.80	1.94
-1	93	0.70	0.01	0.10	0.25	0.70	1.62
0	100	0.55	0.03	0.09	0.21	0.58	1.28
1	9	0.02	0	0	0	0	0
2	2	0.01	0	0	0	0	0
3	1	0.00	0	0	0	0	0

Table 3: Evolution of the treated stock holdings

The table shows evolution of terminated hedge funds' positions in the treated stocks around closures. *Quarter* displays the quarter relative to the last quarter before closure. *% own* shows the percentage of treated stocks that was reported in Form 13F filings. *Mean* shows the weighted average holdings of the terminated hedge funds in the treated stocks (in percentage of shares outstanding). Column *pN* presents percentile *N* of the distribution of the stock holdings.

Panel A. Control variables for the matching

Name	Description	Data sources
MC_{ann}	Median daily market capitalization calculated over (-4, 0] ($MC = \|PRC\| \cdot SHROUT$).	CRSP
BM_{ann}	Median book-to-market ratio calculated over time points {-3, -2, -1}. Book equity is the book value of shareholders' equity ($SEQQ$, then $CEQQ + PSTKQ$, then $ATQ - LTQ - MIBQ$, if available) + balance sheet deferred taxes and investment tax credit ($TXDITCQ$, if available; 0 otherwise) − the book value of preferred stock ($PSTKQ$, if available; 0 otherwise). Market capitalization is estimated at the last trading day in the quarter.	CRSP, Compustat
$TrVol_{ann}$	Median daily trading volume (VOL) as fraction of shares outstanding ($SHROUT$) calculated over (-4, 0].	CRSP
$IVOL_{ann}$	Standard deviation of errors from a model over (-4, 0]. The model is a linear regression of (log) excess stock returns on (log) excess market returns, SMB, HML, RMW, CMA, and MOM factors estimated over (-8, -4].	CRSP, FF
HF_{ann}	Median hedge fund ownership as fraction of shares outstanding calculated over time points {-3, -2, -1}.	CRSP, TR 13F, WRDS 13F
$ShtInt_{ann}$	Median biweekly short interest as fraction of shares outstanding calculated over (-4, 0].	CRSP, Compustat Short Interest
MF_{ann}	Median mutual fund ownership as fraction of shares outstanding calculated over time points {-3, -2, -1}.	CRSP, TR MF, CRSP MF
$Analyst_{ann}$	Median *Analyst* calculated over time points {-3, -2, -1, 0}. *Analyst* is the number of equity analysts with at least one quarterly forecast issued for a stock within the previous 90 days.	I/B/E/S

Panel B. Variables used in the analysis

Name	Description	Data sources
HF_{hold}	Ownership of hedge funds that mention a stock in their Form 13F filings as a fraction of total shares outstanding.	CRSP, TR 13F, WRDS 13F
HF_{num}	Number of hedge funds that mention a stock in their Form 13F filings.	TR 13F, WRDS 13F
$EffSpr$	Share-weighted average of the effective spread during the trading day (excluding the first half hour). For each transaction, the effective spread is $2 \times \|TransactionPrice - Midpoint\|$, where $Midpoint = (Ask + Bid)/2$ valid one second before the transaction.	TAQ

$PrcImp$	Share-weighted average of the price impact during the trading day (excluding the first half hour). For each transaction, the price impact is $2 \times (Midpoint5 - Midpoint)$, where $Midpoint = (Ask + Bid)/2$ valid one second before the transaction and $Midpoint5 = (Ask + Bid)/2$ valid five minutes after the transaction.	TAQ
$RealSpr$	Share-weighted average of the realized spread during the trading day (excluding the first half hour). For each transaction, the realized spread is $2 \times \mathbb{I}_{Buy/Sell} \times (TransactionPrice - Midpoint5)$, where $\mathbb{I}_{Buy/Sell} = 1$ for a buy transaction and $\mathbb{I}_{Buy/Sell} = -1$ for a sell transaction and $Midpoint5 = (Ask + Bid)/2$ valid five minutes after the transaction. Trades are signed using the Lee and Ready (1991) algorithm.	TAQ
MF_{hold}	Ownership of mutual funds that mention a stock in their Form 13F filings as a fraction of total shares outstanding.	CRSP, TR MF, CRSP MF
$ShtInt_{hold}$	Ownership of short-sellers as a fraction of total shares outstanding.	CRSP, Compustat Short Interest

Table 4: Description of variables used in the analysis

Panel A summarizes how control variables for the matching are constructed. Time point 0 is set at the last day of the last quarter before closure. Time is counted in quarters. Thus, time interval (-1, 0] covers all days between the first and the last day of the last quarter before closure. I use slope winsorization following Welch (2019) for $IVOL_{ann}$, with the following boundaries: $|\beta_{mkt-rf} - 1| \leq 3$, $|\beta_i| \leq 3$ for $i \in \{smb, hml, rmw, cma, mom\}$. An equity analyst is assumed to follow a stock on a certain day if there is at least one quarterly forecast issued by the analyst in the previous 90 days.

Panel B presents details on the construction of variables used in the analysis.

CRSP is the abbreviation for the Center for Research in Security Prices. TR 13F stands for Thomson Reuters s34 Master File (it is used before 2013 Q2). WRDS 13F means WRDS SEC Analytics Suite 13F Holdings File (it is used starting from 2013 Q2). FF stands for the Fama-French factors from the website of Kenneth R. French.

	No matching				1:1 with repl.				Final			
Name	Mean	p50	VR	CDF	Mean	p50	VR	CDF	Mean	p50	VR	CDF
MC_{ann}	44	-22	32.5	22.4	-12	-14	0.96	13	-3.6	-8.5	1.26	10
BM_{ann}	9.0	16	1.06	11	-0.9	2.6	0.76	7.0	1.5	5.0	0.99	3.8
$TrVol_{ann}$	-76	-68	0.54	34	-20	-16	0.70	7.5	-6.0	-4.7	0.88	3.8
$IVOL_{ann}$	-19	-20	1.03	14	-1.1	1.5	0.89	2.6	1.6	1.3	1.02	4.3
HF_{ann}	-98	-92	0.60	48	-20	-19	0.96	10	-5.2	-8.0	1.17	9.0
$ShInt_{ann}$	-8.0	-11	1.19	8.2	-1.1	2.6	0.91	3.2	3.3	2.9	1.08	4.0
MF_{ann}	-6.9	-4.9	1.26	5.9	4.6	-0.8	0.76	8.0	-0.8	-3.6	1.00	3.8
$Analyst_{ann}$	-31	-32	0.75	22	-7.2	-6.6	0.76	6.8	-0.5	-4.5	0.97	3.3
Dist used	3.49				1.00				1.32			
Dist obtained	2.36				1.00				0.65			

Table 5: Balance for different matching techniques

The table shows the balance between treated and control stocks after applying different matching techniques. Three matching techniques are compared: (1) *No matching* (each treated stock is matched with an equally weighted portfolio of all available control stocks), (2) *1:1 with repl.* (each treated stock is matched with the nearest control stock), and (3) *Final* (the matching technique described in the Appendix in Section 8.2). Euclidean distance in the space of normalized matching characteristics is used. Matching characteristics are normalized in each quarter on the corresponding interquartile range that is estimated based on all NYSE stocks with available data. *Mean* is the mean difference between normalized matching characteristics of control and treated stocks multiplied by 100. *p50* is the median difference between normalized matching characteristics of control and treated stocks multiplied by 100. *VR* is the ratio of variances of control stocks to treated stocks. *CDF* is the maximal difference in empirical CDF of normalized matching characteristics for treated and control stocks multiplied by 100. *Dist used* shows the average of the weighted average distance between stocks used for construction of synthetic controls and the corresponding treated stocks scaled by similarly constructed distance for *1:1 with repl.* matching technique. *Dist obtained* shows the average distance between constructed synthetic controls and treated stocks scaled by similarly constructed distance for the *1:1 with repl.* matching technique.

Qtr	HF_{hold}	$\ln(HF_{hold})$	HF_{num}
-4	0.43*	5.52***	-0.82*
	(1.76)	(2.61)	(-1.85)
-3	0.25	2.40	-0.58
	(1.24)	(1.33)	(-1.48)
-2	-0.10	-2.22	-0.26
	(-0.65)	(-1.53)	(-0.76)
-1	-0.09	-0.89	-0.91***
	(-0.82)	(-0.88)	(-3.34)
1	-0.29***	-1.85*	-1.12***
	(-2.66)	(-1.80)	(-4.14)
2	-0.47***	-3.71**	-1.11***
	(-2.96)	(-2.52)	(-3.18)
3	-0.43**	-2.64	-1.57***
	(-2.33)	(-1.53)	(-3.80)
4	-0.51**	-3.92**	-1.41***
	(-2.35)	(-2.00)	(-3.23)
5	-0.40	-3.77*	-1.54***
	(-1.64)	(-1.77)	(-3.42)
Obs	140	140	140

Table 6: Results for direct evidence of the treatment

The table shows results of the difference-in-differences analysis applied to hedge fund trading activity. *Qtr* is the event quarter in the event window. HF_{hold} is the percentage of shares outstanding that are cumulatively held by hedge funds at the end of the quarter based on Form 13F filings. HF_{num} is the number of hedge funds that mentioned the stock in their Form 13F filings at the end of the quarter. The coefficient of $\ln(HF)$ is multiplied by 100. *Obs* shows the number of terminated hedge funds in the analysis. Stock-clustered t-statistics are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels, respectively.

Qtr	$\ln(EffSpr)$	$\ln(PrcImp)$	$\ln(RealSpr)$
-4	-2.02	-2.66	-5.16*
	(-1.50)	(-1.19)	(-1.70)
-3	-1.62	-2.27	-1.43
	(-1.47)	(-1.12)	(-0.50)
-2	0.74	-1.21	2.59
	(0.79)	(-0.64)	(1.02)
-1	0.95	-0.26	1.22
	(1.38)	(-0.15)	(0.56)
1	-2.05***	-4.25***	-4.01*
	(-2.66)	(-2.69)	(-1.67)
2	-0.94	-6.53***	2.40
	(-0.83)	(-3.14)	(0.96)
3	1.23	-3.46	4.92*
	(0.90)	(-1.56)	(1.88)
4	0.59	-2.99	-0.39
	(0.36)	(-1.23)	(-0.14)
5	0.58	-3.00	3.17
	(0.33)	(-1.13)	(1.04)
Obs	71	71	71

Table 7: Results on TAQ liquidity measures

The table shows difference-in-differences analysis applied to the price impact measures. *Qtr* is the event quarter relative to the last quarter before hedge funds' terminations. $EffSpr$ is the daily share-weighted average effective spread. $PrcImp$ is the daily share-weighted average price impact. $RealSpr$ is the daily share-weighted average realized spread. All coefficients are multiplied by 100. *Obs* shows the number of terminated hedge funds in the analysis. Stock and calendar day two-way clustered t-statistics are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels, respectively.

Qtr	*mktDelay*	*eaDelay*
-4	1.73	1.49
	(0.60)	(0.20)
-3	-1.00	5.17
	(-0.39)	(0.62)
-2	1.75	-7.27
	(0.63)	(-1.02)
0	-0.78	16.36**
	(-0.28)	(1.98)
1	5.65*	13.42*
	(1.84)	(1.74)
2	5.20*	5.59
	(1.86)	(0.82)
3	-0.87	-4.75
	(-0.32)	(-0.53)
4	0.63	1.50
	(0.21)	(0.19)
5	-0.52	3.36
	(-0.19)	(0.45)
Obs	140	119

Table 8: Results on information incorporation

The table shows difference-in-differences analysis applied to information incorporation measures. *Qtr* is the event quarter relative to the last quarter before hedge funds' terminations. MF is the percentage of shares outstanding cumulatively held by all mutual funds at the end of the quarter. *ShortInt* is the percentage of shares outstanding that are cumulatively shorted in the quarter. *Obs* shows the number of terminated hedge funds in the analysis. t-statistics with stock – calendar day two-way clustered standard errors for *mktDelay* and stock-clustered standard errors for *eaDelay* are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels, respectively.

	MF_{hold}		$ShtInt_{hold}$	
Qtr	(1)	(2)	(3)	(4)
-4	0.26	-0.13	0.29**	-0.02
	(1.06)	(-0.91)	(1.99)	(-0.21)
-3	0.43**	-0.08	0.25*	0.02
	(2.15)	(-0.63)	(1.91)	(0.24)
-2	0.23	-0.16	-0.02	-0.10
	(1.53)	(-1.47)	(-0.20)	(-1.18)
-1	0.11	-0.16*	0.04	-0.12*
	(1.10)	(-1.90)	(0.52)	(-1.85)
1	0.01	0.02	-0.04	-0.01
	(0.11)	(0.30)	(-0.55)	(-0.13)
2	0.14	0.14	-0.11	-0.04
	(0.86)	(1.19)	(-0.97)	(-0.61)
3	0.10	0.11	-0.02	-0.05
	(0.51)	(0.75)	(-0.16)	(-0.59)
4	0.13	0.13	-0.09	-0.27**
	(0.52)	(0.79)	(-0.60)	(-2.42)
5	0.17	0.22	-0.08	-0.06
	(0.61)	(1.11)	(-0.50)	(-0.60)
Obs	140		140	

Table 9: Results on replacement of closed hedge funds

This table shows difference-in-differences analysis applied to mutual fund holdings and shorted holdings. Qtr is the event quarter relative to the last quarter before hedge funds' terminations. MF_{hold} is the percentage of shares outstanding cumulatively held by all mutual funds at the end of the quarter. $ShtInt_{hold}$ is the percentage of shares outstanding that are cumulatively shorted in the quarter. Columns (1) and (3) show coefficients of the interaction terms $Treated \times \mathbb{I}(q = Qtr)$. Columns (2) and (4) show coefficients of the interaction terms $Treated \times \mathbb{I}(q = Qtr) \times Shares$, where $Shares$ is the demeaned holdings of the defunct hedge funds in the last quarter before liquidation (event quarter $q = 0$). Obs shows the number of terminated hedge funds in the analysis. Stock-clustered t-statistics are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels, respectively.

Panel A: Probability of staying in the same investment group

Current group	Future quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
1	55.7	52.2	51.2	50.5	50.5	49.1	49.9	51.1	49.9	49.2	49.1	49.6
2	35.6	33.5	34.0	33.2	32.5	32.0	32.0	33.2	32.9	31.8	32.1	32.9
3	28.5	26.1	25.4	26.2	25.4	25.0	24.7	24.6	25.0	23.7	24.2	24.3
4	25.6	24.0	23.3	22.9	22.5	23.2	22.7	22.3	21.9	20.9	21.7	21.0
5	25.0	22.9	22.1	21.6	21.4	20.5	19.6	19.5	20.0	18.5	19.1	18.4
6	25.2	23.3	21.8	21.5	20.6	19.9	19.7	19.6	19.1	18.5	18.5	18.8
7	27.0	24.7	23.6	22.6	21.7	20.8	20.8	21.5	20.5	19.6	18.1	19.0
8	31.7	28.1	27.0	26.2	25.0	24.1	22.4	23.0	22.0	21.8	21.0	21.0
9	38.7	34.4	32.2	31.5	30.0	29.1	28.0	28.5	27.2	26.1	25.6	26.0
10	57.2	50.2	47.7	46.0	43.2	42.8	40.6	40.4	39.3	38.4	37.1	36.6

Panel B: Probability of staying in the same group or moving to the nearest investment group

Current group	Future quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
1	77.1	74.9	73.9	74.0	74.4	72.3	72.9	72.4	71.7	71.9	72.0	72.6
2	78.1	76.8	77.2	76.4	76.0	76.6	76.2	75.6	76.1	76.6	76.1	75.4
3	69.7	66.8	65.9	66.3	66.1	64.2	65.0	64.7	65.6	64.5	63.4	65.2
4	64.4	60.8	60.4	59.9	59.1	58.2	57.6	58.7	58.5	57.3	56.6	57.6
5	64.0	59.7	57.6	58.8	56.6	54.5	53.8	55.0	53.9	52.8	51.7	52.3
6	64.5	60.1	57.4	57.1	55.8	54.6	52.8	52.7	52.1	52.1	51.1	51.0
7	65.5	62.0	59.3	58.1	57.2	56.0	54.6	54.9	54.5	53.2	52.7	52.3
8	71.8	67.3	65.6	64.6	63.2	61.6	59.4	58.6	58.3	58.0	56.6	56.8
9	80.3	77.4	75.3	73.5	72.1	70.9	70.4	69.6	68.6	66.4	65.9	65.3
10	79.0	73.5	72.1	71.2	68.5	66.9	65.5	64.3	64.7	63.6	62.2	61.9

Table 10: Persistence of trading activity of hedge funds

The table reports transition probabilities between trading activity deciles for hedge funds. The sample consists of all hedge fund quarter pairs from 1999 Q4 to 2020 Q4 with hedge funds reporting at least one stock at the end of the current and each of the previous three quarters. All observations are pooled and split into deciles from the least active (decile 1) to the most active (decile 10) based on reallocated portfolio weight between the current and the previous quarter. The resulting group ranges in percents are: (1) [0, 5.7), (2) [5.7, 11), (3) [11, 16.3), (4) [16.3, 22), (5) [22, 28.3), (6) [28.3, 35.3), (7) [35.3, 43.6), (8) [43.6, 52.9), (9) [52.9, 66.1), (10) [66.1, 100]. Panel A reports probabilities of hedge funds staying in the same group in the next one to 12 quarters. Panel B reports probabilities of hedge funds staying in the same group or moving to the nearest group in the next one to 12 quarters. The intensity of the cell color grows linearly from the smallest value (18.1 in Panel A, 51.0 in Panel B) to the largest value (57.2 in Panel A, 80.3 in Panel B).

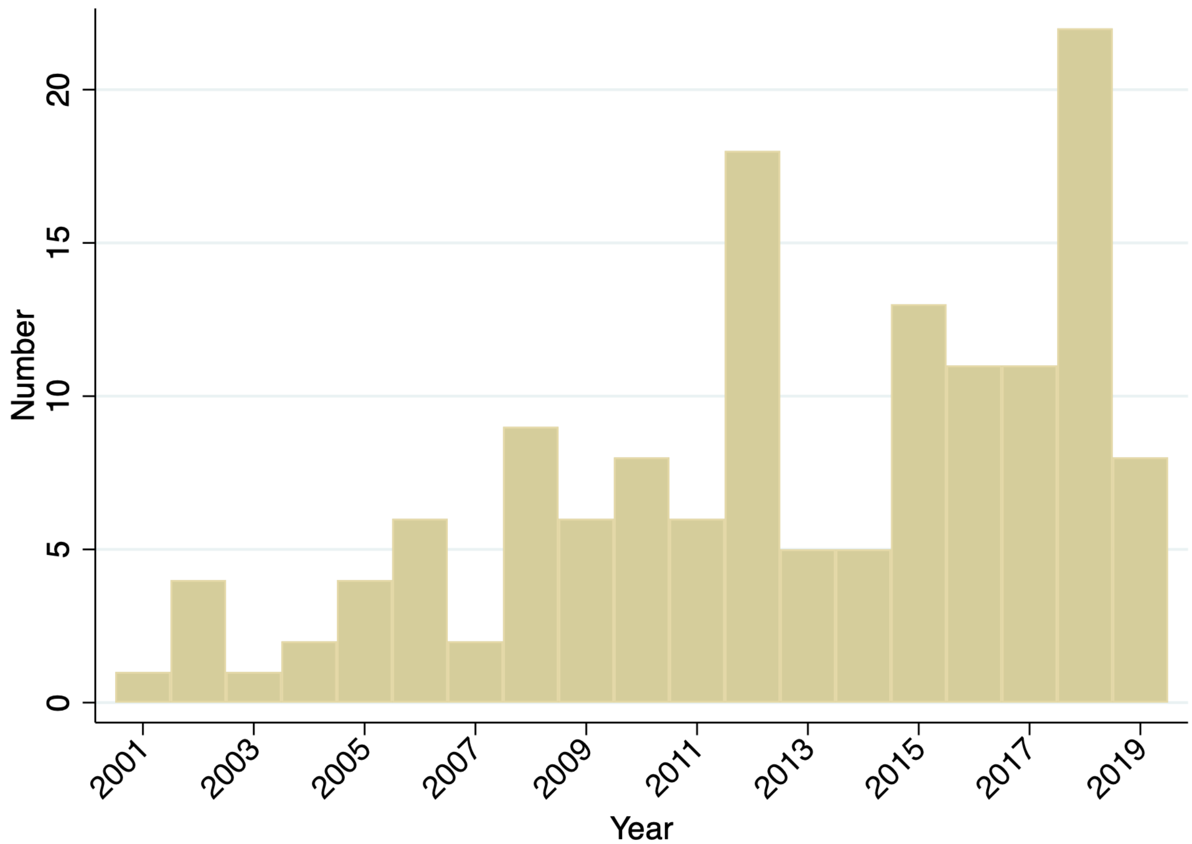

Figure 1: Distribution of hedge fund closures over time

The figure shows the distribution of 140 terminated hedge funds from the final sample over time.

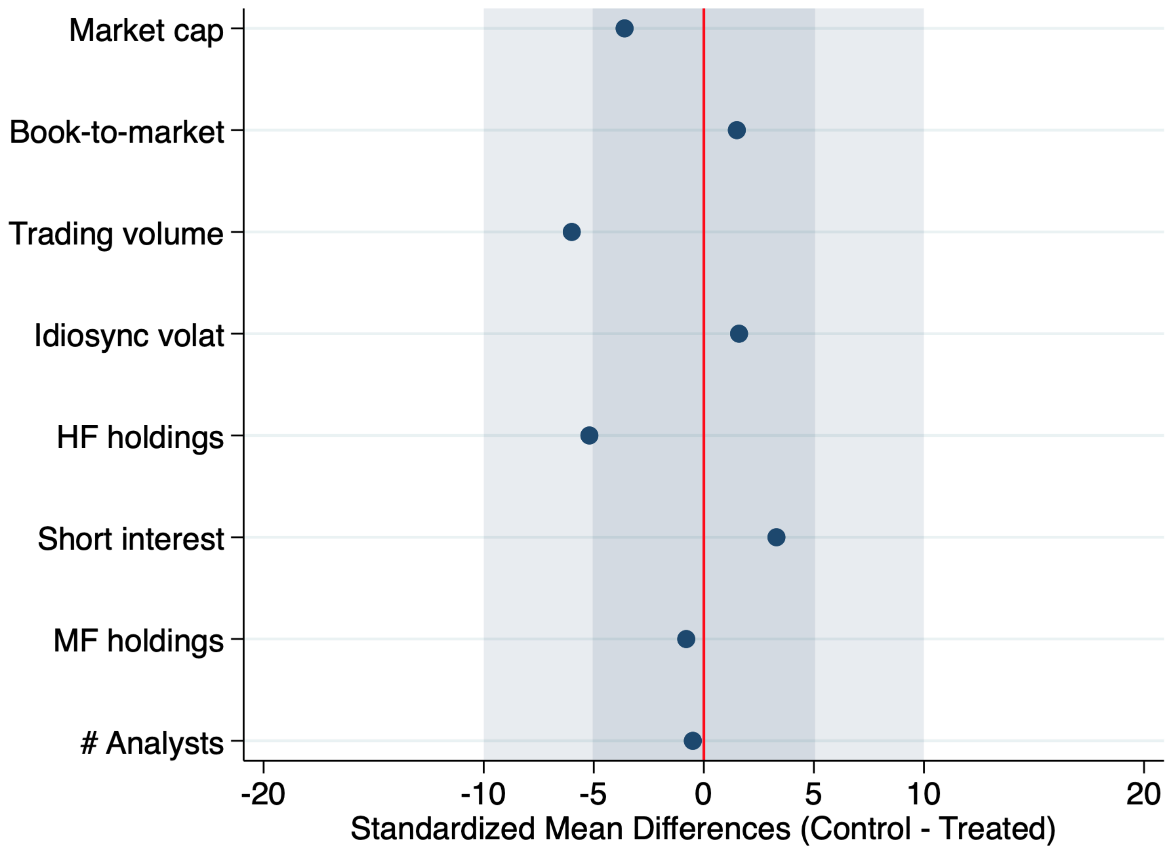

Figure 2: Balance between treated and control stocks

The figure shows the standardized mean differences of the matching characteristics between control and treated stocks from Table 5 column *Final − Mean* (measured in percents of the interquartile range of a characteristic).

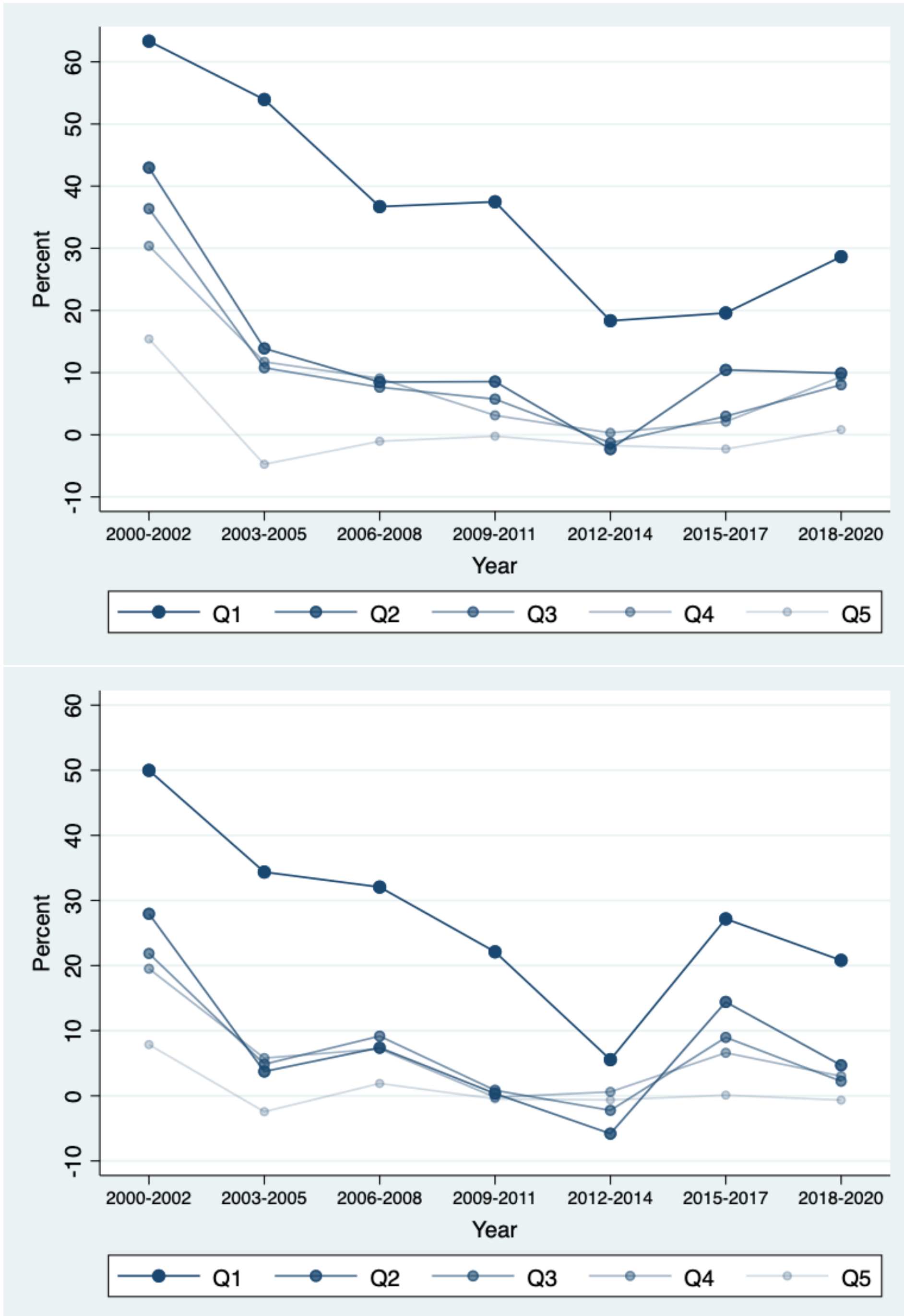

Figure 3: Market information incorporation delay (days 1-20 and days 1-4)

The figure shows the evolution of the market information incorporation delay over time by stock size quintile. The sample includes all NYSE, Amex, and NASDAQ stocks with at least 250 trading days in a time period. Size quintiles are based on NYSE breakpoints. The delay is constructed by estimating the regression $R_{i,t} = \alpha_i + \beta_0 Mkt_t + \sum_{l=1}^{L} \beta_l Mkt_{t-l} + \epsilon_{i,t}$ on all stocks in a certain time period and size group and taking the fraction of the residual sensitivity to market movements ($\sum_{l=1}^{L} \beta_l$) to the full sensitivity ($\sum_{l=0}^{L} \beta_l$). L equals 20 for the top graph and 4 for the bottom graph. The CRSP value-weighted index is used as the market index. Returns of a stock are removed from the index and its lags to avoid a mechanical relationship.

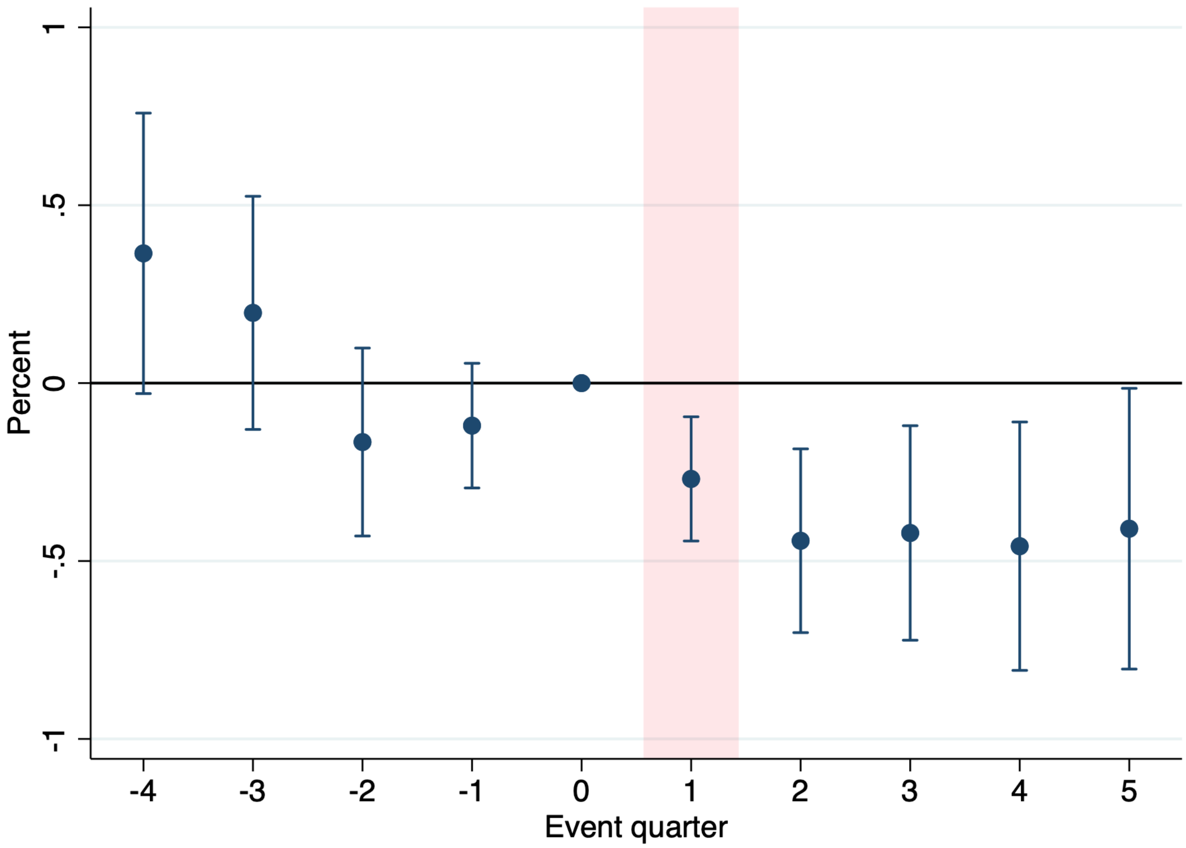

Figure 4: Difference-in-differences analysis for hedge fund ownership

The figure shows the difference-in-differences analysis applied to hedge fund holdings of the treated and control stocks. The red area highlights the first quarter after terminated hedge funds filed their last Form 13F. 90% confidence intervals are constructed using stock-clustered standard errors.

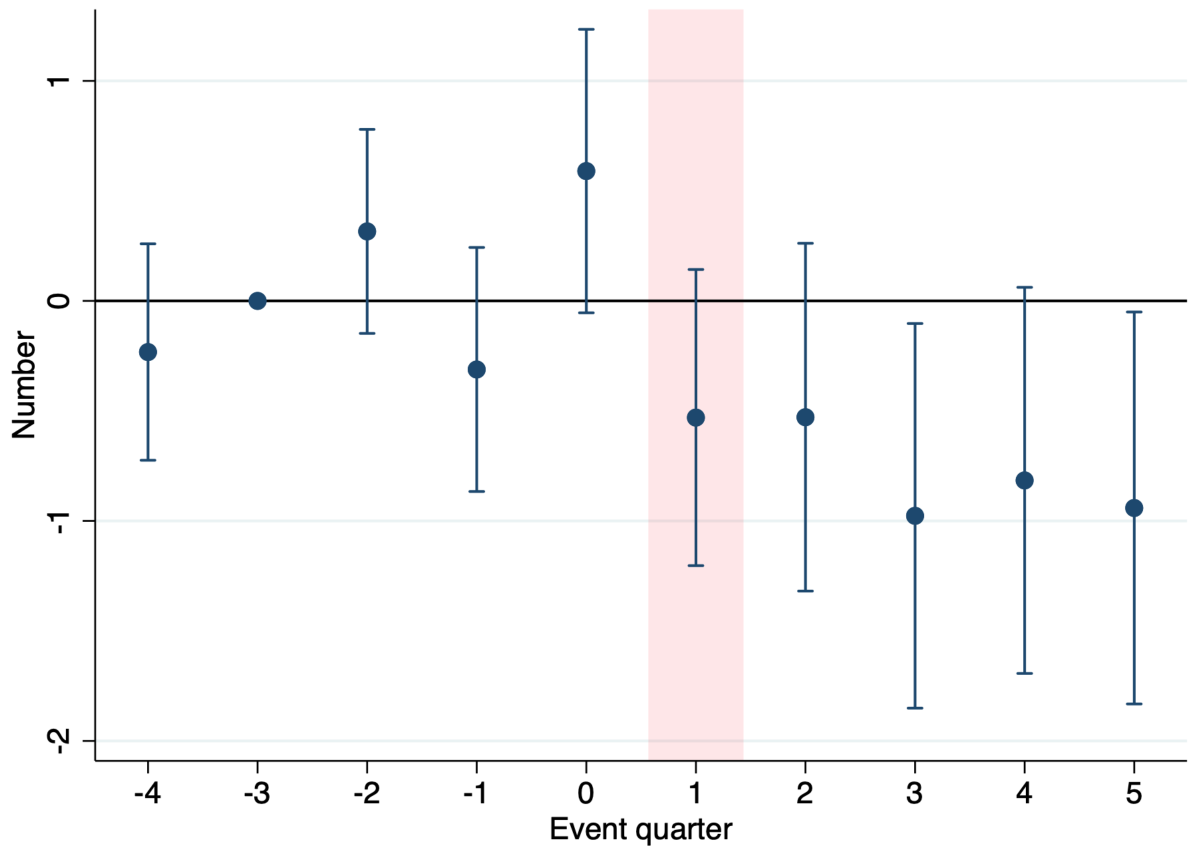

Figure 5: Difference-in-differences analysis for the number of hedge funds

The figure shows the difference-in-differences analysis applied to the number of hedge funds that reported the treated and control stocks in Form 13F filings. The red area highlights the first quarter after terminated hedge funds filed their last Form 13F. 90% confidence intervals are constructed using stock-clustered standard errors.

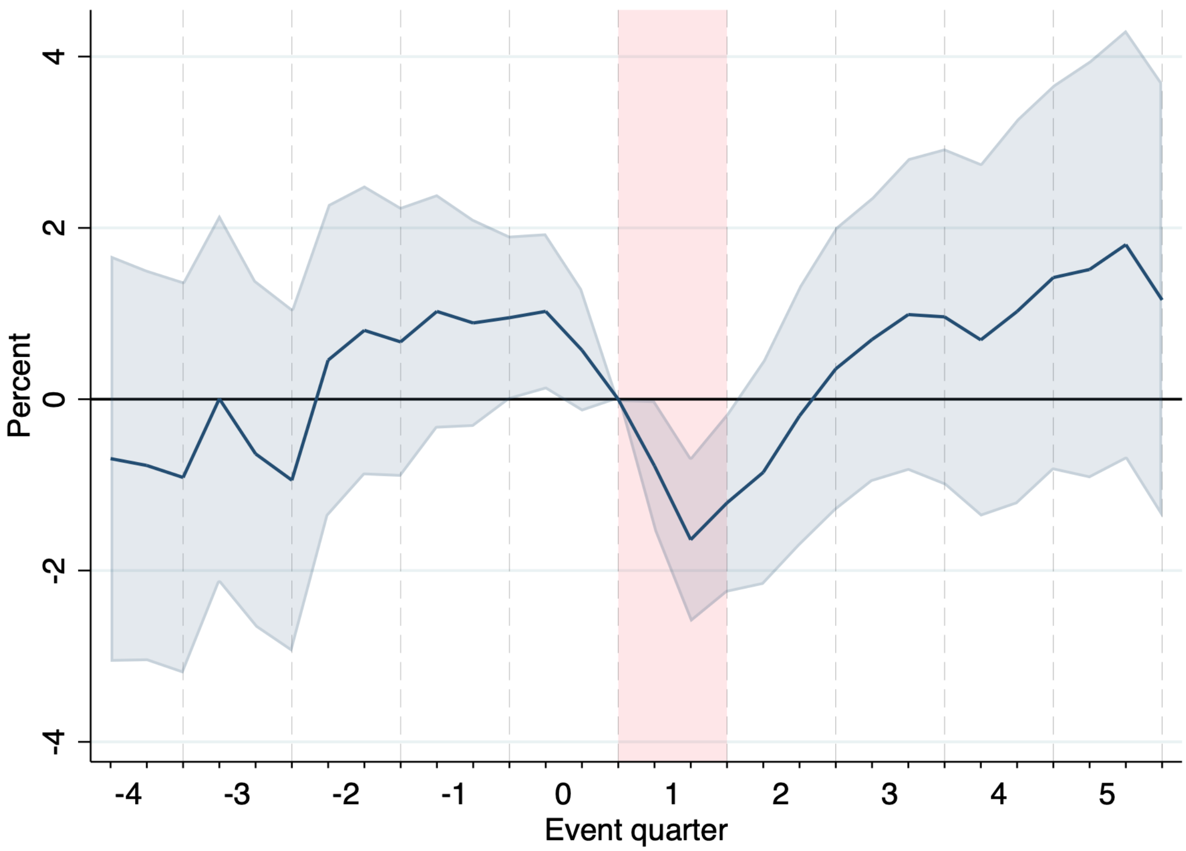

Figure 6: Difference-in-differences analysis for cumulative buy-and-hold stock returns

The figure shows the difference-in-differences analysis applied to cumulative buy-and-hold stock returns of the treated and control firms. The holding period starts four quarters before hedge fund termination and ends five quarters after. The red area highlights the first three months after terminated hedge funds filed their last Form 13F. 90% confidence intervals are constructed using stock and calendar month two-way clustered standard errors.

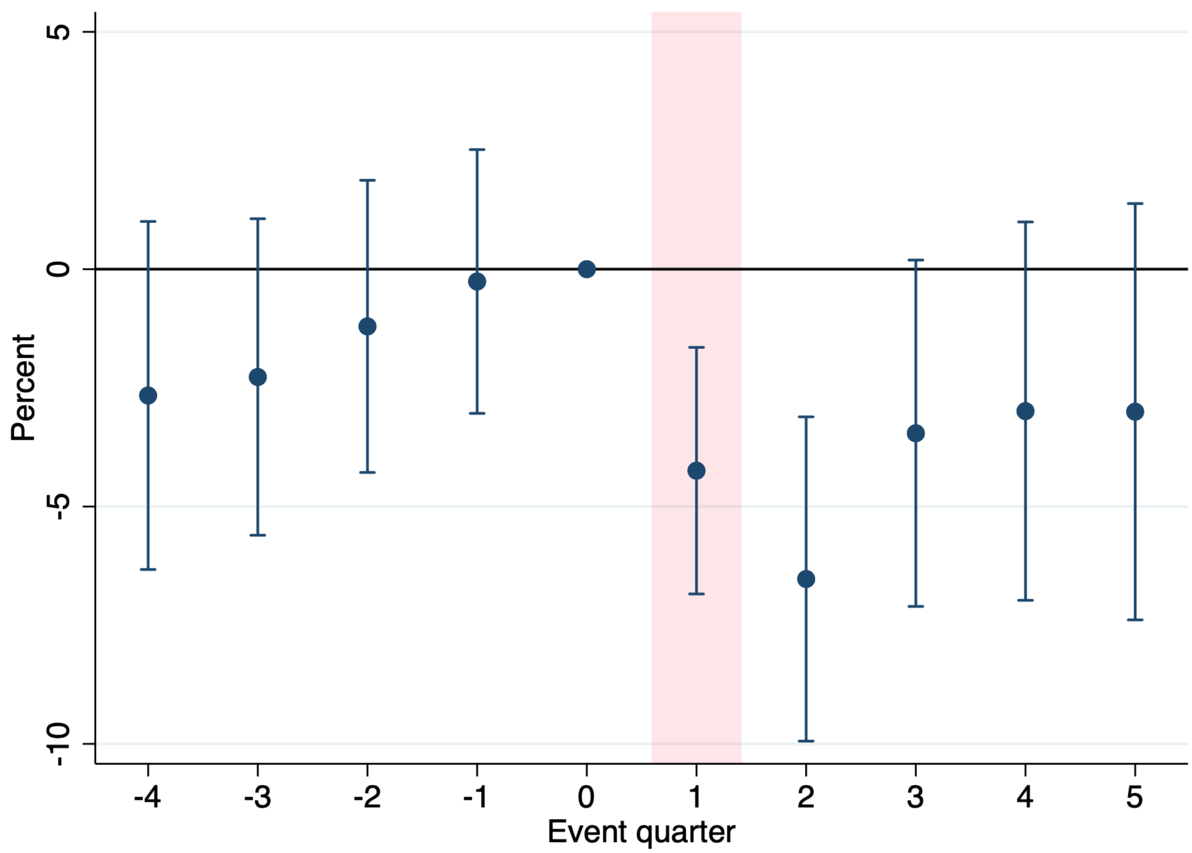

Figure 7: Difference-in-differences analysis for the TAQ price impact measure

The figure shows the difference-in-differences analysis applied to the logarithm of the TAQ price impact measure. The red area highlights the first quarter after terminated hedge funds filed their last Form 13F. 90% confidence intervals are constructed using stock and calendar day two-way clustered standard errors.

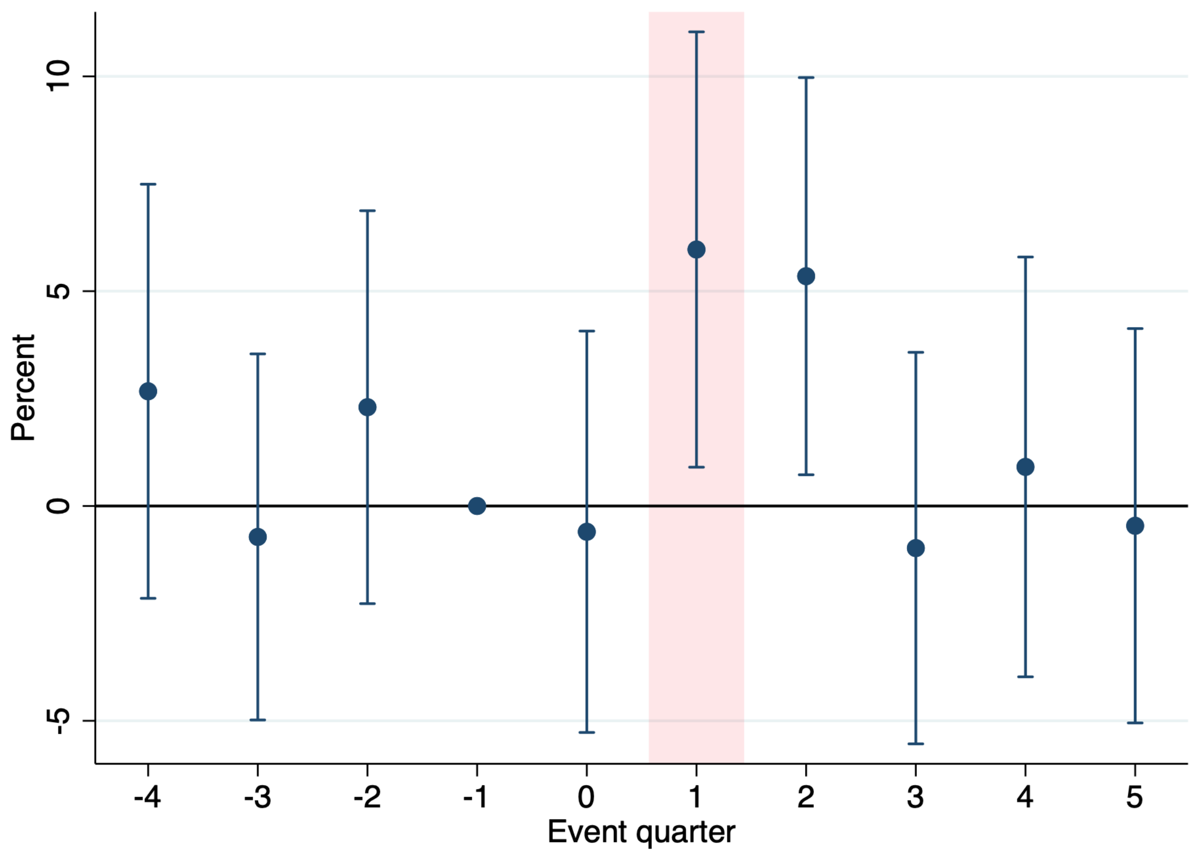

Figure 8: Difference-in-differences analysis for the delay of market information incorporation

The figure shows the difference-in-differences analysis applied to market information incorporation delay. The red area highlights the first quarter after terminated hedge funds filed their last Form 13F. 90% confidence intervals are constructed using stock and calendar day two-way clustered standard errors.

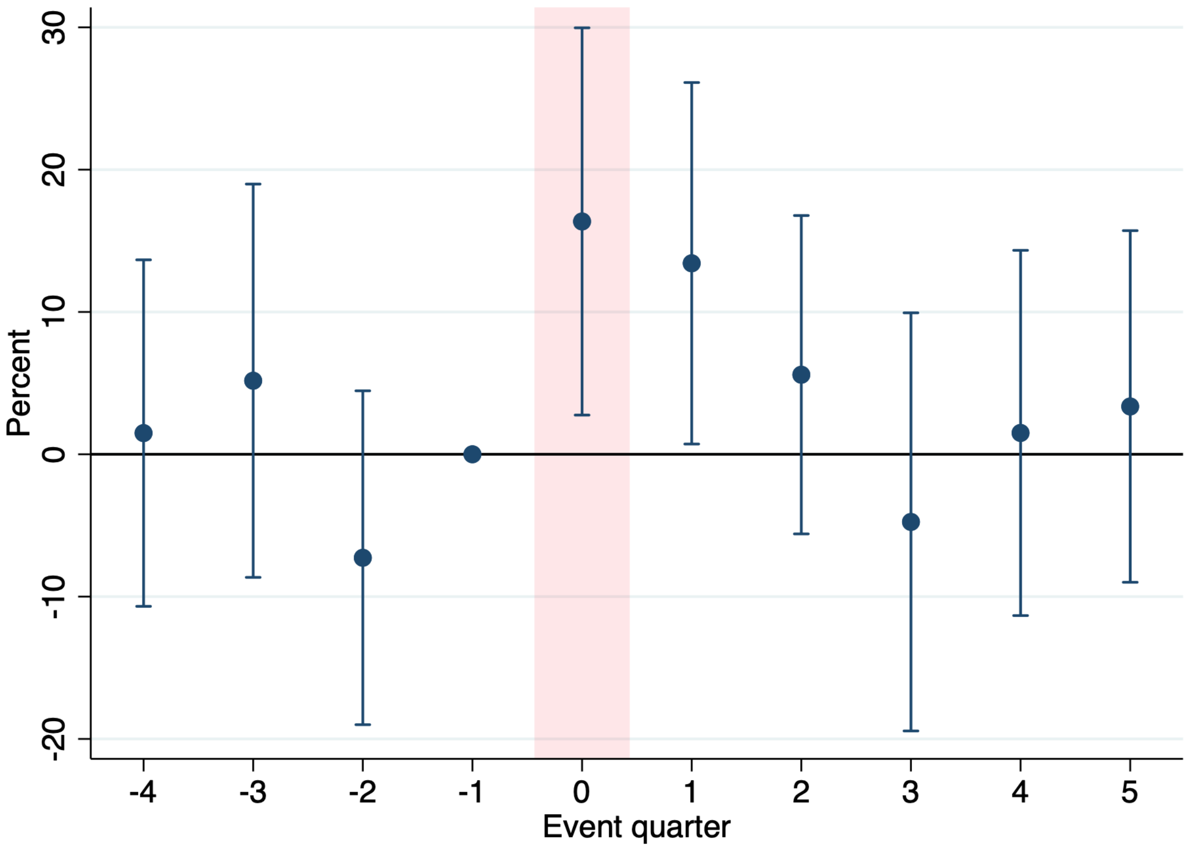

Figure 9: Difference-in-differences analysis for the earnings information incorporation delay

The figure shows the difference-in-differences analysis applied to earnings information incorporation delay. The red area highlights the first quarter after terminated hedge funds filed their last Form 13F. 90% confidence intervals are constructed using stock-clustered standard errors.

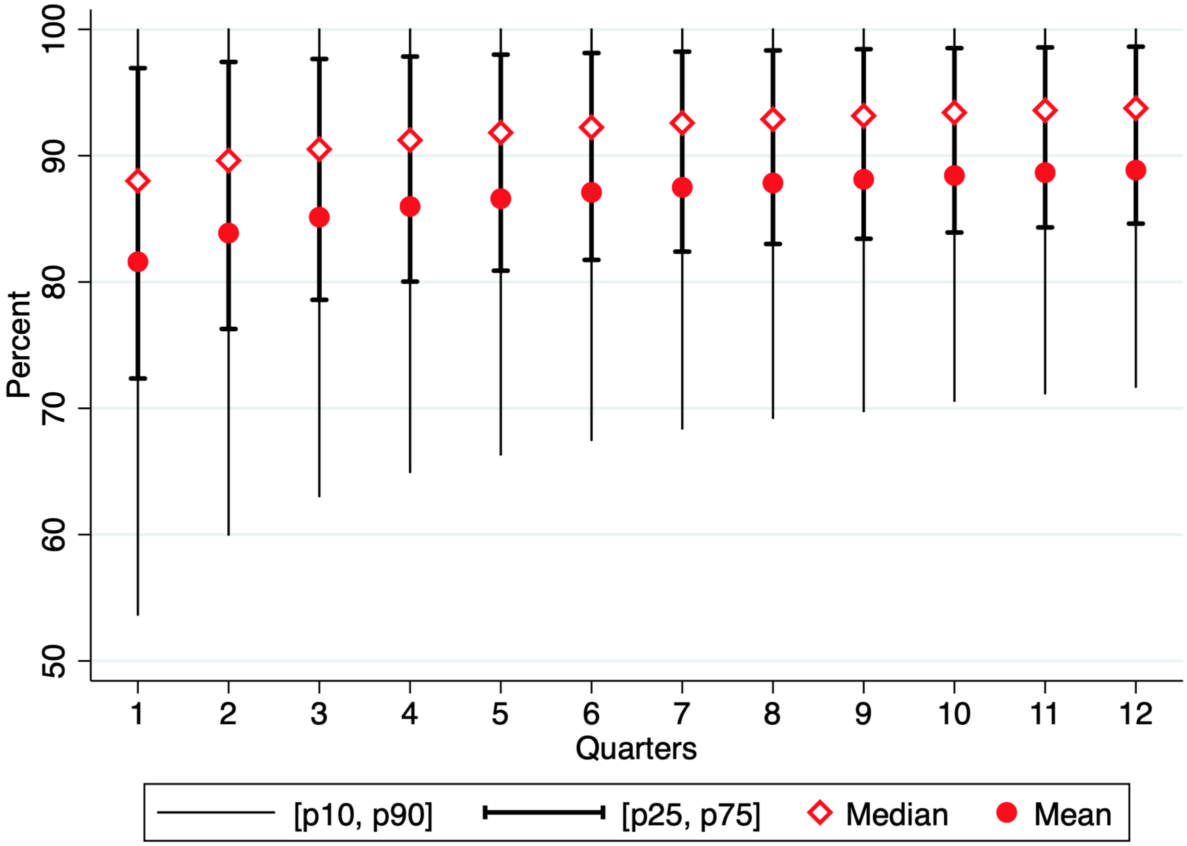

Figure 10: Persistence of the set of stocks held

The figure shows the distribution of the portfolio weight of stocks held in the current quarter that were ever held in the previous one to 12 quarters. The sample consists of all hedge fund and quarter pairs from 2002 Q1 to 2020 Q4 with hedge funds reporting at least one stock in the current and each of the previous 12 quarters.

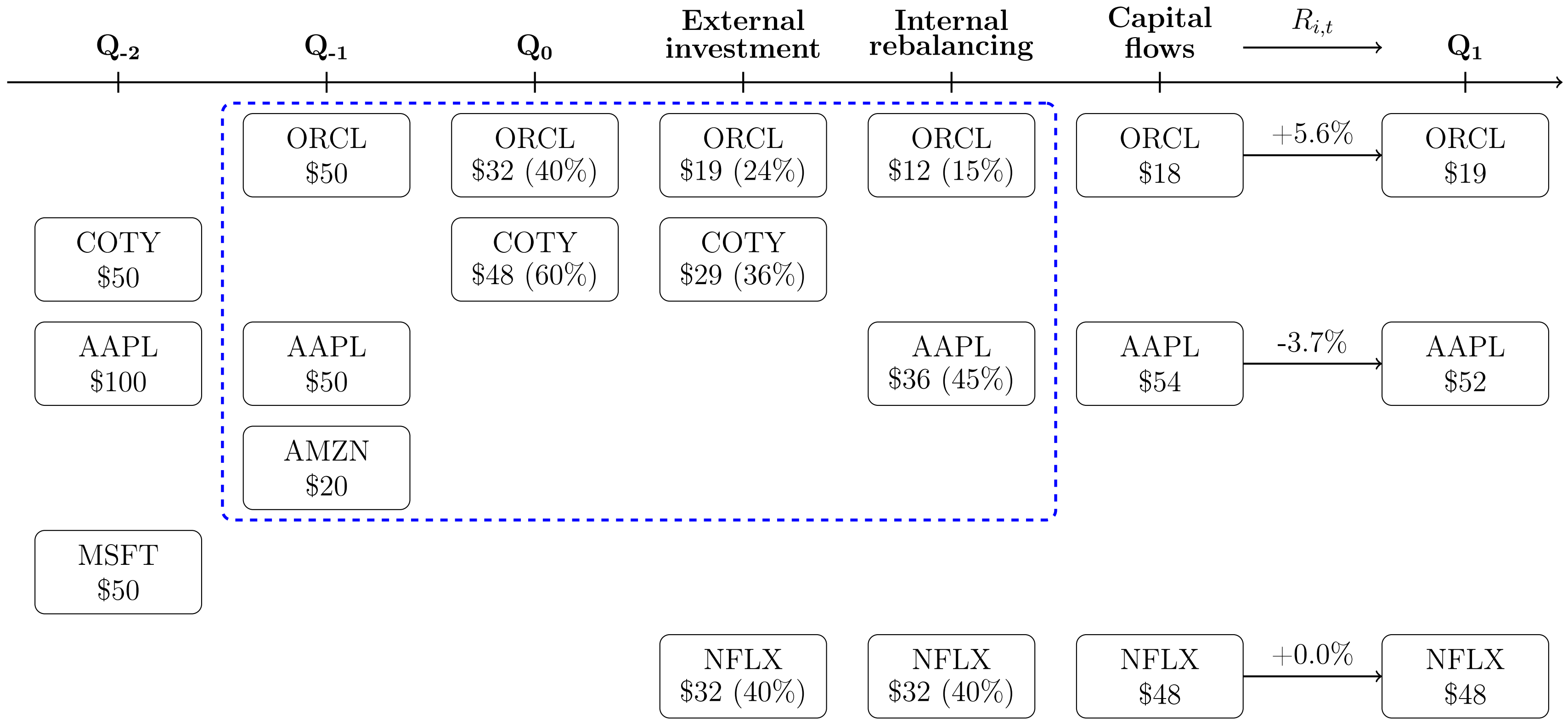

Figure 11: Illustration of how trading activity is estimated

The figure shows how trading activity is estimated when investment universe of a fund is assumed to be two quarters. Actual fund holdings at the end of quarters Q_i for $i \in \{-2, -1, 0, 1\}$ are displayed below the corresponding ticks. All stocks that were reported at least once in Q_0 and Q_{-1} constitute the investment universe of the fund at Q_0 (these are ORCL, COTY, AAPL, and AMZN). Fund trading right after Q_0 is decomposed into three phases: *External investment*, *Internal rebalancing*, and *Capital flows*. First, the fund manager proportionately scales stock holdings at Q_0 down to invest into stocks that are outside of the fund's investment universe (NFLX) during the *External investment* phase. Second, the fund manager reallocates funds between stocks in the investment universe during the *Internal rebalancing* phase. Third, the fund manager proportionately scales the obtained stock holdings depending on the realized flows during the *Capital flows* phase. Finally, the fund manager keeps the obtained portfolio till the end of Q_1, so stock holdings change only because of stock returns $R_{i,t}$ during Q_1. The blue dashed rectangle highlights the *External investment* and *Internal rebalancing* phases for stocks in the investment universe of the fund at Q_0.