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

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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' clients are more likely to predate on the liquidating funds than to provide liquidity. Predation leads to profits of about 25 basis points over ten days and increases the liquidation costs for the distressed fund by 40%. This evidence suggests a role of information leakage in exacerbating fire sales.

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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). Moreover, if the liquidation occurs at times of market stress, predatory trading can make the market more illiquid and amplify adverse shocks (Greenwood, Landier, and Thesmar, 2015). Given this possibility, some observers suggest that reducing the frequency of portfolio disclosure can be a desirable measure to prevent predatory behavior (Brunnermeier and Pedersen, 2005).

However, market participants may 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 infer 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. Thanks to this information, brokers are best placed 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 market participants. They may have an incentive to do so in order to establish a reputation as a source of valuable information and attract new business. Other investors can use this information to predate on the distressed fund. On the other hand, brokers may be reluctant to foster predatory trading against a client, as it may harm their reputation. 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.[1] Accordingly, we exploit proprietary trade-level data and identify 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. We verify that the stock price movements resulting from this sale are only temporary, consistent with the notion that we identify liquidity events. Price impact would have to display a permanent component, if sales were motivated by fundamental reasons.

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 (on average 29). Hence, we label as *aware* only the brokers that intermediate a large enough fraction of volume. 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. While liquidity provision also takes place among clients of aware brokers, this activity does not appear to be as prevalent as predatory trading.

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

[1] 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.

investor-broker relation, we use the trading volume and the commissions generated by a client.[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.[3] Hence, the evidence suggests that predation is more likely than liquidity provision among the best clients of the brokers that intermediate fire sales. The magnitude is economically significant as the net probability of predation more than doubles for the best clients of aware brokers relative to the small clients of the aware brokers. Consistent with predatory trading, we find that a significant fraction of positions that are sold by other managers than the distressed fund during the fire sale period, ranging from 30% to 42%, are bought back in the ten days following the fire sale.

We provide an array of 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 information signal. For instance, we exclude from our sample all the events that occurred during recessions and 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 the data provider Ravenpack. 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 signal on the stock.

To strengthen the identification of fire sale events, we focus on a natural experiment in which some mutual funds were forced to liquidate their holdings. Specifically, as a consequence of the late-trading scandal of 2003, 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. Crucial for our purposes, the brokers of the liquidating funds

[2] We find 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.

[3] We control for time, manager, event, stock, and broker fixed effects. Hence, differences across stocks, such as their liquidity, or across brokers, such as their ability to execute, cannot explain our results. 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.

were aware of the specific stocks that were being sold and of the timing of these liquidations. We 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.

One of the contributions of the paper concerns the value of the order-flow information. We compute the profits that the asset managers make during the fire sales and show that the best clients of the aware broker, who are the most-likely investors to benefit from information leakage, are able to generate an additional 25 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.

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 volume-weighted percentage difference between the execution price and a benchmark price. We find that price impact is higher by about 40% when the trades are executed through brokers that are aware of the liquidations. We interpret this spread as the cost of predation. Also important, our evidence highlights one important amplification mechanism for asset price fluctuations.

We conclude by addressing another important question: Do brokers gain from leaking order flow information? We compute the brokers' commissions and show that the best clients who take advantage of the order flow information by preying on the liquidating funds pay, relative to the other clients of the brokers and relative to the period before the fire sale, 16% higher commissions in standard deviation units, confirming that brokers get rewarded for the information they provide.

Overall, our findings point out 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, i.e. those larger than 1% of average daily volume, 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 future order flow.

Our paper bridges two strands of the literature. First, there is a vast literature on fire sales.[4] 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, 2018; 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.[5]

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 (2018) 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 the interplay among institutional investors and we detect a trading behavior by other investors that is harmful to the

[4] 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. 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.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.

[5] Our findings also relate 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*, a feature currently missing in the existing theoretical literature and a driver of network formation 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.

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.[6] Third, we identify institutional brokers as instrumental in spreading order flow information and fostering predation. Finally, we highlight the systemic threat caused by predatory trading as it can amplify price dislocations during fire sales.[7]

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, while Section 5 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), responds to these requirements. 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.

[6] 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 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).

[7] 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.

We have access to identifiers for managers that initiate the trades and brokers that intermediate those trades from 1999 to 2014.[8] 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 information about institutions that were reporting in the past but at some point terminated their relationship with Ancerno.

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

[8] 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.

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.[9] At the stock level, the liquidation volume needs to make a sufficient fraction of total trading volume.

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 $\mathrm{Z}_{\mathrm{t}}^{\mathrm{m}}$ 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 A8 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

[9] 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.

information. Focusing on liquidations of a large number of stocks makes it less likely that the sales are information driven.

Next, 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 the 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 (for thresholds from 1% to 5%). 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 of the fire sale event (for $N = 1, 5, 10$).

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 A2 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 marked with red squares, the number of events does not spike. This confirms that our methodology identifies funds subject to idiosyncratic shocks rather than market-wide events.[10]

[10] 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.

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 A1 shows the distribution of these events as a function of the number of stocks, from events involving 10 to 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 1.7. Furthermore, the price of the stocks sold in the fire sale declines by 83 basis points on average during the first five days of the event (Table 1, Panel C), but there is significant variation. In fact, for the bottom quartile, the price drops by more than 3%.

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. For each stock in the fire sale, we compute the fraction of the total volume in the fire sale that it represents. Panel E 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 reconstructed 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 studying the 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 reconstructed 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 F 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 1 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 the daily order imbalance is smaller in magnitude after five days, it is still negative even after 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 2, 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.

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

To disentangle whether brokers foster predatory trading or liquidity provision we estimate the following specification

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

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, $Net\ Predation_{m,i,b,t,e}$, is constructed as the difference between the probability of predation and the probability of liquidity provision. In turn, the probability of predation 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.[11] Symmetrically, the probability of liquidity provision is 1 if the client trades in the opposite direction of the fire sale, and 0 otherwise. We also estimate specifications in which the dependent variable is defined as the net predation variable 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.[12] 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 (Table A6).

We present the results in Table 2, Panel A. Columns (1)-(2) focus on *Net Predation*, i.e. the difference between the predation and the liquidity provision dummies, while columns (3)-(4) present the results for the volume-weighted version of the dependent variable. For each dependent variable, we modify the baseline specification by adding day-by-stock fixed effects to the existing set of fixed effects. In particular, manager and 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-

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

[12] 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.

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 between 11% and 20% higher difference in the probability of predation relative to the probability of liquidity provision.[13] The analysis of volume in columns (3)-(4), confirms the finding.

In Panels B and C, we separately study the relation between broker awareness and the probabilities of predation and liquidity provisions, respectively. While there is a significant relation between broker awareness and predation, the effect on liquidity provision is not clear and it is positive and significant only in the specifications where liquidity-provision volume is the dependent variable. Even there, the effect is smaller than for predatory volume.

Another way of investigating predation and liquidity provision is to compare the cumulative order imbalance from the start of the fire sale, where order imbalance is the difference between buy and sell trades divided by the sum of the two. We report the series for the aware and the unaware brokers with standard errors bands during the events in Figure 3. Confirming the regression evidence in Table 2, the imbalances through the aware brokers are negative during the first several days of the liquidation and are significantly lower than those of the unaware brokers.

Overall, 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. Instead, the evidence that aware brokers facilitate liquidity provision is scanty at best.

[13] In Internet Appendix Table A9, we report results from specifications without the fixed effects. In these specifications, the constant, i.e. the level for unaware brokers, is virtually zero, while the slope on the aware dummy is 23%. Hence, the economic magnitude is substantial.

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 and construct two measures of relationship strength (the 'Best Client' proxies). The first variable is defined as the volume generated by the client as a fraction of the total volume intermediated by the broker and expressed in decimal units. The other measure is computed in a similar fashion, but the dollar volume is replaced by the dollar trading commissions generated by the manager. Summary statistics are reported in Panel D of Table 1. These variables are highly persistent, with an autocorrelation of 90% at the monthly frequency. 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.

To study the role of broker-client relationships in information diffusion, we estimate the following specification

$$\begin{aligned} Net\ Predation_{m,j,b,t,e} = {} & \beta_1 Best\ Client_{m,b,t} \times Liquidation\ Period_{t,e} + \\ & \beta_2 Best\ Client_{m,b,t} + \beta_3 Liquidation\ Period_{t,e} + \varepsilon_{m,j,b,t,e}, \end{aligned} \tag{3}$$

where index *j* runs over stocks, index *b* over brokers, index *e* over events, index *m* over managers and index *t* over days. As for equation (2), our main dependent variable is the difference between the probability of predation and the probability of liquidity provision. As in the case of Table 2, we also use a version of this variable that is multiplied by the volume of the trade. The dummy *Liquidation period* indicates 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 (at the monthly frequency), 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.[14]

Table 3 presents the results. We find that the asset managers in a closer relationship with the fire-sale-aware broker are significantly more likely to sell their holdings of the fire-sale stock with the same broker during the liquidation period. The magnitude is economically significant as the net probability of predation more than doubles for the best clients of aware brokers (top decile) relative to the small clients of the aware brokers (bottom decile).[15]

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 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 3 reports the results from the following specification

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

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

[14] In robustness tests provided in Panel B of Internet Appendix Table A6, 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.
[15] To reach this conclusion we use the estimates from the regressions without fixed effects in Table A10, Panel B. In particular, the net probability of predation moves from 1% in the bottom decile to 2.1% in the top decile of best clients.

aware of the fire sale event e on a stock j we assign $Aware_{j,b,e} = 1$. Results from this specification are reported in Panel B of Table 3 and confirm that clients with stronger ties to the aware broker are significantly more likely to sell the stock involved in the liquidation than the best clients of the other brokers involved in the liquidation. Results are robust across the two 'Best Client' measures.

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.[16]

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 A3 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 explore 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 question in Internet Appendix Table A12. We find that the best clients of the aware brokers are significantly faster in predation. In particular, the average predator starts predating on the third day of the liquidation, while best clients of aware brokers start already on the second day, on average. This

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

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 A10, 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, clients with closer ties to the brokers do enjoy an advantage when they need to liquidate.

Finally, using reconstructed portfolios, 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.[17]

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

[17] Table A2 in the Internet Appendix 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.

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 in Table 2) already helps to rule out these hypotheses. Nonetheless, we provide several other 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 A3 of the appendix presents this analysis. 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 A3 of the appendix 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 C of Table A3 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 D of Table A3 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 4 reports results where the outcome variable is the number of fire-sale stocks for which the manager sells its holdings in columns (1)-(2), and the fraction of stocks involved in the fire sales for which we observe predatory behavior in columns (3)-(4). We find that top-decile clients of the aware brokers tend to sell about 8 more stocks than bottom-decile clients do (column (1)), and to predate about 33% more of the stocks involved in the fire sale (column (3)).[18]

[18] The bottom decile of the Best Client proxy based on volume is 0, while the value for the top decile 0.58 is (median point between the 90th percentile and the max of the distribution). Hence, we get an increase of 14.5×0.58 = 8.4 stocks, while the increase in the fraction of predated stocks is: 57.8×0.58 = 33.5%.

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.

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 over he 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 across clients of the aware brokers before and after the fire sale events. The liquidating funds are excluded from the sample.

In Table 5, 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 are motivated by the prospect of short-term gains at the expense of the liquidating fund.[19]

[19] 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 A4 in the Internet Appendix compares the unwinding of predators' trades after the fire sale to trades on placebo days, where predators are managers trading in the same direction of the fire sale and placebo days are days are in intervals in which no fire sale takes place. 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 another alternative interpretation to the proposed view that order flow leakage by brokers explains our evidence. Specifically, 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.

To further rule out this alternative, 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 crucial 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.[20]

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[20] 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

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 6 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 to liquidate the same stocks after the scandal broke out. For example, in Column (1), there is a 6.2% higher probability of non-charged managers to trade in the same direction as a charged manager on the same day through the same broker relative to the pre-scandal period (i.e. 8.7% - 2.5%).

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

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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.

trading ideas seems implausible, given that there is no reason for this activity to increase after the breakout of the scandal or for stocks liquidated by the implicated funds.

3.7 Heterogeneity

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).

Table A4 in the Appendix reports the estimates of Equation (3) for hedge funds and other institutions. The results clearly show that the hedge funds are the main culprits of predation. The statistical significance, as well as the economic significance, is weaker for 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 in Appendix Table A7 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.

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.[21]

We start by showing in the left panel of Figure 5 the profits of managers that are best clients (defined as those generating more than 5% of the volume intermediated by the broker in the previous semester) 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 of the liquidation, while the trades of the clients of unaware brokers do not generate significant profits. The profits for the best clients peak at about 25 bps on the ninth day from the start of the fire sale. Importantly, most of the profits are generated in the first five days, i.e. while the price of the fire-sold stocks is still decreasing and it makes sense to predate. The profits that are generated later in the period are instead consistent with liquidity provision.

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

$$Profits_{m,j,b,t} = \beta_1 Best\ Client_m \times Post[0,9]_t + \beta_2 Best\ Client_m + \beta_3 Post[0,9]_t + \varepsilon_{m,j,b,t}, \tag{5}$$

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, as a function of clients' proximity to aware brokers.

[21] 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.

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 2).[22]

Table 7 reports the results showing that aware brokers' best clients exhibit significantly higher profits than other managers during the period under consideration. Clients in the top decile of our relationship metric based on trading volume, in the ten days following the beginning of the fire sale, are able to outperform by more than 50 basis points on average relative to the managers in the bottom decile trading on the same stocks in the same period (i.e. (136.56-48.57)×0.58=51 bps, where 0.58 is the value of the Best Client proxy in the top deciles, while it is zero in the bottom decile). Considering the low average performance of institutional asset managers (see, among others, Busse, Goyal, and Wahal, 2010) these 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. Although we already control for manager-fixed effects, we also directly test for this possibility in the right panel of Figure 5, which provides a placebo test for the left panel of Figure 5. The 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 find that the two groups are indistinguishable in terms of their performance during these other times.

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

[22] 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.

from these positions amount on average to $280,449 per event-manager (median: $126,420).[23] 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.[24]

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 4.4, 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.

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

[23] The estimate of 32 bps for additional profits during predation period (Table 7) 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.

[24] 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 7 (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.

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 regressions of price impact onto the broker awareness dummy. In this case, 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 volume-weighted 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 average this quantity at the event-stock-broker level, using as weights the volume of each transaction, to obtain an event-stock-broker level measure of price impact. We then further collapse on the broker dimension to study the price impact at the event-stock level.

Results are reported in Table 8. In specifications (1)-(3), we regress the event-stock level price impact measures on the dummy denoting events in which there is at least one aware broker. Consistently across measures, we show that the price impact costs borne by the liquidating funds are higher when at least one broker is aware of the liquidation event, and statistically significant in two cases out of three. The estimates are also economically significant as the price impact increases by at least 14 bps and up to 36 bps, which amounts to a two-fold increase in the baseline average price impact. In specifications (4)-(6), 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.[25]

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 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 4 plots the cumulative return of the fire sale stocks during fire sale events. The red line with squares represents the cumulative

[25] To further 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 4 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.

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 column (3) of Table 8, 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 4 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 -105 bps with aware brokers and about -75 bps in case of unaware brokers, i.e. the case in which we conjecture that no leakage occurs, a 40% increase. These results speak to the role of information leakage in exacerbating fire sales.[26]

4.3 Persistence in Broker-Manager Relationships

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. The

[26] In Appendix Table A11, 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).

autocorrelation of our relationship measures at the monthly frequency is above 90%. Table A13 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.

4.4 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. In Table 9 we regress 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. 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.[27]

[27] To get a sense of magnitude, a top-decile client (for which the Best Client proxy based on volume is 0.58) after the fire sale event pays 16% of a standard deviation higher commissions per dollar relative to smaller clients. In Table A14 of the Internet Appendix we show that this estimate increases to 24% when we restrict to mangers which generated the highest profits during the event.

5 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 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.[28] 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.[29]

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

[28] 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)).
[29] 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.

intentions of the broker, the evidence that we present in the paper shows that liquidity provision is lower among aware brokers than other brokers. 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.

Finally, our results shed light on a recent debate over the exchanges' and brokers' use of their access to market data to sell data products.[30] Critics maintain that 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 benchmark, and probably a lower bound, for the costs associated with releasing such data products.[31]

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.

[30] 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).

[31] 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."

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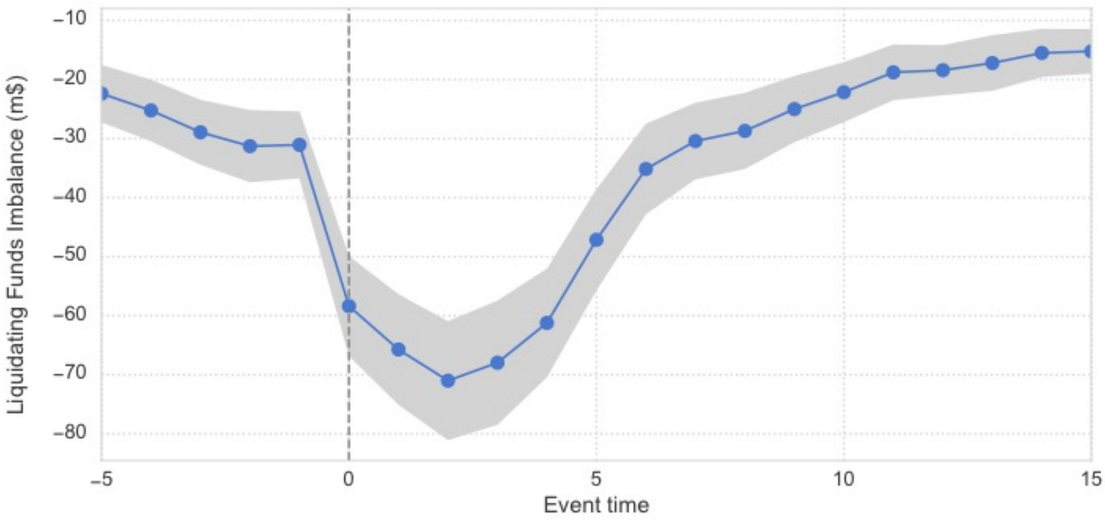

Figure 1: Liquidation Volume and Price Pattern. The figure plots the average daily signed volume (i.e. order imbalance) of the fire sale originator on the fire sale stocks, expressed in Million Dollars.

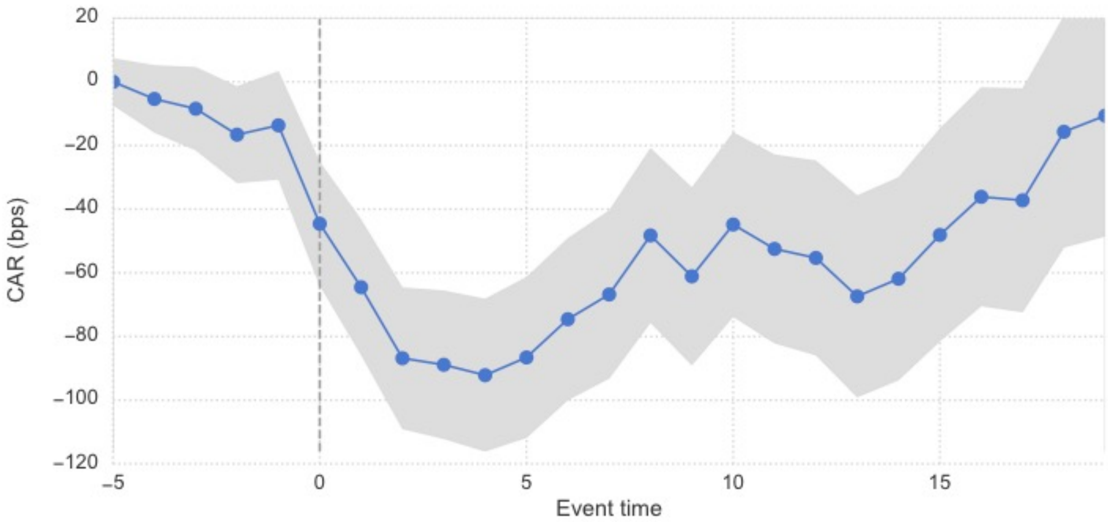

Figure 2: Price Pattern. The figure plots the average DGTW-adjusted cumulative returns for the stocks sold during the fire sales along with 95% confidence bands.

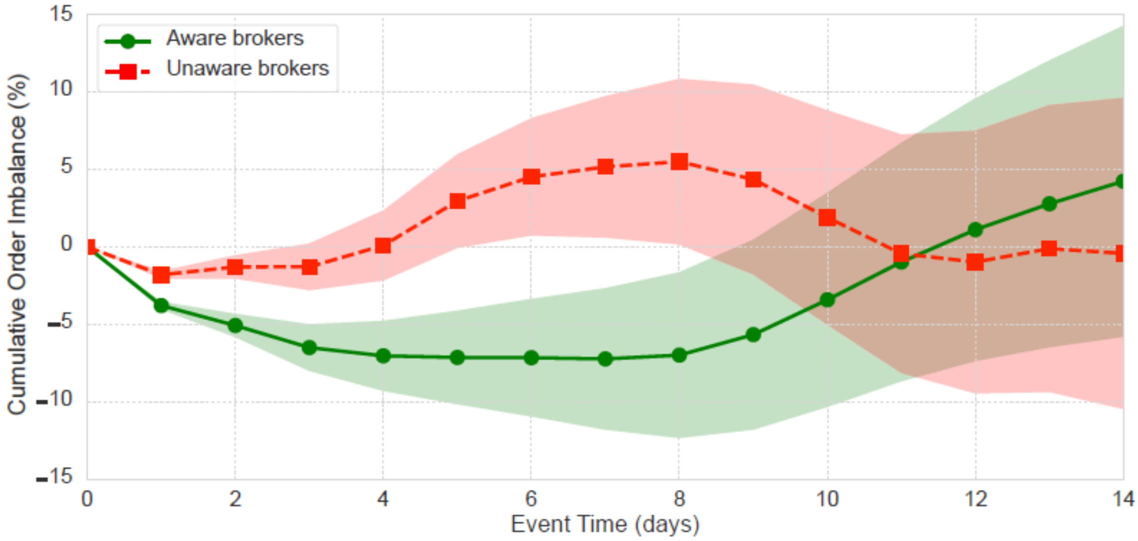

Figure 3: Order Flow through Aware Brokers. The figure plots the cumulative order imbalance of the transactions intermediated by the aware brokers (green solid line) and unaware brokers (red dashed line) on the fire sale stocks, excluding those generated by the liquidating funds. The daily order imbalance 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.

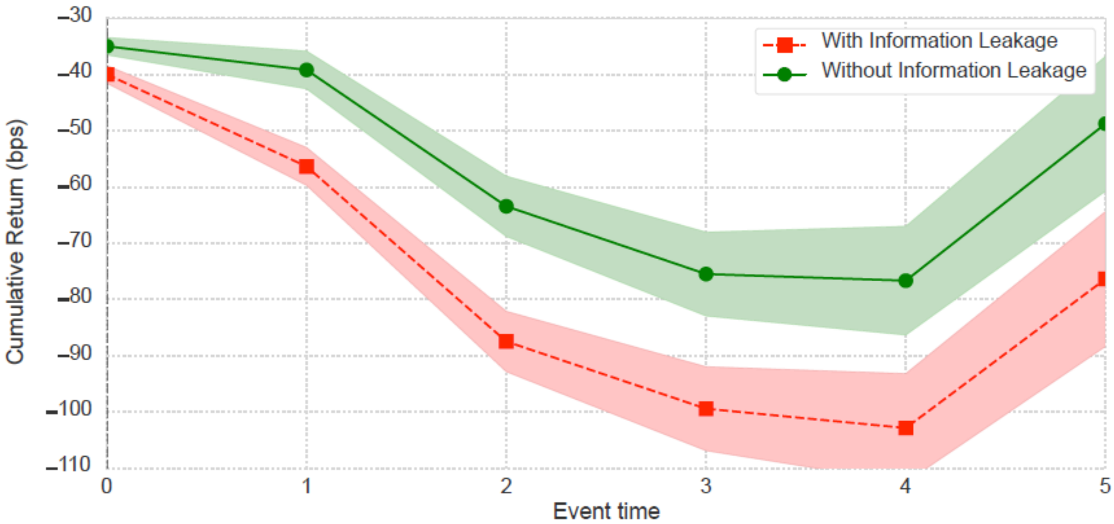

Figure 4: Price Paths with and without Information Leakage. The figure plots the cumulative return of the fire sale stocks during fire sale events involving at least one aware broker. The red line with squares represents the cumulative return averaged across stocks and events in which aware brokers are 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 8, but run on daily observations.

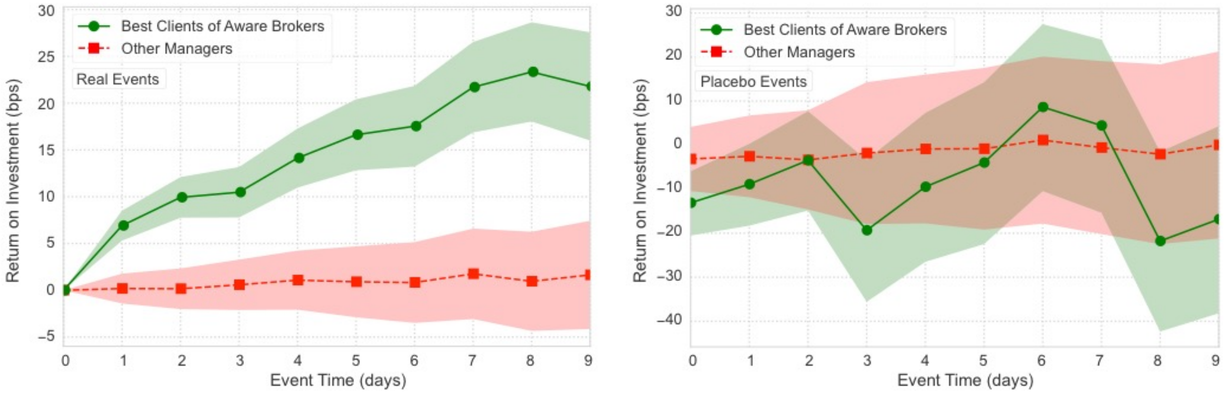

Figure 5: Profitability of Predatory Trades: Liquidation Events (left) and Placebo Sample (right). The left panel of the figure plots the profits of the managers that are best clients of the aware (green solid line with circles) and unaware (red dashed line with squares) brokers during the fire sale events. Best clients of a broker are defined as the managers generating more than 5% of the volume intermediated by that broker in the previous semester. The right panel repeats the exercise for random event windows other than the actual fire sales employed in the analysis.

Table 1
Summary Statistics

In Panels A, B, and C, we report summary statistics for the volume Z-score and the 385 fire sale events identified by our methodology. In Panel D we report summary statistics for the manager-broker relationship proxies employed in the paper, expressed in percentage units. 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. In Panel E 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 F 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. T-statistics 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

Pure anel 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%
Price Decrease in [0,4]	Percentage	8438	0.831%	4.613%	-1.904%	0.666%	3.388%	7.131%
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: Manager-Broker Relashionship Proxies

	Obs	Mean	S.D.	Min	25%	50%	75%	90%	Max
Ranking based on Volume	501568	0.035	0.079	0.000	0.000	0.004	0.031	0.101	0.965
Ranking based on Commission Paid	501568	0.032	0.071	0.000	0.000	0.005	0.032	0.088	0.924

Panel E: 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 F: 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)-(2) of Panel A the dependent variable is the difference between a dummy indicating predation and a dummy indicating liquidity provision, 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), it equals negative one if the trade is in the opposite direction (i.e. a buy trade) and equals zero if the manager is not trading that stock on that particular day. In Columns (3)-(4) of Panel A we multiply the above described dependent variable by the volume of the trade as a fraction of market capitalization, standardized. 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 volume which is above 2% of the average daily volume of stock *j*. In Panel B we focus only on predation, using the above defined *predation* dummy as dependend variable in columns columns (1)-(2) and its volume-weighted counterpart in columns (3)-(4). In Panel C we focus only on liquidity provision, using the above defined *liquidity provision* dummy as dependend variable in columns columns (1)-(2) and its volume-weighted counterpart in columns (3)-(4). All specifications include date, manager, and broker fixed-effects. We further add broker-stock fixed effects in odd-numbered columns and day-stock fixed effects in even-numbered columns. Standard errors are clustered at the broker level. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Net Predation

Dependent Variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Aware Dummy	0.202***	0.113***	0.039***	0.027**
	(7.142)	(5.199)	(3.080)	(2.323)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Brokers × Stock FEs	Yes		Yes	
Day × Stock FEs		Yes		Yes
Observations	487,605	462,841	487,605	462,841
R-squared	0.203	0.229	0.136	0.159

Panel B: Predation

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

Panel C: Liquidity Provision

Dependent Variable	Probability of Liquidity Provision		Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Aware Dummy	-0.099***	0.011	0.022**	0.024**
	(-6.806)	(0.716)	(2.483)	(2.448)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Brokers × Stock FEs	Yes		Yes	
Day × Stock FEs		Yes		Yes
Observations	487,605	462,841	487,605	462,841
R-squared	0.369	0.263	0.155	0.173

Table 3
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 stock-day-manager-broker level, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In all specifications the dependent variable is the difference between a dummy indicating predation and a dummy indicating liquidity provision, 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), it equals negative one if the trade is in the opposite direction (i.e. a buy trade) and equals zero if the manager is not trading that stock on that particular day. In Panel A we regress the dependent variable on the continuous variable *Best Client*, measuring the strength of the manager-broker relation, the dummy *Liquidation Period*, indicating the first 5 days of the fire sale, and the interaction of the two. The relationship strength variables are definined as follows: (i) $\mathrm{RVol}_{\mathrm{m,b,t}}$ is the fraction of dollar volume intermediated by broker b in the semester preceeding day *t* which is generated by manager m and (ii) $\mathrm{RCom}_{\mathrm{m,b,t}}$ is the fraction of dollar commissions earned by broker b in the semester preceeding day *t* which is generated by manager. Both variables are expresse in decimal units and thus take values in the interval $[0,1]$. The dummy *Liquidation Period* is zero in 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 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 variables: *Aware Broker* indicating that the broker is aware, *Best Client*, and *Liquidation Period* indicating the first 5 days of the fire sale. Time fixed effects are at the monthly frequency. Standard errors are clustered at the event-stock-manager level. T-statistics of the differences are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Difference in Differences

Dependent variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.055***	0.081***	0.124***	0.127***
	(3.181)	(4.182)	(3.236)	(2.806)
Best Client	0.023	0.048**	-0.001	0.003
	(1.427)	(2.500)	(-0.038)	(0.096)
Liquidation Period	0.006***	0.005***	0.002	0.003
	(5.683)	(4.942)	(0.618)	(0.661)
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	501,567	501,567	501,567	501,567
R-squared	0.046	0.046	0.013	0.013

Panel B: Triple Interaction

Dependent variable	Probability of Predation - Probability of Liquidity Provision			
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
Aware Broker × Best Client × Liquidation Period	9.814***	11.589***	9.184***	10.794***
	(4.527)	(4.927)	(4.356)	(4.756)
Best Client × Liquidation Period	1.752***	1.287***	1.554***	1.157***
	(5.664)	(5.220)	(4.989)	(4.634)
Aware Broker × Liquidation Period	0.011***	0.011***	0.011***	0.011***
	(10.252)	(9.552)	(10.196)	(9.578)
Best Client × Aware Broker	7.466***	9.082***	7.500***	8.949***
	(3.893)	(4.018)	(3.755)	(3.750)
Best Client	3.747***	2.969***	3.664***	2.931***
	(18.986)	(14.932)	(13.956)	(10.602)
Aware Broker	0.006***	0.005***	0.003***	0.003***
	(7.138)	(5.686)	(4.035)	(3.550)
Liquidation Period	0.012***	0.012***	0.011***	0.011***
	(39.642)	(41.789)	(34.415)	(36.251)
Constant	0.021***	0.022***		
	(99.348)	(100.764)		
Time Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Event Fixed Effects			Yes	Yes
Stock Fixed Effects			Yes	Yes
Broker Fixed Effects			Yes	Yes
Observations	4,226,877	4,226,877	4,128,803	4,128,803
R-squared	0.005	0.004	0.022	0.022

Table 4
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 the first two specifications, 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 the relationship strength assigned to each manager is the value of the best relationship across 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 specification (3)-(4), 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-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Number of Predated Stocks		Fraction of Predated Stocks	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client	14.551***	15.066***	57.855***	59.791***
	(4.864)	(4.516)	(5.148)	(4.855)
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	0.390	0.386	0.465	0.461

Table 5
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 $Post = [0,9]$, 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 across clients with different relationship strength with the aware brokers before (Pre) and during ($Post$) the fire sale events. Liquidating funds are excluded from the sample. In columns (1)-(2) we present results for the specifications without fixed effects, while in columns (3)-(4) we report results with time, stock, and manager fixed effects. Standard errors are clustered at the manager level. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Percentage of Positions Reversed			
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Post[0,9]	25.091***	24.110***	23.352***	20.676***
	(11.788)	(7.413)	(5.404)	(4.151)
Best Client	5.128***	6.448***	-7.022**	-1.939
	(3.441)	(2.791)	(-2.010)	(-0.526)
Post[0,9]	11.427***	12.764***	16.287***	18.320***
	(17.298)	(19.318)	(14.256)	(15.494)
Constant	2.723***	2.878***		
	(5.788)	(6.116)		
Time Fixed Effects			Yes	Yes
Stock Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Observations	37,276	37,276	31,000	31,000
R-squared	0.028	0.023	0.258	0.256

Table 6
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. We then regress the probability of predation minus the probability of liquidity provision (defined as in Table 3) on the interaction between $Selling_{b,j,t}$ and the dummy $Post\ Scandal_t$. Standard errors are clustered by manager-stock to and T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Probability of Predation - Probability of Liquidity Provision				
	(1)	(2)	(3)	(4)	(5)
Selling × Post Scandal	0.087***	0.097***	0.069***	0.060***	0.046***
	(11.406)	(12.800)	(9.261)	(8.220)	(6.342)
Selling	0.147***	0.141***	0.148***	0.152***	0.179***
	(23.040)	(22.135)	(22.406)	(23.537)	(28.281)
Post Scandal	-0.025***				
	(-9.289)				
Time Fixed Effects		Yes	Yes	Yes	Yes
Manager Fixed Effects			Yes	Yes	Yes
Stock Fixed Effects				Yes	Yes
Broker Fixed Effects					Yes
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

Table 7
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. The profitability measure which we use as dependent variable in all spefications is defined by the following formula

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

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 relate the profitability (expressed in basis points) of trades executed by aware brokers to our relationship strength proxies (i.e. the fraction of the volume intermediated by the broker over the previous semester generated by the manager, expressed in decimal units, as well as the fraction of the commissions) in the pre- and post- fire sale periods, using event-manager-stock level observations. In rows (1)-(2) we present results for the specifications without fixed effects, while in rows (3)-(4) we report results with time, stock and manager fixed effects. Standard errors are clustered at the manager level. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Return on Capital (basis points)			
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 × Post[0,9]	136.558**	144.821**	147.847**	159.582**
	(2.355)	(2.235)	(2.110)	(1.966)
Best Client	-48.574	-61.826	-78.883**	-108.693***
	(-1.145)	(-1.303)	(-2.414)	(-2.929)
Post[0,9]	-7.160***	-7.102***	-7.719**	-7.665**
	(-2.783)	(-2.761)	(-2.520)	(-2.503)
Constant	8.646***	8.697***		
	(4.651)	(4.679)		
Time Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Observations	263,346	263,346	263,211	263,211
R-squared	0.000	0.000	0.034	0.034

Table 8
Price Impact and Broker Awareness

This table reports results on the price impact experienced by the fire sale originators. Considering all trades by fire sale originators from the beginning of each fire sale event (t=0) to the last day of the fire sale (i.e. the last day on which the criteria for a fire sale definition are satisfied), 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 specifications (1)-(3) we regress the price impact measures on a dummy indicating the presence of at least one aware broker at the event-stock level and the total volume of other managers 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 specifications (4)-(6), we repeat the exercise at the event-stock-broker-level and also add broker fixed effects. Continuos explanatory variables are standardized and standard errors are clustered by event. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Price Impact (basis points)					
Granularity	Stock Level			Broker-Stock Level		
Benchmark Price	(1) First Placement Price	(2) Market Open Price	(3) First Transaction Price	(4) First Placement Price	(5) Market Open Price	(6) First Transaction Price
Aware Broker Dummy	25.176*	36.194**	14.250	11.901***	11.320**	8.970**
	(1.849)	(2.503)	(1.442)	(2.764)	(2.217)	(2.496)
Followers Volume	23.801***	24.286***	8.520*	4.882**	4.898*	2.457
	(2.787)	(2.710)	(1.680)	(2.020)	(1.815)	(1.259)
Generator Volume	6.996	8.560	0.520	21.760***	20.890***	11.607**
	(0.646)	(0.706)	(0.067)	(3.691)	(3.293)	(2.449)
Amihud Ratio	-19.080	-20.435	-18.598	-12.067	-6.532	-8.238
	(-1.070)	(-1.101)	(-1.382)	(-1.262)	(-0.703)	(-1.437)
Number of Brokers	-3.489	1.193	-1.938	6.359	9.710	4.731
	(-0.515)	(0.152)	(-0.373)	(1.137)	(1.509)	(1.334)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects				Yes	Yes	Yes
Observations	6,291	6,291	6,291	28,265	28,265	28,265
R-squared	0.430	0.430	0.415	0.323	0.338	0.265

Table 9
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. Standard errors are clustered by event-broker-manager to account for time-series autocorrelation in commissions paid. T-statistics 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	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Post	1.659***	0.909***	1.608***	0.863***
	(6.977)	(3.657)	(7.986)	(3.872)
Best Client	-13.032***	-9.626***	-5.306***	-1.701***
	(-31.531)	(-24.702)	(-20.886)	(-6.460)
Post	-0.381***	-0.345***	-0.565***	-0.530***
	(-14.035)	(-12.774)	(-22.084)	(-20.803)
Constant	6.296***	6.126***		
	(198.908)	(195.180)		
Time Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Broker Fixed Effects			Yes	Yes
Observations	1,168,535	1,168,535	1,168,521	1,168,521
R-squared	0.029	0.014	0.303	0.301

Brokers and Order Flow Leakage: Evidence from Fire Sales

Andrea Barbon Marco Di Maggio Francesco Franzoni Augustin Landier

INTERNET APPENDIX

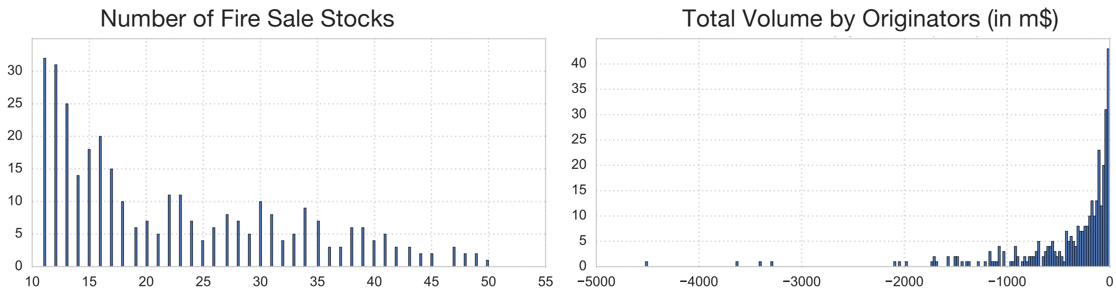

Figure A1: Number of Stocks and Liquidation Volume. The left panel shows the histogram of events with different number of stocks involved in the fire sale. The right panel shows the distribution of the total volume executed by the liquidating funds.

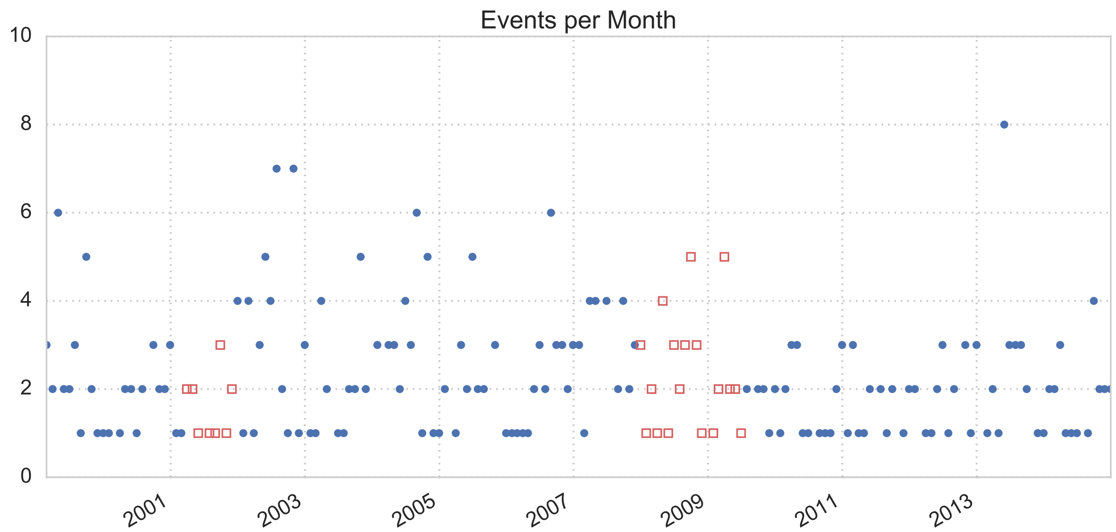

Figure A2: Fire Sale Events. The figure plots the number of fire sales events by month. Hollow red squares identify events happening during the two NBER recessions in our sample period.

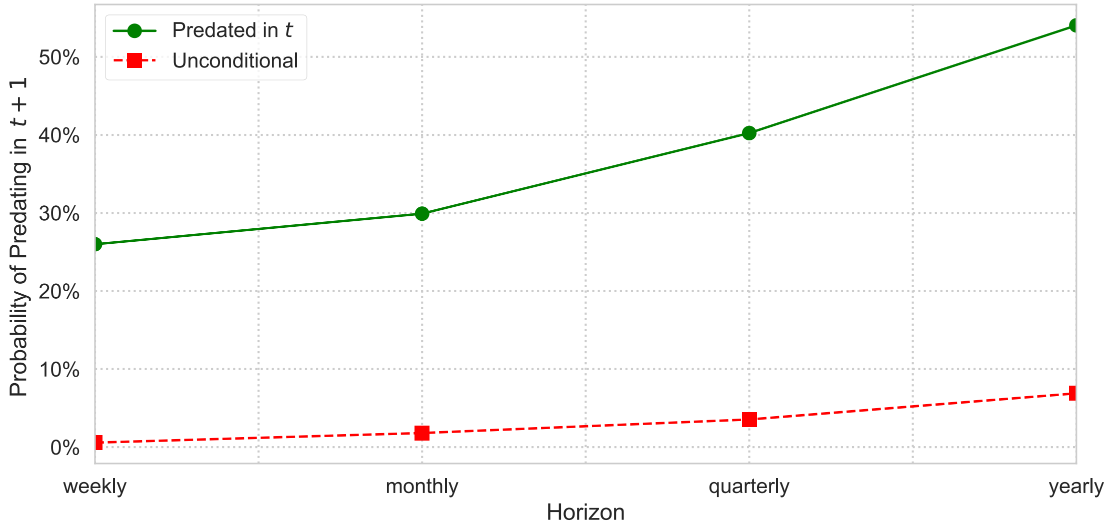

Figure A3: Predators Persistence. The figure compares the unconditional probability of predation with the probability of predation conditional on having predated at least once in the previous period. Subsequent periods are defined over weekly, monthly, quarterly and yearly horizons.

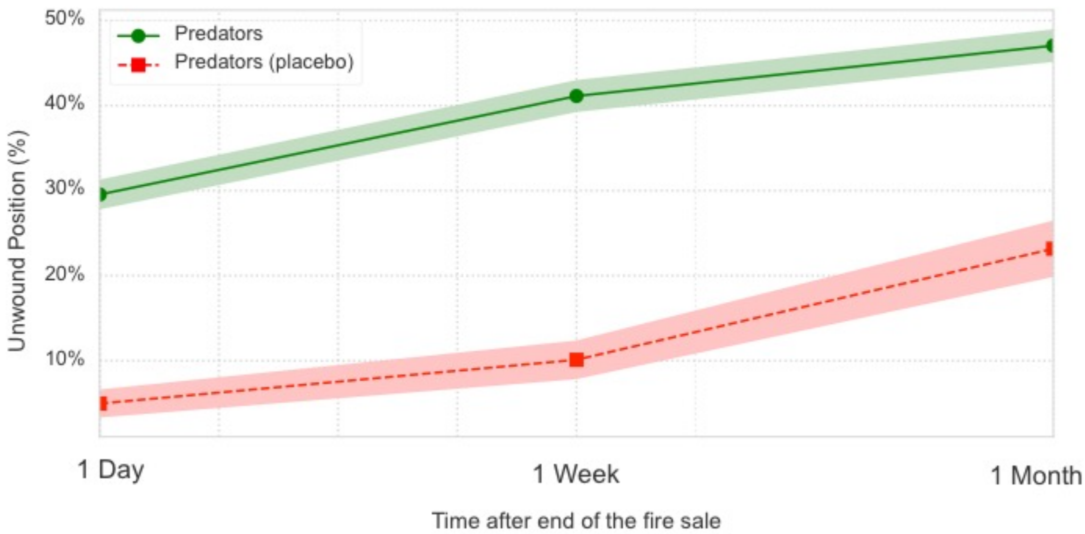

Figure A4: Unwinding of Predatory Positions. The figure plots the average percentage amount of predatory positions built during the fire sales by predators (managers who trade in the same direction of the liquidating fund during the fire sales) after one day, one week and one month after the end of the 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 different definitions of the broker awareness measure. We 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 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-statistics 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 table. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	N	X=1%	X=2%	X=5%
Predatory Behavior and Broker Awareness	1	0.203***	0.195***	0.168***
		(6.414)	(5.595)	(4.092)
Table 2 - Panel A	5	0.161***	0.157***	0.144*
		(5.177)	(3.951)	(1.951)
	10	0.148***	0.166**	0.191**
		(2.919)	(2.398)	(2.088)
Predatory Behavior and Broker Awareness	1	0.038***	0.043**	0.054**
		(2.651)	(2.505)	(2.242)
Table 2 - Panel A	5	0.056***	0.074***	0.117***
		(2.982)	(2.972)	(2.636)
	10	0.060*	0.074	0.131*
		(1.769)	(1.532)	(1.836)
Probability of Predation and Broker-Client Relationship Strength	1	0.040***	0.055***	0.060***
		(2.631)	(3.181)	(2.690)
Table 3 - Panel A	5	0.052*	0.090***	0.165***
		(1.948)	(2.868)	(3.678)
	10	0.068*	0.135***	0.086
		(1.949)	(3.202)	(1.313)
Predators' Position Reversal	1	11.815***	11.594***	10.981***
Table 5		(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)

	N	X=1%	X=2%	X=5%
Excluding Negative News	1	0.044***	0.052***	0.050**
Table A3 - Panel B		(2.657)	(2.801)	(2.087)
	5	0.050*	0.089***	0.166***
		(1.834)	(2.804)	(3.642)
	10	0.075**	0.137***	0.092
		(2.108)	(3.166)	(1.364)
Excluding Negative Momentum Stocks	1	0.040**	0.070***	0.092***
Table A3 - Panel C		(1.979)	(3.016)	(3.081)
	5	0.062*	0.103**	0.181***
		(1.691)	(2.383)	(2.873)
	10	0.092*	0.227***	0.201**
		(1.946)	(4.119)	(2.297)
Excluding High Short Interest Stocks	1	0.036**	0.050***	0.061***
Table A3 - Panel D		(2.280)	(2.849)	(2.658)
	5	0.054**	0.101***	0.177***
		(2.002)	(3.187)	(3.915)
	10	0.070**	0.138***	0.084
		(1.997)	(3.252)	(1.282)
Excluding NBER Recessions Periods	1	0.039**	0.052***	0.059**
Table A3 - Panel A		(2.357)	(2.816)	(2.509)
	5	0.077***	0.117***	0.190***
		(2.745)	(3.562)	(4.053)
	10	0.085**	0.157***	0.084
		(2.340)	(3.603)	(1.231)

Table A2
Characteristics of Predated Stocks

The table reports 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 (defined as those generating at least 5% of the volume intermediated by the broker over the previous semester) of aware broker *P* divided by the number *N* of managers actively trading during the fire sale event on that stock. The ratio *P/N* is then used to split the set of fire sale stocks into two parts, using the median of this variable 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-statistics of the differences are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	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 A3

Robustness: Excluding Bad News and Underperforming Stocks

The table reports results on a first set robustness checks on the results presented in Table 3. 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. In Panel C we exclude stocks expriencig negative returns in a window of 10 days preceding the start of the fire-sale event. In Panel D, we exclude stocks with high short interest in the 2 weeks preceding the fire sale event, as proxied by a value of utilization 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 cluster standard errors at the event-stock-manager level. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Excluding NBER Recessions Periods

Dependent variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.052***	0.077***	0.115***	0.113**
	(2.816)	(3.740)	(2.814)	(2.289)
Best Client	0.027	0.055***	-0.001	0.008
	(1.498)	(2.600)	(-0.029)	(0.226)
Liquidation Period	0.006***	0.005***	0.003	0.003
	(5.113)	(4.459)	(0.690)	(0.776)
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	428,314	428,314	428,314	428,314
R-squared	0.048	0.048	0.016	0.016

Panel B: Excluding Negative News

Dependent variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.052***	0.076***	0.102***	0.110**
	(2.801)	(3.600)	(2.748)	(2.295)
Best Client	0.017	0.046**	0.011	0.013
	(0.966)	(2.217)	(0.350)	(0.349)
Liquidation Period	0.006***	0.006***	0.003	0.003
	(5.531)	(4.874)	(0.779)	(0.755)
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	447,504	447,504	447,504	447,504
R-squared	0.047	0.048	0.013	0.013

Panel C: Excluding Negative Momentum Stocks

Dependent variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.070***	0.107***	0.125***	0.148***
	(3.016)	(4.062)	(3.170)	(2.601)
Best Client	0.034*	0.061**	-0.019	-0.012
	(1.717)	(2.551)	(-0.578)	(-0.280)
Liquidation Period	0.004***	0.003**	0.001	0.001
	(3.159)	(2.425)	(0.327)	(0.227)
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	289,082	289,082	289,082	289,082
R-squared	0.051	0.051	0.025	0.025

Panel D: Excluding High Short Interest Stocks

Dependent variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.050***	0.078***	0.090***	0.101**
	(2.849)	(3.915)	(2.735)	(2.345)
Best Client	0.025	0.053***	0.013	0.017
	(1.511)	(2.645)	(0.448)	(0.517)
Liquidation Period	0.005***	0.005***	0.002	0.002
	(4.991)	(4.229)	(0.522)	(0.476)
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	477,463	477,463	477,463	477,463
R-squared	0.043	0.043	0.013	0.013

Table A4
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 3, but restricting to managers identified as hedge funds in Panel A and to the complementary set of other institutions in Panel B. We cluster standard errors at the event-stock-manager level. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Probability of Predation - Probability of Liquidity Provision			
Subsample	Hedge Funds		Other Institutions	
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.065***	0.083***	0.034	0.069**
	(3.189)	(3.692)	(1.201)	(2.068)
Best Client	0.034	0.027	0.003	0.062*
	(1.467)	(1.027)	(0.114)	(1.921)
Liquidation Period	0.006***	0.006***	0.006***	0.005***
	(4.182)	(3.796)	(3.978)	(3.287)
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	230,780	230,780	270,784	270,784
R-squared	0.055	0.055	0.061	0.062

Table A5
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 stock-day-manager-broker level, excluding trades by managers originating the fire-sale of interest or another overlapping fire-sale. In all specifications, the dependent variable is the difference between a dummy indicating predation and a dummy indicating liquidity provision, 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), it equals negative one if the trade is in the opposite direction (i.e. a buy trade) and equals zero if the manager is not trading that stock on that particular day. We regress the dependent variable on the proxies for the manager-broker relationship strength, a dummy indicating the first 5 days of the fire sale, and the interaction of the two variables. The liquidation period 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. In the first two specifications we include broker×manager fixed effects and in the last two specifications we include broker×originator fixed effects, where the originator is the manager initiating the fire sale. Standard errors are clustered by event-stock-manager and T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	Probability of Predation - Probability of Liquidity Provision			
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Liquidation Period	0.059***	0.088***	0.056***	0.083***
	(3.402)	(4.475)	(3.203)	(4.261)
Best Client	-0.027	0.003	0.028*	0.049***
	(-1.136)	(0.111)	(1.749)	(2.735)
Liquidation Period	0.009***	0.008***	0.009***	0.008***
	(3.854)	(3.512)	(3.403)	(3.122)
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		
Broker-Originator Effects			Yes	Yes
Observations	501,562	501,562	501,567	501,567
R-squared	0.081	0.081	0.062	0.063

Table A6
Alternative Clustering of Standard Errors

The table presents robustness tests on the results in Tables 2, Panel A, and Table 3, Panel A, based on alternative ways to cluster the standard errors. In particular, Panel A presents robustness for Table 2, Panel A, and Panel B reports robustness for Table 3, Panel A. T-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Predatory Behavior and Broker Awareness

Dependent Variable	Probability of Predation - Probability of Liquidity Provision			Predatory Volume - Liquidity Provision Volume		
	(1)	(2)	(3)	(4)	(5)	(6)
Aware Broker	0.195***	0.195***	0.195***	0.043**	0.043***	0.043**
	(5.595)	(5.551)	(5.509)	(2.505)	(2.626)	(2.519)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	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	0.065	0.065	0.065	0.017	0.017	0.017

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

Dependent Variable	Probability of Predation - Probability of Liquidity Provision		
	(1)	(2)	(3)
Best clients proxy	Ranking based on Volume	Ranking based on Volume	Ranking based on Volume
Best Client × Liquidation Period	0.059***	0.059***	0.059***
	(3.404)	(4.068)	(3.458)
Best Client	0.023	0.023**	0.023
	(1.464)	(1.979)	(1.459)
Liquidation Period	0.008***	0.008***	0.008***
	(3.588)	(4.212)	(3.562)
Time FE	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes
Clustering	Event-Stock-Manager	Event-Stock-Date	Event-Stock-Broker
Observations	501,567	501,567	501,567
R-squared	0.053	0.053	0.053

Table A7
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, Panel 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-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: VIX Above Median

Dependent Variable	Probability of Predation - Probability of Liquidity Provisio		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Aware Dummy	0.217***	0.216***	0.043	0.045
	(6.265)	(6.478)	(1.542)	(1.586)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects		Yes		Yes
Observations	211,876	211,750	211,876	211,750
R-squared	0.058	0.064	0.008	0.018

Panel B: VIX Below Median

Dependent Variable	Probability of Predation - Probability of Liquidity Provision		Predatory Volume - Liquidity Provision Volume	
	(1)	(2)	(3)	(4)
Aware Dummy	0.176***	0.165***	0.042***	0.041***
	(4.409)	(4.111)	(2.800)	(2.708)
Time Fixed Effects	Yes	Yes	Yes	Yes
Manager Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects		Yes		Yes
Observations	284,761	284,654	284,761	284,654
R-squared	0.071	0.077	0.019	0.022

Table A8
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 A9
Regressions without Fixed Effects

The table revisits our main results in Tables 2 and 3, Panel A, using specifications without fixed effects. In Panel A we report results for a specification similar to that of Panel A of Table 2, but without fixed effects. In Panel B we report results for a specification similar to that of Panel A of Table 3, 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-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Predatory Behavior and Broker Awareness

Dependent Variable	Probability of Predation - Probability of Liquidity Provision	Predatory Volume - Liquidity Provision Volume
	(1)	(2)
Aware	0.232***	0.054***
	(5.175)	(3.078)
Constant	-0.022	-0.002
	(-1.119)	(-1.166)
Observations	496,729	496,729
R-squared	0.002	0.000

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

Dependent Variable	Probability of Predation - Probability 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	0.065***	0.092***	0.138***	0.140***
	(3.763)	(4.697)	(3.611)	(3.081)
Best Client	0.055***	0.068***	0.058***	0.067**
	(4.024)	(4.339)	(2.715)	(2.512)
Liquidation Period	0.006***	0.005***	0.002	0.003
	(6.008)	(5.255)	(0.642)	(0.719)
Constant	0.004***	0.004***	-0.006***	-0.006***
	(5.701)	(5.243)	(-3.108)	(-2.915)
Observations	501,568	501,568	501,568	501,568
R-squared	0.001	0.001	0.000	0.000

Table A10
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, i.e. the manager generated at least 5% of the volume intermediated by the aware broker in the previous semester. We then interact this dummy with the broker awareness dummy defined in Table 2 and run 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 Table 3 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 Table 3 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-statistics 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 A11
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 entire Ancerno dataset: (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 dollar millions; (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-statistics for 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 A12
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 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 3. In rows (1)-(2) we present results for the specifications without fixed effects, while in specifications (3)-(4) we report results with day, manager, and stock fixed effects. Standard errors are clustered at the broker level and t-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent variable	First Day of Predation			
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Aware Broker	-1.202***	-1.379***	-0.697**	-0.787**
	(-7.725)	(-7.941)	(-2.364)	(-2.447)
Best Client	-0.357***	-0.275***	-0.254***	-0.173***
	(-11.381)	(-6.911)	(-5.002)	(-2.773)
Aware Broker	0.118***	0.129***	-0.023	-0.015
	(6.004)	(6.611)	(-0.800)	(-0.566)
Constant	2.203***	2.187***		
	(304.624)	(305.812)		
Time Fixed Effects			Yes	Yes
Stock Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Observations	98,771	98,771	98,411	98,411
R-squared	0.003	0.002	0.237	0.236

Table A13
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 - defined as $(H - 1/N)/(1 - 1/N)$ where N is the number of brokers in our sample and H is the usual Herfindahl Index - 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-statistics 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 A14
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	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Post	2.493***	1.537***	2.234***	1.327***
	(6.923)	(4.254)	(7.317)	(3.982)
Best Client	-13.523***	-10.269***	-5.990***	-2.456***
	(-21.484)	(-18.022)	(-14.568)	(-5.932)
Post	-0.418***	-0.376***	-0.595***	-0.556***
	(-10.372)	(-9.355)	(-15.528)	(-14.495)
Constant	6.395***	6.246***		
	(138.850)	(136.728)		
Time Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Broker Fixed Effects			Yes	Yes
Observations	531,527	531,527	531,516	531,516
R-squared	0.027	0.014	0.304	0.302

Panel B: Predators Only

Dependent variable	Commissions per dollar (basis points)			
	(1)	(2)	(3)	(4)
Best clients proxy	Ranking based on Volume	Ranking based on Commissions Paid	Ranking based on Volume	Ranking based on Commissions Paid
Best Client × Post	1.629***	1.086***	1.598***	1.093***
	(6.463)	(4.062)	(7.167)	(4.406)
Best Client	-10.619***	-7.594***	-4.681***	-1.334***
	(-25.839)	(-19.411)	(-17.674)	(-4.662)
Post	-0.477***	-0.441***	-0.641***	-0.607***
	(-14.362)	(-13.385)	(-20.418)	(-19.469)
Constant	5.881***	5.685***		
	(149.915)	(146.372)		
Time Fixed Effects			Yes	Yes
Manager Fixed Effects			Yes	Yes
Broker Fixed Effects			Yes	Yes
Observations	706,703	706,703	706,690	706,690
R-squared	0.030	0.013	0.321	0.319