How do hedge funds affect stocks that they trade? Evidence from hedge fund closures*

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Abstract

I examine how hedge funds affect stock price informativeness and liquidity. Using liquidations of hedge funds as a quasi-natural experiment, I find that hedge funds are important for the timely incorporation of bad news: treated stocks react less to negative earnings surprises on earnings announcement days compared to control stocks after hedge fund terminations. Consistent with adverse selection theories, I find that price impact drops after hedge fund closures. These findings reveal a trade-off: although hedge fund trading activity improves stock price efficiency, it worsens stock liquidity. The exogeneity assumption is supported by quick reversion of stock prices after hedge fund liquidations and anecdotal evidence.

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1 Introduction

Hedge funds have increased in importance over the last two decades with assets under management growing from approximately \$0.2 trillion in 2000Q1 to \$4.3 trillion in 2021Q2.[1] Although hedge funds pursue different trading strategies, approximately 35% of funds (and 51% of assets under management) are devoted to equities.[2] Since hedge funds are considered to be among the most sophisticated investors, it is usually assumed that they improve stock market efficiency by reducing deviations of stock prices from fundamental values and speeding up information incorporation. Consistent with this view, Akbas et al. (2015), Kokkonen and Suominen (2015), and Cao et al. (2018) find that capital flows to hedge funds are associated with corrections of mispricing. However, an alternative view contends that hedge funds can damage stock market efficiency. For instance, Brunnermeier and Nagel (2004) document that hedge funds exacerbated the technology bubble rather than corrected it, and Stein (2009) in his Presidential Address cautions against the overcrowding of sophisticated strategies.

Assessing how hedge funds affect stock price efficiency is an empirical challenge. Importantly, price efficiency and hedge fund trading activity can be driven by a common omitted variable (e.g., analyst coverage). Likewise, reverse causality may be driving the relationships: rather than improving stock price efficiency, hedge funds may simply be attracted to more efficiently priced stocks. Finally, there are serious data limitations: available quarterly snapshots of hedge fund holdings reveal little information about actual trading by hedge funds.

In this paper, I overcome this challenge by identifying variations in hedge fund activity that are exogenous to stock characteristics and that reveal trading intentions of hedge fund

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

[2] The estimate is based on single-strategy hedge funds (form PF for 2021Q1, 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

managers. These variations are generated by hedge fund closures.[3] Through a rigorous search of SEC filings, media articles and other sources, I hand-collect data on 318 hedge funds that terminated between 1999 and 2020 and liquidated their positions. I identify stocks that closed hedge funds traded before liquidation (treated stocks), match them with comparable control stocks, and explore the consequences of hedge fund closures using a difference-in-differences design.

My first set of results is related to the effect of hedge funds on stock price informativeness. I find that treated stocks' prices react less to negative earnings surprises after hedge fund closures. This is consistent with hedge funds being active at trading on negative information. This finding is important in light of empirical evidence that it takes more time for bad news to get reflected in stock prices compared to good news (Hong et al., 2000).

In addition, I explore how hedge funds affect stock liquidity. On the one hand, I find evidence that hedge funds are liquidity providers: almost 28% of terminating hedge funds' holdings are held by other hedge funds one quarter after hedge funds' closures. At the same time, there is no change in holdings of mutual funds and short-sellers. On the other hand, liquidity (as measured by intraday price impact) drops following hedge fund closures. The effect is more pronounced for treated stocks in which closing hedge funds had larger holdings before liquidation. Coupled with the fact that terminating hedge funds are not fully replaced, this finding is consistent with adverse selection theories (Grossman and Stiglitz (1980) and Kyle (1985)).

Overall, the findings suggest that there is a trade-off between informativeness and liquidity. Consistent with hedge funds being sophisticated investors, I find that hedge fund trading makes stock prices more informative. However, this benefit comes at a cost of worse liquidity since other investors refrain from trading in stocks that attract attention of hedge funds.

[3] Similar identification approaches are used in other settings. For instance, Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012) use brokerage firms' closures and Johnson et al. (1985) examine the unexpected deaths of senior corporate executives.

Using hedge fund closures as a quasi-natural experiment resolves the endogeneity concerns if hedge fund closures are not related to treated firms' characteristics. Empirically, I find that the reasons for hedge fund closures are consistent with the above: closing hedge fund managers mostly mention personal reasons, poor market conditions or losses combined with investor redemptions when ceasing operations. As an additional support to the exogeneity assumption, I show that the price decline caused by closed hedge funds when liquidating their holdings is temporary: although treated stocks underperform relative to control stocks on 2% in the first two months after hedge fund terminations, this difference completely disappears in the next two months (when the market learns about hedge fund liquidations).[4] This evidence is not consistent with a story in which hedge fund managers choose to close in anticipation of bad news about stocks in their portfolios. Moreover, I find no differences in profitability of the treated and control firms after hedge fund closures.

The most closely related quasi-natural experiment for identification of hedge fund impact on firms is the collapse of Lehman Brothers studied by Aragon and Strahan (2012). In their setting, hedge funds that used Lehman Brothers as a prime broker lost their ability to trade after the Lehman Brothers bankruptcy. Effectively, those hedge funds were "turned off", with their assets being frozen. By contrast, terminating hedge funds liquidate their holdings, and are replaced by other investors. This implies that hedge fund closures are an ideal setting to check whether the impact of hedge funds on financial markets is substituted by other investors. Therefore, this study 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 growing 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 had a reduction in coverage by

[4]Terminating hedge funds on average liquidate 0.8% of shares outstanding of the treated firms in the sample, implying that price elasticity of the treated stocks is larger than 2. This is in line with Koijen et al. (2020) who show that hedge funds are among the most influential investors per dollar of assets under management.

equity analysts. My paper provides evidence of hedge funds helping to incorporate negative information revealed on earnings announcement days into stock prices.

Second, I contribute to the large literature that examines whether hedge funds are liquidity providers. Aragon and Strahan (2012) show that liquidity worsens after hedge funds stop trading. Moreover, Jylhä et al. (2014) provide evidence that hedge funds are suppliers of liquidity in illiquid markets. My finding that terminating hedge funds are to a large extent immediately replaced by other hedge funds is in line with this literature.

Finally, my paper adds to the broad 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 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 worse incorporation of bad news into stock prices, implying that hedge funds exert effort on information collection.

The rest of the paper is organised as follows. Section 2 covers the methodology of the study; section 3 describes the data; section 4 presents the results; section 5 concludes.

2 Methodology

2.1 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 firms and investors. That is, every hedge fund A which trades stocks of firm B in the first universe has a copycat hedge fund A' which trades stocks of a copycat firm B' in the second universe. In this setting, hedge fund A's impact on firm B can be identified by exogenously closing hedge fund A and comparing changes in the stock characteristics of firm B relative to firm B'. The average impact of hedge funds on stocks can be estimated by exogenously terminating a randomly selected subset of hedge funds and averaging out the estimated differences between affected firms in the first universe and unaffected firms in the second universe.

Although it is impossible to conduct this experiment in reality, it is useful for understanding the caveats of using hedge fund closures as a quasi-natural substitute. The most important threat for identification is that hedge funds *choose* to shut down. This choice can potentially depend on treated firms' characteristics. Stock performance is an obvious candidate since it directly affects hedge funds' portfolios.

Therefore, it is crucial to measure the reasons for hedge fund closures since these same reasons might cause changes in stock characteristics and lead to incorrect inferences. For example, an industry-wide negative shock can force a specialized hedge fund to close down.[5] Suppose that this shock forces some mutual fund to terminate as well. If the mutual fund was mainly responsible for information incorporation into stock prices, then we could erroneously conclude that it was hedge fund's disappearance which caused stock price informativeness to decline. I address this concern with the following steps. First, I check what the most common reasons for hedge fund closures are and control for them in the analysis. Second, I examine fundamental characteristics of treated firms around hedge fund closures and show that they are comparable with the control sample. Finally, I check what happens with other institutional investors after hedge funds' terminations to make sure that the effect is driven by hedge fund closures.

Another potential threat is that terminating hedge funds might be different from the average hedge fund. For instance, hedge fund managers with low skill should be more likely to close down. This selection issue should bias the results compared with those that could be obtained in an ideal experiment with an average hedge fund. Although I cannot fully

[5]This 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)

eliminate this issue, there are two reasons why it is not a major concern. First, all closed hedge funds in my sample are relatively large (they filed forms 13F at least once) and existed for more than 5 years on average. It seems unlikely that hedge fund managers with low skill can attain such scale (Berk and Green (2004)). Second, this bias should decrease the magnitude of the results. For example, if a hedge fund manager did not trade on information, then I should find no effect on stock price informativeness after hedge fund closure. This means that if I find a significant effect (and I do), then it is an estimate from below of the true impact of the average hedge fund termination.

Furthermore, there is no identical firm B' which can be used as a counterfactual to firm B. To circumvent this issue, I find a comparable firm $\tilde{B}$ which can be used instead (the details of the matching procedure are described later in section 3.5).

The next two potential threats are related to short positions. First, I cannot include firms in which a terminating hedge fund had short positions in the set of treated firms since short positions are not required to be reported in forms 13F. The bias this introduces has clear direction for some variables. 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 should underestimate the average impact of hedge funds on stock price informativeness.

Similarly, it is possible that a treated firm is matched with a control firm that is itself shorted by a closing hedge fund. This should also lead to an underestimation of the effect: a difference-in-differences comparison might detect no impact of hedge fund closures if both treated and control firms' stock characteristics are affected in a similar way by hedge fund terminations. 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.[6] Furthermore, I address this concern by employing a portfolio of control firms as a benchmark.

[6]See footnote 2 for details.

3 Data

I start with a description of how I identify closed hedge funds. The filters used to construct the sample of closed hedge funds are summarized in Table 1 Panel A. Then I clarify which stocks are selected as treated stocks. The corresponding steps are summed up in Table 1 Panels B and C. Next, I describe other data sources used for this paper. Table 5 summarizes the construction of all variables used in further analysis. Finally, I describe the matching procedure.

3.1 Identification of the closed hedge funds

First, I 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.[7] At the beginning I check whether an entity submitted at least one form ADV.[8] 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.[9] Otherwise, I use Google and Factiva to determine whether an

[7]The main difference between the outlined procedure and the one described in Brunnermeier and Nagel (2004) is accounting of private funds. SEC started to demand more information on private funds following the implementation of 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: (a) it uses information related to the whole business of an entity (both private and non-private funds are taken into account), and (b) it can be applied to Exempt Reporting Advisers (ERA) – a group of investment advisers that doesn't submit information about its advisory business in part 1A item 5 of forms ADV.

[8]I find 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 forms 13F (before June 2013). I then manually link CIK with CRD using entity's name and address on IAPD website (https://adviserinfo.sec.gov). CRD are entity identifiers in forms ADV (part 1A item 1 question E) and forms ADV-W (item 1 question C) available at SEC website (https://www.sec.gov/foia/docs/form-adv-archive-data.htm).

[9]By way of illustration, suppose that an entity submitted its first form ADV on March 1st, 2010, the second form ADV on March 11th, 2010, and a form ADV-W for termination of registration with SEC on March 26th, 2010. Suppose that the first form ADV identifies an entity as a hedge fund while the second form ADV does not. Then, an entity was a hedge fund for 10 days (between the first and the second forms ADV) and was not a hedge fund for 15 days (between the second form ADV and the form ADV-W) implying that, on average, an entity was not a hedge fund.
If an entity did not submit a form ADV-W, then its latest form ADV is assumed to last for the median number of days between any two consecutive forms ADV submitted by one entity. Moreover, in order to reduce the impact of outliers, all forms ADV are winsorized to last no longer than 365 days.

entity was called a "hedge fund" in 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 (a) it is not a "fund of funds", and (b) its type is a "hedge fund".[10] Non-private fund's assets are considered to be related to hedge fund activity if (a) the majority of an entity's clients consists of either high net worth individuals or pooled investment vehicles, and (b) an entity charges performance-based fees.[11]

Second, I identify hedge funds that closed not later than two quarters after submitting their last forms 13F. I define closures as situations when hedge funds fully or partially terminate their trading activity.[12] I searched for evidence of closures in the following sources: (a) media articles (via Google and Factiva),[13] (b) forms ADV-W,[14] (c) notes in forms 13F,[15] and (d) LinkedIn.[16] I keep hedge fund closures that happened close to the last submitted forms 13F to make sure that I have reliable information on which stocks hedge funds traded

[10]Information about private funds is reported in Schedule D Section 7.B.(1) part A. Question 8 asks whether a private fund is a "fund of funds". Question 10 asks to specify the type of a private fund. Question 11 asks to report gross asset value of a private fund.

[11]Information about an entity's advisory business is reported in Part 1A Item 5. Question D asks about an entity's clients (this question asks about clients of *non-private* funds after Dodd-Frank Act was implemented). Question E asks about compensation arrangements. An entity charges performance-based fees if it ticks E(6) or mentions 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.

[12]A hedge fund fully terminates if it liquidates its entire portfolio and stops all job contracts. Examples of partial terminations included in the sample: (1) a hedge fund returns outside capital and becomes a family office, and (2) an entity manages several hedge funds before it decides to close some of them. I do not include cases when hedge funds closed because they were acquired. The decision to liquidate stocks can be driven by fundamental reasons in these cases.

[13]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, 27Sep2012)

[14]Each entity reports why it terminates registration with SEC in Item 2 question B. The reason should be related to the closure of an entity (e.g., *"No longer in business or closing business"*).

[15]An example of a relevant note in a 13F form: *"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 30Sep2013)

[16]I count a situation when (i) a hedge fund stops to submit forms 13F when it should not, (ii) its key employees simultaneously switch jobs, and (iii) there is no evidence of a merger as a closure. According to rule 13f-1(a)(1) of the Securities Exchange Act, an institutional investor who files forms 13F can stop doing it only in the third quarter of a year. I use Schedule A of forms ADV and media articles for identification of key employees (e.g., CIO) of hedge funds. I then use LinkedIn to track their job changes.

before termination.

Third, a hedge fund should liquidate at least 75% of its portfolio when closing.[17] This condition filters out partial closures with small changes in hedge funds' portfolios.[18] I remove such closures because of two concerns related to these cases: (a) operational activity likely remains unaffected, and (b) the assets to be liquidated are chosen by the manager. My focus on the liquidation of (almost) entire portfolio mitigates concerns that it was driven by unobservable firm-specific factors.

Fourth, I check that at least 50% of control over a terminating hedge fund belongs to its employees.[19] If a closing hedge fund is a subsidiary, then its termination might marginally affect operating activity of a parent firm and the treated stocks as a result.

Finally, a terminating hedge fund should have filed at least six forms 13F before closure. This filter is necessary for identification of treated stocks with long-term interest by closed hedge funds.

The final sample consists of 327 hedge funds which closed between 2000 and 2020.[20] Table 2 summarizes the distribution of closures in time. Figure 1 illustrates several observations from Table 2. First, hedge fund closures are dispersed in time (the bar chart in the left graph). For example, the financial crisis of 2008-2009 accounts for 41 closures that correspond to roughly 13% of the sample. This feature is a benefit since it mitigates concerns that findings are attributed to a specific time period.

Second, the number of closed hedge funds in the sample grows over time. Two reasons contribute to this pattern. The first reason is the growth pattern of the whole hedge fund industry: it grew rapidly before 2008, and then its growth slowed down (the green squares in

[17] I first search for the fraction of a portfolio which is liquidated in media articles (see an example in footnote 18). If such information is not available, I look at changes in total values of forms 13F after closure.

[18] 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, 26Jul2011)

[19] I collect this information from Schedule A in forms ADV for entities which are registered with SEC. I check media articles for other entities.

[20] There are few hedge fund closures in the sample in 2020 because I finished data collection in early 2020.

the lower graph). Combined with almost constant attrition rate before and after the financial crisis of 2008-2009 (the blue triangles in the lower graph), the total number of closed hedge funds increased over time.[21] The second reason is better detection of hedge fund closures after 2011 using forms ADV-W.

Table 3 Panel A summarizes some properties of the closed hedge funds. An average (median) hedge fund reports 535 (180) $ mln in the last form 13F before closure. It has open positions in 46 (18) stocks that jointly represent 58.2% (63%) of the reported portfolio. Its first form 13F was submitted 25 (20) quarters ago implying that a hedge fund existed for at least 6 (5) years before termination. 22% of the closed hedge funds had filed at least one form 13D. The second part of Panel A presents the estimates of the duration model that is described in Appendix section 6.1. The model reveals that closed hedge funds have different investment horizons: the average duration of an open position ranges from 2.1 quarters for the 10$^{\text{th}}$ percentile to almost 11 quarters for the 90$^{\text{th}}$ percentile.

The first column of Table 4 shows the evolution of the reported total values in forms 13F around closures. Overall, the closed hedge funds shrank before deciding to terminate. The average total value in forms 13F drops on 39% (=[535-877]/877) over a year before closure. This decrease is quite smooth: the average hedge fund loses 12.4% (=[768-877]/877), 8.6% (=[702-768]/768), 12.8% (=[612-702]/702), and 12.6% (=[535-612]/612) in the quarters preceding the decision to cease operations.The last two columns of Table 4 suggest that closed hedge funds don't change their investment strategies before ceasing operations. The fraction of equities in the shrinking portfolios of closed hedge funds remains the same over a year before liquidation as is the dollar-weighted average liquidity of the equity portfolios.

Closed hedge funds liquidate their portfolios pretty quickly according to Table 4. Around 86% (=[74-535]/535) of the total value is liquidated over one quarter. Approximately 70% of closed hedge funds either report zero total values or did not submit the next form 13F after closure.

[21] The same patterns appear in Hedge Fund Research data which tracks all hedge funds and funds of hedge funds (Table 2 section *Hedge Fund Research* columns *All* and *Attrition*).

3.2 Why do hedge funds close?

3.2.1 Reported reasons

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

I checked 120 hedge fund closures so far (33% of the sample). I found at least one reason for closure for 60 cases (50% of the checked subsample).[22] Three dominant reasons for terminations are: (a) personal reasons,[23] (b) worsening market conditions,[24] and (c) poor performance.[25] The last two reasons are usually mentioned together with losses and investor redemptions. This is consistent with contraction of closed hedge funds' assets reported in Table 4.

3.2.2 Unreported reasons: Selection based on skill

The slowing growth of the number of hedge funds in Figure 1 suggests that competition in the industry intensifies over time. Tougher competition makes it harder for hedge fund managers to attract investors' capital and erases profitable investment opportunities. As a result, hedge fund managers with low skill should be squeezed out of the market.

I check whether there is evidence for the selection story by examining the profitability of closed hedge funds' long-term portfolios after closure.

[22] I contacted 121 former hedge fund employees from 64 hedge funds for which (a) I failed to find relevant information in media articles, and (b) I found employees who worked at the time the closure took place. I got replies from 14 former hedge fund employees (13 closed hedge funds).

[23] An example: *"We have taken the decision to return investors' funds and go private ... we are keen for the investment flexibility that running our own money will deliver."* Randel Freeman from Centaurus Capital (Reuters, 2May2013). Retirement of partners and desire to spend more time with family are other reasons from this group.

[24] See footnote 5 for an example of a sudden market-wide shock. This category also includes closures caused by changes in regulation (Dodd-Frank act) and increased competition in hedge fund industry.

[25] For instance, *"Hedge fund Three Bays Capital plans to shutter after years of weak performance"* (Bloomberg, 31Oct2018)

3.3 Identification of the treated stocks

I next apply three filters to stocks in closed hedge funds' portfolios. First, I focus on stocks in which closed hedge funds had a long-term interest. That is, a treated stock should appear in at least three of the last four forms 13F before a hedge fund's closure. This condition guarantees that a closed hedge fund followed a stock over several quarters before closure. This condition creates a time period where the parallel trends assumption should hold.

Unfortunately, this filter removes roughly half of the sample because closed hedge funds have relatively high turnover.[26] However, this is a necessary evil. Regretfully, I don't know whether closed hedge funds paid attention to a particular stock unless it was mentioned in their 13F form. I require the stock to appear in multiple forms 13F to be sure that the closed hedge fund traded this stock for a relatively long time period before closure.

Next, I exclude stocks that were ever mentioned in 13D forms filed by closed hedge funds. This condition removes activism as the channel through which closed hedge funds could affect characteristics of the treated stocks.

Finally, I remove stocks with large weight (more than 20%) in portfolios of closed hedge funds to ensure that a hedge fund's decision to close is not driven by poor behavior of several influential stocks in their portfolios.

Row *% treated* in Table 3 Panel A shows that closed hedge funds are differently affected by the above filters. This is likely because of different trading strategies that hedge funds pursued. Yet almost all closed hedge funds remain in the sample, implying that they had long-term interest in a subset of stocks in their portfolios.

Table 6 clarifies how closed hedge funds accumulated positions in treated stocks before termination. Roughly 37% (=100%-63%) of treated stocks were not reported in forms 13F by closed hedge funds a year before closure. This number drops to 9% (=100%-91%) half a year before closure and stays on this level. The size of the position gradually grows until

[26] Almost 30% of stocks that were reported in the last forms 13F before closures were not reported in any of the previous three forms 13F.

reaching the peak half a year before closure based both on the mean (*Cum. position*) and the median (*p50*) estimates. The difference in the size of the position over the last two quarters before closure is quite modest (up to 20% based on the median estimate). This evidence suggests that the first phase (accumulation) finishes on average two quarters before closure.

At the same time, there is a sharp drop in holdings during the first quarter after closure. Approximately 90% of treated stocks disappear from 13F forms of closed hedge funds and the average position size drops on 85%. This evidence supports conclusion from Table **??** that liquidations occur mostly within one quarter.

Another important observation from Table 6 is that closed hedge funds did not passively hold treated stocks before closure (the difference in percentiles would be small if this was the case). Together with evidence of high turnover reported earlier, this indicates that there was noticeable trading activity within quarters by closed hedge funds.

There are cases with at least two hedge funds closing in the same quarter and holding the same treated stock. Since I cannot disentangle the effect of each closing hedge fund on the treated stock without additional assumptions, I therefore aggregate the holdings of closed hedge funds across treated stocks (step 0 in Table 1 Panel C). Next, I remove stocks with missing data in at least one quarter in the event window.

The goal of the final filter is to identify treated stocks for which the effect from hedge fund closures is expected to be the most pronounced. I use the average size of the position in a treated stock over a year before closure as a measure of impact that hedge fund closure should have on a stock.

Strictly speaking, this filter is not essential. Its obvious drawback is decline of power of tests because of decreased sample size. However, reduction of the final sample with an increased focus on the treatment from closed hedge funds is beneficial for the following two reasons. First, it mechanically fleshes out the contribution of closed hedge funds, thus increasing the power of tests. Second, it increases the pool of control firms for matching. I find that this filter improves the balance between treatment and control groups, and thus the credibility of the obtained results.

Several properties of the selected treated stocks are presented in Table 3 Panel B. They are mostly held by one closing hedge fund before its termination (mean = 1.09, median = 1). The average (median) size of the position in the last quarter before closure is 0.95% (0.47%) of shares outstanding. In terms of the relative impact, terminating hedge funds constitute roughly 8% of all hedge fund holdings in treated stocks.

3.4 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 13F forms is obtained from Thomson Reuters s34 Master File (before 2013Q2) and WRDS SEC 13F Holdings Data (starting from 2013Q2).[27] 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 from the website of Kenneth R. French.[28] Proxies of algorithmic trading are constructed using Market Information Data Analytics System (MIDAS).

Table 5 summarizes key variables.

3.5 Matching

As discussed, a matching procedure is required to identify control firms for the treated firms (in the absence of a true counterfactual). I match on a set of ten characteristics that can affect information production and trading activity of market participants to make sure that treated and control firms are comparable. I next motivate the need for inclusion of these

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

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

controls. Table 5 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)).

Performance controls are: (3) return of a stock over a year before hedge fund closure ($AnnBHRet$), and (4) return of a stock over a quarter before hedge fund closure ($QtrBHRet$). It is crucial to control for stock returns because poor hedge fund performance is one of the main reasons for hedge fund closures. I control for stock returns in the long-run (one year) and in the short-run (one quarter) to ensure that I capture poor stock performance that might be (partially) responsible for hedge fund closures.

Liquidity control is: (5) 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: (6) 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: (7) hedge fund ownership (HF_{ann}), (8) aggregate short interest ($ShInt_{ann}$), (9) mutual fund ownership (MF_{ann}), and (10) number of equity analysts who follow a stock ($Analyst_{ann}$). The first two variables control for hedge fund 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.[29] The activity of short-sellers is associated with more efficient stock prices (Boehmer and Wu (2013)) as is the activity of all institutional investors in general (Boehmer and Kelley (2009)). Equity analysts collect and analyse public information, their presence increases the informativeness of stock prices (Bennett et al. (2020), Chen et al. (2020)).

[29]Hedge funds accounted for 85% of total shorting volume in 2009 according to the "Hedge fund trend monitor" report by Goldman Sachs.

Except for three matching characteristics (two stock return proxies and idiosyncratic volatility), all variables are estimated as medians over at least three quarters before hedge fund closures. This approach mitigates issues related to mean reversion of matched controls that can be confused with the treatment effect.

There are several restrictions on firms to be selected in the pool of control firms. First, a control firm should have data on all matching characteristics. Second, closing hedge funds should not hold more than 0.2% of the control firm's outstanding shares in any of the last two quarters before closure. This condition ensures that control firms are exposed to marginal treatment (if any) from closed hedge funds.

I construct a counterfactual to every treated firm in the following way. First, I make all matching characteristics comparable with each other and across time. I normalize each matching characteristic by subtracting its median and dividing on its interquartile range quarter by quarter using all firms with data available on all matching characteristics. Second, I determine the distance between each treated and all suitable control firms using the Euclidean distance in the space of normalized matching characteristics. Finally, every treated firm is paired with a synthetic portfolio of the nearest 16 control firms (the details are provided in the Appendix in section 6.2). It is possible that the same control firm appears in matched portfolios of different treated firms. I take this into account by aggregating weights of control stocks from portfolios of different treated firms before clustering standard errors at the firm level (the details are provided in the Appendix section 6.3).

3.6 Information revelation on earnings announcements

I use earnings announcements as a laboratory for studying the contribution of hedge funds to stock price informativeness. These events have several properties that are helpful for identification. First, earnings announcements are scheduled and relatively frequent 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 which was revealed to the market on the earnings announcement day. If hedge funds can 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.[30] Moreover, 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 smaller post-earnings announcement drift.

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 larger than 5 days. For those earnings announcements 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 60 calendar days before the earnings announcement. I keep the latest earnings forecast if an analyst made several forecasts before the announcement. Let $e_{t,k}$ be the earnings per share announced in quarter t for company k and $\hat{e}_{t,k}$ be the consensus forecast for company k for this quarter. The earnings surprise $s_{t,k}$ is:

$$s_{t,k} = \frac{e_{t,k} - \hat{e}_{t,k}}{P_{t,k}}$$

where $P_{t,k}$ is the price of the shares of company k 5 trading days before the announcement in quarter t. All variables are split-adjusted.

I next divide all earnings announcements into 11 bins based on earnings surprise quarter by quarter. The intermediate bin (#6) contains all earnings announcements with zero surprise. All positive surprises are split into 5 equal groups and numbered from #7 (small positive surprise) to #11 (large positive surprise). Similarly, all negative surprises are split into 5 equal groups and numbered from #1 (large negative surprise) to #5 (small negative surprise). I then match each treated stock with the closest 10 neighbours based on the set

[30] Although managers are not allowed to give privileged access to information to institutional investors after Regulation Fair Disclosure, there are other sources of information that can be used for predicting future earnings. For example, satellite images of parking lots can signal about the flow of customers.

of 13 matching characteristics conditionally on each control stock being located in the same surprise bin. This sample is later used for analysis of the contribution of hedge funds to stock price informativeness.

4 Results

I first present evidence that closed hedge funds indeed liquidated their positions in the treated stocks. These results are followed by a discussion of who replaces closed hedge funds. I then explore what happens with stock price informativeness and liquidity after hedge funds' terminations. Finally, I run an exogeneity test. The goal of the test is to provide support for the assumption that the decision to terminate a hedge fund was not driven by differential fundamental characteristics of the treated and control firms.

4.1 Evidence of the treatment

I now present direct evidence of the treatment. Since 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 7 shows that this is indeed the case. There is a significant drop in hedge fund ownership and the total number of hedge funds in the first quarter after a terminating hedge fund disappeared. Hedge fund ownership of the treated stocks falls, on average, on 0.58% of total shares outstanding by the end of the first quarter (roughly 5% of the overall hedge fund holdings). The drop in holdings persists to the second quarter, then it starts to recover. The difference in hedge fund holdings of the treated and control firms becomes insignificant three quarters after hedge fund closures. Meanwhile, the number of hedge funds does not recover even six quarters following hedge fund terminations.

The evidence presented so far does not guarantee that closed hedge funds liquidated their positions in the treated stocks: closed hedge funds are not required to file forms 13F if they turned into family offices. This would incorrectly show up as a decrease in reported holdings. For this reason, I provide additional evidence that is consistent with closed hedge funds selling stocks in their portfolios.

If terminating hedge funds indeed liquidate their holdings, then they should induce price pressure on the treated stocks. Figure 2 confirms this hypothesis. Stock returns of the treated firms are on average 2% smaller by the end of the second month after terminating hedge funds filed their last forms 13F. This suggests that terminating hedge funds start to liquidate their portfolios immediately after filing their last forms 13F.

The figure also shows that this drop in stock prices fully recovers by the end of the fourth month after closing hedge funds filed their last forms 13F. This implies that the price impact from hedge fund closures is temporary. Therefore, it seems unlikely that closing hedge funds liquidated their holdings because of privately collected negative information about the treated stocks.

4.2 Who replaces closed hedge funds?

Given that hedge funds liquidate their holdings before closure, somebody should buy shares of the closed hedge funds. It is important to understand who replaces closed hedge funds for correct interpretation of further results.

Table 7 provides evidence that other hedge funds partially replace closed hedge funds. The total hedge fund holdings of the treated stocks fall on average on 0.58% of shares outstanding relative to control stocks while closed hedge funds liquidate approximately 0.80% of shares outstanding in the first quarter. Thus, 0.22% of shares outstanding (= 0.80% - 0.58%, or roughly 28% of the 0.80% that are liquidated) go to other hedge funds. This evidence is consistent with Aragon and Strahan (2012) and Jylhä et al. (2014) who find that hedge funds are liquidity providers.

It turns out that mutual funds do not replace closed hedge funds, as is shown in the Table 8. On average, there is no significant increase in mutual fund holdings after hedge fund closures (model (1), column *Const*). Moreover, the change in mutual fund holdings of the treated firms does not depend on the average size of the position which hedge funds liquidated (model (1), column HF_{Hold}). There is also no change in the shorting activity. This implies that hedge fund closures are not anticipated by short-sellers.

Since there is a large fraction of the position that is liquidated and which goes neither to other hedge funds nor to mutual funds, I hypothesize that investors who get these shares are less sophisticated compared to closed hedge funds. Consistent with this hypothesis, Table 9 shows that there is a drop in algorithmic trading after hedge fund closures. $Trade{-}to{-}Order$ increases more for treated firms in which closing hedge funds had larger positions before closure (column HF_{Hold} in both models). Interestingly, treated stocks with large hedge fund holdings before closure experience a marginally larger increase in $Trade - to - Order$ than treated stocks with small hedge fund holdings if comparing the average over quarters 1, 2, 3 to the average over a year before hedge fund closures (HF_{Hold} = 1.71, t-stat = 1.64). This means that some of the effect persists after hedge funds liquidated their portfolios. A similar effect is apparent for $Cancel - to - Trade$ ratio. The rate of cancellations drops more for the treated stocks with larger hedge fund holdings before closure. This effect continues beyond the first quarter when hedge funds liquidated their portfolios.

4.3 Impact on stock price informativeness

I now explore how hedge funds contribute to information incorporation around earnings announcements. The next three subsections test whether hedge funds affect the pre-earnings announcement drift, information incorporation during earnings announcement, and the post-earnings announcement drift, respectively. In each subsection I split all earnings surprise bins into three groups based on the magnitude of the surprise. The group with bins #1–#3 contains large negative earnings surprises. The group #4–#8 mixes small negative surprises, zero surprises, and small positive earnings surprises. Finally, the group #9–#11 contains large positive earnings surprises.

I next evaluate whether sensitivity to earnings surprises changes for treated stocks after hedge fund closures. Effectively, I conduct the difference-in-difference-in-differences analysis: I check whether the difference in returns of the treated stocks from two different surprise groups changes compared to the corresponding difference of returns of control stocks when comparing quarters before and after hedge fund closures.

4.3.1 Pre-earnings announcement drift

Table 10 examines whether there is any difference in how treated and control stocks react to earnings surprises before and after hedge fund liquidations. The right part of the table shows that there is no differential reaction of treated and control stocks to future earnings surprises. In other words, this implies that pre-earnings announcement drift of the treated stocks is not affected by hedge fund closures.

4.3.2 Earnings announcement days

Table 11 checks whether treated stocks behave differently compared to control stocks on earnings announcement days before and after hedge fund closures.

There are two important findings. First, there is significant change in reactions of the treated and control stocks to news in quarter 0. This is exactly the quarter when hedge funds liquidate their positions. Although the returns of the treated stocks fall relative to control stocks in all surprise groups, the difference between earnings surprise groups is not significant. This supports the assumption that hedge fund closures are not driven by fundamental characteristics of firms.

Second, treated stocks become less sensitive to negative earnings surprises in the first quarter after hedge fund closures. In other words, the treated stocks experience a milder drop compared to control stocks when both are exposed to earnings surprises of the same magnitude. This effect is pronounced only in the first quarter after hedge fund closures. It suggests that investors who replace closed hedge funds trade on negative information to a smaller extent. This is consistent with hedge funds being most valuable for correcting overpricing rather than underpricing.

4.3.3 Post-earnings announcement drift

Finally, Table 12 shows results related to treated and control stocks' sensitivity to earnings surprises after earnings announcements. Overall, there are no significant differences between treated and control stocks when comparing different surprise groups before and after hedge fund closures. The absence of post-earnings announcement drift in my sample is consistent with Martineau (2021).

To sum up, the analysis suggests that the largest contribution of hedge funds is related to incorporation of negative surprises into stock prices during earnings announcement days.

4.4 Impact on stock liquidity

I now check what happens to liquidity after hedge fund terminations. First, I use two price impact measures: $OCAM$ (a modification of the illiquidity measure introduced by Amihud (2002), and which Barardehi et al. (2021) show is better at explaining the cross-section of stock returns) and price impact estimated using TAQ data.[31] Both of these measures are proxies of Kyle's lambda (Kyle (1985)).

Table 13 shows some evidence in favor of adverse selection theories. There is a significant drop in $OCAM$ at q=1 (which might be driven by larger increase of the trading volume compared to the change in daily returns) which persists in the next quarters (albeit not being statistically significant). $PriceImpact$ shows a similar pattern, but there the improvement is stronger for treated firms with larger hedge fund holdings before closure in the second quarter. This might reflect the market learning about hedge fund closures.

The obtained findings complement those of Peress and Schmidt (2019). In their paper, the disappearance of noise traders (uninformed investors) leads to worse liquidity. In my

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

setting, the disappearance of hedge funds (informed traders) leads to better liquidity.

4.5 Exogeneity test

In general, it is plausible that hedge fund closures in my sample are strategic: hedge fund managers could have decided to close funds in anticipation of bad news about stocks in their portfolios. If this is the case, then treated stocks should have worse fundamentals than control stocks following hedge fund liquidations.

I check this hypothesis by comparing profitability of treated and control stocks after hedge fund liquidations. Table 14 shows the results of the difference-in-differences analysis applied to firms' profitability. The analysis reveals that there are no significant changes in profitability of treated stocks relative to control stocks around hedge fund terminations. Together with the absence of differential stock price reaction of treated and control firms after hedge fund closures, this evidence is not consistent with hedge fund managers strategically closing hedge funds.

5 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 closures as a quasi-natural experiment. Consistent with the general perception of hedge funds as sophisticated investors and adverse selection theories, I find that stock prices become less efficient and liquidity improves following hedge fund terminations. More specifically, I show that stock prices react less to negative information on earnings announcement days and that intraday measures of price impact drop after hedge fund closures.

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6 Appendix

6.1 Duration analysis

I develop a simple duration model in this section. The goal of the model is to find the expected duration of open positions in case a hedge fund remains open.

Let l denote the duration of an open position. Suppose that the probability of a position remaining open in the next quarter conditional on it being open in the current quarter is:

$$Pr(l \geq k+1 | l \geq k) = \begin{cases} p_k, & k \in \{1, 2, ..., s-1\} \\ p, & k \geq s \end{cases}$$

The index k denotes the current duration of an open position; s indicates the start of the "tail" - the conditional survival probability for positions that are open for at least s quarters.

Given this structure, the probability of having an open position for n consecutive periods is equal to:

$$Pr(l = n) = \begin{cases} \left(\prod_{i=1}^{n-1} p_i\right)(1-p_n), & n \in \{1, 2, ..., s-1\} \\ \left(\prod_{i=1}^{s-1} p_i\right) p^{n-s}(1-p), & n \geq s \end{cases}$$

If the position is observed for m periods, but is censored at the start or at the end of the sample, then the probability of observing a position for at least m periods is:

$$Pr(l \geq m) = \begin{cases} \prod_{i=1}^{m-1} p_i, & m \in \{1, 2, ..., s-1\} \\ \left(\prod_{i=1}^{s-1} p_i\right) p^{m-s}, & m \geq s \end{cases}$$

Suppose that there is a sample of $\{N_k\}_{k=1}^{s-1}$ closed positions with corresponding lengths $l = k$ and N closed positions with lengths $\{l_i\}_{i=1}^{N}$ being at least equal to s. In addition, there are $\{M_k\}_{k=1}^{s-1}$ censored positions with observed lengths $l = k$ and M censored positions with lengths $\{l_j\}_{j=1}^{M}$ being at least equal to s. The sample is obtained from portfolio holdings of a hedge fund over T quarters. The likelihood function for this sample is:

$$
\begin{aligned}
L\left(\{p_k\}_{k=1}^{s-1}, p\right) = \prod_{q=1}^{s-1} \left\{ \left[\left(\prod_{i=1}^{q-1} p_i \right) (1-p_q) \right]^{N_q} \left[\prod_{i=1}^{q-1} p_i \right]^{M_q} \right\} \times \\
\times \prod_{j=1}^{N} \left\{ \left(\prod_{i=1}^{s-1} p_i \right) p^{l_j - s}(1-p) \right\} \times \prod_{j=1}^{M} \left\{ \left(\prod_{i=1}^{s-1} p_i \right) p^{l_j - s} \right\} = \\
= \left(\prod_{i=1}^{s-2} p_i^{\sum_{q=i+1}^{s-1}(N_q+M_q)+N+M} (1-p_i)^{N_i} \right) \left[p_{s-1}^{N+M} (1-p_{s-1})^{N_{s-1}} \right] \times \\
\times p^{\sum_{j=1}^{N} l_j + \sum_{j=1}^{M} l_j - s(N+M)} (1-p)^N
\end{aligned}
$$

Maximization of the log-likelihood function determines the optimal probabilities:

$$
\begin{aligned}
p_k &= \frac{\sum_{q=k+1}^{s-1}(N_q+M_q)+N+M}{N_k + \sum_{q=k+1}^{s-1}(N_q+M_q)+N+M}, \; k \in \{1, ..., s-2\} \\
p_{s-1} &= \frac{N+M}{N_{s-1}+N+M} \\
p &= \frac{\sum_{i=1}^{N} l_i + \sum_{j=1}^{M} l_j - s(N+M)}{N + \sum_{i=1}^{N} l_i + \sum_{j=1}^{M} l_j - s(N+M)}
\end{aligned}
$$

Intuition for the obtained estimates is straightforward. Each estimate $\{p_k\}_{k=1}^{s-1}$ is the number of positions that survived for $k+1$ quarters to the number of positions that survived for k quarters. The estimate p is the probability of survival when all positions with duration of at least s quarters are pooled together.

Finally, the expected continuation of a censored position of length m is estimated recursively:

$$
\mathbb{E}\left[l-m|l \geq m\right] = \begin{cases} \frac{p}{1-p}, & m \geq s \\ p_m \Big(1 + \mathbb{E}\left[l-m-1|l \geq m+1\right]\Big), & m \in \{1, ..., s-1\} \end{cases}
$$

The only free parameter in the model is s - the quarter starting from which the conditional probability of a position staying open becomes fixed. This parameter is chosen for each hedge fund separately. The choice of s is driven by data availability issues: there might be no positions for estimation of p_{s-1} for large values of s. Therefore, I determine s in a way that controls that there is sufficient number of observations for estimation of conditional survival probabilities. I start with $s = 1$. Then, at a step $s = k$ I check that there are at least 30 observations for estimation of both p_s and p if s is increased to $s = k + 1$. If this is the case, then s is increased. The algorithm stops if there are not enough observations for estimation of conditional probabilities for larger values of s or if s hits $T - 3$.

The model can give an estimate $\hat{p}$ that translates into the expected continuation of a censored position that is larger than the estimation period T. For instance, this can happen if a hedge fund with stable portfolio composition is observed for a relatively short period of time. In this case, I winsorize the average continuation of positions to T and determine $\hat{p}$ from a reversed formula for the expected continuation:

$$\hat{p} = \frac{T}{1 + T}$$

6.2 Matching algorithm

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

6.2.1 Preparations before matching

I normalize each matching characteristic by subtracting its median value and dividing on its interquartile range quarter by quarter to make all matching characteristics comparable with each other and across time. Then, for every treated firm I rank all suitable control firms from the nearest to the furthest using the Euclidean distance measure (overlap in control firms across treated firms is allowed). Weights for each matched control firm are determined further.

6.2.2 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 firms. Control firms are numbered by index c from 1 (the closest) to C (the furthest). The treated firm has index $c = 0$.

Let's determine several objects:

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

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

The vector of weights w should solve 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 firm. Importantly, the weights of the control firms should be non-negative. If there exist several synthetic controls that solve this optimization problem, then the one with the closest control firms should be selected.

The formulated problem can't be solved analytically because of complementary slackness conditions on vector w. However, there exists a closed form solution to the simplified problem with no constraint on positive weights. I next find the solution to the simplified problem and explain how it is used for numerical identification of the solution to the full problem.

Let's 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:

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

Use the constraint to determine λ_0:

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

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 not optimal to 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 firms with non-negative weights that sum to one. If the treated firm does not belong to $\mathbb{S}$, then the optimal synthetic control is the closest point of $\mathbb{S}$ to the treated firm. In this case, construct a hyperplane which contains the optimal synthetic control and that is orthogonal to the vector that connects the treated firm and the optimal synthetic control. Each control firm will either be on this hyperplane or in the subspace that does not contain the treated firm. This separating feature of the hyperplane suggests how to search for the optimal synthetic control when the treated firm does not belong to $\mathbb{S}$.

The algorithm is the following: (0) select any control firm as the starting synthetic control, (1) build the hyperplane which contains the current synthetic control and that is orthogonal to the vector that connects the treated firm with the synthetic control, determine the location of all control firms relative to this hyperplane,[32] (2) if there are no control firms in the subspace with the treated firm, then the current synthetic control is optimal. Otherwise, add any of the control firms from the subspace with the treated firm 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 a combination of control firms that should be removed from the synthetic control so that all remaining control firms have positive weights and the distance between the new synthetic control and the treated firm is reduced.

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

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

control firm is also crucial for replication of the treated firm if a set of control firms with indices $c \in \{1, ..., 38, 50\}$ doesn't contain a synthetic control which replicates the treated firm.

6.2.3 Outer optimization procedure

6.2.4 Choice of the parameters for the matching algorithm

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

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

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

where index $q \in [q_{min}, q_{max}]$ covers all quarters with hedge fund closures, T_q is the number of treated stocks in quarter q. An associated pooled empirical CDF of control stocks is:

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

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. That is, all control stocks which are used in construction of synthetic controls are pooled together with the corresponding weights. The maximal distance between the two functions is a measure of balance for a matching

[33] I literally follow Ho et al. (2007) by trying to get the best possible 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."* Similar suggestion was offered by Rosenbaum (2020): *"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."*

characteristic k:

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

The aggregated measure, $KS = \sqrt{\sum_{k=1}^{K} KS_k^2}$, captures the overall balance. I set $C = 16$ for the final sample since it produces the lowest KS.

6.2.5 Discussion of the matching algorithm

At the end, I chose the matching algorithm that produced the best balance which I managed to get. Table 15 compares the obtained balance for different matching techniques. It shows how balance improved while moving to the final sample.

6.3 Difference-in-differences estimation with synthetic controls

I first describe the baseline approach how to estimate treatment effect for multiple treated units when they receive treatment simultaneously and when each treated unit is matched with potentially overlapping portfolios of control units. I next explain how I modify this approach to the setting of closed hedge funds.

Suppose that there are $T + C$ units indexed by u from 1 to $T + C$. The first T units are treated, they are additionally indexed by i from 1 to T. The remaining C units are not treated. These are control units indexed by j from 1 to C. Units exist in two time periods ($t \in \{0, 1\}$). All treated units receive treatment at $t = 1$, their values $Y_{i,t}$ are increased on D then. Control units are not affected by the treatment.

I assume that each unit receives treatment with a probability that is a continuous function of a set of unit characteristics X at $t = 0$. That is, two units with identical characteristics X are equally likely to receive treatment at $t = 1$. Since treated and control units in general have different characteristics X, it is important that treatment effect is estimated on similar units. This is where matching comes into play.

The role of matching is to get a sub-sample of control units that is comparable to the sample of treated units w.r.t. the set of characteristics X. Matching creates a matrix of size $T \times C$ with each cell containing weight $w_{i,j}$ of a control unit $j \in \{1, ..., C\}$ in a portfolio matched to a treated unit $i \in \{1, ..., T\}$. The sum of weights across all control units that correspond to a treated unit is normalized to one: $\sum_{j=1}^{C} w_{i,j} = 1$ for all $i \in \{1, ..., T\}$. I assume that matching produces a good balance between treated and control units so that there is no need for introduction of characteristics X as additional controls in the post-matching analysis.

The variable of interest Y of the units evolves according to the following equation:

$$Y_{u,t} = \alpha_u + \gamma_t + D\mathbf{1}_{u\in\{1,...,T\},t=1} + \epsilon_{u,t}$$

Unit and time fixed effects are captured by α_u and γ_t respectively. The variable $\mathbf{1}_{u\in\{1,...,T\},t=1}$ equals 1 for treated units at $t = 1$ and zero otherwise.

Treatment effect D can be estimated using the difference-in-differences method:

$$\hat{D} = \frac{1}{T}\sum_{i=1}^{T}\left[(Y_{i,1} - Y_{i,0}) - \sum_{j=1}^{C} w_{i,j}(Y_{j,1} - Y_{j,0})\right] =$$
$$= D + \frac{1}{T}\sum_{i=1}^{T}\left[(\epsilon_{i,1} - \epsilon_{i,0}) - \sum_{j=1}^{C} w_{i,j}(\epsilon_{j,1} - \epsilon_{j,0})\right]$$

Let's assume that $\epsilon_{i,t}$ are random variables with mean zero. In this case, the suggested estimate $\hat{D}$ is an unbiased estimate of D.

The standard deviation of $\hat{D}$ is necessary for testing the significance of the estimated effect. Bootstrap is the baseline approach when there is only one treated unit (Abadie (2021)). Generalizing to T treated units, an empirical distribution of $\hat{D}$ can be constructed by repeating the following procedure: (1) randomly choose T units from the pool of all $T + C$ units, (2) find new matching between the chosen units and the remaining units, and (3) estimate $\hat{D}_b$ for the constructed sample. Significance of the effect $\hat{D}$ can then be assessed using the empirical distribution of "placebo" estimates $\{\hat{D}_b\}_{b=1}^{B}$ for a relatively large B. Although this approach is simple and intuitive, it might be time consuming. Instead, I use an approach which is based on asymptotic distribution of $\hat{D}$ for estimation of its standard deviation.

I rewrite $\hat{D}$ in the following form:

$$\hat{D} = D + W^T \epsilon$$

where ϵ is the vector of all error terms and W is the vector of the corresponding weights. Then:

$$\mathbb{V}\left[\hat{D}\right] = W^T \mathbb{E}\left[\epsilon \epsilon^T\right] W = W^T \Omega W$$

where Ω is the covariance matrix of error terms. I assume that error terms can be correlated within units, so the co-variance matrix Ω is clustered on the unit level (i.e. $\mathbb{E}\left[\epsilon_{u_1,t_1}\epsilon_{u_2,t_2}\right] = 0$ for $u_1 \neq u_2$). The true matrix Ω is not observed, but it can be estimated using the following procedure: (1) subtract $\hat{D}$ from $Y_{i,1}$ of the treated firms, (2) regress $Y_{u,t}$ on unit and time fixed effects, (3) get residuals $\hat{\epsilon}_{u,t}$ from the regression as estimates of $\epsilon_{u,t}$, and (4) construct $\hat{\Omega}$ by replacing non-zero co-variance terms $\mathbb{E}\left[\epsilon_{u,t_1} \cdot \epsilon_{u,t_2}\right]$ in Ω with $\hat{\epsilon}_{u,t_1} \cdot \hat{\epsilon}_{u,t_2}$ for arbitrary u, t_1 and t_2. Although each estimate $\hat{\epsilon}_{u,t}$ is an inconsistent estimate of the corresponding error term $\epsilon_{u,t}$, the constructed estimate $\hat{\mathbb{V}}\left[\hat{D}\right] = W^T \hat{\Omega} W$ is a consistent estimate of $\mathbb{V}\left[\hat{D}\right]$ when T grows.

With an assumption that error terms $\epsilon_{u,t}$ are normally distributed random variables, the estimate $\hat{D}$ is also a normally distributed random variable with mean D and standard deviation $\sqrt{\mathbb{V}\left[\hat{D}\right]}$.[34] Under a null hypothesis that there is no effect ($D = 0$), the absolute value of the t-statistics for the observed effect $\frac{\hat{D}}{\sqrt{\hat{\mathbb{V}}[\hat{D}]}}$ should be below 1.96 at a 5% significance

[34]The introduced assumption can be replaced with a milder one that is based on the central limit theorem for identically distributed random variables.

level.

The introduced baseline approach should be modified because hedge funds closed in different time periods. I solve this caveat by stacking quarters with hedge fund closures like in the event study. In addition, it will be useful to have (a) several time periods after the treatment to capture the evolution of the treatment effect, and (b) several time periods before the treatment to test for parallel trends. These changes lead to the final model:

$$Y_{u,q} = \alpha_u + \gamma_q + \sum_{\tau=q_{min}, \tau\neq 0}^{q_{max}} D_\tau \mathbf{1}_{u\in\{1,\dots,T\}, q=\tau} + \epsilon_{u,q}$$

where u stands for the unit index and q indexes event quarters of the study ($q \in [q_{min}, q_{max}]$); $q = 0$ corresponds to the last event quarter before hedge fund closures).

The treatment effect D_τ is then estimated as the average difference-in-difference estimate over all treated units in the event window. Standard deviation of $\hat{D}_\tau$ is estimated as was described before with Ω being clustered on the unit level.

Panel A. Closed hedge funds in the sample

	Filter description	# obs	% change
0.	Initial sample of mgrno from Thomson Reuters s34 Master File	9 198	
1.	An entity is a hedge fund	2 416	-73.7%
2.	A hedge fund terminates not later than two quarters after filing its last 13F form	427	-82.3%
3.	A closing hedge fund liquidates at least 75% of its portfolio	405	-5.2%
4.	At least 50% of control over a hedge fund belongs to its employees	382	-5.7%
5.	There are at least six 13F forms before closure	327	-16.8%

Panel B. Treated stocks in portfolios of closed hedge funds

	Filter description	# obs	% change
0.	Initial sample of closed hedge fund - stock pairs from the last 13F forms before termination	14 859	
1.	A stock is followed for at least three quarters before closure	7 633	-48.6%
2.	A stock is expected to stay in a hedge fund's portfolio for at least 3 more quarters on average	6 940	-9.1%
3.	There is no evidence of activism by a closed hedge fund in a stock	6 916	-0.3%
4.	The maximum weight of a stock in hedge fund's portfolio over a year before closure is at most 20%	6 779	-2.0%

Panel C. Treated stocks in the sample

	Filter description	# obs	% change
0.	Initial sample of treated stock - quarter pairs	6 420	
1.	Closures take place between 1999Q4 and 2019Q2	6 274	-2.3%
2.	There is data on matching characteristics in each quarter over a year before hedge fund closures	5 821	-7.2%
3.	The maximal position of closed hedge funds in a stock over a year before closure is at least 0.2% of shares outstanding	1 588	-72.7%

Table 1: Filters for identification of the treated stocks

Panel A shows filters that lead to the final sample of closed hedge funds. Panel B summarizes steps for identification of the treated stocks in portfolios of closed hedge funds. Panel C 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 percent of observations that are removed by a filter.

	Sample					Hedge Fund Research		
Year	Closed	Left 13F	Closed (%)	All 13F	Left 13F (%)	Closed	All	Attrition
2000	0	14	0.0	244	5.7	-	-	-
2001	2	25	8.0	301	8.3	-	-	-
2002	5	27	18.5	293	9.2	300	4 457	6.7
2003	2	40	5.0	375	10.7	238	5 379	4.4
2004	7	18	38.9	450	4.0	267	6 297	4.2
2005	7	41	17.1	563	7.3	848	7 436	11.4
2006	9	46	19.6	668	6.9	717	8 661	8.3
2007	7	46	15.2	788	5.8	563	9 462	6.0
2008	24	143	16.8	901	15.9	1 471	10 096	14.6
2009	17	159	10.7	827	19.2	1 023	9 284	11.0
2010	16	61	26.2	756	8.1	743	9 045	8.2
2011	9	67	13.4	833	8.0	775	9 237	8.4
2012	31	97	32.0	884	11.0	873	9 575	9.1
2013	19	84	22.6	908	9.3	904	9 810	9.2
2014	18	69	26.1	1 007	6.9	864	9 966	8.7
2015	29	102	28.4	1 094	9.3	979	10 142	9.7
2016	28	128	21.9	1 111	11.5	1 057	10 131	10.4
2017	29	91	31.9	1 099	8.3	784	9 803	8.0
2018	41	91	45.1	1 132	8.0	659	9 754	6.8
2019	23	104	22.1	1 175	8.9	738	9 656	7.6
2020	4	193	2.1	1 191	16.2	770	9 398	8.2
Avg	15.6	78.4	20.1	790	9.4	767	9 068	8.5

Table 2: Distribution of hedge fund closures in time

The *Sample* section is based on Thomson Reuters s34 Master File: *Closed* shows the distribution of 327 hedge fund closures in time; *Left 13F* shows the number of hedge funds that filed forms 13F at the end of the previous year but did not file forms 13F at the end of the current year; *Closed (%)* is the fraction of *Closed* to *Left 13F*; *All 13F* is the total number of hedge funds at the beginning of the current year; *Left 13F (%)* is the fraction of *Left 13F* to *All 13F*. The *Hedge Fund Research* section contains information on the whole hedge fund industry: *Closed* shows the total number of hedge funds and funds of hedge funds that closed in a particular year; *All* shows the total number of hedge funds and funds of hedge funds at the beginning of a year; *Attrition* is the fraction of *Closed* to *All*. The *Avg* row shows the average of the *Sample* (*Hedge Fund Research*) section from 2000 (2002) till 2020.

Panel A. Properties of the closed hedge funds

	Mean	St.Dev.	p10	p25	p50	p75	p90
Size	535	1 115	46	100	180	432	1 178
# stocks	45.7	124	3	9	18	32	75
% equity	58.2	27.5	16	41	63	80	91
Age	25.2	17.5	8	11	20	36	50
13D	0.22	0.41	0	0	0	0	1
s	4.7	3.5	1	2	4	6	8
p_1	62.1	17.1	43	50	60	74	86
p_2	73.6	13.4	58	68	74	83	89
p_3	74.9	13.9	57	69	76	85	91
p_4	77.2	13.6	61	73	80	86	91
p	79.1	14.4	62	74	82	89	94
Horizon	5.5	4.6	2.1	2.9	3.9	6.3	10.7

Panel B. Properties of the treated stocks

	Mean	St.Dev.	p10	p25	p50	p75	p90
# closed HF	1.08	0.29	1	1	1	1	1
% owned	0.87	1.53	0.07	0.15	0.34	0.85	2.11
Days to sell	3.92	16.8	0.06	0.16	0.43	1.20	4.70
% of all HF	7.76	13.3	0.59	1.26	3.14	8.21	19.0

Table 3: Properties of the final sample of closed hedge funds and treated stocks

Panel A reports properties of 327 closed hedge funds from the final sample. *Size* is the total value reported in the last forms 13F before closure ($ mln). *# stocks* represents the number of assets with CRSP share codes 10 or 11 in the last forms 13F before closure. *% equity* represents the percent of total value that comes from assets with CRSP share codes 10 and 11 in the last forms 13F before closure. *Age* is one plus the number of quarters between the first and the last reported forms 13F. *13D* is a binary variable which equals one if a hedge fund filed form 13D at least once and zero otherwise. s, p_1, p_2, p_3, p_4, and p are the estimates of the duration model (Appendix section 6.1). s is the quarter starting from which the conditional survival probability is assumed to be constant (p). p_1 (p_2, p_3, p_4) is the probability of a position that is open for one (two, three, four) quarter(s) to remain open in the next quarter (in percent). *Horizon* is the expected duration of an open position of a closed hedge fund based on the model.

Panel B reports properties of 1 588 treated stocks from the final sample. *# closed HF* shows how many closed hedge funds held a treated stock in the last quarter before closure. *% owned* presents the percent of treated stock shares owned by closed hedge funds in the last quarter before closure. *Days to sell* is the fraction of stock holdings of closed hedge funds in the last quarter before closure to the median daily trading volume estimated over a year before closure (winsorized at 1%). *% of all HF* is the fraction of stock holdings of closed hedge funds in the last quarter before closure to stock holdings of all hedge funds in this quarter (multiplied by 100).

	13F value		# stocks		% equity		Liquidity	
Quarter	Mean	Median	Mean	Median	Mean	Median	Mean	Median
-5	894	326	57	23	59	64	1.05	0.96
-4	877	328	55	23	60	63	1.04	0.94
-3	768	313	53	21	65	64	1.05	0.95
-2	702	279	51	20	58	63	1.05	0.93
-1	612	228	52	19	57	60	1.05	0.96
0	535	180	46	18	58	63	1.06	0.92
1	74	0	5	0	-	-	-	-
2	13	0	1	0	-	-	-	-

Table 4: Dynamics of hedge fund characteristics around closures

The table shows the dynamics of several hedge fund characteristics around terminations of 327 closed hedge funds. *Quarter* is the quarter relative to the last quarter before closure. *13F value* shows the mean and the median total value from 13F forms (in $ mln). # *stocks* displays the mean and the median number of assets with CRSP share codes 10 and 11 in 13F forms. % *equity* is the mean and the median percent of total 13F value that comes from assets with CRSP share codes 10 and 11. *Liquidity* shows the mean and the median position-weighted average liquidity of stocks in hedge funds' portfolios. Liquidity is proxied by the median daily relative trading volume estimated over a year that ends in the current quarter. Relative trading volume is the percent of shares outstanding that is traded during a day.

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
$AnnBHR$	Buy-and-hold stock returns calculated over (-4, 0].	CRSP
$QtrBHR$	Buy-and-hold stock returns calculated over (-1, 0].	CRSP
$TrVol_{ann}$	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
$ShInt_{ann}$	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
$Profit$	Operating income after depreciation ($OIADPQ$) scaled by the average total assets (ATQ) over the latest four quarters	Compustat
HF	Ownership of hedge funds which file forms 13F as a fraction of total shares outstanding	CRSP, TR 13F, WRDS 13F
HF_{num}	Number of hedge funds	TR 13F, WRDS 13F
IO	Ownership of all investors which file forms 13F as a fraction of total shares outstanding	CRSP, TR 13F, WRDS 13F

Table 5: 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 2013Q2). WRDS 13F means WRDS SEC Analytics Suite 13F Holdings File (it is used starting from 2013Q2). FF stands for the Fama-French factors from the website of Kenneth R. French.

Quarter	% own	Cum. position	p10	p25	p50	p75	p90
-5	54	0.85	0	0	0.3	1.6	4.3
-4	63	0.95	0	0	0.7	1.9	4.7
-3	77	1.04	0	0.1	1	2.2	4.8
-2	91	1.17	0.1	0.7	1.2	2.3	5.3
-1	91	1.12	0.1	0.7	1.1	1.8	3.6
0	100	1	1	1	1	1	1
1	10	0.15	0	0	0	0	0
2	1	0.02	0	0	0	0	0

Table 6: Distribution of the relative position in treated stocks around closures

The table shows the distribution of the relative positions of closing hedge funds which submitted forms 13F at least 6 times before closure in 7 039 treated stocks. *Quarter* displays the quarter relative to the last quarter before closure. *% own* shows the percent of treated stocks which were reported in forms 13F. *Cum. position* shows the fraction of the cumulative stock ownership across all closing hedge funds to the cumulative stock ownership across closing hedge funds in the last quarter before closure. Column *pN* presents percentile *N* of the distribution of the fractions of the stock ownership to the stock ownership in the last quarter before closure across closing hedge funds.

Qtr	HF	$\ln(HF)$	HF_{num}
-3	0.16	0.00	-0.58*
	(0.73)	(0.00)	(-1.80)
-2	-0.05	-0.58	-0.07
	(-0.28)	(-0.47)	(-0.25)
-1	-0.10	-0.55	-0.32
	(-0.81)	(-0.61)	(-1.37)
1	-0.58***	-5.13***	-0.91***
	(-4.77)	(-5.14)	(-3.72)
2	-0.80***	-6.22***	-1.29***
	(-4.43)	(-4.30)	(-4.01)
3	-0.55**	-4.87***	-0.87**
	(-2.43)	(-2.82)	(-2.51)
4	-0.38	-3.02	-0.77*
	(-1.48)	(-1.49)	(-1.92)
5	-0.11	-0.41	-0.85**
	(-0.39)	(-0.19)	(-2.06)
6	0.06	2.02	-0.98**
	(0.21)	(0.86)	(-2.24)
Obs	988	988	988

Table 7: Results for direct evidence of the treatment

This table shows difference-in-differences analysis applied to the treated firms and the corresponding portfolios of control firms. *Qtr* is the event quarter relative to the last quarter before hedge funds' terminations. HF is the percent of shares outstanding which are cumulatively held by all hedge funds at the end of the quarter. HF_{num} is the number of hedge funds that mentioned the stock in their forms 13F at the end of the quarter. The coefficient of $\ln(HF)$ is multiplied by 100. *Obs* shows the number of treated stocks in the analysis. t-statistics with stock clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

	MF		$ShortInt$	
Qtr	$Const$	HF_{Hold}	$Const$	HF_{Hold}
-3	-0.13	-0.01	0.28*	-0.23*
	(-0.63)	(-0.04)	(1.84)	(-1.74)
-2	-0.17	-0.00	0.16	-0.15
	(-1.06)	(-0.03)	(1.22)	(-1.52)
-1	-0.07	0.01	0.12	-0.04
	(-0.64)	(0.15)	(1.54)	(-0.65)
1	-0.04	-0.03	-0.01	-0.03
	(-0.35)	(-0.39)	(-0.07)	(-0.51)
2	-0.00	0.08	-0.09	-0.10
	(-0.03)	(0.67)	(-0.69)	(-0.79)
3	-0.06	0.21	-0.14	-0.10
	(-0.27)	(1.35)	(-0.84)	(-0.70)
4	-0.09	0.09	-0.12	-0.04
	(-0.34)	(0.53)	(-0.60)	(-0.29)
5	-0.19	0.26	-0.00	0.01
	(-0.63)	(1.30)	(-0.02)	(0.08)
6	-0.31	0.28	0.10	0.05
	(-0.95)	(1.29)	(0.47)	(0.27)
Obs	988		988	

Table 8: Results on replacement of closed hedge funds

This table shows difference-in-differences analysis applied to the treated firms and the corresponding portfolios of control firms. *Qtr* is the event quarter relative to the last quarter before hedge funds' terminations. The treatment effect is considered to be a linear function of the demeaned percent of shares outstanding that closing hedge funds held in the treated firms in the last quarter before closure (HF_{Hold}). MF is the percent of shares outstanding cumulatively held by all mutual funds at the end of the quarter. $ShortInt$ is the average percent of shares outstanding that are cumulatively shorted in the quarter. *Obs* shows the number of treated stocks in the analysis. t-statistics with stock clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

	$Trade-to-Order$				$Cancel-to-Trade$			
	(1)		(2)		(1)		(2)	
Qtr	$Const$	HF_{Hold}	$Const$	HF_{Hold}	$Const$	HF_{Hold}	$Const$	HF_{Hold}
-3	0.51	0.46			-1.22	0.26		
	(0.36)	(0.36)			(-0.91)	(0.21)		
-2	-0.23	-0.03			-0.74	-0.21		
	(-0.19)	(-0.04)			(-0.65)	(-0.23)		
-1	0.01	0.15			0.05	0.04		
	(0.02)	(0.23)			(0.05)	(0.05)		
1	1.36	1.93**	1.28	1.79*	-1.49	-2.23**	-1.01	-2.25**
	(1.36)	(1.98)	(1.16)	(1.72)	(-1.30)	(-2.16)	(-0.83)	(-2.12)
2	0.30	1.77	0.22	1.62	0.67	-1.88	1.14	-1.90
	(0.25)	(1.45)	(0.18)	(1.35)	(0.51)	(-1.36)	(0.88)	(-1.42)
3	0.80	1.86	0.73	1.71	0.63	-2.16	1.11	-2.18*
	(0.55)	(1.26)	(0.48)	(1.30)	(0.43)	(-1.46)	(0.75)	(-1.65)
4	2.15	1.11	2.08	0.96	-0.67	-2.40	-0.19	-2.42*
	(1.30)	(0.72)	(1.22)	(0.69)	(-0.41)	(-1.48)	(-0.12)	(-1.67)
5	1.85	1.20	1.78	1.05	-0.36	-2.22	0.12	-2.25
	(1.00)	(0.75)	(0.96)	(0.74)	(-0.20)	(-1.31)	(0.07)	(-1.54)
6	2.37	1.57	2.30	1.43	-1.11	-2.38	-0.63	-2.40
	(1.24)	(0.92)	(1.21)	(0.91)	(-0.62)	(-1.35)	(-0.37)	(-1.55)
Obs	575		575		575		575	

Table 9: Results on algorithmic trading around hedge fund closures

This table shows difference-in-differences analysis applied to the treated stocks and the corresponding portfolios of control stocks. Qtr is the event quarter relative to the last quarter before hedge funds' terminations. The treatment effect is considered to be a linear function of demeaned average hedge fund holdings in the treated stocks before closure (HF_{Hold}). Model (1) uses the last quarter before hedge fund closures for comparison (quarter 0). Model (2) uses the average over the last year before hedge fund closures for comparison (quarters -3, -2, -1, and 0). $Trade-to-Order$ is the logarithm of the fraction of the total volume traded to the total volume ordered. $Cancel-to-Trade$ is the logarithm of the fraction of cancelled orders to executed trades. Obs shows the number of treated stocks in the analysis. t-statistics with stock clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

Qtr	Bottom #1 − #3	Middle #4 − #8	Top #9 − #11	M vs B	T vs M	T vs B
-3, -2, -1	0.91	0.53	0.02			
	(0.74)	(0.90)	(0.04)			
0	-2.38	-1.05	-1.33	1.71	0.23	1.93
	(-1.24)	(-1.05)	(-1.23)	(0.76)	(0.14)	(0.79)
1	0.20	0.68	-1.36	0.85	-1.53	-0.67
	(0.09)	(0.71)	(-1.30)	(0.35)	(-1.01)	(-0.26)
2	2.25	-0.41	0.98	-2.28	1.89	-0.39
	(1.12)	(-0.42)	(0.90)	(-0.93)	(1.15)	(-0.15)
3, 4	0.18	0.61	-0.94	0.80	-1.04	-0.24
	(0.11)	(1.00)	(-1.17)	(0.41)	(-0.82)	(-0.11)
5, 6	-0.05	-0.47	0.23	-0.04	1.21	1.17
	(-0.03)	(-0.73)	(0.26)	(-0.02)	(0.91)	(0.55)

Table 10: Information incorporation before earnings announcements

This table shows the aggregated differences in cumulative abnormal returns of the treated and control stocks which are located in the same surprise bin from day -60 to day -1 relative to the earnings announcement day. Bins #1–#3 (#4–#8, #9–#11) contain negative (zero, positive) earnings surprises. t-statistics with stock-clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

Qtr	Bottom #1 − #3	Middle #4 − #8	Top #9 − #11	M vs B	T vs M	T vs B
-3, -2, -1	0.75*	0.38	0.07			
	(1.55)	(1.37)	(0.28)			
0	-0.81	0.15	-1.24***	1.33	-1.10	0.23
	(-1.05)	(0.36)	(-2.74)	(1.42)	(-1.63)	(0.24)
1	2.28***	-0.62	0.01	-2.54**	0.94	-1.60
	(2.78)	(-1.30)	(0.02)	(-2.54)	(1.34)	(-1.59)
2	-0.27	-0.72	-0.05	-0.08	0.97	0.89
	(-0.31)	(-1.52)	(-0.12)	(-0.07)	(1.31)	(0.81)
3, 4	0.42	0.59**	-0.42	0.54	-0.70	-0.17
	(0.71)	(2.12)	(-1.24)	(0.66)	(-1.26)	(-0.20)
5, 6	0.63	0.00	0.02	-0.26	0.28	0.02
	(1.14)	(0.01)	(0.06)	(-0.34)	(0.49)	(0.03)

Table 11: Information incorporation during earnings announcements

This table shows the aggregated differences in cumulative abnormal returns of the treated and control stocks which are located in the same surprise bin on the earnings announcement day. Bins #1–#3 (#4–#8, #9–#11) contain negative (zero, positive) earnings surprises. t-statistics with stock-clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

Qtr	Bottom #1 – #3	Middle #4 – #8	Top #9 – #11	M vs B	T vs M	T vs B
-3, -2, -1	0.34	-0.30	0.15			
	(0.29)	(-0.46)	(0.25)			
0	-0.58	-1.21	-0.34	0.01	0.42	0.42
	(-0.26)	(-1.28)	(-0.33)	(0.00)	(0.27)	(0.17)
1	2.95*	-0.47	-1.17	-2.78	-1.15	-3.93
	(1.65)	(-0.47)	(-1.06)	(-1.22)	(-0.66)	(-1.60)
2	1.65	-2.31**	-0.34	-3.32	1.51	-1.81
	(0.78)	(-2.16)	(-0.29)	(-1.36)	(0.82)	(-0.72)
3, 4	0.36	0.35	0.62	0.63	-0.18	0.45
	(0.24)	(0.56)	(0.79)	(0.33)	(-0.14)	(0.22)
5, 6	-1.62	-1.48*	-0.10	0.78	0.93	1.71
	(-1.15)	(-1.87)	(-0.11)	(0.40)	(0.67)	(0.89)

Table 12: Information incorporation after earnings announcements

This table shows the aggregated differences in cumulative abnormal returns of the treated and control stocks which are located in the same surprise bin from day 1 to day 60 relative to the earnings announcement day. Bins #1–#3 (#4–#8, #9–#11) contain negative (zero, positive) earnings surprises. t-statistics with stock-clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

	ln($OCAM$)				ln($PriceImpact$)			
	(1)		(2)		(1)		(2)	
Qtr	$Const$	HF_{Hold}	$Const$	HF_{Hold}	$Const$	HF_{Hold}	$Const$	HF_{Hold}
-3	1.86	-0.35			-1.19	0.08		
	(0.80)	(-0.15)			(-0.78)	(0.07)		
-2	0.09	-0.87			0.20	0.06		
	(0.05)	(-0.49)			(0.16)	(0.07)		
-1	-1.08	-0.17			0.86	-0.29		
	(-0.83)	(-0.17)			(0.86)	(-0.41)		
1	-3.59***	-1.59	-4.11**	-1.61	-2.59**	-1.20	-2.56**	-1.16
	(-2.54)	(-1.16)	(-2.39)	(-1.08)	(-2.31)	(-1.49)	(-2.04)	(-1.40)
2	-1.67	-1.53	-2.12	-1.36	-1.23	-2.42**	-1.20	-2.39**
	(-0.75)	(-0.59)	(-0.93)	(-0.65)	(-0.76)	(-2.31)	(-0.71)	(-2.14)
3	-1.58	1.24	-2.13	-1.16	-0.66	-1.36	-0.62	-1.33
	(-0.62)	(-0.43)	(-0.85)	(-0.53)	(-0.36)	(-1.22)	(-0.34)	(-1.14)
4	-1.41	0.26	-1.84	0.38	-1.03	-1.00	-1.00	-0.97
	(-0.48)	(0.08)	(-0.66)	(0.16)	(-0.54)	(-0.86)	(-0.51)	(-0.81)
5	-3.32	-1.37	-3.81	-1.14	-0.07	-0.68	-0.04	-0.64
	(-1.03)	(-0.43)	(-1.23)	(-0.44)	(-0.03)	(-0.59)	(-0.02)	(-0.52)
6	-4.23	-1.78	-4.83	-1.64	-0.92	-0.83	-0.89	-0.79
	(-1.20)	(-0.56)	(-1.43)	(-0.63)	(-0.44)	(-0.66)	(-0.43)	(-0.65)
Obs	988		988		457		457	

Table 13: Results on price impact proxies around hedge fund closures

This table shows difference-in-differences analysis applied to the treated firms and the corresponding portfolios of control firms. *Qtr* is the event quarter relative to the last quarter before hedge funds' terminations. The treatment effect is considered to be a linear function of demeaned average hedge fund holdings in the treated firms before closure (HF_{Hold}). Model (1) uses the last quarter before hedge fund closures for comparison (quarter 0). Model (2) uses the average over the last year before hedge fund closures for comparison (quarters -3, -2, -1, and 0). $OCAM$ equals to the average daily stock return (from open to close) which are driven by 1$ of trading volume. *PriceImpact* is the average daily price impact estimated using TAQ data over 5-minute intervals. *Obs* shows the number of treated stocks in the analysis. t-statistics with stock clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

Qtr	$Profit$
-3	-0.14*
	(-1.77)
-2	-0.07
	(-0.89)
-1	-0.03
	(-0.42)
1	0.05
	(0.72)
2	0.03
	(0.31)
3	0.02
	(0.29)
4	0.06
	(0.74)
5	0.16
	(1.61)
6	0.18*
	(1.70)
Obs	988

Table 14: Results for the exogeneity test

This table shows difference-in-differences analysis applied to profitability of the treated firms and the corresponding control firms. *Qtr* is the event quarter relative to the last quarter before hedge funds' terminations. *Obs* shows the number of treated firms in the analysis. t-statistics with firm clustered standard errors are in parentheses. *, **, and *** correspond to 10%, 5%, and 1% significance levels respectively.

	No matching			1:1 with repl.			Synthetic			Final		
Name	Mean	VR	CDF	Mean	VR	CDF	Mean	VR	CDF	Mean	VR	CDF
MC_{ann}	128	5.4	**15**	-9.0	1.0	**7.7**	-4.5	1.1	**6.6**	0.4	1.1	3.9
BM_{ann}	9.8	1.3	**10**	0.4	0.8	**7.4**	1.7	0.9	4.4	-0.1	0.9	3.6
$AnnBHRet$	-11	0.9	**5.8**	-7.1	0.7	5.0	-5.3	0.8	2.3	-0.1	0.9	2.6
$QtrBHRet$	8.4	1.2	5.4	0.1	0.8	3.5	1.1	1.0	2.2	0.3	1.0	2.5
$TrVol_{ann}$	-70	0.5	**30**	-21	0.7	**8.3**	-16	0.8	**6.2**	-1.4	0.9	3.9
$IVOL_{ann}$	-2.8	1.6	**13**	-5.2	0.9	4.8	-1.8	1.0	4.4	0.3	1.0	1.8
HF_{ann}	-87	0.6	**42**	-22	0.9	**9.7**	-19	1.0	**9.3**	-1.0	1.1	3.5
$ShInt_{ann}$	-40	0.7	**19**	-7.7	0.9	3.6	-2.8	1.0	2.3	0.3	1.0	2.4
MF_{ann}	-21	1.4	**16**	-1.0	0.9	3.2	-2.9	1.1	3.6	-1.0	1.0	2.2
$Analyst_{ann}$	-29	0.9	**20**	-9.3	0.8	**6.9**	-6.7	0.9	**5.6**	0.1	0.9	3.0

Table 15: Balance for different matching techniques

The table shows the obtained balance after applying different matching techniques. There are four matching techniques: (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 closest control stock), (3) *Synthetic* (each treated stock is matched with the nearest synthetic portfolio built from 16 closest control stocks), and (4) *Final* (it is *Synthetic* matching technique which is additionally modified in a way that attempts to equalize mean values of the distributions of treated and control stocks in each quarter). Euclidean distance in the space of normalized matching characteristics is used. Matching characteristics are normalized in each quarter on the corresponding interquartile range which is estimated based on all stocks with available data. *Mean* is the difference in means of the distributions of normalized matching characteristics for treated and control 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. Values which are larger than 5.5 are highlighted (CDF of treated and control stocks are different at 10% based on Kolmogorov-Smirnov test for two samples with 988 observations).

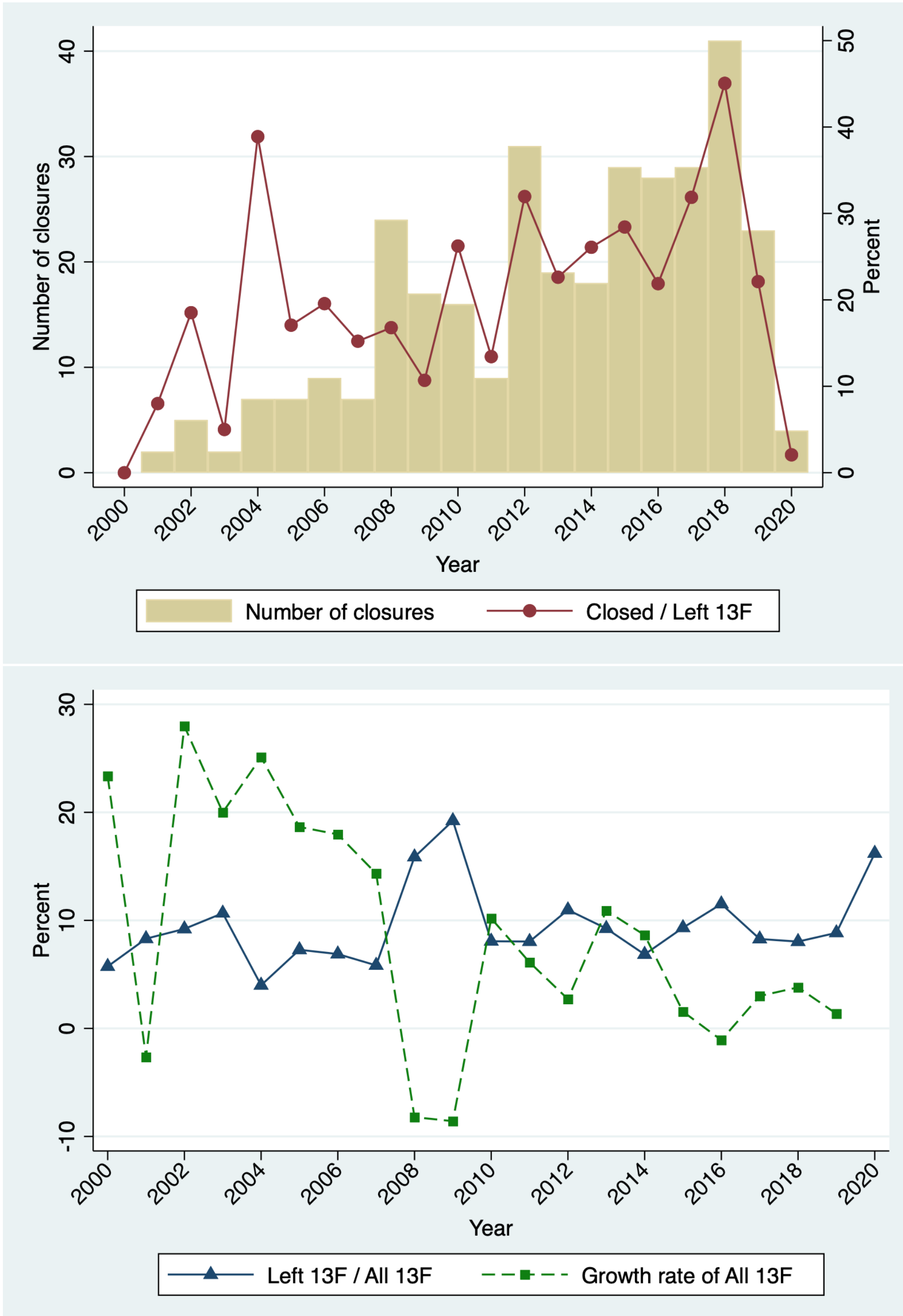

Figure 1: Distribution of hedge fund closures in time

All graphs are built from Table 2 *Sample* section. The first graph: bar chart shows the distribution of closed hedge funds in time (column *Closed*); red circles show the fraction of closed hedge funds to the total number of hedge funds that disappeared from Thomson Reuters s34 Master File during a year (column *Closed (%)*). The second graph: blue triangles represent the fraction of the total number of hedge funds that disappeared during a year to the total number of hedge funds at the beginning of a year (column *Left 13F (%)*); green squares show the percentage change of the total number of hedge funds per year (constructed from column *All 13F*).

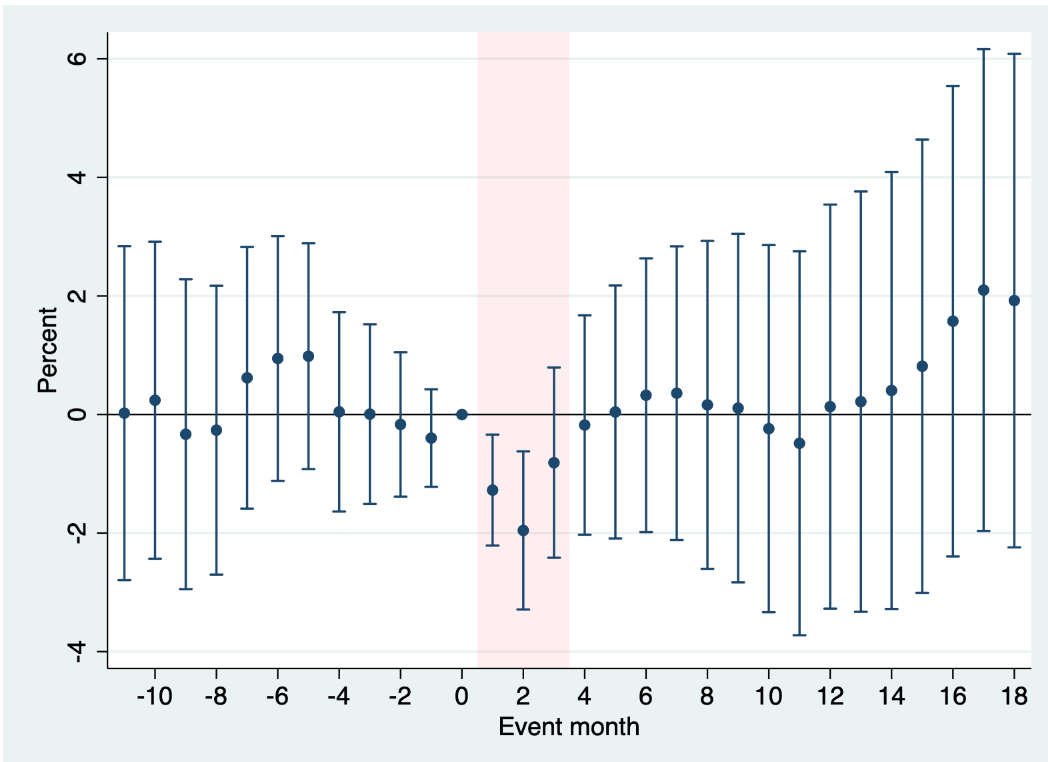

Figure 2: Difference-in-differences analysis for cumulative stock returns

The graph shows the difference-in-differences analysis applied to cumulative abnormal stock returns of the treated and control firms. Abnormal returns are estimated relative to a 6-factor asset pricing model (Fama-French 5 factor model and momentum). The coefficients of the asset pricing model are estimated over a three-year interval before the event window. Abnormal returns are accumulated starting from one year before hedge fund closures. The red area highlights the first three months after closed hedge funds filed their last forms 13F. 95% confidence intervals are constructed using stock clustered standard errors.