Brokers and Order Flow Leakage: Evidence from Fire Sales[1]

Andrea Barbon Marco Di Maggio Francesco Franzoni Augustin Landier

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Abstract

Using trade-level data, we study whether brokers play a role in spreading order flow information in the stock market. We focus on large portfolio liquidations, resulting in temporary price drops and identify the brokers that intermediate these trades. These brokers' best clients predate on the liquidating funds: they first sell their holdings in the liquidated stocks, and then cover their positions once asset prices recover. This strategy increases the best clients' returns by about 32 basis points over ten days and increases by 50% the liquidation costs for the distressed fund. This evidence suggests a role of information leakage in exacerbating fire sales and raises a red flag for regulators.

[1] Barbon: USI Lugano and Swiss Finance Institute (email: andrea.barbon@usi.ch); Di Maggio: Harvard Business School and NBER (email: mdimaggio@hbs.edu); Franzoni: USI Lugano and Swiss Finance Institute (email: francesco.franzoni@usi.ch); Landier: Toulouse School of Economics (email: augustin.landier@tse-fr.eu). We thank Malcolm Baker, John Campbell, Laurent Frésard, Slava Fos (discussant), Joel Hasbrouck, Terry Hendershott (discussant), Gary Gorton, Owen Lamont, Jongsub Lee (discussant), Andrew Lo, Toby Moskowitz, Abhiroop Mukherjee (discussant), Erik Stafford, and seminar/conference participants at Aalto University, the Becker Friedman Institute CITE conference on New Quantitative Models of Financial Markets, Bocconi University, EIEF, FCA, FINRA Market Structure conference, FIRS, LAEF 2nd OTC Markets and Securities Workshop, INSEAD, Macro-Prudential Conference ECB, New York Federal Reserve Bank, AQR, UC Dublin, WFA for helpful comments.

1 Introduction

Large institutional orders are typically split in smaller amounts over time to avoid market-impact (see Garleanu and Pedersen, 2013, Di Mascio et al., 2016). One concern when executing an order slowly over time is that other traders might anticipate the intent to trade the stock in the near future and take advantage by trading in the same direction to benefit from the future price impact. This problem is particularly pronounced in the case of fire sales, during which the seller is forced to bring to the market a large quantity of assets in a limited amount of time (Coval and Stafford, 2007; Ellul, Jotikasthira, and Lundblad, 2011). Price impact from fire sales can in turn generate a cascade effect potentially leading to systemic instability (Greenwood, Landier, and Thesmar, 2015).

Predatory trading has strong theoretical support (Brunnermeier and Pedersen, 2005) and is borne out by anecdotal evidence. For example, during the unwinding of LTCM's portfolio in 1998, the fund's typical trading and lending counterparties, which were privy to its portfolio positions, also sold the same assets. Given that predatory trading can make the market more illiquid at times of crisis and amplify adverse shocks, some observers suggest that reducing the frequency of portfolio disclosure can be desirable (Brunnermeier and Pedersen, 2005). Accordingly, hedge funds support regulations that limit the granularity of their reporting (IAFE, 2001).

One wonders, however, if restricting the diffusion of public information is a sufficient measure to prevent predatory behavior. In fact, the anecdotal evidence mentioned above suggests that market participants possess information about forced liquidations thanks to their close relationship with the liquidating managers. Among all actors in the market, brokers are in the privileged position of observing the daily trades of a fund. In the case of hedge funds, prime brokers operate also as lenders and risk managers, so that they are aware whether the fund is about to breach some risk limit and deleverage its portfolio. They can also observe the trading habits of their clients, such as whether they tend to cut trades in small orders over several days when executing a large order. In sum, brokers are in a privileged position to predict the future trades of their clients.

Brokers may decide to spread the news that a client's large trade is likely to extend over time to other traders. They may have an incentive to do so in order to establish a reputation as a source of valuable information and attract new business. On the other hand, brokers may care about the long-term relationship with their clients. Hence, brokers may be reluctant to foster predatory trading against a client. Rather, according to this argument, they should invite other traders to provide liquidity and take the other side of the slow trade. It remains, therefore, an open empirical question whether brokers foster predatory trading or liquidity provision in case of slow trading by a client. The paper aims to address this question.

Forced liquidations of portfolio holdings offer an ideal setting to investigate these issues. Other traders, if made aware of the liquidation, can exploit these opportunities to sell the same assets in anticipation of the price drop and reverse the trade once the price has fallen. This opportunistic behavior makes liquidations more costly for the liquidating manager because it exacerbates the adverse price move. We decide to focus on large liquidations (which we label "fire sales" for convenience), and do not include large purchases in our analysis, because we aim to have a clean identification of liquidity-motivated trades. First, in our data, the majority of institutional investors are long-only (about 90%). Hence, it is somewhat less likely for a sale to be information motivated (as the manager would need to have the stock already in the portfolio) than for a buy transaction. Second, large cash inflows can be allocated slowly over time and are, therefore, less likely to impose a concentrated liquidity demand on the market than large outflows. Moreover, fire sales can pose a systemic threat if they cause a propagation of idiosyncratic shocks to the balance sheets of other investors. Hence, studying the effect of information leakage on fire sales is especially relevant, including from the regulatory perspective.

We exploit proprietary trade-level data and focus on asset managers that sell a significant fraction of their portfolio during a relatively short amount of time. We restrict attention to asset managers whose order flow is abnormally negative for at least five days in a row. Moreover, we focus on managers that liquidate multiple stocks (on average about 20 stocks) at a significantly faster pace than usual. We identify about four hundred of these events in the period between 1999 and 2014. Because we are only interested in liquidations due to purely liquidity motives, such as the need to meet large redemptions, we verify that the stock price movements resulting from this sale are only temporary and that the asset managers do not buy back those stocks. Price impact would have to display a permanent component, if sales were motivated by fundamental reasons. Interestingly, controlling for the portfolio weights, we show that managers are more likely to sell large, liquid, and low-volatility stocks, as well as past winners. This evidence can inform the theoretical debate on optimal liquidation policy (e.g. Scholes 2000, Brown, Carlin, and Lobo 2010).

Our empirical strategy takes advantage of two key sources of variation. First, not all brokers employed by the liquidating fund are going to be aware that the fund is in distress. The liquidating fund has little incentive to disclose its intention to liquidate a large fraction of its portfolio; in fact, it is likely to use multiple brokers to minimize price impact and info leakage. Hence, only brokers that observe a large enough order flow are deemed *aware*. Second, we should not expect all traders to predate; in fact, brokers are likely to selectively disclose the order flow information to maximize their rents.

Our first result is that there is a significantly higher probability of predatory behavior for orders executed through aware brokers. Specifically, the clients of the aware brokers are much more likely to execute sell trades in the same stocks with the same broker over the same period. We also show that the clients of the aware brokers are not only more likely to sell the same stocks of the liquidating funds, but also sell a higher volume in those stocks.

Next, we explore the heterogeneity across the different clients of the aware brokers. If the brokers are spreading information about order flow, they are more likely to do so with their best clients, from which the brokers can extract the highest rents. As a proxy for the strength of the investor-broker relation, we use the trading volume and the commissions generated by a client.[1] Our baseline specification focuses on an event window starting ten days before the beginning of the fire sale up to five days afterwards. We control for time, manager, event, stock, and broker

[1] We show that these relations are extremely persistent, consistent with the findings in Goldstein, Irvine, Kandel, and Wiener (2009), corroborating the hypothesis that brokers might have an incentive to nurture such relations.

fixed effects. Hence, differences across stocks, such as their liquidity, or across brokers, such as their ability to execute, cannot explain our results.[2]

The main result of this analysis is that the best clients of the aware brokers are significantly more likely than other clients to sell the stocks that the liquidating manager is offloading *during* the fire sale with respect to immediately before the fire sale. Additionally, extending the analysis to all brokers, we find this effect to be present only among aware brokers. The results are also economically significant, in fact, on average the best clients of the aware brokers are about 50% more likely to follow a predatory strategy.[3]

Then, we test whether the same asset managers that are predating during the fires are also likely to cover their positions by repurchasing the stock in the following days. Consistent with this hypothesis, we find that a significant fraction of their positions, ranging from 30% to 42%, are covered in the five days following the fire sale. This gives strong indication that these managers were motivated by the prospect of short-term gains at the expense of the liquidating fund.

One potential concern with our results is that fire sales might cluster in some periods and be correlated across funds. For instance, during the financial crisis most asset managers were trying to offload their positions in financial stocks. We address this concern in several ways. First, we show that our definition of fire sales leads to relatively short-term price reversals, rather than the prolonged asset prices swings that occurred during the crisis. In fact, our events are evenly distributed across time, showing only mild increases during the 2001 or the 2008-09 crises. Then, we also focus on events that are likely driven by funds' idiosyncratic shocks by excluding from our sample months in which there are more than ten different fire sales. In addition, our results are conditional on the predators executing their orders with the same broker that is employed by the liquidating fund, while a correlated response to a common shock would predict trades that are more diffuse across brokers. The evidence, therefore, corroborates the hypothesis of a *quid pro quo* between investors and brokers and points out an active role of the broker in leaking the news

[2] We also provide a specification in which we control for broker-manager relationship fixed effects, which controls for the matching between asset managers and brokers. These results are in the Internet Appendix.
[3] We also exploit the granularity of our data to corroborate our interpretation of the results by showing that the hedge funds, rather than the mutual funds or pension funds, are those for which the evidence of predation is most significant.

of a fire sale. Similarly, we provide an array of additional robustness checks to rule out the possibility that the originator of the fire sale and the followers are trading as a response to the same public news. For instance, we exclude from our sample all the events that occurred during recessions and show that the results are unaffected. We also exclude all events occurring around earning announcements, changes in analyst recommendations, or any other type of negative news as reported by the press and classified by Ravenpack.[4] We also exclude stocks with negative momentum and high short interest to address the concern that selling managers follow similar trading strategies founded on a negative view on the stock.

Another way to rule out the alternative hypothesis that the observed predatory trading is due to a reaction to stock-specific news is to look at the number of stocks involved in the fire sale that the best clients also sell. The idea is that if sales were motivated by stock-specific news or similar trading strategies, we should observe the best clients focusing on one or two stocks, whereas if they knew about the liquidation, it would be more profitable to prey on multiple stocks at the same time. Consistent with predatory behavior, we find that the best clients of the aware brokers are significantly more likely to sell a higher number and a higher fraction of stocks involved in the liquidation event.

To strengthen the identification of fire sale events, we focus on a natural experiment in which a few funds were forced to liquidate their holdings. Specifically, on September 3, 2003, the New York Attorney General Eliot Spitzer announced the issuance of a complaint due to the discovery of illegal late trading and market timing practices on the part of certain hedge fund and mutual fund companies. As a consequence of the scandal, twenty-seven fund families experienced significant outflows. Anton and Polk (2014) use these outflows to identify an exogenous driver of mutual funds' selling activity. Kisin (2011) estimates that funds of implicated families lost 14.1% of their capital within one year and 24.3% within two years. These outflows continued until the end of 2006. We start by matching the names of these fund families with the manager names in our trade-level dataset to identify the brokers employed by these funds to liquidate their portfolios

[4] Ravenpack is a dataset collected by analyzing financial news outlets using a machine learning algorithm to differentiate between positive and negative news about a company.

to meet investors' redemption demands. Crucially, the brokers were aware of the specific stocks that were being sold and of the timing of these liquidations. We then show that the clients of the relevant brokers were significantly more likely to liquidate the same stocks after the scandal broke out on the same days on which the implicated funds are also selling. This test reassures us that, even when we consider plausibly exogenous variation in the source of the liquidation, we find very similar behavior.

An important question at this point, and one of the key contributions of the paper, concerns the value of the order-flow information.[5] We are in a unique position to address this question by investigating whether the asset managers that receive the information from the aware brokers are able to generate higher returns. We compute the profits that these asset managers make during the fire sales and show that those who prey on the liquidating managers, e.g. the best clients of the aware broker, are able to generate an additional 32 bps in the few days of the fire sale. Given average fund performance, these results suggest that being able to predict fire sales can be quite profitable.[6]

We also provide evidence on the externalities arising from the previous findings, i.e. the losses incurred by managers exposed to predation. We focus on the execution shortfall, computed as the percentage difference between the execution price and a benchmark price. We find that price impact is significantly higher when the trades are executed through brokers that are aware of the large liquidation. These estimates allow us to compute the counterfactual cumulative return in a hypothetical scenario in which none of the brokers is aware. We can then show that the transaction cost of the liquidating funds almost increases by 50% in the presence of predatory trading.

We conclude by addressing another important question: Do brokers gain from leaking order flow information? We compute the brokers' commissions and show that the clients who take advantage of the order flow information by preying on the liquidating funds pay, relative to the

[5] Recent anecdotal evidence about Citadel paying about $100 million upfront to eTrade to receive their retail order flow would suggest that having access to this information in real time might be a very valuable piece of information. See: http://blogs.reuters.com/commentaries/2009/08/14/citadels-etrade-bonanza/ .

[6] A placebo test in which we show that the profits of these two groups are indistinguishable in a random sample of event windows reassures us that the additional profits are indeed driven by the access to the fire sales information, and not by manager characteristics.

other clients of the brokers, 10%-25% higher commissions after these fire sales events, compared to the months before. This finding confirms that the brokers get rewarded by their clients for the order flow information they provide.

Overall, our evidence highlights and quantifies one important amplification mechanism for asset price fluctuations. Brokers can disseminate order flow information for opportunistic reasons. This behavior reinforces the price dislocations due to fire sales.

Another general implication of our findings is that there exists an important trade-off between slow trading execution meant to reduce price impact, e.g. as in Kyle (1985), and leakage of order flow information. The latter becomes more likely when the asset managers trade in the same direction over an extended period of time. This consideration is not confined to fire sales events. In fact, we find that the autocorrelation among large trades in our data is about 35%. Hence, as a rule, managers tend to trade in the same direction over multiple days, which opens the possibility for the brokers to predict order flow, and for the order flow information to be disseminated from the brokers to other market participants.

Finally, our findings also have important implications for regulation. For instance, our results shed light on a recent debate over the exchanges' and brokers' use of their access to market data to sell data products.[7] Critics maintain that pension funds and other institutional investors, who routinely need big trades to be executed anonymously, can be negatively impacted as these products could be used to "reverse-engineer" their strategies and lead to front-running. Our findings show that, even in the absence of such supplemental information, a number of large investors, who entertain a strong business relation with brokers, are able to exploit order flow information at the expense of those seeking liquidity provision. Our estimates might serve as a

[7] The most recent dispute involves NASDAQ seeking the SEC's approval for an options-data service called the "Intellicator Analytic Tool." This new service would provide *market color* to subscribers by revealing whether a trade was initiated by a small investor or a big money manager. This story was reported in a recent WSJ article "*Wall Street Fears Nasdaq Proposal Would Expose Trading Secrets*" (available at https://www.wsj.com/articles/could-the-intellicator-spill-the-markets-secrets-1510223403?tesla=y#comments_sector).

benchmark, and probably a lower bound, for the costs associated with releasing such data products.[8]

Our paper bridges two strands of the literature. First, there is a vast literature on fire sales. Theoretically, Shleifer and Vishny (1992, 1997), and Kiyotaki and Moore (1997) suggest that fire sales occur when the natural buyers are unable to purchase the assets due, for instance, to agency problems. However, Brunnermeier and Pedersen (2005) and Di Maggio (2016) show that the market might become illiquid exactly when liquidity is needed most due to unconstrained arbitrageurs taking advantage of the temporary price pressure by selling and then buying back the asset only after the fire sale has ended.[9] Second, there is a growing number of studies investigating the importance of the network of relations among market participants in various domains, e.g. Li and Schürhoff, 2018; Di Maggio, Franzoni, Kermani, Sommavilla, 2016; Di Maggio, Kermani, and Song, 2017; Hollifield, Neklyudov, and Spatt, 2016; Afonso, Kovner, and Schoar, 2013; Hendershott, Li, Livdan, and Schürhoff, 2016. Our novel contribution is to highlight the key role played by brokers during fire sales, which might be amplified due to brokers leaking order flow information.

Our findings are also related to a growing literature examining the way in which information spreads in financial markets due, for instance, to information percolation (Duffie, Malamud, and Manso, 2009, 2014), or network effects (Babus and Kondor, 2016 and Walden, 2016). We contribute to this literature by providing empirical support to the notion that information can be readily disseminated through interactions between intermediaries and market participants. Furthermore, our results can also inform the theoretical developments of this literature as we point out that this information dissemination is *strategic*. In fact, the brokers selectively disclose order

[8] Our results also highlight the importance of the fiduciary duty between broker-dealers and their clients. A few states in the U.S. are moving in the direction of tightening such duty for brokers. For instance, Nevada is considering an expanded interpretation of fiduciary duty in which the brokers would be required to "disclose to a client, at the time advice is given, any gain [the broker] may receive, such as profit or commission, if the advice is followed."

[9] See Shleifer and Vishny (2011) for a survey of this literature. A complete list of works on fire sales and price dislocations in financial markets is beyond the scope of the paper, but it includes among others Allen and Gale (1994), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Acharya, Gale, and Yorulmazer (2011), Garleanu and Pedersen (2011). Recently, Yang and Zhu (2016) provided a two-period Kyle (1985) model of "back-running," where in addition to informed and noise traders there is an investor who learns from the order-flow generated by the informed speculator after the order is filled.

flow information only to some of their clients. This key feature is missing in the existing theoretical literature and might drive how networks emerge in financial markets. Also related to our paper, Farboodi and Veldkamp (2017) provide a long run growth model where traders have the option to extract information from order flow data mining and study the implication for price informativeness and market liquidity. Our results suggest that, indeed, order flow information is important in generating investors' returns and might significantly impair liquidity provision when liquidity is needed the most.

Evidence that brokers leak valuable information to selected clients is present in Irvine, Lipson and Puckett (2006) regarding future analyst recommendations, in McNally, Shkilko and Smith (2015) regarding brokers passing on information about firm insiders' order flow, and in Di Maggio, Franzoni, Kermani, and Sommavilla (2016) regarding informed order flow.

Closest to our work, a recent paper by van Kervel and Menkveld (2018) studies the behavior of HFTs around large orders of institutional investors. The authors find that HFTs provide liquidity if the order is short-lived (below seven hours), but they back run on the order if it lasts for several hours within a day, that is, HFTs trade in the same direction of information-motivated orders. The latter behavior increases the trading costs for the institution, as predicted by the theory of Yang and Zhu (2016). Similar to van Kervel and Menkveld (2108), we also study interplay among institutional investors and we detect a trading behavior by other investors that is harmful to the initiator of a larger order. Our evidence differs and complements their results in several dimensions. First, we focus explicitly on liquidity-motivated orders (i.e. fire sales) and show that predation occurs also in these circumstances and not just around information-motivated trades. Second, we show that predatory behavior characterizes also traditional asset managers, not just HFTs.[10] Third, we identify institutional brokers as instrumental in spreading order flow

[10] Our paper does not focus on high-frequency predation because HFTs are not present in our data. Yet, the question of liquidity provision vs. predation, which we address, has received special attention in the HFT literature. Moreover, the destabilizing effect of predation during fire sales that we document also finds a counterpart in the studies focusing on the impact of HFTs on market efficiency and volatility. Biais and Foucault (2014), O'Hara (2015), and Menkveld (2016) provide surveys of the rapidly growing HFT literature. Several empirical studies find that HFT activity is beneficial in that it reduces transaction costs (Hendershott, Jones, and Menkveld, 2011; Hasbrouck and Saar, 2013; Menkveld, 2013; Brogaard et al., 2015; van Kervel, 2015) and it improves price efficiency (Boehmer, Fong, and Wu, 2014; Brogaard, Hendershott, and Riordan, 2014). The evidence on the relation between HFTs and short-term volatility and crashes is mixed. Some studies document a negative relation (Hasbrouck and Saar, 2013; Chaboud et

information and fostering predation. Finally, we highlight the systemic threat caused by predatory trading as it can amplify price dislocations during fire sales.[11]

The remainder of the paper is organized as follows. Section 2 describes the data sources and summary statistics and Section 3 discusses our main results on the behavior of asset managers and the role of brokers during fire sales. Section 4 presents the results on the value of order flow information, Section 5 provide further evidence to corroborate the mechanism identified in the paper, while Section 6 concludes.

2 Data and summary statistics

In order to analyze whether and how brokers leak order flow information during fire sales, one needs a detailed trade-level dataset that also reports information on the institutional investors and brokers involved in each trade. Abel Noser Solutions, formerly Ancerno Ltd. (we retain the name 'Ancerno' for simplicity), fittingly provides this information. Ancerno performs transaction cost analysis for institutional investors and makes these data available for academic research under the agreement of non-disclosure of institutional identity.

We have access to identifiers for managers that initiate the trades and brokers that intermediate those trades from 1999 to 2014.[12] There are several advantages to this dataset. First, clients submit this information to obtain objective evaluations of their trading costs, and not to advertise their performance, suggesting that the data should not suffer from self-reporting bias. Furthermore, Ancerno collects trade-level information directly from hedge funds and mutual funds when these use Ancerno for transaction cost analysis. However, another source of information derives from pension funds instructing the funds they have invested in to release their trading activities to Ancerno for an independent check. Third, Ancerno is free of survivorship biases as it includes

al., 2014; Hasbrouck, 2015) whereas others document a positive relation (Gao and Mizrach, 2013; Ye, Yao, and Gai, 2013; Boehmer, Fong, and Wu, 2014; Kirilenko et al., 2017).

[11] Our results are also consistent with Chung and Kang (2016), who use monthly hedge fund returns to document comovement in the returns of hedge funds sharing the same prime broker.

[12] Relative to the standard release of Ancerno that is available to other researchers, we managed to obtain manager and broker identifiers also for the latest years (that is, after 2011), under the agreement that no attempt is made to identify the underlying institutional names.

information about institutions that were reporting in the past but at some point terminated their relationship with Ancerno. Finally, the dataset is devoid of backfill bias, as Ancerno reports only the trades that are dated from the start of the client relationship.

Previous studies, such as Puckett and Yan (2011), Anand, Irvine, Puckett, and Venkataraman (2012, 2013), have shown that the characteristics of stocks traded and held by Ancerno institutions and the return performance of the trades are comparable to those in 13F mandatory filings. Furthermore, Goldstein, Irvine, Kandel, and Wiener (2009), using an earlier version of our data, provide a useful description of the institutional brokerage industry. They show that institutions value long-term relations with brokers. Also, consistent with our results, the best institutional clients are compensated with the allocation of superior information around changes of analyst recommendations.

Ancerno information is organized on different layers. At the trade-level, we know: the transaction date and time at the minute precision (only for a subset of trades), the execution price; the number of shares that are traded, the side (buy or sell) and the stock CUSIP. Our analysis is carried out at the ticket level, i.e. we aggregate all trades on the same stock, on the same side of market (buy or sell), by the same manager, executed through the same broker, on the same day.

Next, we provide the definition of a fire sale event. Our goal is to identify liquidity-motivated sales that attract brokers' attention and are likely to generate a significant but temporary price impact. Hence, we impose two requirements. For a given manager, the selling amount needs to exceed the manager's standard trading volume for a protracted period.[13] At the stock level, the liquidation volume needs to make a sufficient fraction of total trading volume.

[13] Our level of analysis is at the manager code level; hence, at the level of the management company. Our decision to focus on the management company level is founded on several arguments. First, our definition of fire sales selects events that are particularly large for an asset manager. In this sense, it is more likely that fire sales arise when multiple clients withdraw their funds from a management company. Focusing on a specific client-manager relationship then has the potential to miss these larger events. Second, if only one fund in the company was in distress, or just a few, other funds could help by providing liquidity. Specifically, the healthier funds could relieve the distressed fund of some of its assets by engaging in cross-trading, a practice that is described in Gaspar, Massa, and Matos (2006), and more recently in Eisele, Nefedova, Parise, and Peijnenburg (2017) using Ancerno data. The possibility of intra-family subsidization, then, motivates us to focus on events that involve the entire family of funds. Finally, the choice to focus on the management company, as opposed to specific funds within the family, is also dictated by data availability. In the version of Ancerno that is available to us, the alphanumeric identifier for the specific fund (manager) is often missing or not meaningful.

In more detail, to identify liquidating funds we start by computing the signed volume Z-score for each manager m on day t as

$$\mathrm{Z}_{\mathrm{t}}^{\mathrm{m}} = \frac{DVol_t^m - E(DVol_t^m)}{\sigma(DVol_t^m)}, \tag{1}$$

where $DVol_t^m$ is the portfolio level dollar volume traded by manager m on day t, and its mean and standard deviation are estimated over a rolling window of 120 trading days ending one week before day t. Then, for a given manager, we require that during a fire sale event if $\mathrm{Z}_{\mathrm{t}}^{\mathrm{m}}$ is below -0.25 for at least five trading days in a row. This requirement ensures that the sale is taking place on a sufficiently long period of time for the broker to realize about the fire sale and for it to represent a significant event in the life of the fund. Given this condition, all the fire sales that we identify corresponds to events in which the order imbalance at the fund level is negative, as evident from Table A7 in the Internet Appendix.

In addition, we impose a filter at the stock level to ensure that the sale volume is large enough to generate price pressure. For stock j to be part of the fire sale event, we require that the volume traded by the manager is at least 1% of the CRSP volume on day t for at least four out of the five fire sale days.

We decide to keep events in which at least 10 stocks are involved in a fire sale. The goal is to reduce the probability that liquidating funds are selling as a consequence of stock-specific information. Focusing on liquidations of a large number of stocks makes it less likely that the sales are information driven.

We distinguish between *aware* and *unaware* brokers. Intuitively, we define a broker as aware that a stock is subject to fire sale pressure if it intermediates a sufficiently large volume on that stock arising from the originator. In detail, the variable *Aware* is a dummy, defined at the event-broker-stock-day level, indicating that the broker is aware of the fire sale happening on a given stock-day. That is, for broker b, stock j on day t, and event e, the aware dummy $Aware_{j,b,t,e}$ equals one if the volume on stock j originated by liquidating fund that is intermediated by broker b on day t is above 2% of the average daily volume (ADV) for that stock. Note that this does not require the broker to have knowledge of the overall size of the liquidation, but just realizing that the distressed fund is responsible for a significant fraction of the daily volume. In Table A1 of the Internet Appendix we demonstrate the robustness of our main results to several changes in the ADV-related threshold used to identify aware brokers. Further, we show that our results are robust to the additional requirement that the broker needs to intermediate a large volume of at least *N* stocks in the fire sale basket to become aware.

Panels A and B of Table 1 provide the summary statistics for the key variables in our analysis. We identify a total of 385 fire sale events over the 1999-2014 period, each lasting at least 5 days and with the liquidating funds selling on average $377 million worth of stock (median: $177 million). Figure 1 displays the distribution of events over our sample period. It shows that the events are evenly distributed over time; in fact, even during the recessions highlighted in red, the number of events does not spike. This confirms that our methodology identifies funds subject to idiosyncratic shocks rather than market-wide events.[14]

We can compute the fraction of the liquidated portfolio that the liquidation volume represents. In particular, we estimate the liquidating funds' portfolios by cumulating their trades over the two years prior to the fire sale. Then, we divide the total volume of sold stocks by the reconstructed portfolio size. We find this fraction to be sizeable at 9.16%, on average. Arguably, this methodology tends to underestimate the liquidating managers' actual portfolio because we do not know their positions at the beginning of the estimation period, so that the fraction provides an upper bound. In any event, this evidence suggests that these large sales are unlikely to be inspired by stock-specific information.

On average, 22 stocks are heavily sold during a fire sale event, with about $17.2 million sold in each stock, which indicates that these events involve more than just isolated stocks. Figure 2 shows the distribution of these events as a function of the number of stocks, from events involving 10 to

[14] The lack of clustering of fire sale events during crisis periods results as an intentional feature of our definition of fire sales. In computing the Z-score, at the numerator, we subtract from a given day's order flow the average daily order flow over the prior six months. Hence, if the order flow is negative over a protracted period, such as during the crisis, at some point the Z-score will cease to identify fire sales. The desirability of this feature is that we do not generate a sample of fire sales in which the crisis is overly represented.

50 stocks, as well as the distribution of the volume of trades by the liquidating fund that can even reach more than two billion dollars in some cases.

Fire sales are intermediated by an average of 29 brokers, while the number of aware brokers per event is on average less than 2. Furthermore, the price of the stocks sold in the fire sale declines by 1% on average during the first five days of the event, but there is significant variation. In fact for the bottom quartile, the price drops by more than 5%.

Using TAQ data, we can report that the fire sale volume is on average 50% of the TAQ order imbalance (median 10%) and it is on average 27% of TAQ sell volume (median 19%). We conclude that the liquidating fund imbalances constitute a sizeable fraction of the TAQ imbalance for the fire sale stocks.

Finally, we provide evidence on the type of stocks the liquidating managers are selling. We construct a proxy for the portfolios of the liquidating managers by cumulating their trades over the prior 2 years. Then, for each stock in the fire sale, we compute the fraction of the total volume in the fire sale that it represents. Panel C of Table 1 shows the results from regressions of the fraction of the fire sale that stock j represents on its weight in the selling manager's portfolio, market capitalization, volatility, the Amihud (2002) ratio, and various measures of past performance at different horizons. We find that, after controlling for the quantity held by the manager (i.e. portfolio weight), the funds tend to sell the larger, more liquid, and less volatile stocks in their portfolio. Also, asset managers tend to sell the stocks with higher past performance. These findings resonate with the predictions of theoretical models discussing the optimal liquidation strategies in case of distress (Scholes 2000, Brown, Carlin, and Lobo 2010).

Corroborating our identification strategy for fire sales, the highly significant positive coefficient on the portfolio weight suggests that the liquidating funds are not building short positions; rather, they are selling positions that are already present in their portfolio.

In addition to the extensive margin, we have also investigated the sequence of the sales by changing the dependent variable to "first day in which the stock is sold", defined as the number of business days from the first day of the fire sale in which a particular stock is sold the first time.

The results are reported in Panel E of Table 1 and show that the most liquid and less volatile stocks are sold earlier.

3 Main Results

This section starts by discussing our empirical strategy and then presents the main evidence on the role of brokers in spreading order flow information during fire sale events.

3.1 Fire Sales

We start our analysis by characterizing the fire sale events. Figure 3 plots the average (across stocks and events) daily signed volume (i.e. order imbalance) for the liquidating fund during the event window, where the zero is defined as the first day of the five-day window over which we identify the fire sale. The large negative volume before day 0 is due to the fact that, while liquidations likely start earlier, we impose stringent criteria for them to be defined a fire sale. We note that, although order imbalance starts recovering after about five days, it is still below zero after about fifteen days. This is important, because it highlights the nature of the sale: the liquidating fund does not repurchase the stocks back (even when we extend the horizon further out). Hence, this fact weakens the possibility that the liquidating fund is short selling the stock because it expects the price to decline, and then buys the stock back.

Figure 4, instead, plots the average DGTW adjusted cumulative returns for the stocks included in the fire sales across all the events. The returns are mostly flat pre-event and then start precipitating quite rapidly while the liquidating fund (for simplicity, the *originator*) is selling most intensely, i.e. during the five-day interval [0,4], then to slowly recover over time. Specifically, we find that after about twenty days they are back to the pre-event levels. This is a faster reversal than what is found in the existing literature on fire sales (Coval and Stafford, 2007). On average, the price drops by almost 1% during the five-day event-time interval [0, 4], which we label *liquidation period*. Importantly, the fact that we observe a reversal over such a short horizon tends to rule out the possibility that the liquidation and the price decline are due to negative fundamental news on the stock. On the contrary, the price path is strongly consistent with price pressure following liquidity motivated trades.

Next, we turn to the tests trying to detect information leakage by brokers. First, if brokers are exploiting their privileged position, we should expect the trades that go through aware brokers to be more subject to predation than those that go through unaware brokers. We can formally test this hypothesis by estimating the following specification

$$Predation_{m,i,b,t,e} = \beta_1 Aware_{i,b,t,e} + \varepsilon_{m,i,b,t,e}, \tag{2}$$

where $Aware_{i,b,t,e}$ is a dummy equal to one if broker b executing the trades is aware of the fire sale on stock i on day t of event e, i.e., it is defined at the event-broker-stock-day level. The dependent variable, $Predation_{m,i,b,t,e}$, is a dummy equal to one if the client m of broker b trades in the same direction as the originator, i.e. demanding liquidity, on a stock i on day t of event e. The dummy equals zero if the client provides liquidity by trading in the opposite direction of the originator or the client does not trade on that stock-day.[15] We also estimate specifications in which the dependent variable is defined as the predation dummy multiplied by the ratio of dollar volume of the broker's clients to the market capitalization of the stock (this variable is standardized by subtracting the mean and dividing by standard deviation). The sample includes trades executed by all managers with all brokers in the database on the fire sale stocks. These specifications rely on heterogeneity across brokers for identification: some brokers are more exposed to order flow information as they intermediate a higher fraction of the order flow by the liquidating fund. Standard errors are clustered at the broker level. In the Internet Appendix, we report equivalent results with clustering at the broker and stock level, and the broker and day level.

We present the results in Table 2. Columns (1)-(4) focus on the predation dummy, while columns (5)-(8) present the results for the volume-weighted dependent variable. Each column modifies the baseline specification (1) by adding different fixed effects. In the most conservative specification, we include day, manager, broker, and day-by-stock fixed effects. Manager and

[15] To identify non-trading clients, we consider all the managers that traded with the broker in that stock over the previous 20 business days.

broker fixed effects ensure that our estimates are not driven by unobservable broker or manager characteristics. Day-by-stock fixed effects aid in ruling out two alternative explanations. First, asset managers might sell the stock due to stock-specific public news, then, day-stock fixed effects would capture this potentially important confounding factor. Second, predation might be driven by information about prices and trades, rather than by information leakage. For instance, the liquidating managers create price impact and abnormally high volume in the market, which is a source of public information that asset managers can use to spot trading opportunities, without relying on brokers.

We find that trades executed by aware brokers have 6% higher probability of predation, or equivalently, the volume of predatory trades is about 14% of a standard deviation larger for the clients of aware brokers.[16] This is the first step towards a better understanding of the role of brokers in fostering predatory trading. The results show that the brokers who are more likely to realize that the fund is engaged in a large liquidation are also more likely to intermediate trades that are consistent with predatory trading.[17]

3.2 Liquidity Provision

The theoretical literature makes mixed predictions on whether other market participants that anticipate a large liquidity order will predate upon it or, instead, provide liquidity. Brunnermeier and Pedersen (2005) and Di Maggio (2016) predict that investors that become aware of a liquidation will predate on the distressed fund and deteriorate market quality. On the other hand, Admati and Pfleiderer (1991), in their "sunshine trading" model, argue that investors credibly announcing their intention to transact for non-fundamental attract natural liquidity providers to the market. The empirical work by Bessembinder, Carrion, Tuttle, and Venkataraman (2016) provide evidence that is consistent with this prediction in the context of predictable roll trades of oil futures

[16] In Internet Appendix Table A8, we report results from specifications without the fixed effects. These specifications allow us to conclude that the probability of predation is about 60% for trades through aware brokers, a 70% increase relative to the baseline probability, which amounts to 35%.

[17] We find that the subset of brokers that are deemed aware during our sample period amounts to roughly 10% of the brokers present in Ancerno.

contracts by a large ETF. Therefore, a priori, type of behavior that other market participants adopt vis-à-vis a liquidating fund remains an open empirical question.

Then, to examine the amount of liquidity provision that occurs through aware brokers and compare it to predatory trades, we replace the dependent variable in Equation (2) with two alternative variables. First, we use the difference between the probabilities of predation and the liquidity provision. The probability of predation is defined as a dummy variable equal to 1 for trades in the same direction as the liquidating fund, 0 when no trading occurs or for trades in the opposite direction. The probability of liquidity provision is a dummy variable equal to 1 for trades in the opposite direction of the liquidating fund, 0 when no trade occurs or for trades in the same direction. Second, we also look at the difference between predatory volume and liquidity provision volume in the five days of the fire sale. Those are defined by multiplying the transaction-level unsigned dollar volume with the *probability of predation* dummy and *probability of liquidity provision* dummy, respectively.

This analysis allows us to disentangle whether the aware brokers induce more predation than liquidity provision or vice versa. We report the results in Panel C of Table 2. For both dependent variables, we find that there is a stronger connection between aware brokers and predatory trades. This evidence further corroborates the interpretation that aware brokers are more likely to foster predatory trading by leaking the liquidity needs of the distressed funds.

Another way of investigating predation and liquidity provision is to compare the cumulative order imbalance, i.e. the difference between buys and sells divided by the sum of the two, for the aware and the unaware brokers. We report the two series with standard errors bands during the events in Figure 5. On the one hand, the imbalances for the aware brokers are negative during the first several days of the liquidation and are significantly lower than those of the unaware brokers. This evidence confirms the regression estimates of Table 2 with a significant slope on the aware dummy. On the other hand, the cumulative order imbalance for aware brokers does not fall below 8% of the total trading volume by these brokers. This fact implies that by no means all the trades through aware brokers are in the direction of predation. In that case, we would find an order imbalance of -100%. It is instead the case that in important fraction of the trades (i.e. 46% of the total volume) are in the direction of liquidity provision.

3.3 Best Clients and Predatory Trading

To sharpen our identification, we focus on the aware brokers and test yet another implication of our information leakage hypothesis. If the aware brokers provide information about order flow from liquidating managers, and if the information rents can be dissipated by leaking to too many traders, we should expect this disclosure to be selective and to allow the broker to extract the highest rents. Thus, we should expect the brokers to favor their best clients. To proxy for the strength of the manager-broker relationship, we use information about both the volume and the commissions generated by manager *m* with broker *b* in a window of 6 months ending one month before the fire sale event. We use this data to form five different proxies for "best clients", which we employ throughout our analysis.

First, we define a dummy indicating clients that generate at least 5% of the total volume intermediated by the broker, which results into about 6% of managers tagged as *best clients*, on average. Second, we define another dummy indicating clients that generate at least 5% of the total commissions earned by the broker. The third proxy is a continuous variable with support in the unit interval, defined as the volume generated by the client as a fraction total volume intermediated by the broker. The fourth measure is computed in a similar fashion, but the dollar volume is replaced by the dollar trading commissions generated by the manager.

To show that these variables identify a meaningful source of variation across managers, Table 3 regresses each measure on its previous quarter lag, controlling for broker and manager fixed effects. Consistent across proxies, we find that the manager-broker relationships are very persistent. This fact suggests that brokers might have an incentive to nurture these relationships over time and that the heterogeneity across clients of the same broker might be a relevant source of variation for identifying the effect of interest.

Having established the importance of these manager-brokers relationships, we can now introduce our baseline specification:

$$Predation_{m,j,b,t,e} = \beta_1 Best\ Client_{m,b,t} \times Liquidation\ Period_{t,e} + \beta_2 Best\ Client_{m,b,t} + \beta_3 Liquidation\ Period_{t,e} + \varepsilon_{m,j,b,t,e}, \quad (3)$$

where, as before, our main dependent variable is the dummy indicating that manager *m* sells its holdings of stock *j* with the broker employed by the liquidating fund. This dependent variable has the advantage of being scale independent, i.e. the size of manager *m* does not matter for our results. *Best Client* is a dummy in the first three columns and a continuous measure in Columns (4) and (5), depending on the measure employed to proxy for the strength of the relationship. *Liquidation period* is a time dummy equals to one for the first five days of the fire sale, that is, for the period of most intense liquidation by the fund in distress. The reference period is the time before the beginning of the fire sale. All specifications include time, manager, event, stock and broker fixed effects. We conservatively double-cluster the standard errors at both the stock and manager level, which allows for arbitrary correlation within trades in the same stock and by the same manager.[18]

Table 4 presents the results. We find that the asset managers in a closer relationship with the fire-sale-aware broker are much more likely to sell their holdings of the fire-sale stock with the same broker during the liquidation period. The results are both statistically and economically significant with the best clients being more than 2% more likely to prey on the liquidating fund, which is equivalent to about a third of the baseline predation probability, whose average is about 5.5%.[19] The results are also very consistent across proxies, which reassures us of the robustness of the estimates.[20]

A more stringent identification strategy exploits variation across managers as well as across brokers. That is, we compare the difference between the behavior of the best clients of the brokers

[18] In robustness tests provided in Panel B of Internet Appendix Table A5, we cluster standard errors along alternative multiple dimensions: Event, Stock, and Manager; Event, Stock, and Day; Event, Stock, and Broker level. The results remain significant across alternative specifications.

[19] The estimate of the baseline probability can be inferred from as can be inferred from the specification without fixed effects reported in Table A8 of the appendix.

[20] To sharpen the identification, Table A2 in the appendix also reports the same specification with higher-dimensional fixed effects. Specifically, we include broker-manager and broker-originator fixed effects. This allows us to keep the pair broker-manager or broker-originator constant in our analysis: the variation comes from changes in the trading patterns between before and after the start of the liquidation, controlling for the typical trading pattern that characterizes a given pair. The results are unaffected.

that are aware of the fire sale and the behavior of the best clients of the brokers that are unaware, relative to the non-best clients of both types of brokers. Formally, Panel B of Table 4 reports the results from the following specification

$$\begin{aligned} Predation_{m,i,b,t,e} = \; & \beta_1 Best\ Client_{m,t} \times Aware_{j,b,e} \times LiquidationPeriod_{t,e} \\ & + \beta_2 Best\ Client_{m,t} \times Aware_{j,b,e} \\ & + \beta_3 Best\ Client_{m,t} \times Liquidation\ Period_{t,e} \\ & + \beta_4 Aware_{j,b,e} \times Liquidation\ Period_{t} \\ & + \beta_5 Best\ Client_{m,t} + \beta_6 Liquidation\ Period_{t,e} + \beta_7 Aware_{j,b,e} \\ & + \varepsilon_{m,j,b,t,e}. \end{aligned} \tag{4}$$

In this specification, we define $Aware_{j,b,e}$ at the event-broker-stock level by collapsing awareness on the time dimension by taking the max, i.e. to each broker b which eventually becomes aware of the fire sale event e on a stock j we assign $Aware_{i,b,e} = 1$. This specification confirms that the best clients of the aware broker are significantly more likely to sell the stock involved in the liquidation compared to the best clients of the other brokers involved in the liquidation. The results are consistent across measures of relationship, with the largest effects for the first measure based on size: the clients that submit at least 5% of an aware broker's volume are 11% more likely to prey on the liquidating fund. In the next set of robustness checks, for ease of exposition, we are going to present the results focusing on the set of aware brokers and exploit only variation across clients in terms of the strength of the broker-client relationship.

Panel D of Table 4 examines the characteristics of the stocks that are more subject to predation. We split the sample of fire sale stocks by the median of the amount of predation. In turn, this quantity is the number of manager-days in which a client of an aware broker trades in the same direction as the liquidating fund. Then, for different variables, we compute the average for stocks that are liquidated in events above the median (More Predation) and below the median (Less Predation). The overall evidence is that the events with stronger predatory activity involve larger, more liquid, and less volatile stocks.

Next, we modify the dependent variable in Equation (3) using the difference between the probabilities of predation and the liquidity provision, as in Panel C of Table 2. This specification allows us to address a concern that results in Panel A are driven by a mechanical correlation in probability of predation and the best client variables. If best clients trade more in general, they may be more likely to display a higher probability of predation. Separating the cases in which the clients trade in the opposite direction than the liquidation from the cases in which no trade occurs addresses this concern. We show in Panel C of Table 4 that our results are robust to this change of dependent variable.

One interesting question at this point is whether there is significant persistence in the set of asset managers that predates and in those that get predated. We find that more than 60% of the victims were predated only once. The median is thus 1, while the average is 3.13 times. This suggests that the liquidations we are focusing on are unlikely to happen frequently enough for the funds to become aware of that and potentially punish the broker. In fact, even among those funds who are predated more than 2 times, the average time between two consecutive events is 2.86 years. It is thus difficult for a manger to learn about the brokers' leakage, given that, from a manger's perspective, predation happens rarely and inference is very noisy.[21]

From the perspective of the predators, we also show that this is a concentrated activity. In fact, among all the predators in our sample, 30% of them predate on more than 10 events during our sample period. Predatory behavior is persistent: conditional on having predated at time *t*, the probability of the same manager predating again in *t+1* is more than twice as large. Figure A1 in the Internet Appendix presents the result for different time horizons. Therefore, the evidence suggests that, consistent with our hypothesis, the brokers leak their information to a restricted number of clients that are likely to take advantage of this information.

One additional dimension that we can take advantage of is *when* the predators start trading in the same direction. Intuitively, if the predator starts on the first day of liquidation, it is potentially much more harmful than if the predator starts on the last day of the liquidation. We examine this

[21] We also find that, among the funds involved in a fire sale, 40% also acted as a predator at least once.

question in Internet Appendix Table A11. We find that the best clients of the aware brokers are significantly faster in predation. In particular, the average predator starts predating after 3 days from the beginning of the liquidation, while best clients of aware brokers start already on the second day, on average. This is interesting because suggests that the best clients of the aware brokers are rewarded through early access to information.

Further, we can test whether brokers give a preferential treatment to their best clients when they need to liquidate. In Internet Appendix Table A9, we find there is less predation when the fund in distress is one of the broker's best clients. We do not find significantly more liquidity provision, but the results are confirmed when we look at the difference between predatory and liquidity provision volumes. Overall, best clients do enjoy an advantage when they need to liquidate.

Finally, using these reconstructed holdings, we find that predators appear to short the fire-sale stocks in 43% of the cases. We caveat, however, that this estimate is exposed to large measurement error due to the approximation of the true portfolio. From a theoretical point of view, we do not have a strong prior as to whether predation should occur with stocks that are already in the predator's portfolio or stocks that the predator needs to short. Empirically, given that the stocks that are most likely to be predated tend to be the largest and most liquid stocks in the market, it is somewhat more likely that these stocks are already in the predators' portfolios. This fact can explain why a slight majority of predatory trades consists of sales of existing positions.

3.4 Robustness to Aggregate and Stock-Specific News

Having established that the best clients of the aware brokers are more likely to sell the same stock as the distressed fund during the liquidation period, we examine whether the results can be driven by other factors than information leakage by the broker. The main alternative hypothesis that might explain these results is that asset managers are responding to the same common shock occurring during the same event windows. This might occur for two reasons. First, there might be a common disruption in the market that leads funds to offload their positions. Alternatively, news about the specific stocks might be released, triggering the funds' trading behavior.

As already discussed, some of our prior evidence (e.g. the fact that we control for stock-by-day fixed effects) already helps to rule out these hypotheses. Nonetheless, we provide several direct tests to rule out these alternative explanations. The first step to ensure that the correlation among traders is not due to general disruption in the market is to exclude the two recessions in our sample, i.e. the tech crunch and the financial crisis. Panel A of Table 5 presents these results. It shows that the results are robust to this change in the estimation sample, with both the economic and statistical significance being unaffected.

Next, we test if negative stock-specific news might explain our baseline results. To do so, we collect information about earnings announcements and changes in analyst recommendations. Intuitively, earning announcements might work as a catalyst, and a negative surprise might trigger a series of liquidations. We exclude ten trading days around the announcements. Another important piece of fundamental information that might drive funds' behavior is changes in analyst recommendations. One might reasonably expect that multiple liquidations might follow a downgrade, especially an unexpected one. Therefore, we also exclude these events from our sample. Earnings announcements and analyst recommendations are not the only news that might trigger a coordinated response from market participants. In order to have the most comprehensive information about stock-specific news, we use the data provided by Ravenpack. The dataset is generated as the result of a comprehensive analysis of all types of information from newswires about each stock, from lawsuit to mergers and acquisitions. A machine learning algorithm is then employed to classify the news in good and bad on a scale from 0 to 100, where 50 is the cutoff below which news are identified as bad. Even in the restricted sample excluding bad news, we confirm in Panel B of Table 5 that the best clients of aware brokers are more likely to predate on the liquidating manager.

Another instance in which fund managers might find themselves trading in the same direction is when the stocks belong to the same strategy, e.g. momentum, which might be commonly adopted by multiple funds. Furthermore, asset managers might be liquidating underperforming stocks. Then, as an additional robustness check, in Panel A of Table 6 we exclude from our sample all stocks exhibiting negative momentum. Specifically, we compute the returns of the stocks sold during the fire sale and exclude those with negative returns in the week preceding the fire sale. The results are unaffected.

To check whether our results could be driven by changes in investors' expectations about the stocks, Panel B of Table 6 also considers short selling data from Markit (formerly DataEx database). Intuitively, stocks with high short interest might be subject to correlated sales across funds, which might be triggered by company specific events or investors' common beliefs about the stock performance, rather than by the desire to take advantage of a liquidating fund. Then, we show the robustness of our results to the exclusion of events where the liquidated stocks exhibit a significant level of short interest, defined as a utilization ratio (i.e. shares on loan divided by shares available to lend) in the top quartile.

As an additional test to rule out the alternative hypothesis that funds are responding to similar shocks rather than deliberately taking advantage of the fire sale, we explore the number of stocks that are affected by the predatory behavior of the aware broker's clients. The idea is that if investors are simply responding to a common shock to a stock, we might find that their sales are concentrated on that particular stock. On the other hand, if multiple stocks out of the 20 that are involved on average in a fire sale are sold by the best clients of the aware broker, predation on the liquidating fund seems more likely. To test this conjecture, Table 7 reports results where the outcome variable is the number of fire-sale stocks for which the manager sells its holdings (Panel A), and the fraction of stocks involved in the fire sales for which we observe predatory behavior (Panel B). We find that best clients of the aware brokers tend to sell their holdings on 3 to 4 more stocks, and to predate about 15% more of the stocks involved in the fire sale.[22]

[22] As further robustness test, in Table A3 in the appendix, we report the baseline regressions of Table 4 using as main dependent variable the predation dummy multiplied by the trading volume as a fraction of the stock market capitalization. Panel A shows the results for the whole sample, while, for brevity, Panel B shows the results for the most restrictive subsample, i.e. the one excluding at the same time recession, negative news, as well as high short interest and negative momentum stocks. The results are statistically significant, with best clients generating larger selling pressure in dollar terms during the liquidation period. This wedge is also economically significant, as it corresponds to an average increase of up to 13% of a standard deviation of their order flow in the direction of the originator.

3.5 Evidence of Trade Reversion

To corroborate the hypothesis that our results are driven by predatory behavior by the asset managers who are able to acquire order flow information via the broker, we test whether these same asset managers are also likely to cover their positions by repurchasing the stock in the following days. As predicted by Brunnermeier and Pedersen (2005) and Di Maggio (2016), asset managers who prey on liquidations should sell the asset while its price is moving away from fundamentals and then revert their positions once the liquidating fund has stopped exerting selling pressure pushing the price upwards.

To this purpose, we compute the fraction of a manager's negative position that is subsequently reversed. In detail, the percentage of position reversed for manager m during event e for stock j is defined as the ratio $Rev_{e,m,j} = BoughtBack_{e,m,j} \, / \, Sold_{\mathrm{e,m,j}}$, where $Sold_{\mathrm{e,m,j}}$ is the dollar sum of all sell orders in that period, and $BoughtBack_{e,m,j}$ is the dollar sum of buy orders during the period, where we sum only the buy orders that are preceded by a negative cumulative order flow. Our motivation is to avoid counting as reversals the buy orders that occur before sales have taken place. We compute this measure around each fire sale event, for the ten days before and after the fire sale. We then compare the percentage of position reversed by Best and Non-Best clients of the aware brokers before and after the fire sale events. The liquidating funds are excluded from the sample.

In Table 8, we find that a significant fraction of the predating managers' positions is covered in the ten days following the fire sale. We interpret this evidence as strong indication that the predating managers were motivated by the prospect of short-term gains at the expense of the liquidating fund.[23]

[23] To give a sense of the magnitude if the trade reversal, we compare this unwinding activity to the reversal of sell trades by the same group of predatory managers taking place over a random sample of five-day intervals that do not include a fire sale (a placebo sample). Figure A2 in the Internet Appendix compares the unwinding of predatory trades after the fire sale to the placebo trades. It is evident that reversal is significantly higher after the fire sales. In particular, already one day after the fire sale 30% of the sell positions are bought back, while the number is closer to 3% in the placebo sample. After one month the reversal plateaus at about 50% of the positions, while it is below 25% in the placebo sample. We conclude that the evidence of trade reversal after fire sales is economically significant. The fact that not all sell trades are reversed suggests that either some investors already intended to sell the stock and took the opportunity of a price decline to do it, or that some investors mistook the price drop for a negative signal on the stock and decided to drop it from the portfolio.

3.6 Late-Trading Scandal as a Natural Experiment

We can envisage two further alternative interpretations to the proposed view that order flow leakage by brokers explains our evidence. First, selling pressure on a stock might be generated by changes in market sentiment about that stock rather than by a shock to the fund holding that stock. Second, the intermediating broker can be the original source of the information about the liquidated stocks, which then triggers the large sale as well as smaller sales by other managers in the same direction.

The evidence so far seems to weaken the validity of these alternative explanations. First, our identification of fire sales suggests that these liquidations involve a large fraction of a manager's portfolio (9.16% on average) and involve at least 10 different stocks (on average 22 stocks). Hence, it is unlikely that the liquidating managers are responding to stock-specific information or to a broker trading tip. Second, the robustness tests in Tables 5 and 6 show that the evidence remains unchanged when removing stock-specific and aggregate informational events from the sample.

To further rule out these alternative explanations, we identify an exogenous determinant of fire sales. In particular, we need a driver of liquidations that is manager-specific, i.e. it is not inspired by the broker, and which does not depend on the identity of the liquidated stocks or the composition of the manager's portfolio.

Anton and Polk (2014) use the liquidations triggered by outflows following the late-trading scandal as a natural experiment to identify exogenous selling activity (also see, Kisin 2011). We follow these authors and focus on the mutual fund scandal that erupted in September 2003. At the time, the New York Attorney General Eliot Spitzer announced the discovery of illegal late trading activities and market timing practices on the part of several hedge fund and mutual fund companies. The scandal had a significant impact on the 27 fund families involved: they experienced significant outflows as they lost 14.1% of their capital within one year and 24.3% within two years (Kisin, 2011). This is an ideal experiment for our purposes because it allows us to identify stocks that for exogenous reasons are subject to selling pressure. Although market participants were aware that these fund families were experiencing investors' outflows, the brokers' vantage point allows them to pin down *when* these funds were liquidating and *which* stocks were involved in the liquidation. Both pieces of information are fundamental in making the predation profitable and they are not publicly available.

To test whether even in this case, the brokers are responsible for leaking information about the stocks that are liquidated and the timing of these liquidations, we manually match the identity of the fund families included in Spitzer's complaint with our trade-level dataset, in order to identify the sales trades of these fund families and the brokers through which they execute them.[24] Corroborating the validity of our matching procedure, we find that the matched managers rank in the top quartile by sales in the two-year period following the breakout of the scandal.

Then, we focus on daily transactions of the managers that are not involved in the scandal for a period of four years centered on the month of the announcement of the complaint by Spitzer (September 2003) and define a dummy $Post\ Scandal_t$, indicating the two years after the complaint broke out. Next, we define a broker-stock-day level dummy variable, $Selling_{b,j,t}$, indicating that at least one of the charged funds is selling stock j on day *t* through broker *b*. Then, we define the dependent variable *Probability of Predation* as a dummy variable that equals 1 if a non-charged manager is selling stock j on day *t* through broker *b*. The dependent variable equals 0 if a non-charged manager trades on a different day, or on a different stock, or with a different broker. In a difference-in-differences setting, we regress the probability of predation on the interaction between $Selling_{b,j,t}$ and the dummy $Post\ Scandal_t$.

Table 9 reports the estimates. Consistently with the previous baseline results, we find that the clients of the brokers employed by the funds involved in the scandal were significantly more likely

[24] A complete list of the fund families involved in the scandal arising from Spitzer's complaint can be found on the webpage: https://en.wikipedia.org/wiki/2003_mutual_fund_scandal#List_of_implicated_fund_companies.5B4.5D.5B5.5D. Out of the 27 families that are involved, we are able to find a match in our dataset for 19 of them. These 19 managers are responsible for 7 out of the 31 fire-sale events in the two-year-period after the scandal broke out, i.e. they late-trading scandal families generate 23% of the fire sales. Importantly, the implicated funds represent only about 2.1% of the managers in the database (i.e. 19/900). Hence, the implicated families weigh about 10 times more than the other managers in generating fire sales in those two years.

to liquidate the same stocks after the scandal broke out. For example, in Column (1), there is a 4.3% higher probability of non-charged managers to trade in the same direction as a charged manager on the same day through the same broker.

These results corroborate the interpretation that the clients of the aware brokers adopt predatory trading strategies to take advantage of temporary price movements due to fire sales, and that these results cannot be explained away by shocks to the market or to the single stocks as well as by a common response to the release of public information, given that the timing of the sales and the identity of the stocks that are sold is information to which only the intermediating brokers have access. Moreover, the interpretation relying on the idea that brokers are generating stock-specific trading ideas seems implausible, given that there is no reason for this activity to increase after the breakout of the scandal.

3.7 Heterogeneity

We exploit the granularity of our data to further explore whether the predatory trading behavior depends on the characteristics of the clients.

We should expect the most active managers in the sample to be the ones more willing and capable of taking advantage of the liquidating funds' trades. To proxy for these characteristics, we can investigate whether the results differ for hedge funds and other institutions. Intuitively, hedge funds are more likely to have the ability to promptly react to information released by the brokers than mutual funds or pension funds. We manually identify the hedge funds in Ancerno following the procedure in Franzoni and Plazzi (2015).

Panel A of Table 10 reports the baseline specification in Equation (1) for hedge funds, while Panel B focuses on other institutions. The results clearly show that the hedge funds are the main driver of our results. In fact, the magnitude of the coefficients is higher than in the baseline regressions of Table 4, while the statistical significance, as well as the economic significance, is weaker for the non-hedge funds. This evidence corroborates the hypothesis that the behavior we observe is a deliberate attempt by the *smart money* to take advantage of temporary price fluctuations.

To investigate whether predation is even more prominent in periods of financial distress, we split our sample based on the value of the VIX during each fire sale event. The results (reported in Appendix Table A6) show that predation through aware brokers is somewhat stronger during periods of financial distress. This finding may result from the fact that liquidations are more significant during times of market stress. Additionally, the price impact of liquidations is also larger because the market is more illiquid. This fact creates additional room for predators to profit from the liquidation.

4 The Value of Order Flow Information

4.1 Profitability of Predatory Strategies

An important question at this point is whether the asset managers that receive the information from the broker are able to generate higher abnormal returns. Hence, we study whether predatory trading is indeed profitable.

To address this question, we compute the profits that asset managers generate during the fire sales. In particular, starting from the first day of the liquidation (day 0), at the close of each day we compute the marked-to-market value of the net position in a given stock and subtract from this value the net cash amount that was necessary to build that position over the period. To express these profits as a fraction of capital at risk, we divide them by the absolute value maximum dollar outlay over the period in which the profits are computed. [25]

We start by showing in Figure 6 the profits of managers that are best clients of aware and unaware brokers at the daily frequency after the start of the fire sale. Intuitively, if as shown in Table 2 the trades executed by unaware brokers are significantly less likely to be predatory, we should find that their clients are also less likely to profit from these fire sales events. Indeed, the figure shows that the clients of aware brokers are able to capture significant returns after the start

[25] To be clear, we subtract stocks that are sold from stocks that are bought to compute the net position, which can end up being negative, as in a short sale. The net cash amount to build the position can also be negative if the sell transactions exceed in dollar value the buy transactions. This fact implies that when we compute the maximum exposure, we need to use the absolute value.

of the liquidation, while the trades of the clients of unaware brokers do not generate significant profits. The profits for the best managers peak at about 25 bps 9 days after the start of the fire sale.

Next, to provide more systematic evidence from regression analysis, we estimate the following specification:

$$Profits_{m,i,b,t} = \beta_1 Best\ Client_m \times Liquidation\ Period_t + \beta_2 Best\ Client_m + \beta_3 Liquidation\ Period_t + \varepsilon_{m,i,b,t}, \quad (5)$$

which tests whether a manager m's profits are significantly higher in the ten days after the start of the fire sale relative to the prior ten days, whenever the manager is one of the best clients of the aware broker. Intuitively, as with the estimation of the predation probability, we are comparing the behavior of managers that should be aware of the fire sale, given their relationship with the broker, with those who are likely not, before and after the beginning of the fire sale. We choose a ten-day window to allow managers the time to close the predatory short positions that they likely accumulate during the first five days of the fire sale, which is the period over which on average the stock price declines (see Figure 4).[26]

Table 11 reports the results showing that aware brokers' best clients exhibit significantly higher profits than other managers. On average the best clients, in the ten days following the beginning of the fire sale, are able to over-perform by more than 30 basis points relative to the other managers trading on the same stocks in the same period. Considering the low average performance of institutional asset managers (see, among others, Busse, Goyal, and Wahal, 2010) these higher returns are, indeed, highly economically significant.

One might wonder whether the clients of aware brokers are always able to generate higher profits than the clients of unaware brokers. If this were the case, then what we have shown in the previous table could be explained by the different characteristics of the managers rather than by the privileged access to order flow information. Although we already control for manager-fixed effects, we also directly test for this possibility in Figure 7, which provides a placebo test. The

[26] Of course, the positions could be closed before day 5 and still be profitable. Our methodology for computing profits is flexible enough to allow for all such possibilities.

figure reports the profits for the two groups of managers, but for a random sample of event windows other than the ones included in our fire-sale analysis. We show that the two groups are indistinguishable in terms of their performance during these other times, which corroborates the interpretation that the superior performance we document in Table 11 is made possible by the access to the fire sale information.

We can provide more details regarding the profitability of managers that are strictly defined as predators, that is, the aware brokers' clients that trade in the same direction as the liquidating fund during the five days of the fire sales. Considering all the predated stocks, the average predatory position of a predator during a fire sale event is \$10 million (median \$6 million). The profits arising from these positions amount on average to \$280,449 per event-manager (median: \$126,420).[27] Next, these predatory profits correspond to 2.1 bps of the portfolio value (median: 0.9 bps). This percentage profit is generated over 10 trading days on a predatory trade involving about 4 stocks on average. Thus, it seems a significant source of returns, given the limited amount of capital that is required to carry it out.[28]

We can also quantify the commissions generated by the predators' trades. Each of the aware brokers earns an average of \$40,407 per fire sale event, considering only predatory trades by their best clients on the fire sale stocks, which corresponds to roughly 50% of the total commission these brokers earn on those stocks during the liquidation period (excluding those generated by the liquidating funds). This said, we expect most of the benefits for the brokers to originate from the future business that the improvement in relationship with tipped predators brings about. In particular, in Section 5.2, we show that in the two years following the fire sale event, the predators pay higher commissions per dollar traded to the tipping broker than other clients.

[27] The estimate of 32 bps for additional profits during predation period (Table 11) is computed averaging over all best clients of the aware brokers (to avoid hardwiring the result). Additionally, it results from difference-in-difference regressions including fixed effects. For this reason, this estimate is lower than the estimate of 280 bps (= \$280,449/ \$10 million) that we obtain for the average profits of the predators only.

[28] Because we compute profits using transaction prices, the price impact component of transaction costs is already accounted for. To account for the explicit component of transaction costs, we can use the estimates provided in Ross, Israel, Moskowitz and Serban (2017), based on AQR's internal data. For US equity trades they report that commissions, fees, and taxes erode about 0.3 bps of the notional per trade. Therefore, assuming the trades involve roundtrip transactions, accounting for explicit costs would reduce our estimated average trade-level profit in Table 11 (column 1) from 32 bps to 31.4 bps for the best clients of aware broker. Instead, for the subset of predators, the profits as a fraction of the value of the open position drop from 280 to 279.4 bps.

4.2 Price Impact

Having established that the predatory traders are able to capture significant returns, we investigate the dark side of predation. The conjecture is that predatory volume causes stock prices to decline significantly more than what they would do in the absence of predation. In turn, this steeper decline in prices leads the liquidating fund to achieve lower returns on its sale trades.

Testing this conjecture requires the specification of a counterfactual. Fortunately, we can identify fire sales events for which there are no aware brokers. These are 29 events (i.e. 7.5%) out of a total of 385 events. In these situations, no broker observes a large enough fraction of the liquidation to be deemed aware according to the criteria specified in Section 2. According to our identification strategy, no information leakage occurs on these events. More realistically, the information leakage is expected to be significantly lower.

Based on this strategy, we run event-stock level regressions of price impact onto the broker awareness dummy. The broker awareness dummy denotes situations in which there is at least one aware broker for that stock-event. The price impact is computed as execution shortfall, i.e. the percentage difference between the execution price and a benchmark price (e.g. Keim and Madhavan, 1997).

We use three different benchmarks to show that our results do not crucially depend on a single measure. Specifically, we use the price at the placement time of the first fire sale trade, the open price of the day of the first fire sale trade, and finally the transaction price of the first fire sale trade. In all specifications, we control for the volume in the fire sale, the volume of the following trades (i.e. the trades in the same direction over the same five-day window), and the liquidity of the stock (Amihud, 2002, Illiquidity Ratio), as they are all potentially important drivers of price impact. In more detail, for each benchmark price we compute the implementation shortfall at the ticket-level for the sales by the liquidating funds during the liquidation period as

$$\frac{TransactionPrice - BenchmarkPrice}{BenchmarkPrice}. \tag{6}$$

We then average this quantity at the event-broker level, using as weights the volume of each transaction, to obtain an event-broker level measure of price impact.

Results are reported in Table 12. In Panel A, we regress these price impact measures on the aware broker dummy. Consistently across measures, we show that the price impact costs borne by the liquidating funds are significantly higher when they trade with brokers who are aware of the liquidation event. The estimates are also economically significant as the price impact increases by at least 25 bps and up to 36 bps, which amounts to a two-fold increase in the baseline average price impact. These numbers amount to between 17% and 24% in standard deviation units. In Panel B, we exploit the granularity of our data and run a similar specification in an event-stock-broker level sample. In this case, for the same stock-event, we can have aware and unaware brokers. We can then include broker fixed effects to control for the possibility that heterogeneity in price impact results from difference in broker execution quality. The results remain significant and the magnitude decreases only slightly.[29]

We can also reduce concerns that our findings are driven by expectation of larger price impact affecting awareness rather than the opposite. The literature on block trading in equities (e.g. Seppi, 1990) suggests that this alternative interpretation might be due to the fact that brokers generally frown upon clients breaking up a large order if this large order is likely to create meaningful price impact. Therefore, the liquidating manager on this particular large order may pick very few brokers if he anticipates price impact. This is a plausible alternative channel, given the argument that the clients might refrain from splitting large orders if they are likely to generate a bigger price impact. However, we can address this issue empirically by including in our main specification the number of brokers used by the liquidating fund. With this control, the identification arises from comparing aware and unaware brokers *conditional* on the number of brokers used in the liquidation. This

[29] To fix ideas in terms of orders of magnitude, we can look at Ross, Israel, Moskowitz and Serban (2017), based on AQR's internal data: the paper documents price-impact for a long-only momentum fund with USD 1.6B under management as of 2016. They report that during 2009-2016, market impact was in the range of 6-11 bps per dollar traded. By comparison, in our sample of liquidations, the average execution shortfall is 52 bps per dollar traded by the liquidating funds (median 40 bps). This puts us far away from typical price-impact range. One might also be concerned whether the liquidations might be too small to attract arbitrage capital. However, Table 7 shows that predators are able to trade multiple stocks from a given liquidation event, which through diversification increases the Sharpe ratio of this type of trade.

specification alleviates the concern that broker awareness is an endogenous variable, where the endogeneity emerges because liquidating funds choose to use fewer brokers when they expect higher price impact. On the contrary, our results show a positive (although not statistically significant) correlation between price impact and the number of brokers used in the liquidation.

Finally, we can provide a graphical description of the difference in price paths between the case in which brokers have the possibility to leak (aware brokers) and the case in which brokers do not have information about the liquidation (unware brokers). Figure 8 plots the cumulative return of the fire sale stocks during fire sale events. The red line with squares represents the cumulative return averaged across these stocks and events for the aware brokers. The green line with circles is an estimation of the counterfactual cumulative return, based on unaware brokers. The series draw on estimates from a regression specification similar to the one reported in Table 12, Panel B, but run on daily observations starting on day 0. More precisely, the vertical distance between the two series is the estimate of the aware broker dummy for a specific day of the interval.

Figure 8 is a useful way to show that the transaction cost of the liquidating funds significantly increases in the presence of predatory trading. At the trough of price impact, fifth day of the fire sale, the cumulative return is about -100 bps with aware brokers and about -70 bps in case of unaware brokers, i.e. the case in which we conjecture that no leakage occurs.[30] These results also speak to the role of information leakage in exacerbating fire sales.

[30] In Appendix Table A10, using the full Ancerno sample, we compute the characteristics of managers that during fire sale events trade with aware/unaware brokers. The table shows that managers trading with aware brokers during a fire sale, in general, generate more trading volume (row 1). Accordingly, they have more relations with brokers (row 2). However, they use a significantly lower number of brokers per million dollars that they trade (row 3). This fact suggests that, typically, the managers that face predation (i.e. those that turn to aware brokers) are less in the habit of splitting their volume across multiple brokers. Moreover, we look at the commissions that are generated by the managers. Given that they trade more, the managers that deal with aware brokers pay in general more commissions (row 4). In terms of the repartition of their commission to different brokers, we find that the first category of managers pay more commissions to aware brokers than to unaware brokers, even outside of fire sale events, both per dollar traded (row 5) and in total dollar amounts (row 6). Using Ancerno, Goldstein, Irvine, Kandel, and Wiener (2009) classify broker-manager relationships into premium and discount. The evidence in the table suggests that managers that are predated are more likely to have a premium relationship with aware brokers. Overall, it appears that managers that end up being predated have a more focused relationship with brokers. In particular, they appear to be premium clients who entrust the aware brokers with a larger fraction of their traders. Possibly, these predated clients are trading off the risk of being predate against the advantages in terms of information generation, IPO allocation, etc., which originate from being a premium customer of a broker (Goldstein, Irvine, Kandel, and Wiener, 2009).

5 Further Evidence

In this section, we provide further evidence that is consistent with the interpretation founded on order flow leakage and predatory trades.

5.1 Persistence in the Number of Brokers

One could wonder why the liquidating funds do not better hide their trades to avoid this higher price impact. There are several non-mutually exclusive explanations. First, the evidence suggests that in fact they try to hide their trades as they tend to employ an average of about 29 brokers to intermediate these trades. Second, the funds are most likely in a rush to liquidate, which makes them prioritize execution speed over price impact. For the same reason, they are likely to rely on familiar brokers, as opposed to search for other brokers, which can take time. Third, there is a significant amount of stickiness in the trading relationships between brokers and their clients. We reported in Table 3 the persistence of these relationships. Here, we provide information on the persistence in the number of brokers that managers use. Table 13 reports the autocorrelation of various measures of concentration, such as the number of brokers and the Herfindahl index, both on average and during fire sales events. The relevant finding is that indeed there is significant persistence in the concentration of asset managers' trades among brokers. This result holds both when managers are seeking liquidity, i.e. during fire sales, and when they are not. It appears, therefore, that managers find it difficult to start interacting with new brokers, i.e. building new relationships with brokers, at the time when a timely execution of their trades is needed to meet investors' redemptions demands.

5.2 Quid Pro Quo

Another natural question is whether brokers gain from leaking order flow information about their clients. One might argue that it would be in their best interest to build a reputation as a loyal trading partner by keeping the order flow information private. On the other hand, brokers have an incentive to increase the volume they intermediate as they are paid on commissions. We can address this question by exploiting the granularity of our data and testing whether best clients tend to reward the brokers by channeling more trades to them. Table 14 regresses the average $Commission\ per\ dollar_{e,m,b,t}$ paid by manager m to broker b during month t, defined as the ratio of the total amount in dollars paid in commissions and the total dollar volume traded by manager m and intermediated by broker b in that month, on the interaction of the dummy variable identifying the two years following the fire sale event with each of our Best Clients proxies.[31] We find that the clients who are more likely to receive order flow information tend to increase their commissions to the brokers, which strongly suggests a *quid pro quo* between these parties.

6 Conclusion

This paper studies whether brokers' incentives to attract and retain clients crucially induce sharing of order flow information with other market participants. The evidence suggests that brokers tend to reveal the occurrence of a fire sale to their best clients, allowing them to generate significant profits by predating on the liquidating fund. Furthermore, this information leakage comes at the expense of higher price impact, and leads to a more costly liquidation for the fire sale originator.

These findings have implications for academics, practitioners, and policy makers. First, our results indicate an important cost associated with slow execution. Slow execution has been widely advocated by academics as a way to minimize price impact since Kyle (1985) and routinely implemented by practitioners. In fact, according to our results, executing large trades over multiple days allows the brokers to forecast order flow and to trigger predatory behavior by other market participants. This might adversely affect price impact.

Information leakage might be a source of concern for regulators as well, since it might exacerbate the costs associated with fire sales, especially at times of scarce liquidity. Regulations are unclear on what type of information the brokers can and cannot share with their clients. As

[31] We have performed a similar analysis in which, instead of the proxies for best clients, we look at the clients that are more likely to predate on that stock in that event, which we identify as those that are in the top half of the distribution of profitability in the ten-day window after the event. Also, we run the same analysis focusing on brokers' clients that trade in the same direction as the liquidating fund during the liquidation periods. In both cases, the results (reported in Appendix Table A4, Panels A and B) are very similar to those in Table 14.

pointed out by Fox, Glosten, and Rauterberg (2015), a broker has a legal duty not to use knowledge of a client's order to its own advantage. Hence, a broker trading on its own behalf, before the client's order reaches the market, violates such duty.[32] By extension of this notion, even if a broker receives an indirect benefit from leaking order flow information to a third party, the broker is in violation of the aforementioned legal duty.[33]

This said, brokers can always argue that information leakage occurs while they are still respecting the fiduciary duty of best execution vis à vis their clients. In particular, information may leak while the brokers search for counterparties for a large trade. Irrespective of the fraudulent intentions of the broker, the evidence that we present in the paper shows that liquidity provision is lower among aware brokers than other brokers. Thus, from an objective point of view, the brokers' actions are not in their clients' best interest. Yet, a regulatory attempt to stop information leakage is likely to be challenging, because it will have to deal with the brokers' need to operate as deal-makers, as well as with the reluctance of many asset managers to disclose more information about their trading activities.

A fruitful avenue for further research is to build upon the insights of this paper towards a more articulated theory of how the relationship between asset managers and intermediaries, such as brokers, affects trading behavior and asset prices. Specifically, one could structurally estimate how the flow of information diffuses among market participants and address questions about the efficiency of such strategic behavior by the brokers for price discovery and asset allocation, as well as providing insights into the counterfactual results in the presence of new regulations aimed at curbing this practice.

[32] This situation describes front running, which is prohibited under common law (e.g. Opper v. Hancock), federal law (Section 10(b) of the Exchange Act and Rule 10b-(5)), and industry self-regulatory standards (FINRA Rule 570(a)).

[33] Moreover, a broker passing information concerning a customer order to a third party is violating its agency duties of confidentiality, as well as provisions of Regulation ATS (if the broker is an operator of an Alternative Trading System, such as a dark pool), and probably its own marketing material. See RESTATEMENT (THIRD) OF AGENCY (2006) Section 8.05(2); and Rule 301(b)(10) of Regulation ATS.

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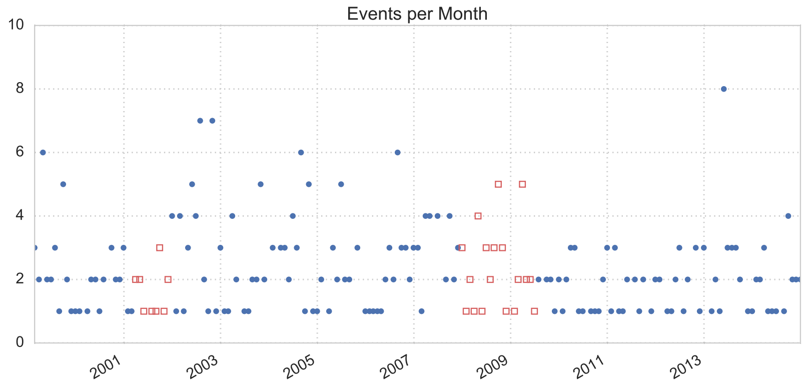

Figure 1: Fire Sale Events. The figure plots the number of fire sales events by month. Hollow red squares identify events happening during the two NBER recessions in our sample period.

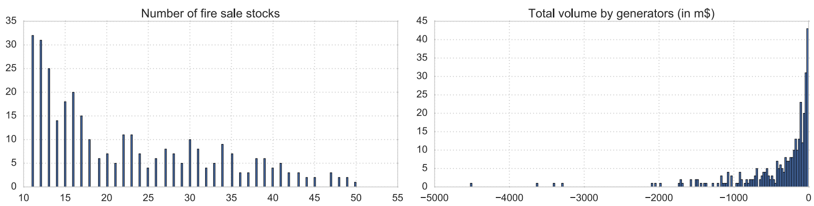

Figure 2: Number of Stocks and Liquidation Volume. The left panel shows the histogram of events with different number of stocks involved in the fire sale. The right panel shows the distribution of the total volume executed by the liquidating funds (*generators*).

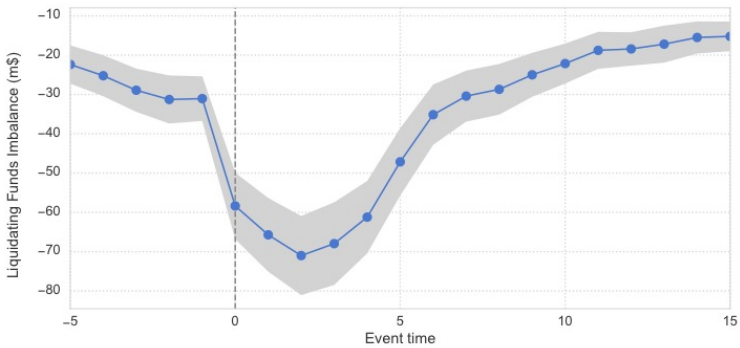

Figure 3: Liquidation Volume. The figure plots the average daily signed volume (i.e. order imbalance) of the fire sale originator on the fire sale stocks, expressed in Million Dollars.

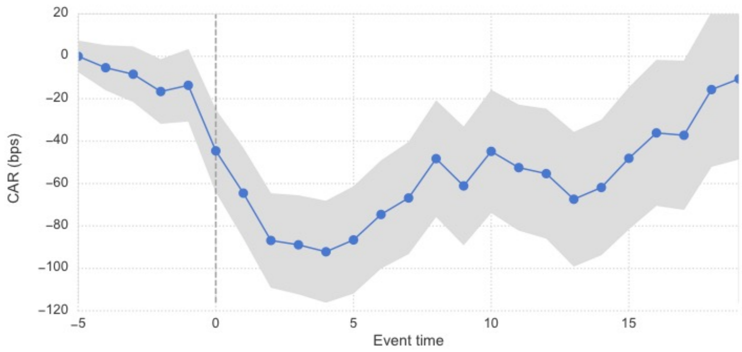

Figure 4: Price Pattern. The figure plots the average DGTW-adjusted cumulative returns for the stocks sold during the fire sales along with 95% confidence bands.

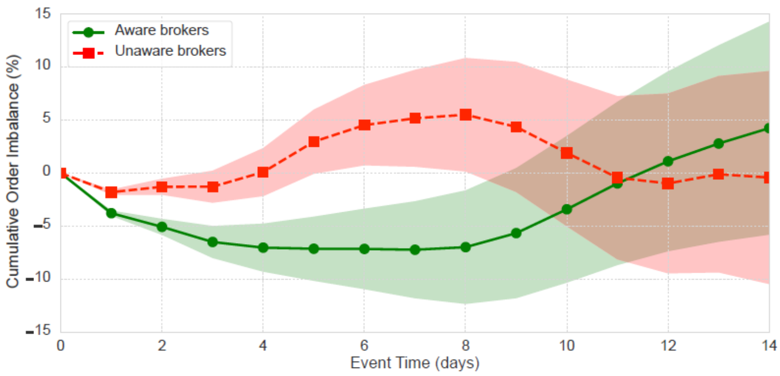

Figure 5: Order Flow through Aware Brokers. The figure plots the cumulative order imbalance of the transactions intermediated by the aware brokers (green solid line) and unaware brokers (red dashed line) on the fire sale stocks, excluding those generated by the liquidating funds. The daily order imbalance computed as the difference of the volume of buy and sell orders divided by the total absolute volume. The measure is then averaged across fire sales in event time.

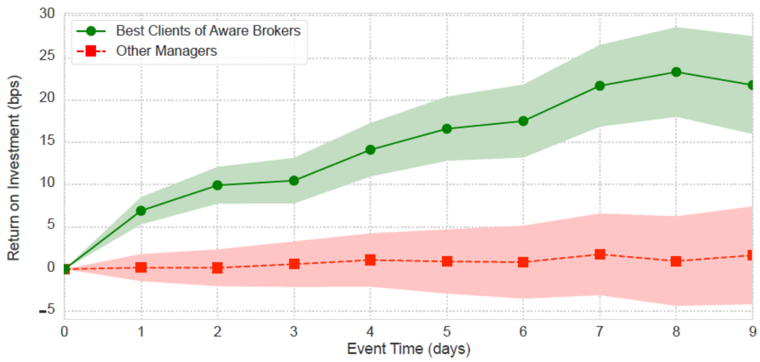

Figure 6: Profitability of Predatory Trades. The figure plots the profits of the managers that are best clients of the aware (green solid line with circles) and unaware (red dashed line with squares) brokers during the fire sale events.

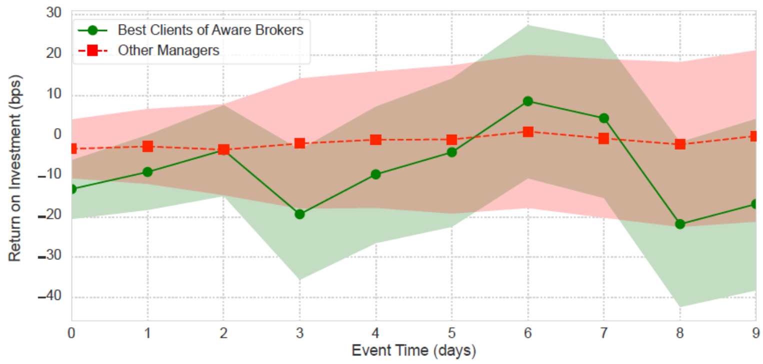

Figure 7: Placebo Test. The figure plots the profits of the managers that are best clients of the aware (green solid line with circles) and unaware (red dashed line with squares) brokers during random event windows other than the actual fire sales employed in the analysis.

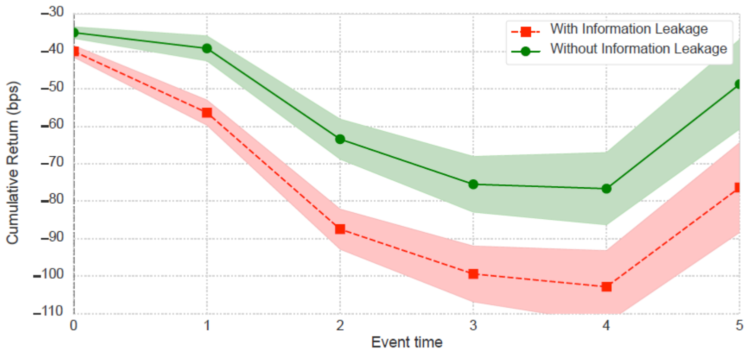

Figure 8: Price Paths with and without Information Leakage. The figure plots the cumulative return of the fire sale stocks during fire sale events involving at least one aware broker. The red line with squares represents the cumulative return averaged across stocks and events in which aware brokers are present. The green line with circles represents the cumulative return averaged across stocks and events in which no aware brokers are present. The series are based on estimates from a regression specification similar to the one reported in Table 12, but run on daily observations.

Table 1
Summary Statistics

Panel A, Panel B and Panel C we report summary statistics for the volume Z-score and the 385 fire sale events identified by our methodology. In Panel D we regress the amount sold of each stock as a fraction of the total fire sale volume on a set of stocks characteristics, while in Panel E we regress the first day in which each stock is sold the first time by the liquidating fund, in event time, on the same set of stocks characteristics. To identify fire sale events, we start by computing the signed volume Z-score Z_t^m for each manager m on day t as $Z_t^m = (DVol_t^m - E(DVol_t^m))/\sigma(DVol_t^m)$, where $DVol_t^m$ is the portfolio level dollar volume traded by manager m on day t, and its mean and standard deviation are estimated over a rolling window of 120 trading days ending one week before day t. Then, at the portfolio level, we define manger m as *liquidating* if Z_t^m is below -0.25 for at least 5 trading days in a row. Next, we impose a filter at the stock level: for stock j to enter the fire sale basket we require that the volume traded by the manager is above 1% of the CRSP daily volume for at least 4 of the fire sale days. Finally, we keep events in which at least 10 stocks are sold by the liquidating fund. Standard errors are clustered at the event level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Volume Z-Score

	Obs	Mean	S.D.	Min	0.25	0.5	0.75	Max
All Managers-Days	941219	-0.035	3.249	-41.714	-0.369	0.027	0.394	35.889
Fire Sales Days	2210	-2.075	4.518	-41.714	-1.768	-1.038	-0.616	-0.251
Fire Sales Events	385	-2.002	3.410	-37.818	-1.672	-1.172	-0.878	-0.344

Panel B: Fire Sale Events

	Unit	Obs	Mean	S.D.	25%	50%	75%	90%
Dollar Volume	Million Dollars	385	-377.062	534.635	-503.571	-177.461	-50.544	-18.244
Fraction of Portfolio	Percentage	385	9.164%	23.921%	1.224%	2.274%	5.879%	15.828%
Number of Stocks		385	21.917	10.090	13	18	29	38
Event Length	Trading Days	385	5.766	1.439	5	5	6	7
Number of Brokers		385	28.803	16.095	18	27	39	52
Number of Aware Brokers		385	1.694	0.968	1	2	2	3

Panel C: Fire Sale Stocks

	Unit	Obs	Mean	S.D.	25%	50%	75%	90%
Dollar Volume	Million Dollars	8438	-17.204	20.305	-23.401	-11.246	-3.542	-1.366
CRSP volume ratio	Percentage	8438	-14.576%	16.000%	-18.749%	-9.922%	-4.585%	-2.409%
Number of Brokers		8438	5.737	5.039	2	4	8	13
Number of Aware Brokers		8438	0.522	0.603	0	0	1	1

Panel D: Fire Sale Stocks Selection

Dependent Variable	Amount Sold as a Fraction of the Fire Sale					
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Weight	1.863***	1.830***	1.319***	1.805***	1.301***	1.318***
	(6.522)	(6.427)	(5.875)	(6.540)	(5.815)	(5.842)
Amihud Ratio		-0.691***			-0.486***	-0.506***
		(-8.419)			(-6.579)	(-6.775)
Market Cap			2.614***		2.427***	2.441***
			(11.580)		(10.926)	(10.977)
Volatility				-6.698***	-3.838***	-3.394***
				(-12.549)	(-7.296)	(-6.438)
One Month Return						0.112
						(0.981)
Six Months Return						0.209*
						(1.741)
One Year Return						0.340***
						(2.783)
Observations	7,948	7,948	7,948	7,948	7,948	7,948
R-squared	0.134	0.142	0.237	0.164	0.253	0.257
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Fire Sale Stocks Timing

Dependent Variable	First Day In Which The Stock Is Sold					
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Weight	-0.034***	-0.033***	-0.026***	-0.033***	-0.025***	-0.025***
	(-3.862)	(-3.732)	(-3.218)	(-3.831)	(-3.128)	(-3.184)
Amihud Ratio		0.028***			0.025***	0.025***
		(4.008)			(3.515)	(3.530)
Market Cap			-0.040***		-0.036***	-0.037***
			(-5.736)		(-5.233)	(-5.319)
Volatility				0.113***	0.055	0.050
				(2.982)	(1.443)	(1.311)
One Month Return						0.011
						(1.228)
Six Months Return						0.002
						(0.189)
One Year Return						-0.018*
						(-1.785)
Observations	7,948	7,948	7,948	7,948	7,948	7,948
R-squared	0.209	0.211	0.213	0.211	0.215	0.215
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2
Predatory Behavior and Broker Awareness

The table reports results on the likelihood of a broker to attract predatory trades. The regressions are run at the ticket-level, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In Columns (1)-(4), the dependent variable is a dummy indicating predation, i.e. it takes value one when the trade is in the same direction of the volume by the liquidating fund for that stock on that day (i.e. it is a sell trade), while it equals zero if the trade is in the opposite direction (i.e. a buy trade), or if the manager is not trading that stock on that particular day. The independent variable *Aware* is a dummy, defined at the event-broker-stock-day level, indicating that the broker is aware of the fire sale happening on the traded stock on that day. Precisely, this means that for broker *B*, stock *j* on day *t* of the fire sale event *e* broker *b* intermediates transactions on stock *j* from the liquidating fund originating *e* amounting to a volumewhich is above 2% of the average daily volume of stock *j*. In Columns (5)-(8), we weight the above described dependent variable by the volume of the trade as a fraction of market capitalization, standardized. Panel A presents the baseline results, while in Panel B we further saturate the model adding Broker-Stock and Day-Stock fixed effects. In Panel C we use as dependent variables the difference between the probability of predation and the probability of liquidity provision (1)-(4) and the difference between predatory volume and liquidity provision volume (5)-(8). Standard errors are clustered at the broker level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Baseline

Dependent Variable	Probability of Predation				Volume of Predatory Trades			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aware Dummy	0.232***	0.192***	0.171***	0.170***	0.103***	0.087***	0.085***	0.081***
	(10.589)	(9.980)	(10.132)	(10.142)	(5.298)	(5.059)	(4.932)	(4.726)
Constant	0.354***				-0.004			
	(33.482)				(-1.084)			
Time Fixed Effects		Yes	Yes	Yes		Yes	Yes	Yes
Manager Fixed Effects			Yes	Yes			Yes	Yes
Broker Fixed Effects				Yes				Yes
Observations	496,729	496,729	496,685	496,555	496,729	496,729	496,685	496,555
R-squared	0.008	0.069	0.103	0.107	0.000	0.014	0.020	0.026

Panel B: Broker-Stock and Day-Stock Fixed Effects

Dependent Variable	Probability of Predation		Volume of Predatory Trades	
	(1)	(2)	(3)	(4)
Aware Dummy	0.124***	0.103***	0.049***	0.062***
	(11.399)	(7.469)	(4.065)	(4.578)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Broker X Stock FEs	Yes		Yes	
Day X Stock FEs		Yes		Yes
Observations	462,841	487,605	462,841	487,605
R-squared	0.274	0.360	0.193	0.189

Panel C: Predation and Liquidity Provision

Dependent Variable	Prob of Predation - Prob of Liquidity Provision				Predatory Volume - Liquidity Provision Volume			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aware Dummy	0.232***	0.237***	0.201***	0.195***	0.054***	0.045***	0.043**	0.043**
	(5.175)	(5.879)	(5.747)	(5.595)	(3.078)	(2.715)	(2.504)	(2.505)
Constant	-0.022				-0.002			
	(-1.119)				(-1.166)			
Time Fixed Effects		Yes	Yes	Yes		Yes	Yes	Yes
Manager Fixed Effects			Yes	Yes			Yes	Yes
Broker Fixed Effects				Yes				Yes
Observations	496,729	496,729	496,685	496,555	496,729	496,729	496,685	496,555
R-squared	0.002	0.023	0.061	0.065	0.000	0.009	0.012	0.017

Table 3
Persistence of Broker-Client Relationship

The table reports results on the persistence of our proxies for the strength of the broker-manager relationship, defined as follows:

(1) Dummy variable indicating that the manager generated at least 5% of the total volume intermediated by the broker over the previous semester.
(2) Dummy variable indicating that the manager generated at least 5% of the total commissions earned by the broker over the previous semester.
(3) Continuous variable with values in the unit interval, ranking of the manager in terms of the volume generated for the broker over the previous semester.
(4) Continuous variable with values on the unit interval, ranking of the manager in terms of the commission paid to the broker over the previous semester.

For each of the above proxies of relationship strength, we run a panel regression of the proxy onto its one-month lagged value. The panel is not fully balanced due to the fact that not all months record a broker-manager interaction. Thus, we fill with zeros the manager-broker pairs for which there is no transaction but for which at least one transaction with another manager or broker is present in Ancerno in that period. Manager and broker fixed-effects are included in the regression. Stardard errors are double-clustered at the manager- and broker-level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Best Client			
Best clients proxy	(1) Volume above 5%	(2) Commissions Paid above 5%	(3) Ranking based on Volume	(4) Ranking based on Commissions Paid
Best Client (Lag)	0.8318***	0.8263***	0.9313***	0.9280***
	(94.2986)	(85.8211)	(248.5710)	(232.4146)
Observations	4,482,135	4,482,135	4,482,135	4,482,135
R-squared	0.6923	0.6825	0.8749	0.8670

Table 4
Probability of Predation and Broker-Client Relationship Strength

The table presents evidence of the effect of broker-client relationship strength on the probability of predatory behavior. The regressions are run at the ticket-level, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In all specifications the dependent variable is a dummy indicating predation, i.e. it takes value one when the trade is in the same direction of the volume by the liquidating fund for that stock on that day (i.e. a sell trade), while it equals zero if the trade is in the opposite direction (i.e. a buy trade) or if the liquidating fund is not trading that stock on that particular day. In Panel A we regress the dependent variable on the dummy *Best Client* indicating if the manager is among the best clients of the broker intermediating the transcation, the dummy *Liquidation Period* indicating the first 5 days of the fire sale, and the interaction of the two dummies. We consider all trades on stock j intermediated by brokers that eventually become aware that the stock is subject to fire sale pressure, i.e. brokers B for which $max_{t\in[0,4]}(AwaBro_t^{Bj}) = 1$, where $AwaBro_t^{Bj}$ is defined as above. The regression is run on a sample that includes five days before the fire sale and five days from the start of the fire sale, defined as the first day in which our liquidation measure crosses the threshold. In Panel B we regress the dependent variable on the triple interaction of the following dummies: *Aware Broker* indicating if the broker is aware, *Best Client* indicating if the manager is among the best clients of the broker intermediating the transcation, and *Liquidation Period* indicating the first 5 days of the fire sale. In Panel C we use as dependent variables the difference between the probability of predation and the probability of liquidity provision (1)-(2) and the difference between predatory volume and liquidity provision volume (3)-(4). We include manager, broker, stock, day and event fixed effects. Standard errors are clustered at the event-stock-manager level. Panel D presents characteristics of the fire sale stocks, partitioned into two groups based on degree of predation they are subject to. More precisely, for each fire sale stock event we record the number of best clients of aware *P* divided by the number *N* of managers actively trading during the fire sale event on that stock. The cross-sectional distribution of the event-stock level variable the ratio *P/N* is then used to split the set of fire sale stocks into two parts, using the median as cutoff. For each of the two groups we take the average of the following quantities, computed at the event-stock level: (i) the dollar volume liquidated during the fire sale; (ii) the volume liquidated during the fire sale as a fraction of the volume recorded in CRSP for that stock; (iii) the first day in which the stock is sold during the fire sale, in event time; (iv) the weight of the stock in the portfolio of the liquidating fund, reconstructed based on previous transactions; (v) the Amihud illiquidity ratio of the stock, computed using data from the semester preceding the fire sale; (vi) the market capitalization of the stock; (vii) the daily return volatility of the stock, estimated using data from the semester preceding the fire sale; (viii) the cumulating return of the stock during the month preceding the fire sale. For each quantity, we report the averages of the two groups and their difference. T-stats of the differences are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Difference in Differences

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.015***	0.016***	0.001***	0.002***
	(7.658)	(7.998)	(10.214)	(10.366)
Best Client	0.005*	0.002	0.000**	0.000
	(1.846)	(0.689)	(2.426)	(1.457)
Liquidation Period	0.021***	0.021***	0.019***	0.019***
	(7.880)	(7.827)	(7.171)	(7.064)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	501,558	501,558	501,558	501,558
R-squared	0.177	0.177	0.178	0.178

Panel B: Triple Interaction

Dependent variable	Probability of Predation			
Best clients proxy	(1) Volume above 5%	(2) Commissions Paid above 5%	(3) Ranking based on Volume	(4) Ranking based on Commissions Paid
Aware Broker × Best Client × Liquidation Period	0.012	0.019**	0.150***	0.163***
	(1.431)	(2.117)	(2.946)	(2.825)
Best Client × Liquidation Period	0.004***	0.002***	0.024***	0.022***
	(5.064)	(3.072)	(6.880)	(5.896)
Aware Broker × Liquidation Period	0.012***	0.011***	0.010***	0.010***
	(5.950)	(5.519)	(4.395)	(4.280)
Best Client × Aware Broker	0.007	0.005	0.131**	0.176**
	(1.164)	(0.867)	(2.137)	(2.280)
Best Client	0.012***	0.009***	0.045***	0.040***
	(14.860)	(10.946)	(13.240)	(9.790)
Aware Broker	0.005***	0.005***	0.002	0.001
	(3.699)	(3.981)	(1.092)	(0.563)
Liquidation Period	0.012***	0.012***	0.012***	0.012***
	(36.427)	(37.568)	(35.691)	(36.247)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,471,501	3,471,501	3,471,501	3,471,501
R-squared	0.023	0.022	0.023	0.023

Panel C: Predation and Liquidity Provision

Dependent Variable	Prob of Predation - Prob of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
Best clients proxy	(1) Ranking based on Volume	(2) Ranking based on Commissions Paid	(3) Ranking based on Volume	(4) Ranking based on Commissions Paid
Best Client × Liquidation Period	0.001***	0.001***	0.001***	0.001***
	(3.073)	(4.127)	(3.297)	(3.014)
Best Client	-0.001***	-0.000	-0.002***	-0.002***
	(-3.231)	(-1.625)	(-3.214)	(-3.037)
Liquidation Period	0.008**	0.007*	0.006	0.006
	(2.121)	(1.921)	(0.820)	(0.813)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	501,558	501,558	501,558	501,558
R-squared	0.133	0.133	0.070	0.070

Panel D: Characteristics of Predated Stocks

	More Predation	Less Predation	Difference	t-stat
Liquidation volume (million $)	18.595	11.056	7.539***	(32.747)
Volume / CRSP volume (%)	12.812	23.633	-10.821***	(-48.060)
First day sold	0.285	0.454	-0.170***	(-25.569)
Portfolio weight (%)	0.409	0.293	0.116***	(15.475)
Amihud ratio	0.019	0.277	-0.258***	(-85.176)
Market Cap (million $)	7.844	0.362	7.482***	(37.504)
Daily Return Volatility (%)	0.425	0.606	-0.181***	(-65.154)
Past month performance (%)	-0.098	-1.659	1.561***	(10.006)

Table 5
Robustness: Excluding Bad News

The table reports results on a first set robustness checks on the baseline results presented in Table 4. In the specifications of Panel A we exclude the fire-sale events happening during NBER recession periods, which in our sample include the burst of the dot-com bubble (March 2001 – November 2001) and the global financial crisis (December 2007 – June 2009). In the specifications of Panel B we exclude stocks subject to negative fundamental news in a window of 5 days before and after the start of the fire-sale event, as proxied by (i) negative earning surprises, (ii) Raven Pack news index in the bottom quartile, (iii) negative analyst reccomendation changes. We include manager, broker, stock, day and event fixed effects and we cluster standard errors at the event-stock-manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Excluding NBER Recessions Periods

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.015***	0.015***	0.001***	0.002***
	(6.934)	(7.147)	(9.542)	(9.590)
Best Client	0.006**	0.003	0.001***	0.000***
	(2.234)	(1.071)	(3.568)	(2.597)
Liquidation Period	0.020***	0.020***	0.018***	0.018***
	(6.774)	(6.714)	(6.104)	(6.011)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	428,305	428,305	428,305	428,305
R-squared	0.178	0.178	0.179	0.179

Panel B: Excluding Negative News

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.014***	0.014***	0.001***	0.001***
	(7.052)	(6.960)	(9.108)	(9.056)
Best Client	0.004*	0.002	0.000**	0.000
	(1.726)	(0.664)	(2.265)	(1.459)
Liquidation Period	0.022***	0.022***	0.021***	0.021***
	(7.938)	(7.939)	(7.315)	(7.233)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	447,495	447,495	447,495	447,495
R-squared	0.182	0.182	0.183	0.182

Table 6
Robustness: Excluding Underperforming Stocks

The table reports results on a set of robustness checks on the baseline results presented in Table 4. In the specifications of Panel A we exclude stocks expriencig negative returns in a window of 10 days preceding the start of the fire-sale event. In Panel B, we exclude stocks with high short interest in the 2 weeks preceding the fire sale event, as proxied by a value of utilisation ratio, computed using data from Markit as shares on loan / shares available from lending, in the top quartile of the cross-sectional distribution in the CRSP universe. We include manager, broker, stock, day and event fixed effects and we cluster standard errors at the event-stock-manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Excluding Negative Momentum Stocks

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.018***	0.018***	0.001***	0.002***
	(6.967)	(6.805)	(8.455)	(8.668)
Best Client	0.003	-0.001	0.000	0.000
	(0.879)	(-0.346)	(1.480)	(0.430)
Liquidation Period	0.018***	0.018***	0.016***	0.016***
	(5.052)	(5.075)	(4.598)	(4.511)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	288,208	288,208	288,208	288,208
R-squared	0.198	0.198	0.198	0.198

Panel B: Excluding High Short Interest Stocks

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.014***	0.014***	0.001***	0.002***
	(7.644)	(7.669)	(9.972)	(10.241)
Best Client	0.007***	0.003	0.000***	0.000*
	(3.344)	(1.185)	(2.909)	(1.952)
Liquidation Period	0.019***	0.019***	0.017***	0.017***
	(7.495)	(7.492)	(6.158)	(6.031)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	596,760	596,760	477,450	477,450
R-squared	0.154	0.154	0.175	0.175

Table 7
Evidence of Predation on Multiple Stocks

The table reports results on the number of stocks experiencing predatory pressure. For each fire sale event we consider the basket of liquidated stocks, and for each manager actively trading at least one stock in the basket we count the number of stocks traded in the same direction of the fire sale originator. In Panel A, we consider event-manager observations and we regress the number of predated stocks on best client proxies. These are constructed by interacting the original best client proxies with the broker awareness dummy at the ticket-level, and then by taking the maximum value at the event-manager level. In other words a manager is tagged as *best client* in this regression if it is among the best clients of at least one of the aware brokers in the fire sale event. Then, the number of predated stocks is calculated considering all of the fire sale stocks predated by the manager across all brokers. In Panel B, we repeat the exercise by adopting as dependent variable the fraction of predated stocks relative to the stocks in the fire sale basket. Event, manager and day fixed effects are included in the regressions and standard errors are double clustered at the manager and event level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Number of stocks

Dependent variable	Number of Predated Stocks			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client	4.3197***	4.1500***	0.1455***	0.1507***
	(10.4125)	(12.1330)	(4.8645)	(4.5162)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Observations	28,168	28,168	28,168	28,168
R-squared	0.4011	0.3938	0.3900	0.3857

Panel B: Fraction of fire-sale basket

Dependent variable	Fraction of Predated Stocks			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client	16.8099***	16.4067***	0.5785***	0.5979***
	(10.1123)	(10.9601)	(5.1482)	(4.8554)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Observations	28,168	28,168	28,168	28,168
R-squared	0.4726	0.4677	0.4647	0.4607

Table 8
Predators' Position Reversal

The dependent variable is the fraction of sales in a given stock that a given manager subsequently reverses. In detail, in a given time period, either before or after the beginning of the fire sale, the percentage of position reversed for manager m during event e for stock j is defined as the ratio $Rev_{e,m,j} = BoughtBack_{e,m,j} / Sold_{\mathrm{e,m,j}}$, where $Sold_{\mathrm{e,m,j}}$ is the dollar sum of all sell orders in that period, and $BoughtBack_{e,m,j}$ is the dollar sum of buy orders during the period, where we sum only the buy orders that are preceded by a negative cumulative order flow. We compute this measure around each fire sale event, for the event time periods $Pre = [-10, -1]$ and $Post = [1,10]$, considering all trades on stock j intermediated by brokers who eventually become aware that the stock is subject to fire sale pressure. We then compare the percentage of position reversed by *Best* and *Non-Best* clients of the aware brokers before (Pre) and during ($Post$) the fire sale events. Liquidating funds are excluded from the sample. Time, stock and manager fixed-effects are added to the regression and standard errors are clustered at the manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Percentage of Positions Reversed			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Dummy[1,10]	11.594***	11.005***	0.234***	0.207***
	(6.104)	(5.787)	(5.404)	(4.151)
Best Client	-6.852***	-5.542***	-0.070**	-0.019
	(-4.536)	(-3.802)	(-2.010)	(-0.526)
Dummy[1,10]	15.074***	15.694***	16.287***	18.320***
	(12.215)	(12.955)	(14.256)	(15.494)
Time Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Observations	31,000	31,000	31,000	31,000
R-squared	0.257	0.257	0.258	0.256

Table 9
Evidence from the 2003 Mutual Fund Scandal

We first match the list of 27 mutual fund families involved in the 2003 late-trading scandal with managers in our dataset and mark them as *charged*. We focus on daily transactions of the managers that are not involved in the scandal for a period of four years centered on the month of the announcement of the complaint by Spitzer (September 2003) and define a dummy $Post\ Scandal_t$, indicating the two years after the complaint broke out. Next, we define a broker-stock-day level dummy variable, $Selling_{b,j,t}$, indicating that at least one of the charged funds is selling stock j on day *t* through broker *b*. Then, we define the dependent variable *Probability of Predation* as a dummy variable that equals 1 if a non-charged manager is selling stock j on day *t* through broker *b*. The dependent variable equals 0 if a non-charged manager trades on a different day, or on a different stock, or with a different broker. In a difference-in-differences setting, we regress the probability of predation on the interaction between $Selling_{b,j,t}$ and the dummy $Post\ Scandal_t$. We include an increasing sequence of day, manager, stock and broker fixed effects. Standard errors are clustered by manager-stock to and T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Probability of Predation				
	(1)	(2)	(3)	(4)	(5)
Selling × Post Scandal	0.043***	0.048***	0.034***	0.030***	0.023***
	(11.409)	(12.790)	(9.259)	(8.220)	(6.339)
Selling	0.074***	0.071***	0.074***	0.076***	0.090***
	(23.090)	(22.191)	(22.444)	(23.573)	(28.319)
Post Scandal	-0.013***				
	(-9.388)				
Observations	12,087,004	12,087,004	12,087,001	12,086,863	12,086,781
R-squared	0.001	0.013	0.068	0.076	0.082
Time Fixed Effects		Yes	Yes	Yes	Yes
Manager Fixed Effects			Yes	Yes	Yes
Stock Fixed Effects				Yes	Yes
Broker Fixed Effects					Yes

Table 10
Hedge Funds vs. Other Institutions

The table reports results on the heterogeneity of the predatory behavior with respect to the characteristics of the clients. We run stock-level regressions with the same specification as in the baseline version of Table 4, but restricting to managers identified as hedge funds in Panel A and to the complementary set of other institutions in Panel B. We include manager, broker, stock, day, and event fixed effects and we cluster standard errors at the event-stock-manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Hedge Funds Sample

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.015***	0.015***	0.001***	0.001***
	(5.498)	(5.495)	(5.388)	(5.556)
Best Client	0.002	-0.003	0.000	0.000
	(0.384)	(-0.883)	(0.669)	(0.142)
Liquidation Period	0.020***	0.020***	0.020***	0.019***
	(5.120)	(5.133)	(5.025)	(4.985)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	230,775	230,775	230,775	230,775
R-squared	0.200	0.200	0.200	0.200

Panel B: Non-Hedge Funds Sample

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.011***	0.013***	0.002***	0.002***
	(4.179)	(4.433)	(8.384)	(8.672)
Best Client	0.009***	0.009**	0.001***	0.001***
	(2.745)	(2.452)	(3.299)	(3.021)
Liquidation Period	0.023***	0.023***	0.020***	0.019***
	(6.161)	(6.105)	(5.287)	(5.095)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	270,778	270,778	270,778	270,778
R-squared	0.193	0.193	0.194	0.194

Table 11
Profitability of Predatory Trades

The table reports results on the profitability of trades by predators around the fire sales events. We divide each event into a pre-fire sale period $[-10, -1]$ and a post-fire sale period [0,9], where zero denotes the day on which the fire sale starts. We then compute the profitability of trades by manager m on stock j over the window $\pi = [t_0, t_1]$, which denotes either the pre or post fire sale period. Profitability is defined as

$$Profitability_{m,j,\pi} = \left(MarkToMarket_{m,j,\pi} - CashFlows_{m,j,\pi} \right)/Exposure_{m,j,\pi}.$$

Here, $MarkToMarket_{m,j,\pi}$ is the marked-to-market dollar value of the position at time t_1, defined as the product of the share position cumulated from t_0 to $t_1$with the market price of stock j on day t_1. $CashFlows_{m,j,\pi}$ is the dollar amount spent to build the position, i.e. the opposite of the dollar volume of each transaction in the stock (based on execution prices) from from t_0 to t_1. $Exposure_{m,j,\pi}$ is the maximum dollar outlay over the relevant period, defined as $\max_{t\in\pi} \left|CashFlows_{m,j,[t_0,t]}\right|$. We compare the profitability (expressed in basis points) of trades by best clients of aware brokers to that of other managers, in the pre and post fire sale periods, using event-manager-stock level observations. Time and manager fixed-effects are added to the regression and standard errors are clustered at the manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Return on Capital (basis points)			
Best clients proxy	(1) Volume above 5%	(2) Top Decile of Volume	(3) Top Decile of Commissions	(4) Ranking based on Volume
Best Client × Post	32.671**	30.289*	1.451**	1.586**
	(2.394)	(1.813)	(2.093)	(1.972)
Best Client	-14.423	-21.446**	-0.745**	-1.062***
	(-1.445)	(-2.375)	(-2.233)	(-2.816)
Post	-7.762**	-7.544**	-7.570**	-7.530**
	(-2.545)	(-2.522)	(-2.493)	(-2.480)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Observations	263,211	263,211	263,211	263,211
R-squared	0.034	0.034	0.034	0.034

Table 12
Price Impact and Broker Awareness

This table reports results on the price impact experienced by the fire sale originators. We construct the following price impact measures: (i) the execution shortfall based on the first placement price, (ii) the execution shortfall based on the first open price, (iii) the execution shortfall based on the first transaction price. We aggregate the measures taking their volume-weighted average across transactions and express them in basis points. In Panel A, we regress the price impact measures on a dummy indicating the presence of an aware broker at the event-stock level and the total volume of other managers (followers) relative to the stock market capitalization. We control for the originator volume relative to the stock market capitalization and the Amihud ratio of the stock, estimated on the previous six months. Time and stock fixed effects are added to the regression. In Panel B we repeat the exercise at the event-stock-broker-level and we add broker fixed effects. Continuos explanatory variables are standardized and standard errors are clustered by event. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Price Impact at the stock-level

Dependent variable	Price Impact (basis points)		
	(1)	(2)	(3)
Benchmark Price	First Placement Price	Open Price	First Transaction Price
Aware Broker Dummy	25.176*	36.194**	14.250
	(1.849)	(2.503)	(1.442)
Followers Volume	23.801***	24.286***	8.520*
	(2.787)	(2.710)	(1.680)
Generator Volume	6.996	8.560	0.520
	(0.646)	(0.706)	(0.067)
Amihud Ratio	-19.080	-20.435	-18.598
	(-1.070)	(-1.101)	(-1.382)
Number of Brokers	-3.489	1.193	-1.938
	(-0.515)	(0.152)	(-0.373)
Time Fixed Effects	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes
Observations	6,291	6,291	6,291
R-squared	0.430	0.430	0.415

Panel B: Price Impact at the broker-level

Dependent variable	Price Impact (basis points)		
	(1)	(2)	(3)
Benchmark Price	First Placement Price	Open Price	First Transaction Price
Aware Broker Dummy	11.901***	11.320**	8.970**
	(2.764)	(2.217)	(2.496)
Followers Volume	4.882**	4.898*	2.457
	(2.020)	(1.815)	(1.259)
Generator Volume	21.760***	20.890***	11.607**
	(3.691)	(3.293)	(2.449)
Amihud Ratio	-12.067	-6.532	-8.238
	(-1.262)	(-0.703)	(-1.437)
Number of Brokers	6.359	9.710	4.731
	(1.137)	(1.509)	(1.334)
Time Fixed Effects	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes
Observations	28,265	28,265	28,265
R-squared	0.323	0.338	0.265

Table 13
Persistence of Broker Concentration

This table reports results on the concentration of brokers employed by asset managers in our sample. We construct three proxies of broker concentration: (i) the Herfindahl Index (HHI) of the trading volumes at the monthly frequency, (ii) the normalized Herfindahl Index (HHI) of the trading volumes at the monthly frequency and (iii) the number of brokers intermediating at least one trade of the manager in the given month. In Panel A, we regress each proxy on their one-month, six-months and one-year lags using observations at the manager-month level. In Panel B, we repeat the same exercise restricting to the sample to fire sale events. All the specifications include month fixed effects. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Unconditional Brokers Concentration

Dependent Variable	HHI	HHI	Normalized HHI	Normalized HHI	Number of Brokers	Number of Brokers
	(1)	(2)	(3)	(4)	(5)	(6)
One Month Lag	0.592***	0.398***	0.388***	0.279***	0.961***	0.756***
	(193.897)	(104.549)	(111.338)	(70.742)	(908.650)	(270.680)
Six Months Lag		0.220***		0.179***		0.144***
		(55.312)		(43.966)		(43.850)
One Year Lag		0.172***		0.156***		0.084***
		(44.943)		(39.187)		(30.395)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,284	60,839	70,284	60,839	70,284	60,839
R-squared	0.362	0.433	0.161	0.215	0.922	0.931

Panel B: Brokers Concentration during Fire Sale Events

Dependent Variable	HHI	HHI	Normalized HHI	Normalized HHI	Number of Brokers	Number of Brokers
	(1)	(2)	(3)	(4)	(5)	(6)
One Month Lag	0.260***	0.222***	0.203***	0.170***	1.038***	1.011***
	(12.642)	(9.749)	(10.445)	(6.796)	(55.184)	(18.047)
Six Months Lag		-0.001		-0.001		0.021
		(-0.292)		(-0.227)		(0.351)
One Year Lag		0.027**		0.032*		0.008
		(2.180)		(1.813)		(0.203)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	322	284	322	284	322	284
R-squared	0.654	0.734	0.590	0.670	0.958	0.957

Table 14
Commissions Paid to Aware Brokers

The table presents evidence on the post-event increase of commissions paid by predators to aware brokers. For each month t on a window starting two years before and ending two year after each fire sale event e, we define the average $Commission\_per\_dollar_{e,m,b,t}$ paid by manager m to broker b as the ratio $Comm_{e,m,b,t}/DVol_{e,m,b,t}$, where $Comm_{e,m,b,t}$ is the total amount in dollars paid in commissions by manager m to broker b during month t and $DVol_{e,m,b,t}$ is the total dollar volume traded by manager m and intermediated by broker b in that month. For each event, we consider brokers which are marked as *Aware* on at least one of the fire sale stocks and managers whose trades are intermediated by at least one of these broker in the ten trading days around the event. We then regress $Commission\_per\_dollar_{e,m,b,t}$ on the interaction of the dummy variable $Post_{e,t}$, indicating the two years following the fire sale event, with each of our *Best Clients* proxies. We add event, manager, and brokers fixed-effects to the regression and we cluster standard errors by event-broker-manager to account for time-series autocorrelation in commissions paid. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Commissions per dollar (basis points)			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Post	0.391***	0.159*	0.013**	0.009
	(5.047)	(1.871)	(2.171)	(1.391)
Best Client	-1.040***	-0.479***	-0.043***	-0.021**
	(-9.226)	(-3.903)	(-5.617)	(-2.530)
Post	-0.609***	-0.568***	-0.583***	-0.565***
	(-11.710)	(-10.990)	(-11.425)	(-11.144)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,168,521	1,168,521	1,168,521	1,168,521
R-squared	0.228	0.227	0.228	0.227

Brokers and Order Flow Leakage: Evidence from Fire Sales

Andrea Barbon Marco Di Maggio Francesco Franzoni Augustin Landier

INTERNET APPENDIX

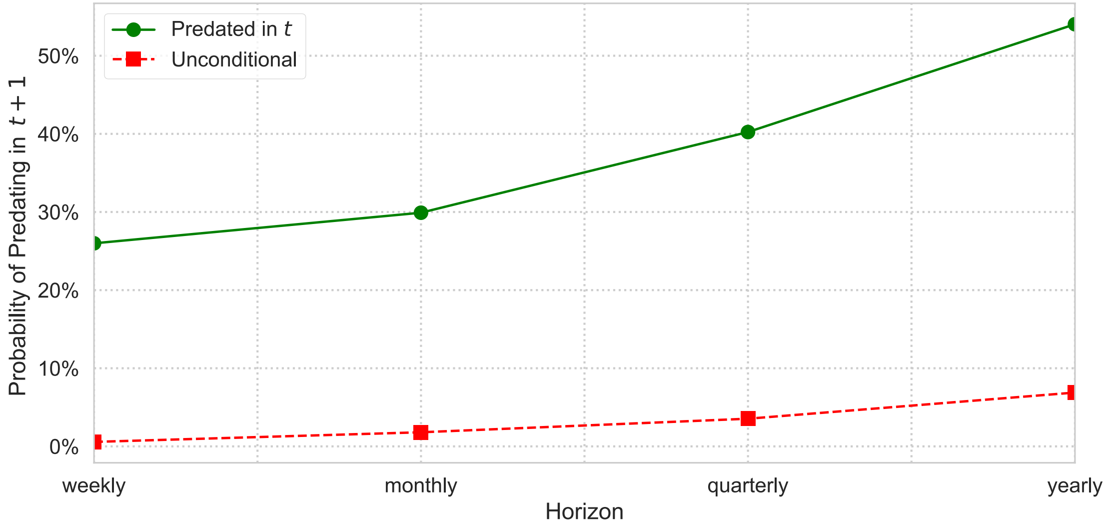

Figure A1: Predators Persistence. The figure compares the unconditional probability of predation with the probability of predation conditional on having predated at least once in the previous period. Subsequent periods are defined over weekly, monthly, quarterly and yearly horizons.

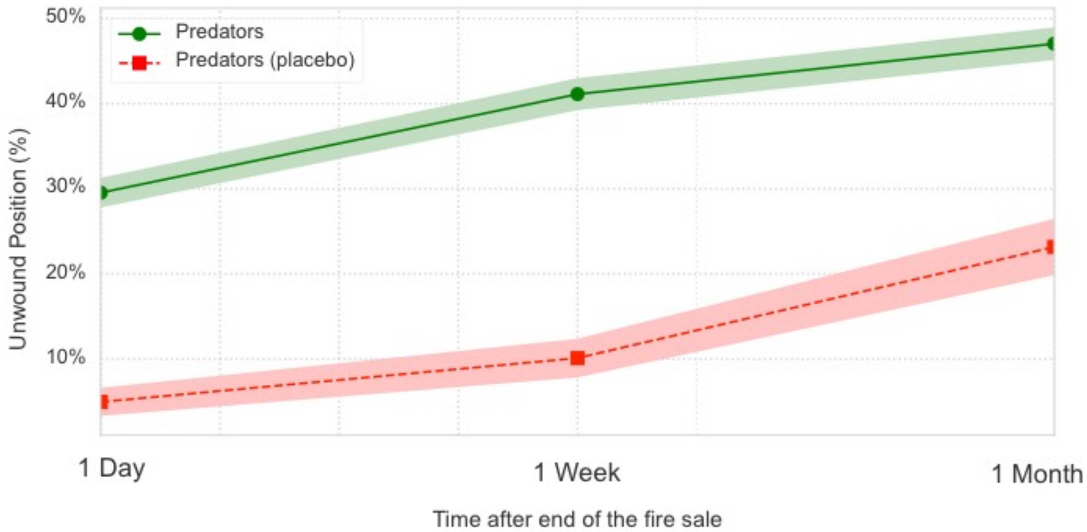

Figure A2: Unwinding of Predatory Positions. The figure plots the average percentage amount of predatory positions built during the fire sales by predators (managers who trade in the same direction of the liquidating fund during the fire sales) after one day, one week and one month after the end of the fire sale (green, solid line). The red dotted line displays results from the same exercise applied to a placebo sample of trades, i.e. sell trades by the same group of predators taking place over a random sample of five-day intervals that do not include any fire sale.

Table A1
Robustness: Broker Awareness Measures

The table shows the robustness of our main results with respect to the definition of the broker awareness measure. Recall that the broker Awareness dummy is defined at the event-broker-stock-day level, indicating that the broker is aware of the fire sale happening on a given stock-day. We now generalize the definition given in the text, by requiring the following two conditions to hold for broker b, stock j on day t, event e and given natural numbers X and N: (i) the liquidation volume on stock j intermediated by broker b on day t is above X% of the average daily volume (ADV) for stock j; (ii) broker b satisfies condition (i) of at least N stocks in the fire sale basket. The Table presents our main results for $X \in \{1,2,5\}$ and $N \in \{1,5,10\}$, reporting only the estimate and T-stats for the main coefficient of interest in the regression (i.e. the one appearing in the first row of the first column in the original Table). Standard errors are clustered as in the corresponding baseline regression (i.e. the one with $X = 2$ and $N = 1$ presented in the main body of the paper). T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	N	X=1%	X=2%	X=5%
Broker direction, Baseline	1	0.232***	0.232***	0.215***
Table 2 - Panel A		(10.589)	(10.589)	(8.322)
	5	0.215***	0.208***	0.198***
		(8.322)	(7.065)	(3.715)
	10	0.198***	0.202***	0.202***
		(5.481)	(4.242)	(4.242)
Broker direction, Baseline (volume)	1	0.103***	0.103***	0.132***
Table 2 - Panel B		(5.298)	(5.298)	(5.398)
	5	0.132***	0.126***	0.198***
		(5.398)	(4.042)	(4.237)
	10	0.097***	0.131***	0.131***
		(2.725)	(2.665)	(2.665)
Best clients, Baseline	1	0.014***	0.015***	0.014***
Table 4 - Panel A		(7.877)	(7.658)	(5.865)
	5	0.014***	0.019***	0.024***
		(5.865)	(5.582)	(4.009)
	10	0.026***	0.035***	0.020**
		(6.210)	(6.244)	(2.237)
Best clients, No recessions	1	0.014***	0.015***	0.015***
Table 5 - Panel A		(7.471)	(6.934)	(5.670)
	5	0.015***	0.023***	0.030***
		(5.670)	(6.083)	(4.604)
	10	0.027***	0.038***	0.038***
		(6.262)	(6.607)	(6.607)

	N	X=1%	X=2%	X=5%
Best clients, No negative news	1	0.014***	0.014***	0.014***
Table 5 - Panel B		(7.571)	(7.052)	(5.469)
	5	0.015***	0.019***	0.023***
		(5.156)	(5.360)	(3.715)
	10	0.026***	0.031***	0.019**
		(6.047)	(5.498)	(1.999)
Best clients, No negative momentum	1	0.015***	0.018***	0.021***
Table 6 - Panel A		(6.490)	(6.967)	(6.143)
	5	0.021***	0.030***	0.044***
		(5.288)	(6.193)	(5.264)
	10	0.038***	0.058***	0.047***
		(6.643)	(8.034)	(3.812)
Best clients, No high short interest	1	0.020**	0.015***	0.016***
Table 6 - Panel B		(2.218)	(7.459)	(6.358)
	5	0.016***	0.020***	0.020***
		(6.358)	(5.828)	(5.828)
	10	0.026***	0.035***	0.020**
		(6.013)	(6.147)	(2.218)
Reversal, Diff-n-Diff	1	11.815***	11.594***	10.981***
Table 8		(6.763)	(6.104)	(4.781)
	5	10.888***	10.107***	7.045*
		(4.252)	(3.459)	(1.707)
	10	10.795***	13.945***	12.260**
		(2.933)	(3.108)	(1.968)

Table A2
Robustness: Broker-Manager Fixed Effects

The table presents evidence of the effect of broker-client relationship strength on the probability of predatory behavior. The regressions are run at the ticket-level, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In all specifications the dependent variable is a dummy indicating predation, i.e. it takes value one when the trade is in the same direction of the volume by the fire-sale originator for that stock on that day, while it equals zero if the trade is in the opposite direction or if the originator is not trading that stock on that particular day. We regress the dependent variable on a dummy indicating if the manager is among the best clients of the broker intermediating the transcation, a dummy indicating the first 5 days of the fire sale, and the interaction of the two dummies. This dummy equals zero for the five days before the fire sale. We consider all trades on stock j intermediated by brokers that eventually become aware that the stock is subject to fire sale pressure, i.e. brokers B for which $max_{t\in[0,4]}(AwaBro_t^{Bj}) = 1$ where $AwaBro_t^{Bj}$ is defined as above. The regression is run on a 5 days window centered at the beginning of the fire sale (t=0), defined as the first day in which our liquidation measure crosses the threshold. We also include Broker×Manager and Broker×Originator fixed effects. Standard errors are clustered by event-stock-manager and T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.015***	0.016***	0.001***	0.002***
	(7.618)	(7.952)	(10.159)	(10.311)
Best Client	0.003	0.002	0.001***	0.001**
	(0.838)	(0.635)	(3.415)	(2.151)
Liquidation Period	0.021***	0.021***	0.019***	0.019***
	(7.836)	(7.784)	(7.132)	(7.025)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Broker-Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker-Originator Effects	Yes	Yes	Yes	Yes
Observations	501,558	501,558	501,558	501,558
R-squared	0.199	0.199	0.200	0.200

Table A3
Evidence of Predation from Trading Volume

The table presents results on the likelihood that managers engage in predation trading in the same direction of the fire-sale originator, weighted by the trading volume. The regressions are run at the ticket-level, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In all specifications the dependent variable is the product of the predation dummy defined in Table 4 multiplied by the volume of the transaction as a fraction of the market capitalization of the traded stock. The independent variables are the same as in the previous specifications. The regression is run on a window of five days on each side of the beginning of the fire sale ($t = 0$), defined as the first day in which our liquidation measure crosses the threshold. In specifications of Panel B we repeat the exercise excluding the NBER recession periods and stocks experiencing negative fundamental news, high short interest or negative momentum. We include manager, broker, stock, day, and event fixed effects and we cluster standard errors at the event-stock-manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Full Sample

Dependent variable	Volume of Predatory Trades			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.081***	0.087***	0.008***	0.009***
	(7.864)	(8.255)	(7.879)	(8.010)
Best Client	-0.040***	-0.030**	-0.001	-0.001
	(-3.442)	(-2.488)	(-1.357)	(-0.767)
Liquidation Period	0.064***	0.063***	0.053***	0.050***
	(4.880)	(4.815)	(3.986)	(3.769)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	489,047	489,047	489,047	489,047
R-squared	0.179	0.179	0.180	0.180

Panel B: Excluding All Negative Events or Stocks

Dependent variable	Volume of Predatory Trades			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.081***	0.089***	0.008***	0.010***
	(6.812)	(7.267)	(6.734)	(6.847)
Best Client	-0.044***	-0.031**	-0.001	-0.000
	(-3.371)	(-2.325)	(-1.016)	(-0.138)
Liquidation Period	0.051***	0.050***	0.039**	0.036**
	(3.346)	(3.259)	(2.530)	(2.312)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	343,462	343,462	343,462	343,462
R-squared	0.197	0.197	0.198	0.198

Table A4
Commissions Paid to Aware Brokers

The table presents evidence on the post-event increase of commissions paid by predators to aware brokers. For each month t on a window of two years around each fire sale event e, we define the average $Commission\_per\_dollar_{e,m,b,t}$ paid by manager m to broker b as the ratio $Comm_{e,m,b,t}/DVol_{e,m,b,t}$ where ratio $Comm_{e,m,b,t}$ is the total amount in dollars paid in commissions by manager m to broker b during month t and $DVol_{e,m,b,t}$ is the total dollar volume traded by manager m and intermediated by broker b in that month. For each event, we consider brokers which are marked as $Aware$ on at least one of the fire sale stocks and managers whose trades are intermediated by at least one of these broker in the ten trading days around the event. We then regress $Commission\_per\_dollar_{e,m,b,t}$ on the interaction of the dummy variable $Post_{e,t}$, indicating the two years after the fire sale event, with each of our *Best Clients* proxies. In Panel A we look at the clients that are more likely to predate on that stock in that event, which we identify as those that are above the median of the distribution of profitability in the ten-day window after the event. In Panel B we run the same analysis focusing only on managers that trade in the same direction as the liquidating fund during the liquidation periods. We add event, manager, and brokers fixed-effects to the regression and we cluster standard errors by event-broker-manager to account for time-series autocorrelation in commissions paid. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Highest Predatory Profits

Dependent variable	Commissions per dollar (basis points)			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Top Decile of Volume	Top Decile of Commissions	Ranking based on Volume
Best Client × Post	0.391***	0.159*	0.013**	0.009
	(5.047)	(1.871)	(2.171)	(1.391)
Best Client	-1.040***	-0.479***	-0.043***	-0.021**
	(-9.226)	(-3.903)	(-5.617)	(-2.530)
Post	-0.609***	-0.568***	-0.583***	-0.565***
	(-11.710)	(-10.990)	(-11.425)	(-11.144)
Event Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,168,521	1,168,521	1,168,521	1,168,521
R-squared	0.228	0.227	0.228	0.227

Panel B: Predators Only

Dependent variable	Commissions per dollar (basis points)			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Top Decile of Volume	Top Decile of Commissions	Ranking based on Volume
Best Client × Post	0.627***	0.494***	0.446***	0.972***
	(4.068)	(2.938)	(2.712)	(3.834)
Best Client	-0.480***	-0.832***	-0.334	-1.604
	(-3.568)	(-2.821)	(-1.097)	(-0.897)
Post	-0.766***	-0.870***	-0.845***	-1.270***
	(-6.960)	(-6.194)	(-6.089)	(-5.710)
Event Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	141,685	141,685	141,685	141,685
R-squared	0.410	0.410	0.410	0.411

Table A5
Alternative Clustering of Standard Errors

The table presents robustness tests on our main empirical findings by T-stats resulting from alternative way to cluster the standard errors. In particular, columns (1)-(3) of Panel A report results on a regression specification identical to that of column (4) of Table 2-A, but T-stats are computed from standard errors clustered also at the broker-stock and the broker-day level. Columns (4)-(6) of Panel A instead refer to the specification in column (8) of Table 2-A. In Panel B we re-run the specification from column (1) of Table 4-A and report T-stats based on standard errors clustered also by Event-Stock-Day and by Event-Stock-Broker. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Predatory Behavior and Broker Awareness

Dependent Variable	Probability of Predation			Volume of Predatory Trades		
	(1)	(2)	(3)	(4)	(5)	(6)
Aware Dummy	0.170***	0.170***	0.170***	0.081***	0.081***	0.081***
	(10.142)	(10.015)	(9.911)	(4.726)	(5.107)	(4.718)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Broker	Broker-Stock	Broker-Day	Broker	Broker-Stock	Broker-Day
Observations	496,555	496,555	496,555	496,555	496,555	496,555
R-squared	0.107	0.107	0.107	0.026	0.026	0.026

Panel B: Probability of Predation and Broker-Client Relationship Strength

Dependent variable	Probability of Predation		
	(1)	(2)	(3)
Best clients proxy	Volume above 5%	Volume above 5%	Volume above 5%
Best Client × Liquidation Period	0.015***	0.015***	0.015***
	(7.658)	(8.905)	(7.768)
Best Client	0.005*	0.005**	0.005*
	(1.846)	(2.379)	(1.818)
Liquidation Period	0.021***	0.021***	0.021***
	(7.880)	(7.377)	(7.252)
Time Fixed Effects	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes
Event Fixed Effects	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes
Clustering	Event-Stock-Manager	Event-Stock-Date	Event-Stock-Broker
Observations	501,558	501,558	501,558
R-squared	0.177	0.177	0.177

Table A6
Predation Conditional on VIX Levels

The table presents evidence of a higher level of predatory activity during periods of market turmoil. We first compute the average level of the VIX Index during each fire sale events, by tanking the average across the fire sale days. We then use the median of the distribution of the event-level VIX to split the sample of fire sale events into two groups. We re-run the regression specifications of columns (3)-(4) and (7)-(8) of Table2-A separately for each of the two subsamples and we report the results in Panel A for events with VIX level above median and in Panel B for events with VIX level below median. Standard errors are clustered at the broker level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: VIX Above Median

Dependent Variable	Probability of Predation		Volume of Predatory Trades	
	(1)	(2)	(3)	(4)
Aware Dummy	0.184***	0.184***	0.098***	0.096***
	(10.167)	(10.469)	(3.443)	(3.316)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects		Yes		Yes
Observations	208,809	208,686	208,809	208,686
R-squared	0.103	0.109	0.019	0.035

Panel B: VIX Below Median

Dependent Variable	Probability of Predation		Volume of Predatory Trades	
	(1)	(2)	(3)	(4)
Aware Dummy	0.155***	0.152***	0.076***	0.072***
	(8.641)	(8.652)	(4.604)	(4.356)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects		Yes		Yes
Observations	287,829	287,723	287,829	287,723
R-squared	0.11	0.116	0.023	0.027

Table A7

Order Imbalance of Liquidating Funds

The table presents summary statistics on the imbalance of liquidating funds during the fire sale periods, including both the volume generated on the fire sale stocks and the other stocks traded by the liquidating fund in that period. We report the net signed dollar volume and the relative order imbalance, defined as the ratio between the net signed share volume and the absolute share volume. In Panel A we aggregate the imbalance measures at the event-level by taking the average across the liquidation days of each fire sale, while in Panel B we report the statistics at the event-day-level, computing the imbalance measures for each day of the fire sale.

Panel A: Day-level

	Count	Mean	S.D.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Dollar Volume (million $)	1920	-83.17	170.16	-4597.74	-274.68	-187.53	-99.22	-42.63	-15.15	-3.98	-1.14	-0.03
Order Imbalance	1920	-0.30	0.27	-1.00	-0.94	-0.74	-0.42	-0.22	-0.11	-0.05	-0.01	-0.01

Panel B: Event-level

	Count	Mean	S.D.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Dollar Volume (million $)	385	-414.79	603.80	-7522.75	-1180.31	-866.21	-548.34	-263.30	-104.67	-41.93	-17.73	-9.74
Order Imbalance	385	-0.30	0.24	-1.00	-0.92	-0.66	-0.39	-0.24	-0.14	-0.08	-0.06	-0.04

Table A8
Univariate Regressions

The table reports our main results on predatory behavior associated to the clients and the best clients of the aware brokers, using regression models without fixed effects. In Panel A we report results on the predatory behavior at the broker-level, running a specification similar to that of Panel A of Table 2, but without fixed effects. In Panel B we report results on the predatory behavior at the manger-level, running a difference-in-difference specification similar to that of Panel A of Table 4, but without fixed effects. In Panel A we cluster standard errors at the broker level, while in Panel B we cluster standard errors at the event-stock-manager level. T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Predatory Behavior and Broker Awareness

Dependent Variable	Probability of Predation	Volume of Predatory Trades
Specification	(1)	(2)
Aware	0.232***	0.103***
	(10.589)	(5.298)
Constant	0.354***	-0.004
	(33.482)	(-1.084)
Observations	496,729	496,729
R-squared	0.008	0.000

Panel B: Probability of Predation and Broker-Client Relationship Strength

Dependent Variable	Probability of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.019***	0.019**	0.002**	0.002**
	(2.679)	(2.413)	(2.500)	(2.460)
Best Client	0.019***	0.015**	0.001***	0.001***
	(2.882)	(2.328)	(2.943)	(2.670)
Liquidation Period	0.026***	0.026***	0.025***	0.024***
	(11.617)	(12.318)	(10.881)	(10.802)
Constant	0.028***	0.028***	0.027***	0.027***
	(16.188)	(15.242)	(15.379)	(15.261)
Observations	501,568	501,568	501,568	501,568
R-squared	0.008	0.007	0.012	0.012

Table A9
Differential Treatment for Best Clients

The table presents evidence of a differential treatment by aware brokers when the liquidating fund is one of their best clients. In details, we first define a dummy $LiquidatingFundBestClient_{e,m,b}$ which is equal to one if the liquidating fund *f* originating the fire sale event *e* is among the best clients of broker *b*, as defined by the first relationship proxy defined in Table 3 (*volume above 5%*). We then interact this dummy with the broker awareness dummy defined in Table 2 and run a difference-in-difference regression at the event-manager-broker-stock level with three different specifications, where the dependent variable is respectively (i) the *predatory volume* (i.e. the product of the *predation dummy* defined in Panel A of Table 4 multiplied by the volume of the transaction as a fraction of the market capitalization of the traded stock); (ii) the *liquidity provision volume* (i.e. the product of the *liquidity provision dummy* defined in Panel D of Table 4 multiplied by the volume of the transaction as a fraction of the market capitalization of the traded stock); (ii) the difference between the *predatory volume* and the *liquidity provision volume*. We include manager, broker and day fixed effects. Standard errors are clustered at the event-stock-manager level and T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	(1)	(2)	(3)
Dependent Variable	Predatory Volume	Liquidity Provision Volume	Predatory Volume - Liquidity Provision Volume
Aware Dummy × Liquidating Fund Best Client	-0.049**	0.001	-0.041*
	(-2.131)	(0.077)	(-1.796)
Aware Dummy	0.108***	0.045***	0.064***
	(4.432)	(2.910)	(2.855)
Liquidating Fund Best Client	-0.002	-0.010**	0.004
	(-0.280)	(-2.297)	(0.798)
Time Fixed Effects	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes
Observations	496,555	496,555	496,555
R-squared	0.026	0.017	0.017

Table A10
Characteristics of Liquidating Funds facing Aware Brokers

The table presents characteristics of the liquidating funds, partitioned into two groups based on the number of aware brokers they face. More precisely, for each fire sale event we record the number of aware brokers *A* divided by the number of fire sale stocks *N*. We then average the ratio *A/N* across all the fire sale events generated by each liquidating fund. The cross-sectional distribution of the manager-level variable is then used to split the set of liquidating funds into two parts, using the median as cutoff. For each of the two groups we take the average of the following quantities, computed at the manager-level using the full Ancerno: (i) the total dollar volume generated by the fund; (ii) the number of broker relations, defined as the number of brokers which intermediated at least one transaction of the fund; (iii) the ration between the number of broker relations and the total dollar volume in million dollars; (iv) the total dollar amount paid in commissions by the manager to all the connected brokers; (v) the ratio between the average commission per dollar paid to aware brokers (i.e. those brokers which are tagged as aware at least once in one fire sale originated by the manager) and the average commission per dollar paid to the complementary set of brokers (unaware); (vi) the ratio between the total dollar commission paid to aware brokers and the total dollar commission paid to unaware brokers; (vii) the ratio between the total volume intermediated by the aware broker and the volume intermediated by the unaware brokers. For each quantity, we report the averages of the two groups and their difference. T-stats of the differences are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	Aware Brokers	Unaware Brokers	Difference	t-stat
Total dollar volume (billion $)	507.333	110.696	396.637***	(5.656)
Total brokers relations	217.925	188.547	29.377**	(2.443)
Number of brokers per million $	0.010	0.026	-0.016**	(-2.432)
Total commissions paid (million $)	153.199	47.783	105.416***	(4.795)
Commission per dollar ratio (aware / unaware)	0.915	0.819	0.096**	(2.559)
Total dollar commission ratio (aware / unaware)	2.663	0.574	2.089**	(2.438)
Volume ratio (aware / unaware)	0.184	0.076	0.108	(1.278)

Table A11
Timing of Predation

The table presents evidence of the effect of broker awareness on the timing of predation. The regressions are run at the event-manager-broker-stock level, focusing on the liquidation period, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In all specifications, the dependent variable is a natural number counting the number of days after the beginning of the fire sale in which the first predatory trade occurred. *Predation* and the *AwareBorker* dummy are defined as in Table 4. Panel A presents results for the baseline specifications, where we saturate the model with day, manager and stock fixed effects. Panel B we report results for univariate regressions without fixed effects. Standard errors are clustered at the broker level and T-stats are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Baseline

Dependent variable	First Day of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Aware Broker	-0.1890***	-0.1591**	-0.0070**	-0.0079**
	(-2.9670)	(-2.0310)	(-2.3640)	(-2.4468)
Best Client	-0.0881***	-0.0305	-0.0025***	-0.0017***
	(-3.1291)	(-0.8686)	(-5.0023)	(-2.7732)
Aware Broker	-0.0049	-0.0088	-0.0226	-0.0146
	(-0.1645)	(-0.2898)	(-0.8000)	(-0.5659)
Time Fixed Effects	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Observations	98,411	98,411	98,411	98,411
R-squared	0.2367	0.2363	0.2367	0.2364

Panel B: Univariate

Dependent variable	First Day of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Volume above 5%	Commissions Paid above 5%	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Aware Broker	-0.2660***	-0.2398***	-0.0120***	-0.0138***
	(-6.4977)	(-5.7087)	(-7.7247)	(-7.9414)
Best Client	-0.1799***	-0.1198***	-0.0036***	-0.0028***
	(-13.2336)	(-8.4588)	(-11.3810)	(-6.9108)
Aware Broker	0.1235***	0.1235***	0.1178***	0.1294***
	(5.9586)	(6.0422)	(6.0037)	(6.6108)
Constant	2.2292***	2.2023***	2.2029***	2.1873***
	(277.5800)	(284.2647)	(304.6236)	(305.8118)
Observations	98,771	98,771	98,771	98,771
R-squared	0.0033	0.0017	0.0026	0.0016