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PH.D THESIS

An Empirical Study of Information Flows and Conflicts of Interests in Brokerage Business and Mutual Fund Industry

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"Work expands so as to fill the time available for its completion."

Cyril Northcote Parkinson

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SUMMARY INTRODUCTION

In my PhD thesis I unveil somewhat controversial trading practices and conflicts of interests in mutual fund industry and brokerage business. I aim to provide empirical evidence of premature information diffusion in capital markets. The novel data and identification approach of the study allows answering the questions so far not answered in the literature. The thesis consists of two chapters: Chapter 1 "Tippers and Tippees: Brokers' Pre-release of Price-sensitive information to their VIP clients" and Chapter 2 "Predation versus Cooperation in Mutual Fund Families".

Chapter 1 Tippers and Tippees: Brokers' Pre-release of Price-sensitive information to their VIP clients

In Chapter I of my thesis, I study a pre-release of research information by brokerage houses to their important clients. I explore whether this activity is empirically detectable. Using high-frequency trading data from Abel Noser Solutions (ANcerno), I investigate trading of individual institutions ahead of recommendation release. First, I find that large institutions and frequent traders trade in the direction of the Strong Buy and Buy initiations in the 5-day period before the announcement. This evidence supports the informed trading taking place in the pre-announcement period. This study shows that specific groups of institutional investors are informed. I further document that brokers' best clients are more likely to trade in advance of the recommendation issue.

According to several research studies, Regulation Fair Disclosure and Global Research Analyst Settlement (GRAS) was effective in decreasing selective disclosure by companies and cutting analysts' access to investment banking information. I provide empirical evidence that tipping of best clients by broekrs increased after the regulation, suggesting that brokers started to look for other means to attract clients. The findings resist to several controls: manager characteristics, stock characteristics and potential news releases.

Some recent empirical studies provided evidence suggestive of brokers tipping their clients with price-sensitive information. Chemmanur et al. (2009) find that institutions use private information in trading before and after a seasoned equity offering. The fact that stock recommendations move stock prices is well documented in the academic literature (see, e.g., Womack (1996)). This makes recommendations a valuable information for investors and represents a good opportunity for breeding client relationship. Christophe et al. (2010) detect abnormal short-selling volume in the 3 days before the recommendation downgrade, and Juergens and Lindsey (2009) find abnormal trading volume at the recommending brokerage firm 2 days before analysts recommendation downgrade (the volume is of the same direction as the recommendation). This evidence is quite suggestive of institutions front running the recommendation issue. In their seminal paper Irvine, Lipson and Puckett (2007) suggest positive abnormal trading volume ahead of analyst buy and strong buy recommendation initiations as the evidence of tipping by brokers. However, the data used in the studies does not allow studying the identity and characteristics of the advantaged investors. Furthermore, the observed increase in the trading volume might happen because analysts often time the release of their research output. Thus, the issue of a recommendation could be the result of investor interest in a stock. Contrary to the existing studies I use trading data with the breakdown into investor-level trades. I analyze information leakage of financial analyst recommendations to their privileged clients, as well as characteristics of the institutional investors receiving such advance knowledge. I provide evidence supportive of the hypothesis that big institutional clients and clients enjoying privileged relationship with their broker receive and use the pre-released research information in their trades.

This study might be of interest for the financial markets regulatory authorities (e.g. Securities and Exchange Commission) dealing with detection of insider trading.

Chapter 2 Predation versus Cooperation in Mutual Fund Families (with Alexander Eisele and Gianpaolo Parise)

In Chapter 2, prepared in collaboration with Alexander Eisele and Gianpaolo Paise, I investigate private information flows and trading practices inside mutual fund families when one of the funds in the family experiences a severe distress due to investor redemptions. In particular, we examine whether funds predate or cooperate with their distressed counterparts. The main academic contribution of the research paper is the empirical evidence in support of a family-coordinated predation of the distressed funds inside investment fund families.

To provide the evidence, we analyze the performance of distressed funds and non-distressed funds inside the fund complexes. We find that non-distressed funds inside families having a distressed member see their performance increasing. At the same time, the results show that the distressed funds in large families experience a substantially lower performance, than do their peers from small families. The paper finds that high-fee funds benefit more from the distress of a family member. This finding is supportive of the performance shifting resulting from a strategy coordinated on the level of a fund complex.

We use 2004 SEC regulation is response to the "late trading scandal" as an exogenous shock, and find that predating behavior inside fund families weakens after the regulation came in vigor. This result is suggestive that the regulation was effective in decreasing the controversial trading practices inside mutual fund families.

We further exploit trading data from ANcerno to shed light on the channel of the performance shifting among funds in the families. We construct a proxy for the cross trades from the data and provide empirical evidence that cross trading activity is the main channel of performance transfer from the distressed funds to other funds in the family: we observe a negative effect of the level of cross-trading activity for the distressed funds and positive effect for the non-distressed siblings. We further show that distressed funds are often used as "waste bins": they buy poor-performing and less liquid positions from their siblings and sell them good and well-performing stocks. Thereafter, we explore pricing of cross trades. We find that sell transactions making part of cross trades bear higher trading costs for the families with at least one distressed member. The cross trading activity shows a discernible time series pattern. It drops significantly around the regulatory change in 2004.

From the practical standpoint, the results of this research work may be useful for mutual fund investors to be better informed on the eventual risks for their investments coming from the incentives distortions inside fund families. The study questions the role of managing companies in providing "better care to their investors" and may bring implications for stronger regulation of the information flows inside mutual fund families.

Chapter 1

Tippers and Tippees: Brokers' Pre-release of Price-sensitive Information to their VIP Clients

1.1 Summary

Using proprietary high-frequency trading data, I analyze information leakage of financial analyst recommendations to their elite clients, as well as characteristics of the institutional investors receiving such advance knowledge. I find that investment managers, who have an established relationship with their brokers, on average buy more than other investors in the 5-day period before positive analyst coverage initiations. My results suggest that clients, who enjoy a privileged relationship with their broker receive and use the pre-released information in their trades.

1.2 Introduction

In 2007 Roberto Casoni, equity analyst from Citigroup, was sued by the UK Financial Services Authority (FSA) for unveiling his upcoming strong buy coverage initiation to select fund managers before making the research report public. Later in 2010 fund managers at Shroders, Oddo Asset Management and Dexia Asset Management, as well as fund manager Guillaume Rambourg from Gartmore, were fined by the Italian regulator Consob[1] for front running based on the information received from Mr. Casoni. The case marked a clear legal borderline for the anticipated research dissemination in Europe.

Five years later, in April 2012, US Securities and Exchange Commission (SEC) charged a $22 million dollar fine against Goldman, Sachs & Co. for not having suitable policies in place to prevent stock research tips being released to a select group of top clients during weekly trading "huddles"[2]. "Despite being on notice from the SEC about the importance of such controls, Goldman failed to implement policies and procedures that adequately controlled the risk that research analysts could preview upcoming ratings changes with select traders and clients", said Robert S. Khuzami, Director of the Commission's Division of Enforcement. Back to 2007, Goldman started the Asymmetric Service Initiative (ASI) under which analysts tipped select clients with information from trading huddles. Critics of the practice have complained that it hurt other clients who were not given a possibility to trade on the information. Many clients of Goldman were unaware of the trading "huddles" practice and were later deceived by discovering they were "at the end of the food chain".

Media cites other cases of private information leakage in brokerage business. Brokers have a clear incentive to engage in such practices in chase of trading commissions and good relationship with their key clients. This study considers a special case of private information flow, which is a pre-release of research information by brokerage houses to their important clients. I explore whether this activity is statistically detectable.

[1] Commissione nazionale per la società e la Borsa

[2] SEC, 2012, SEC charges Goldman, Sachs & Co. Lacked adequate policies and procedures for research "huddles", Press Release 2012-61.

Using high-frequency trading data from Abel Noser Solutions (ANcerno), I investigate trading of individual institutions ahead of analyst coverage initiations. First, I find that large institutions and frequent traders trade in the direction of the recommendation in the 5-day period before the announcement more than small institutions and institutions trading less actively. This evidence supports the informed trading taking place in the pre-announcement period. This result is quite intuitive per se, some existing papers report abnormal institutional volume ahead of major events. However, this paper is the first to show that there is a particular type of institutional investors who are informed. I further document that, more specifically, brokers' best clients are more likely to trade in advance of the recommendation issue. According to several research studies, Regulation Fair Disclosure and Global Research Analyst Settlement (GRAS) managed to reduce selective disclosure by companies and cut analysts' access to investment banking information. I provide empirical evidence of the change in aggregate pre-recommendation trading and trading by brokers' VIP-clients after GRAS. My findings suggest that brokers started looking for other means of attracting clients and raised tips dissemination to select clientele in after-regulation period. My findings are robust to controls: manager characteristics, stock characteristics and potential news releases. Further, I provide evidence that initiations by analysts from large brokers and All-star analysts are associated with increased pre-event buying by brokers' "best clients".

To my knowledge, this study is the first attempt to design a straight-forward empirical strategy to study the role of investor-broker relationship for tipping and characteristics of tipped institutions. The main novelty of this paper compared to the existing studies exploiting ANcerno data, is the use of manager identification files. It allowed this study to explore trading behavior of individual institutions and to distinguish among their characteristics. Identification files of trading institutions were provided by ANcerno in 2010 for a limited period of time. Respecting the non-disclosure agreement with the data provider, this study does not reveal any names of the institutions. Being in possession of the manager and broker identification files enabled me to match them through several databases and construct characteristics of the trading institutions and follow them through time.

This paper relates to several strands of the existing literature. Some recent empirical studies provided evidence suggestive of brokers tipping their clients with price-sensitive information. Kim, Lin, and Slovin (1997) refer to pre-release of analyst's stock recommendation to important clients as a common practice in brokerage business. In their seminal paper Irvine, Lipson, and Puckett (2007) report positive abnormal trading volume ahead of analyst buy and strong buy recommendation initiations. Their evidence is strongly suggestive of tipping activity by brokers. Christophe, Ferri, and Hsieh (2010) detect abnormal short-selling volume in the 3 days before the recommendation downgrade, and Juergens and Lindsey (2009) find abnormal trading volume at the recommending brokerage firm 2 days before analysts recommendation downgrade (the volume is of the same direction as the recommendation). Anderson and Martinez (2009) analyze brokers' daily transactions from the Stockholm Stock Exchange and find that trades through recommending brokers around recommendation upgrades are profitable. The evidence provided by these studies is consistent with institutions front-running the recommendation issue. However, the data and research design used in the studies does not allow to study the identity and characteristics of the advantaged investors. Furthermore, the observed increase in the trading volume might be due to the fact that analysts are often timing the release of their research output. Thus the issue of a recommendation (or initiation) could be a result of investor interest in a stock. In my study I overcome this concern by using trading data with the break-down into investor-level trades.

This paper also adds to the academic literature analyzing the information content and investment value of analyst recommendations. There is a heated debate in the current literature on whether analysts' research output is informative. I show that analysts recommendations (this study examines coverage initiations) benefit a group of brokers' privileged clients. Womack (1996) reports significant initial price and volume reactions to both buy and sell recommendations and documents the presence of the post-recommendation stock price drift over 6 months for sell recommendations (much shorter for buy recommendations). Francis and Soffer (1997) find that analyst recommendation revisions have incremental value to the earnings forecast revisions. Barber, Lehavy, McNichols, and Trueman (2001) propose portfolio strategies based on consensus analyst recommendations producing abnormal gross returns. The returns however vanish after taking into account transaction costs. Ivković and Jegadeesh (2004) find that positive forecast revisions and recommendation upgrades have a superior information content in the week before earnings announcement, than shortly after. This does not hold for negative forecast revisions and recommendation downgrades. Chang and Chan (2008) show that market-adjusted stock returns are correlated with the direction of financial analysts' recommendation revisions, with recommendation downgrades being more informative for investors. On the one hand, it makes recommendations a valuable information for investors, and on the other hand, it represents a good opportunity for breeding client relationship and constitutes the main motivation point for the tipping activity. Kim, Lin, and Slovin (1997) find that initial buy recommendations have an average excess return of about 4% and 7% (for NYSE/AMEX and NASDAQ stocks respectively). Furthermore, they document that profit opportunities related to the coverage initiation disappear in the first fifteen minutes after the public news release and most of the information about the analyst recommendation is included in the opening price. Green (2006) documents the presence of positive short-term (about two hours) profit opportunities after pre-market release of analyst recommendation changes for the issuing broker's clients before the news is published through the news wire. Both studies conclude that mostly informed investors (important broker's clients) should be able to take advantage of the information contained in the recommendations. Recent studies arrive to the opposite conclusions depending on whether they focus on average effects or individual analyst recommendations. Altinkilic and Hansen (2009) provide evidence that on average there is no economically significant reaction to recommendation changes after controlling for confounding firm news. At the same time, Loh and Stulz (2011) study the effect of individual recommendations and find that analysts produce influential recommendations as an outcome of a mixture of skills and circumstances. Similarly, Hess, Kreutzmann, and Pucker (2012) report that more skillful analysts provide more profitable recommendations yielding significant excess returns to investors. Therefore, advance knowledge of the research report content can have an investment value. This study concentrates on the impact of individual recommendations. I exploit the feature of certain individual recommendations to provoke a market reaction and examine whether this quality produces an incentive for brokerage houses to please their important clients by unveiling recommendations to them before the rest of the clientele and public.

Finally, this paper contributes to the academic knowledge on informed trading. Several studies conclude that institutions are informed traders (see, for example Barclay and Warner (1993), Chakravarty (2001) or recently Hendershott, Livdan, and Schürhoff (2011)). The evidence I provide is in line with these findings. I complement the existing research by showing that institutions with specific characteristics are more informed. I also provide evidence that this superior information is partly driven by preferential access to information offered by information-providers (brokers).

The paper is organized as follows. Section 1.3 outlines and provides discussion of the research hypotheses. Section 1.4 describes the data and the construction of the broker-investor relationship proxy. Section 1.5 discusses the empirical findings. Section 1.6 studies the relation of broker and analyst characteristics and pre-release trading. Section 1.7 examines the robustness of the results. Finally, section 1.8 discusses regulation related to tipping and section 1.9 concludes.

1.3 Hypotheses development and related literature

In this section I provide a set of testable hypotheses and describe their empirical predictions in relation to institutional investors' trading behavior in the pre-recommendation period.

It is often argued that institutional investors are informed traders, and they possess superior information due to better access to information and/or more sophisticated information processing skills (Hendershott, Livdan, and Schürhoff (2011)). However, the empirical evidence of information-driven trading by institutions remains mixed. Existing studies use, to a large extent, low-frequency data (13F quarterly holdings of institutions) or high-frequency trading data. Publicly available US data of institutional flows are quarterly institutional holdings (SEC's 13F filings). It is quite hard to imply from quarterly data whether institutions induce stock price movements or respond to them.

Other datasets used by academics to analyze trading by institutions are TAQ, CAUD (NYSE Consolidated Equity Audit Trail Data), NASDAQ PostData, Plexus Group and ANcerno/Abel Noser (used in this study). TAQ database, for example, does not provide any characteristic of the trader and does not classify trades as buys or sells. Research studies analyzing these data apply an algorithm to assign the side of the trade depending whether the trade price is closer to bid or ask. To proxy for an investor type, researchers commonly use trades cutoffs by dollar size (see Lee and Radhakrishna (2000)), block trades (see Kraus and Stoll (1972), more recently Bozcuk and Lasfer (2005)), or a more sophisticated daily trades and quarterly holdings mapping procedure as proposed by Campbell, Ramadorai, and Schwartz (2009).

Using different data sources (CRSP returns for NYSE tender offer targets and TORQ data respectively), Barclay and Warner (1993) and Chakravarty (2001) provide empirical evidence of institutions splitting their trades into medium-sized trades, so called "stealth trading". The authors conclude that in such a way informed investors trade on their private information. The studies do not relate their analysis to any type of information event by selecting stocks with a significant price increase in a sample period. Chakravarty (2001) uses the TORQ dataset (sample of the CAUD data) containing information about individual orders of 144 firms over a very short time period: three-months (63 trading days) during 1990-91 (for electronically routed (SuperDot) orders at the NYSE). TORQ allows to distinguish between the two types of investors: individual and institutional.

Institutional investors are not a homogeneous group. Commonly used high-frequency datasets (including earlier releases of ANcerno) do not allow to distinguish among separate institutions, and for this reason, previous studies refer to the whole group of institutions as informed traders. By the very nature of private information, it is accessible only to a limited number of players. Therefore, being able to identify the trading party is crucial to driving conclusions about which investors are informed. ANcerno database represents a number of advantages over the other databases used in the existing studies: it clearly categorizes trades into buys and sells and in 2010 it has provided identification of trading institutions (subject to non-disclosure agreement) covering the preceding historical data period since 1998. The file maps the trade to the name of the trading institution. *Managercode* allows to trace institutions across time. To my knowledge, this is the first study in the finance literature making use of investor identity.

Hence, I classify single institutions in ANcerno by their size and trading frequency and formulate my first hypothesis:

H1: Informed trading ahead of analyst recommendations

- Big investment managers trade in the direction of the recommendation in the pre-recommendation period
- Frequent traders are more likely to trade in the direction of the recommendation before the recommendation issue

The two predictions would be consistent with investors being informed about the content of the analyst research report, but they do not give a clear indication of the channel by which trading institutions obtained the information. First, institutions may receive information from their broker. Both, large institutions and frequent traders, have it all to become first line clients for brokers, as they are the source of lucrative trading commissions. Preferential disclosure of recommendations could be a part of soft dollar arrangements between a broker and its client.

Another possibility is that important investors get news directly from the companies. Before the Regulation Fair Disclosure (Reg FD) was proclaimed in August 2000, both brokers and important institutions were in the first line to get news from companies early before they become public. After Reg FD, this practice became illegal and firms must disclose all the material information to all investors simultaneously. Therefore, even though some anecdotal cases of selective disclosure may still happen, they presumably should no more be detectable on a large scale.

And finally, it can further be argued that both, large institutional investors and brokers, are getting their information from legitimate sources (e.g.,public news wire). As a result, large institutions, generally believed to possess superior information-processing capacity, respond to the news faster than other market participants and more rapidly than a broker analyst issues a research recommendation. Although I use several filters and control variables to mitigate the effects of confounding news (I delete observations coinciding with the dates of companies' earnings guidance and earnings announcements and control for pre-event period returns), this, however, may not be enough to dissipate concerns of the most severe skeptics. For this reason in my next hypothesis the relationship between brokers and institutions comes under closer scrutiny.

H2: Brokers "tip" their best clients with research report content

- Net trades by important clients of the recommending broker are in the direction of the recommendation in the time window preceding the recommendation announcement

Some recent papers aim to explore private information flows ahead of major corporate events. Griffin, Shu, and Topaloglu (2012) use broker-level trading data to analyze trading inside "connected" brokerage houses ahead of takeover and earnings announcements for NASDAQ-traded firms. The authors test whether brokers connected to firms through investment banking relationship (IPO or SEO advising), lending relationship or superior past trading profitability in the stock are better informed ahead of takeovers. Overall, the authors find no evidence of elevated trading on inside information at the connected brokerage firms, neither by brokers themselves, nor on behalf of their clients. Yet, Jegadeesh and Tang (2010) find that institutions, whose main broker served as a target advisor, are net buyers before the takeover announcement and their trades are significantly profitable. Their finding corroborates the key prediction of this paper: a group of investors may take advantage of the inside information, while inside trading activity may or may not be detectable on average.

Given the differential research design, the results obtained by the authors of the cited papers are not mutually exclusive. Both papers find that trades of institutions ahead of takeover announcements are not profitable on average. Griffin, Shu, and Topaloglu (2012) look at aggregated trades at a broker-level. Institutions are nevertheless unlikely to concentrate all their trades with one broker. Also the chances are low that institutions informed by their broker ahead of a major event concentrate all the trades related to the private information at the involved brokerage house. In this light the findings of Griffin, Shu, and Topaloglu (2012) are not surprising. At the same time, they do not question the existence of profitable strategies of selected groups of investors based on private information flows.

Analyst recommendation issue is a broker-specific information, which makes it a convenient way to study information flows from brokers to their clients. Irvine, Lipson, and Puckett (2007), Juergens and Lindsey (2009) and Christophe, Ferri, and Hsieh (2010) provide some evidence suggestive of front-running trading activity related to analyst recommendations. Hence, I use recommendation initiations in my research design to explore whether selected broker's clients benefit from advance knowledge of research reports.

I construct a measure of broker-client relationship as a percentage of deals in which an institutional investor received shares from the total number of IPO deals underwritten by a broker in three years preceding the recommendation issue. I proxy IPO allocations by closest IPO holdings according to the SEC 13(f) filings. I provide a detailed discussion of the validity of this approach in section 2.4.3.

The analysis of client-broker connections in the setting of private information flows is one of the key distinguishing features of this study from the existing research. The recent (2010) release of the ANcerno data enables me to map individual institutions and their tick-by-tick trades. Elevated buying by best clients ahead of broker recommendations would be indicative of the clients being informed about the content of the research report.

In my third hypothesis I refer to Regulation Fair Disclosure and Global Research Analyst Settlement which shaped the relationship between brokers and their institutional clients. Juergens and Lindsey (2009) suggest that after Regulation FD and Global Analyst Settlement (GRAS), analysts might have stronger incentives to give preferential access to research output to compensate for the censored access to investment banking information and selective disclosure from companies. Later, in April 2012, famous New York Times reporter Ms. Susanne Craig (Craig (2012))[3] linked Goldman's trading "huddles" to the 2003 settlement which put up firewalls between research and investment banking and prohibited the use of banking revenue to subsidize research. According to Ms. Craig, this incited Goldman's executives to search for new opportunities for attracting clients and generating trading commissions and precipitated the emergence of trading huddles. I formulate and test a hypothesis H3 related to the prediction:

H3: Post-GRAS favored access to research for the preferred clients

- Stronger pre-announcement net buying of important clients of the recommending broker in the period after GRAS

Finding that established clients are net buyers ahead of positive recommendation initiations in the post-GRAS period would be consistent with analysts using research output as the means of tipping a privileged circle of their clients. Hence, I would expect a coefficient on the "Best Client" variables to be stronger in the post-GRAS period.

1.4 Data and methodology

In this part I give a detailed explanation of the data sources and identification I used in this study. I employ the following datasets for my analysis: US transaction data from ANcerno, 13f institutional holdings from Thomson Reuters, I/B/E/S financial analysts' stock recommendations, IPO data from Thomson One (SDC Spectrum), earnings guidance data from First Call database and stock prices from CRSP. Section 1.4.1 describes the ANcerno trading data. Section 1.4.2 gives the details of the identification of managing companies and brokers. Section 1.4.3

[3] Ms.Susanne Craig has covered Wall Street for more than 15 years and prior to joining NYT in 2010, she worked as a reporter for The Wall Street Journal

discusses the construction of the broker-client relationship measure. Finally, section 1.4.4 provides the description of the sample selection procedure and summary statistics.

1.4.1 Trading data

I use institutional trading data from ANcerno (Abel Noser Solutions) for the available period 1999-2010[4].

As described on the company's website (www.ancerno.com) "Abel Noser Solutions, Ltd. provides trade cost analysis to institutional investors, advisors, hedge funds, consultants and brokers. Our product suite includes pre-trade, real-time and post-trade tools that enable users to assess trading costs throughout the order lifecycle".

ANcerno provides trade by trade data for money managers, pension fund sponsors and (less frequently) for brokers. Each client of ANcerno is given a unique numerical identifier *clientcode*. *Clienttype* variable allows to differentiate among pension fund sponsors (*clienttype*=1), money managers (*clienttype*=2) and brokers (*clienttype*=3). The data provider does not reveal the identity of the client sending data, however the identity of the trading institution is known thanks to provided identification files. Unique identifier *managercode* allows to study institutional trading both in cross-section and through time. I keep in my sample only clients who are money managers.

An individual fund is identified by *clientcode* and *clientmgrcode*. The latter may sometimes change from one data batch to another. Received data batches are identified by the *lognumber*.

The main variables of interest for the study are *managercode*, *brokercode*, *clientcode*, *clientmgrcode*, *clientbkrcode*, *cusip*, *tradedate*, *Side*, *Price* and *Volume*. This variables allow us to identify a single trade in the data. *Cusip* is a stock identifier, *Side* defines the side of the trade ("1" for a buy, "-1" for a sell), *Price* is the execution price of a trade, *Volume* is a number of shares traded in a transaction.

[4]first record in ANcerno date to 1997, but iclude relatively small amount of observations for the first two years

Table 1.2 gives detailed description of ANcerno database for the sample period. The data includes the total of 260,039,064 transactions for the 1999-2009 sample period. The total number of distinct institutions (*managercodes*) in the database is 860, from which 330 are money managers. The table reports aggregated daily statistics for money managers and all institutions in the sample (Panel A and B). It further includes statistics per manager-day, again for money managers only (Panel C) and all institutions (Panel D).

1.4.2 Identification of managing companies and brokers

ANcerno *clientcode* and *clientmgrcode* enables me to map the trades to the unique *managercode* and names of the trading managing companies. I further manually match ANcerno managing companies to the institutions from Thomson Reuters 13f database. In the same way I link the *brokercode* of the executing broker to ANcerno trades using *clientcode* and *clientbkrcode* and create a linking table across three databases: ANcerno, I/B/E/S analyst recommendation files and brokers from IPO underwriting syndicate from Thomson One Banker, by manually merging brokers by their names.

1.4.3 Measuring broker-client relationship

It is a well-established fact that IPO shares are reserved by brokers for their best clients. Reuter (2006) finds that allocations of underpriced IPOs to institutional investors is related to the brokerage business assigned to the lead underwriter. In other words, this result suggests that the access to underpriced IPOs by a fund family is determined by the strength of business relationship between the family and the lead underwriter. There exist earlier empirical studies. Binay, Gatchev, and Pirinsky (2007) document that brokers privilege investors with whom they have an established relationship by offering them more underpriced IPOs. The authors use prior participation in IPO distributions as a measure of the strength of investor-broker relationship. Goldstein, Irvine, and Puckett (2011) show that stable investors, regularly paying commissions to their broker, are rewarded with

IPO allocations. This evidence supports the vision of IPO allocations to be a suitable metric for broker-investor relationship.

I draw on the existing evidence to construct the measure of broker-client connection for my analysis. I compute it as a percentage of number deals in which an institutional investor received shares from the total number of IPO deals underwritten by a broker. Because IPO allocations are not publicly available, I use the first post-IPO reported institutional holdings from Thomson Reuters 13(f) filings database as a proxy for IPO allocations to institutions. The reporting is quarterly, therefore I obtain holdings data corresponding to the quarter of the IPO.

Several studies use investors' holdings as a proxy for IPO allocations: see, for example, Reuter (2006), Ritter and Zhang (2007), Binay, Gatchev, and Pirinsky (2007) and Goyal and Tam (2009). Ritter and Zhang (2007) provide a discussion and conclude that closest IPO stock holdings represent a valid proxy for IPO allocations. The main argument in support of this view is the minimum position requirement of institutional investors' holding of an IPO discussed by Zhang (2004) and Ritter and Zhang (2007). The requirement implies that if institutional investors do not receive an allocation, they are unlikely to buy shares in the early aftermarket. Ritter and Zhang (2007) examine actual IPO allocations of the sample of 11 IPOs with the corresponding reported holdings in Thomson Reuters Mutual Fund holdings database (s12) and find that although reported holdings tend to understate actual IPO allocations, there is a positive correlation between the actual allocations and reported holdings. This further confirms earlier finding by Hanley and Wilhelm (1995) of high correlation between 13(f) reported holdings and actual IPO allocations. Smaller institutions and investors are not included in my calculations, as they do not have to report their holdings to the SEC. As a result, they do not appear in the Thomson Financial 13(f) database. With this information in hand, I use quarterly holdings as a proxy of IPO allocations.

Hence, I construct the measure of broker-client connection as follows. I define an institution m as the "best client" for the broker b at the time period t (for 3 rolling years) whenever the *IPO participation ratio* is greater or equal to 0.25 (the threshold roughly corresponds to the 10th percentile of the distribution):

$$IPO\ participation\ ratio_{m,b,t} = \frac{IPO\ allocations_{m,b,t}}{IPO\ issues_{b,t}},$$

where $IPO\ allocations_{m,b,t}$ is the number of IPO allocations received by the institution m three years prior the event year t proxied by 13f stock holdings from Thomson Reuters; $IPO\ issues_{b,t}$ is the number of new equity issues underwritten by the broker b over the same time span t (for the 3 years preceding the recommendation issue) calculated using the Thomson One (SDC Spectrum) database.

In Panel A of Table 1.3 I present statistics of initial public offerings from Thomson One Banker (SDC Spectrum): the total number of IPOs in the period from 1995 to 2009, the period on which I compute the 3-year rolling *IPO participation ratio*, and annual number of IPOs. Panel B describes the statistics for the *IPO participation ratio* and its components. An average broker in my final sample serves as an underwriter in 72 IPOs in a 3-year period (with a minimum of 1 and a maximum of 187 for bulge brokers). An institutional investor on average receives allocations in 4.5 IPOs on a 3-year basis, with the range going from 1 to 104. Finally, the participation ratio has an average of 0.107, telling us that on average an institution gets allocations in 10.7% of IPO deals from the total amount of IPOs underwritten by each broker. The ratio ranges from 0.005 to 1. The 10th top percentile represents 25% from the total broker deals and is the threshold I am using to define an institution as a broker's best client.[5]. To ensure the robustness of my results, I compute the *IPO participation ratio* including and excluding the event year and run my tests for both measures (unreported results). Table 1.3 shows statistics for both measures.

1.4.4 Sample selection and descriptive statistics

Analyst recommendations

[5] The results are robust for alternative tresholds

Analyst recommendations data comes from Institutional Brokers Estimate System I/B/E/S from Thomson Reuters. The sample includes individual analyst stock recommendations issued in the period 1999-2009. The period corresponds to the available trading data sample from ANcerno. I exclude recommendations from anonymous analysts since it is not possible to compute recommendation revisions and characteristics for such analysts. I recode all I/B/E/S recommendation codes to make the interpretations of the results more intuitive, with “5" meaning “Strong Buy" and “1" - “Sell". I filter the sample of initiations following Irvine, Lipson, and Puckett (2007). I detect the first recommendation in I/B/E/S provided by a broker and analyst. I keep recommendation initiations only if they were issued by an analyst for the first time on a particular stock. I make sure that the broker and analyst were present in the I/B/E/S database for at least 6 months before an initiation. I then omit all initiations for companies that went public in the six-months period before the initiation. I remove all the recommendations for which another analyst initiated coverage in the 11-day window around the observation. Once again following Irvine, Lipson, and Puckett (2007), I keep only initiations with “Strong Buy" and “Buy" to make sure that the initiation represents a clear investment signal for the investors. In order to separate the effect of contemporaneous release of firm-specific news and analyst recommendations I apply several filters to the sample. To disentangle the effect of earnings announcement and stock recommendation issue as suggested by Loh and Stulz (2011), I remove recommendations which occur in the three days around quarterly earnings announcements. I delete recommendation dates which coincide with earnings guidance communicated by companies (Chen et al.,2005). I take quarterly and annually earnings guidance dates from First Call Earnings Guidelines database. I delete stocks with a price less than $5.

Table 1.4 reports the statistics of recommendation initiations by year and type of initiation. In the whole sample period "Strong Buy" initiations correspond to about 28.3% of the total amount of initiations, "Buy" - 32.6%, "Hold" - 34.8%, with "Underperform" and "Sell" making only 2.9% and 1.4% respectively. I restrict my sample to "Strong Buy" and "Buy" initiations as they represent an unambiguous investment signal.

Sample description

Table 1.5 shows sample summary statistics for the whole sample and separately for the group of best clients and investors not belonging to this category (Panel B and C). It is worth noting again that the relationship is broker-specific. Hence, the same investor maybe the best client for one broker and not for the other. I exclude from my analysis institutions which never participated in IPO allocations, to avoid potential selection bias.

The final matched sample contains 47,727 initiation events, 381 unique brokers matched across ANcerno, SDC Spectrum and I/B/E/S; 85 distinct managing companies from ANcerno merged with Thomson Reuters 13(f); and 5,138 analysts providing reports for 4,044 different stocks matched in ANcerno and CRSP. We can see from the table that select clients on average trade more ahead of recommendations: $344,491 versus $79,123 (9,873 and 3,798 respectively in shares). The difference remains substantial also for the normalized net volume: 0.18 and 0.03 for best clients and the rest of the sample respectively. Best clients are also more frequently net buyers in the event period (68% versus 55%). The sample statistics show that best clients in are more often classified as frequent traders: 54% of cases versus only 35% for a other investors. Statistics for control variables do not differ much between the two groups.

1.5 Empirical Tests and Results

1.5.1 Characteristics of informed investors

At the first step of my empirical analysis, I investigate institutional trading before analyst coverage initiations. I focus on institutional trading in the period of 5 trading days before the initiation (hereafter "event period"). This period is defined empirically by Irvine, Lipson, and Puckett (2007) and is associated with an increase in institutional trading/buying ahead of analyst coverage initiations. This time frame is further validated by the detailed example of the research tips passed by Goldman Sachs to first-line clients provided in the Wall Street Journal article by Craig (2009). According to the internal document of Goldman, research tips were released to a select group of clients 3 trading days before the recommendation upgrade for Janus Capital Group. I compute net dollar trading volume (*Net Trades*) in the 5-day event period in the recommended stocks for each investment manager in the ANcerno database for the entire sample period from 1999 to 2009. I normalize the *Net Trades* by the average dollar volume in the non-event period [-36;-6] days before the event, cumulated over five days. The results remain qualitatively the same when I normalize trading volume by shares outstanding. I also define a dummy variable *Net Buyer*, which equals 1 if the manager's net directional trading volume in the 5-day period before the initiation is positive, and equals 0 otherwise. As suggested by hypothesis H1 in section 1.3, certain groups of investors, like frequent traders and large investment managers, may be better informed about broker coverage initiations. If my prediction is true, we should see elevated buying by frequent traders and/or large managers during the event period. I test this hypothesis using two model specifications, OLS regression model 1.1 and probit model 1.2 separately including *Frequent Trader* and *Manager Size* variables:

$$NetTrades_{m,i,t} = a + \beta X_{m,i,t} + Controls_{m,i,t} + \epsilon_{m,i,t}, \tag{1.1}$$

and

$$P(NetBuyer_{m,i,t} = 1) = \Phi(a + \beta X_{m,i,t} + Controls_{m,i,t}) + \epsilon_{m,i,t}, \tag{1.2}$$

where $X_{m,i,t}$ denotes for investment manager m trading stock i at time t, depending on the specification: either *Frequent Trader*, which is a dummy variable which equals 1 if the manager was in the top 1st decile by their trading frequency in ANcerno, 0 otherwise; or *Manager Size* variable, the log of the manager's stock holdings as reported in 13(f) filings in the quarter preceding a recommendation. Table 1.6 documents both univariate and multivariate results of the tests. Coefficients on the *Frequent Trader* variable in columns (1) and (2) of the table are positive and significant at 1%. They indicate that a manager trading frequently has more chances to be a net buyer in the recommendation pre-announcement

period. I report marginal effects for the probit model in square brackets. The marginal effect for a *Frequent Trader* tells us that the probability for a manager to be a net buyer in the recommended stock increases by 0.008 for a frequent trader, holding all other covariates at their means. The result weakens in columns (3) and (4) when I include as the dependent variable *Net Trades*, however, coefficients keep the positive sign. Columns (5-8) of the Table 1.6 show positive and significant effect of the size of the managing company on the pre-release trading. The coefficients of the probit model (column 5 and 6) show that the probability for a manager to be a net buyer increases with the size of the manager. Marginal effects at means/average marginal effects of the continuous variable *Manager Size* on the probability for a manager being a net buyer is of 0.021 and 0.020 respectively. I include control variables that might have an impact on the trading volume: market capitalization of a stock, analyst coverage, event-day returns and 3-day cumulative return. I also account for the effect of eventual recommendation issues by other brokers happening during the event period or 3 days before the event window by inserting in the specification dummy variables *Upgrade* and *Downgrade*. The detailed description of the variables is provided in Table 1.1. T-statistics based on robust standard errors clustered at the stock-level are reported in parentheses. Following Petersen (2009), I computed standard errors using several other techniques: bootstrap, GLS regression. None of the techniques significantly changed the standard errors. Monthly time effects are included in all specifications.
In sum, the the estimates of the Table 1.6 support the prediction in Hypothesis 1 that pre-recommendation trading may be clustered in specific groups of institutional investors susceptible to be informed: big money managers and frequent traders.

1.5.2 Trading by privileged clients

To measure whether broker's select clients have an informational advantage over other investors (Hypothesis 2), I estimate the models described by equations 1.3 and 1.4:

$$NetTrades_{m,i,t} = a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}, \tag{1.3}$$

$$P(NetBuyer_{m,i,t} = 1) = \Phi(a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t}) + \epsilon_{m,i,t}, \tag{1.4}$$

where the explanatory variable *Best Client*$_{m,b(i),t}$ is a dummy equal one if an investment manager m received at least 25% of IPOs from the IPOs underwritten by the broker b in the 3-year period t preceding the recommendation initiation for the stock i by the same broker. The dependent variables are *Net Trades* and *Net Buyer* as defined in the previous section. I include control variables and monthly time effects as in Table 1.6. Table 1.7 reports both OLS and probit regression estimates. The coefficients on *Best Client* are positive in all specifications. Consistent with Hypothesis 2, the results indicate that brokers' select clients trade more than other institutions in the five days before the coverage initiation. The baseline predicted probability for the manager to be a net buyer before a positive initiation equals 57.14%.The marginal effects in column (1) and (2) show the probability for a manager of being a net buyer in the pre-announcement period is increased by 7.7% (9.5% in univariate identification). The β coefficients reported for *Frequent Trader* dummy in Table 1.6 increase by the order of magnitude for both probit and OLS regressions (all statistically significant at 1% level): for example, β for *Best Client* in column (4) is 0.077, while it is only 0.008 and insignificant for *Frequent Trader*. This result strongly supports my Hypothesis 2 and illustrates the role a broker-client relationship plays in research tips dissemination. In Tables 1.8 and 1.11, I rerun model 1.3 separately for "Strong Buy" and "Buy" initiations and for three market capitalization groups and conclude that "Strong Buy"' initiations and initiations issued for small-capitalization stocks are associated with stronger net buying by best clients of brokers. This provides further evidence in support of Hypothesis 2.

1.5.3 The change in pre-recommendation trading after Global Research Analyst Settlement

In section 1.3 I provided discussion on possible effects of Global Research Analyst Settlement (GRAS) on pre-recommendation period trading and tipping practice in particular. First, I examine the impact of GRAS on institutional trading ahead of recommendation initiations with the help of models 1.5 and 1.6:

$$NetTrades_{m,i,t} = a + \beta \text{post-GRAS} + Controls_{m,i,t} + \epsilon_{m,i,t}, \tag{1.5}$$

$$P(NetBuyer_{m,i,t} = 1) = \Phi(a + \beta \text{post-GRAS} + Controls_{m,i,t}) + \epsilon_{m,i,t}, \tag{1.6}$$

The results from estimating equations 1.5 and 1.6 are reported in Table 1.9. The explanatory variable *post-GRAS* denotes a dummy which equals one whenever an observation dates after year 2003 and 0 otherwise. Negative and significant β coefficients on the *post-GRAS* dummy testifies a strong reduction in net buying in the pre-release period. A possible explanation of this finding is the reduction of information flows from companies to institutional investors and brokers and speaks in favor of the coupled effectiveness of the Reg FD and GRAS regulations.

Next, based on the discussion of the Hypothesis 3 in section 1.3, I test for the possible side effects of the regulation. The testing strategy is described by the equation 1.3. I run the tests separately for the periods before and after GRAS. The results are reported in Table 1.10. The regression results indicate elevated buying volumes privileged clients of brokers in the period after GRAS. The estimated coefficient on the *Best Client* explanatory variable in the post-GRAS period is 0.11, which is twice as large compared to the pre-regulatory period. These findings support Hypothesis 3 and suggest that pre-release of research tips by brokers to their reserved clients has increased since the adoption of Reg FD and GRAS.

1.6 Large brokers, All-star analysts and pre-release trading

1.6.1 The broker size effect

In this section I study how characteristics of the recommending brokers and analysts are related to pre-release trading by investors, in particular by brokers' best clients.

We know from the existing literature that the size of a broker predicts the forecast accuracy (see, for example **?**or **?**). According to **?**, a short-term price reaction to a recommendation is related to a broker size (among other characteristics). This superior ability and investor reaction may be due to the fact that large brokers have better tools for processing public information, because they employ more skillful analysts, because of their access to private information and/or simply because their research output is more visible to investors. Hence, there is an additional incentive for investors to trade ahead of recommendations of large brokers provided they have advance knowledge about the upcoming initiation.

Table 1.12 describes pre-announcement trading by all Ancerno institutions ahead of initiations issued by analysts from large brokerage houses. Following the existing literature, I proxy the size of a broker institution by the number of analysts it employs. The variable of interest in this specification is *Large Broker*, a dummy equal to one whenever a broker employs more than 30 analysts in a given year (the number1Âğ corresponds to the median number of analysts). I obtain the information from I/B/E/S recommendation files. I specify equations 1.7 and 1.8:

$$P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta \text{Broker Size}_{b,t} + Controls_{m,i,t}) + \epsilon_{m,i,t} \quad (1.7)$$

$$NetTrades_{m,i,t} = a + \beta \text{Broker Size}_{b,t} + Controls_{m,i,t} + \epsilon_{m,i,t}, \quad (1.8)$$

where the explanatory variable *Broker Size*$_{b,t}$ is a dummy variable equal to 1 if the broker employs more than 30 analysts in a given year and 0 otherwise. The dependent variables are *Net Trades* and *Net Buyer* as defined in the previous section. I include control variables and monthly time effects in all specifications.

Table 1.12 includes trades of all Ancerno investors. We observe that the coefficients on *Large Broker* are positive and significant, suggesting that more pre-release trading is associated with the coverage initiation by large brokers. The economic magnitude of the coefficients however remains modest: while the baseline probability for an Ancerno investor to be a net buyer before the coverage initiation is 56.8%, it increases only by 0.8% when the issuer is a large broker. In Table 1.13 I run the models 1.3 and 1.4 separately for large and small brokers. *Best Client* is the explanatory variable. The coefficients in columns (1) to (4) are all significant, suggesting that recommendations by large brokers are associated with stronger buying by brokers' first-line clients. In column (2) the coefficient on the *Best Client* is 0.246, with the baseline probability for the client to be a net buyer in the recommended stock equal to 20%, this probability increases by 9.2% whenever the trading investor is the "best client". Multivariate regressions include past 7-day returns as a proxy for the eventual news effects. The results are not significant for small brokers (columns (5) - (8)). Small brokers presumably have less impact and consequently they are less prone to tip. At the same time, investors might anticipate a lower market reaction to recommendations issued by analysts from smaller brokerage houses. The results are consistent with my tip-based trading hypothesis 2.

1.6.2 Initiations by All-star analysts

? find a significant positive relation between analyst reputation (measured by *Institutional Investor* All-American Research rankings) and analyst recommendations. Later, **?** study the quality of analyst earnings forecasts and conclude that analyst reputation plays a role of a disciplinary mechanism against conflict of interests in research: they find that All-star analysts provide less biased earnings forecasts.

In this part of the paper I aim to verify whether initiations by All-star analysts are associated with pre-initiation buying and thus may be subject to potential conflict of interest or, on the contrary, analysts' reputation plays a disciplinary role on tipping behavior. If no information about subsequent recommendation release by the All-star analyst is passed to broker's investors, I would expect the coefficient on the *Best Client* dummy to be insignificant. If however the coefficient would be positive, than this would indicate an eventual presence of information flow from analyst (or their employing brokers) to the select group of clients. I match *Institutional investor* All-star rankings with the I/B/E/S analyst codes by analyst names [6].

I estimate the following equations to test my predictions:

$$P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta \text{All-star}_{a,t} + Controls_{m,i,t}) + \epsilon_{m,i,t} \tag{1.9}$$

$$NetTrades_{m,i,t} = a + \beta \text{All-star}_{a,t} + Controls_{m,i,t} + \epsilon_{m,i,t}, \tag{1.10}$$

where the explanatory variable *All-star*$_{a,t}$ is a dummy variable equal to 1 if the analyst is ranked by the II magazine All-American Research ranking in a given year and 0 otherwise. The dependent variables are *Net Trades* and *Net Buyer* as defined in the previous section. I include control variables and monthly time effects in all specifications.

In Table 1.14 I test the relation of pre-announcement trading and initiations by All-star analysts. The coefficients are insignificant in all settings. The results provided in this table support the conclusion by **?** about disciplinary effect of reputation. However, the picture changes completely when I put the relationship variable *Best Client* into my regressions. Coverage initiations by All-star analysts seem to have a strong positive effect on pre-event trading by good clients of the recommending broker: the coefficient on the *Best Client* dummy is 0.18 in OLS specification and 0.4 in probit setting. The predicted probability for an investor to be a net buyer when the issuing analyst is All-star ranked is 20.7%, it increases by 15.6% when the investor is a "best client". The results from this section suggest that All-star analysts and their employing broker do not seem to pass on

[6] I acknowledge collaboration of my colleague Vassilis Barmpoutis in this time-consuming process. I also thank my colleague Hien Vu who joined the project at a final stage, but whose help was much welcomed

price-sensitive information to an average investor, in the meanwhile the empirical evidence I provide suggests that they might be using this as a means of maintaining a good relationship with their select clients.

1.7 Robustness Checks

In this section I describe some of the robustness checks I performed to ensure the validity of my findings.

I experiment with different thresholds for my explanatory variables: *Best Client*, *Frequent Trader* and *Manager Size*. The results remain qualitatively the same in all identifications. For example, the increase in IPO participation threshold for the *Best Client* dummy, increases the size of the coefficient and indicates larger net buying for the clients ahead of coverage initiation. I rerun my regressions for separate sub-samples: my results hold, although the net trading by select clients is significantly lower in pre-GRAS time period. I discussed this result in section 1.5.3. I further normalize the dependent variable *Net Trades* by shares outstanding instead of non-event dollar volume and get qualitatively similar results.

If institutional clients' trade in the reaction of the research tips from their broker, their trading volume should be higher for "Strong Buy" than for "Buy" initiations, because the "Strong Buy" should represent a stronger signal for investors. Therefore, in Table 1.8, I rerun the regressions for the equations 1.3 and 1.4 separately for the two types of the initiations. The coefficients support my prediction in both specifications: the β coefficients on the *Best Client* variable are larger for "Strong Buy" initiations: 0.108 versus 0.064 for "Buys" in OLS regression setting, and 0.239 versus 0.184 respectively for probit estimates.

In the table 1.11 I examine the trading by best clients in three groups of stocks: small-cap, mid-cap and large-cap. My prediction here is that select clients are more likely to trade in small stocks, as those are the stocks for which analyst recommendation has the strongest impact. The results of the table show that this is indeed the case: the coefficients for the *Best Client* dummy is much higher for small-cap stocks: 0.18 (significant at 5%). It is a tiny 0.08 for large-cap stocks (significant at 5%) and only 0.05 and insignificant for mid-cap stocks.

1.8 Discussion

Although this study does not have the aim of discussing global harm or benefit of tipping activity, it can nevertheless nourish the debate on regulation of this practice, and may have regulatory implications for brokers and investors in several aspects. Analysts' research reports can often cause a stock to rise or fall. Hence, until the research report is made public, any information about its content is material and non-public. As revealed Roberto Casoni's case, British law is very strict with both, analysts disclosing material nonpublic information and with investors trading while in possession of such information. The US SEC enforcement scheme however is argued to contain gray areas in the matter of insider trading (trading based on research tips is denounced by CorpWatch[7] as a "sophisticated and barely legal version of insider trading"). Tipping activity may still fall under the jurisdiction of the 10b5-1 SEC rule, promulgated under Securities and Exchange act of 1934, that prohibits the purchase or sale of a security on the basis of material non public information. Yet, SEC has to prove that the investor was aware of the material non public information at the time of the trade. According to my knowledge, no investor has been so far prosecuted by SEC for trading on research tips.

Furthermore, securities laws oblige firms to engage in "fair dealing of customers" and put in place necessary internal regulations and procedures to ensure it is respected. Research tips to select clients breaches the AIMR Code of Ethics and the principle of equal treatment of clients, unless the tipping practice is disclosed to all broker's clients. This clearly was not the case during Goldman's trading "huddles".

There is a need for financial regulatory authorities to look for the means to level the playing field. There are two ways to do this: one is to regulate and punish and the other is to enhance disclosure and investor knowledge. The mixture of the two is however also possible.

[7] Non-profit organization doing investigate research and journalism

1.9 Conclusion

This paper brings new insights on the information flows among financial market participants. I study trading practices of institutional money managers in advance of stock coverage initiation by brokers. I test my hypotheses on proprietary transaction-level data and find that the relation between broker and investment manager explains an important amount of pre-initiation buying. Furthermore, the precise identification of investors allows me to link investor trading behavior to their characteristics. I find that large institutions and frequent traders trade ahead analyst initiations.

I show empirically that besides decreasing firms' selective disclosure and building "Chinese walls" between analysts and investment banking departments, Reg FD and GRAS were followed by the increase in research tipping by brokers.

My further analysis will concentrate on studying the profitability of pre-recommendation trading.

TABLE 1.1: **Variables Description**

NetBuyer	equals 1 if the manager's net directional trading dollar volume in the 5-day period before the initiation is positive, and equals 0 otherwise
NetTrades	is the net directional dollar volume in the recommended stock 5-day period before the upgrade scaled by the average trading volume by manager-stock in non-event period [-36;-6] days
Best Client	denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The threshold correspons to the top 10th percentile of the distribution
Manager Size	the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation
Frequent Trader	a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno
Market Cap	the log of market capitalization of the recommended stock 1 month before the event
Analyst Coverage	the number of analysts covering the stock
Upgrade/Downgrade	a dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise
Event-day Return	the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day
7-day Cumulative Return	the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period
post-GRAS	a dummy variable equal to one if the initiation took place after Global Research Analyst Settlement (after 2003)
Large Broker	a dummy variable equal to 1 if the broker employs more than 30 analysts in a given year and 0 otherwise
Allstar	a dummy variable equal to 1 if the recommending analyst is an All-star analyst defined by II rankings and 0 otherwise

Table 1.2: **Daily summary statistics of ANcerno institutional trading data**

The table presents daily summary statistics for the ANcerno institutional trading data for the period 1999 to 2009 (share volumes are in millions of shares, dollar volumes are in millions of USD).

	n	Mean	S.D.	Min	p25	Median	p75	Max
Panel A: daily statistics - only mutual funds								
Number of managers	330							
Number of trades	3,023	68,391	49,154	4	28,613	53,894	98,465	332,407
Share Volume	3,020	400	163	2	287	401	492	2,484
Dollar Volume	3,020	11,881	4,605	47	8,681	11,183	14,499	88,465
Share Volume (Buys)	3,023	200	81	0	142	201	249	1,142
Dollar Volume (Buys)	3,023	5,927	2,247	0	4,340	5,596	7,286	41,257
Share Volume (Sells)	3,023	199	86	0	140	198	245	1,342
Dollar Volume (Sells)	3,023	5,942	2,484	0	4,268	5,589	7,249	47,208
Panel B: daily statistics - all institutions								
Number of managers	860							
Number of trades	3,031	97,306	68,414	1	44,564	87,431	132,508	1,711,960
Share Volume	3,028	519	204	.000095	391	521	625	2,997
Dollar Volume	3,028	15,371	6,098	.00065	11,538	14,657	18,576	125,428
Share Volume (Buys)	3,031	259	102	0	194	260	316	1,492
Dollar Volume (Buys)	3,031	7,655	3,026	0	5,736	7,252	9,281	62,877
Share Volume (Sells)	3,031	259	108	0	193	258	314	1,650
Dollar Volume (Sells)	3,031	7,700	3,274	0	5,694	7,284	9,315	62,551
Panel C: manager-day statistics - only mutual funds								
Number of trades	247,110	852	3,852	1	14	107	589	228,971
Share Volume	247,107	5	17	1.0e-06	.1	.62	2.7	2,171
Dollar Volume	247,107	147	550	2.2e-06	2.7	16	76	78,857
Share Volume (Buys)	247,110	2.5	8.7	0	.036	.28	1.3	977
Dollar Volume (Buys)	247,110	74	270	0	.96	7.5	37	36,288
Share Volume (Sells)	247,110	2.5	9.1	0	.03	.27	1.3	1,194
Dollar Volume (Sells)	247,110	74	290	0	.82	7.3	38	42,569
Panel D: manager-day statistics - all institutions								
Number of trades	831,947	366	3,465	1	4	14	71	1,580,073
Share Volume	831,920	1.9	11	1.0e-06	.015	.073	.39	2,488
Dollar Volume	831,920	57	368	1.0e-07	.38	1.9	11	106,842
Share Volume (Buys)	831,947	.96	5.7	0	.0041	.03	.19	1,251
Dollar Volume (Buys)	831,947	28	182	0	.1	.8	5.2	54,186
Share Volume (Sells)	831,947	.96	6.1	0	.0033	.029	.18	1,461
Dollar Volume (Sells)	831,947	29	196	0	.082	.77	5.1	52,657

Table 1.3: **IPO data statistics**

This table reports summary statistics of IPO data from Thomson One Banker (SDC Spectrum) for the period 1995-2009

Panel A: Annual IPO statistics

Year	Number of IPOs
1995	382
1996	577
1997	420
1998	276
1999	419
2000	304
2001	81
2002	94
2003	88
2004	219
2005	202
2006	178
2007	220
2008	31
2009	37
Total	3,598

Panel B: Statistics aggregated for 3 rolling years, * event year not included

	Obs	Mean	SD	Min	Max
(a) IPOs per broker	79,259	72	49	1	187
(b) IPOs per broker *	77,506	66	47	1	187
(c) IPOs per manager-broker	79,259	4.5	6.7	1	104
(d) IPOs per manager-broker *	41,845	6.1	8.2	1	104
(e) IPO participation ratio (a/c)	79,259	0.107	0.151	0.005	1
(f) IPO participation ratio (b/d) *	41,844	0.099	0.114	0.005	1

Table 1.4: **Recommendation initiations statistics**

This table reports summary statistics of recommendations data from I/B/E/S for the period 1999-2009

	Sell	Underperform	Hold	Buy	Strong Buy	Total
1999	36	32	1,347	2,532	2,024	5,971
2000	16	31	1,134	2,415	1,932	5,528
2001	30	38	1,555	2,213	1,474	5,310
2002	80	284	2,411	2,124	1,496	6,395
2003	119	255	2,194	1,299	1,194	5,061
2004	129	169	2,519	1,323	1,417	5,557
2005	94	213	2,251	1,368	1,252	5,178
2006	117	237	2,320	1,426	1,237	5,337
2007	101	198	2,153	1,473	1,320	5,245
2008	125	332	2,295	1,148	1,241	5,141
2009	124	304	2,210	1,152	1,344	5,134
Total	1,104	2,307	28,025	26,289	22,809	80,534

Table 1.5: **Sample summary statistics**

The table presents sample summary statistics for the period 1999 to 2009

Variable	n	Mean	SD	Min	.25	Median	.75	Max
Panel A: sample statistics (in dollar volume (DV) in millions USD, share volume in millions of shares								
Number of managers	85							
Number of brokers	381							
Number of analysts	5,138							
Number of stocks	4,044							
Number of initiations	17,534							
Net Trades DV	47,727	.11	15	-689	-.14	.013	.29	568
Average DV [-36;-6] (AvgDV)	47,727	4.3	12	3.7e-06	.14	.74	3.2	881
Net Trades V	47,727	.0044	.43	-19	-.0046	.0005	.0095	13
Average V[-36;-6] (AvgV)	47,727	.13	.37	1.0e-06	.0052	.024	.096	18
Net Trades DV/AvgDV	47,727	.045	1.7	-4.4	-.31	.029	.48	4.3
Net Buyer	47,727	.57	.5	0	0	1	1	1
Best Client	47,727	.1	.3	0	0	0	0	1
Market Cap	47,727	18,904	45,607	3	1,183	3,584	14,478	546,842
Analyst Coverage	47,727	12	6.7	1	7	11	16	45
Frequent Trader	47727	0.37	0.48	0.00	0.00	0.00	1.00	1.00
Upgrade	47,727	.12	.33	0	0	0	0	1
Downgrade	47,727	.21	.41	0	0	0	0	1
Panel B: Best Client = 0								
Net Trades DV	42,871	79,123	1.5e+07	-6.9e+08	-153,675	9,531	279,956	5.7e+08
Average DV [-36;-6] (AvgDV)	42,871	4.3e+06	1.2e+07	3.7	133,509	721,684	3.2e+06	8.8e+08
Net Trades V	42,871	3,798	435,827	-1.9e+07	-5,198	325	9,500	1.3e+07
Average V[-36;-6] (AvgV)	42,871	124,778	373,011	1	4,962	24,105	96,682	1.8e+07
Net Trades DV/AvgDV	42,871	.03	1.8	-4.4	-.35	.022	.48	4.3
Net Buyer	42,871	.55	.5	0	0	1	1	1
Best Client	42,871	0	0	0	0	0	0	0
Market Cap	42,871	1.9e+10	4.6e+10	3.0e+06	1.2e+09	3.6e+09	1.5e+10	5.5e+11
Analyst Coverage	42,871	12	6.8	1	7	11	16	45
Frequent Trader	42,871	.35	.48	0	0	0	1	1
Upgrade	42,871	.12	.33	0	0	0	0	1
Downgrade	42,871	.21	.41	0	0	0	0	1
Panel B: Best Client = 1								
Net Trades DV	4,856	344,491	1.3e+07	-2.1e+08	-31,142	50,637	321,712	2.7e+08
Average DV [-36;-6] (AvgDV)	4,856	4.8e+06	1.4e+07	554	210,068	872,394	3.3e+06	3.5e+08
Net Trades V	4,856	9,873	346,318	-7.5e+06	-1,034	1,700	9,778	7.5e+06
Average V[-36;-6] (AvgV)	4,856	130,341	378,380	9.5	7,179	26,179	94,305	9.8e+06
Net Trades DV/AvgDV	4,856	.18	1.5	-4.4	-.065	.091	.46	4.3
Net Buyer	4,856	.68	.47	0	0	1	1	1
Best Client	4,856	1	0	1	1	1	1	1
Market Cap	4,856	1.5e+10	4.0e+10	4.3e+07	1.2e+09	3.3e+09	1.1e+10	5.2e+11
Analyst Coverage	4,856	11	6.2	1	7	10	14	43
Frequent Trader	4,856	.54	.5	0	0	1	1	1
Upgrade	4,856	.12	.32	0	0	0	0	1
Downgrade	4,856	.2	.4	0	0	0	0	1

TABLE 1.6: **Are frequent traders and big managers more informed about analyst coverage initiations?**

This table reports OLS estimates of the equation 1.1 (2): $NetTrades_{m,i,t} = a + \beta X_{m,i,t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and probit model estimates of the equation 1.2: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta X_{m,i,t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for a stock i.Unit of analysis is manager-recommendation. The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading volume (in shares) in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the initiation scaled by the average dollar volume for the manager in non-event period [-36;-6] days. X denotes:*Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise, or *Manager Size* - the log of the manager's stock holdings from 13f filings in the quarter preceding a recommendation. The following controls are included: *Market Cap* - the log of market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. The sample includes only "Strong Buy" and "Buy" initiations. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets.

	(1) NetBuyer	(2) NetBuyer	(3) NetTrades	(4) NetTrades	(5) NetBuyer	(6) NetBuyer	(7) NetTrades	(8) NetTrades
Frequent Trader	**0.023***** **(6.14)** **[0.009]**	**0.020***** **(5.29)** **[0.008]**	**0.010*** **(1.88)**	**0.008** **(1.51)**				
Manager Size					**0.058***** **(16.13)** **[0.023/0.022]**	**0.054***** **(14.49)** **[0.021/0.020]**	**0.029***** **(5.94)**	**0.026***** **(5.27)**
Market Cap		-0.025*** (-5.35)		-0.012* (-1.90)		-0.020*** (-4.18)		-0.009 (-1.46)
Analyst Coverage		-0.057*** (-4.58)		-0.047*** (-2.88)		-0.055*** (-4.41)		-0.046*** (-2.82)
Upgrade		0.054** (2.53)		0.052* (1.72)		0.055*** (2.58)		0.053* (1.74)
Downgrade		-0.018 (-1.07)		-0.025 (-1.00)		-0.018 (-1.07)		-0.025 (-1.00)
Event-day Return		0.150 (1.01)		0.027 (0.14)		0.146 (0.98)		0.025 (0.13)
7-day Cumulative Return		0.124 (1.15)		0.197 (1.25)		0.127 (1.17)		0.198 (1.25)
Constant	-0.001 (-0.01)	0.712*** (4.61)	0.144 (0.93)	0.539*** (2.71)	-1.295*** (-8.62)	-0.615*** (-3.26)	-0.509*** (-2.62)	-0.120 (-0.49)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47737	47725	47737	47725	47737	47725	47737	47725
pseudo R^2	0.028	0.030			0.031	0.033		
R^2			0.008	0.009			0.009	0.009

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.7: **Do best clients buy before analyst coverage initiation?**

This table reports OLS estimates of the equation of the equation 1.3: $NetTrades_{m,i,t} = a + \beta\text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and probit model estimates 1.4: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta\text{Best Client}_{m,b(i),t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i. Unit of analysis is manager-recommendation. The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading volume (in shares) in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the event, scaled by the average trading volume for the manager in non-event period [-36;-6] days. *Best Client* denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of the market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. The sample includes only "Strong Buy" and "Buy" initiations. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets.

	(1) NetBuyer	(2) NetBuyer	(3) NetTrades	(4) NetTrades
Best Client	**0.238*****	**0.200*****	**0.095*****	**0.077*****
	(12.16)	**(10.00)**	**(4.11)**	**(3.26)**
	[0.093/0.090]	**[0.078/0.075]**		
Manager Size		0.049***		0.025***
		(12.09)		(4.58)
Frequent Trader		-0.001		-0.002
		(-0.20)		(-0.42)
Market Cap		-0.032***		-0.019***
		(-8.16)		(-3.42)
Upgrade		0.052**		0.048
		(2.46)		(1.59)
Downgrade		-0.030*		-0.034
		(-1.77)		(-1.38)
Event-day Return		0.132		0.030
		(0.88)		(0.15)
7-day Cumulative Return		0.086		0.216**
		(1.23)		(2.02)
Constant	0.141	-0.393**	0.206	0.018
	(1.16)	(-2.11)	(1.38)	(0.07)
Observations	47686	47684	47686	47684
pseudo R^2	0.029	0.034		
R^2			0.008	0.009

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: **Is tipping stronger for Strong Buy initiations?**

This table reports probit model estimates of the equation 1.3: $NetTrades_{m,i,t} = a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and OLS estimates of the equation 1.4 : $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i separately for "Strong Buy" and "Buy" initiations.Unit of analysis is manager-recommendation.The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading dollar volume in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the initiation scaled by the average trading volume by for the manager in non-event period [-36;-6] days. *Best Client* denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets.

	Strong Buy		Buy	
	(1)	(2)	(3)	(4)
	NetBuyer	NetTrades	NetBuyer	NetTrades
Best Client	**0.240*****	**0.108*****	**0.187*****	**0.067****
	(6.86)	**(2.64)**	**(7.32)**	**(2.24)**
	[0.094/0.090]		**[0.072/0.070]**	
Manager Size	0.052***	0.027***	0.047***	0.022***
	(9.12)	(3.43)	(8.78)	(3.10)
Frequent Trader	-0.005	-0.003	0.003	-0.002
	(-0.97)	(-0.32)	(0.57)	(-0.28)
logMcap	-0.032***	-0.026***	-0.032***	-0.013*
	(-5.65)	(-3.22)	(-5.82)	(-1.86)
Upgrade	0.003	0.015	0.092***	0.074*
	(0.08)	(0.35)	(3.13)	(1.81)
Downgrade	-0.011	-0.025	-0.040*	-0.039
	(-0.41)	(-0.69)	(-1.83)	(-1.15)
Event-day Return	0.011	-0.185	0.222	0.184
	(0.05)	(-0.60)	(1.13)	(0.69)
7-day Cumulative Return	0.139	0.317**		0.126
	(1.32)	(2.07)		(0.88)
[1em] Constant	-0.402	0.224	-0.399	-0.125
	(-1.47)	(0.66)	(-1.64)	(-0.38)
Observations	22028	22028	25656	25656
pseudo R^2	0.038		0.036	
R^2		0.013		0.013

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.9: **Has pre-announcement trading changed after Global Research Analyst Settlement (GRAS)?**

This table reports probit model estimates of equation 1.5: $NetTrade_{m,i,t} = a + \beta$post-GRAS + $Controls_{m,i,t} + \epsilon_{m,i,t}$,and OLS estimates of equation 1.6: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta$post-GRAS + $Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager in the 5-day period before analyst coverage initiation. The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading dollar volume in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the initiation scaled by the average trading volume by for the manager in non-event period [-36;-6] days. *post-GRAS* is a dummy variable equal to 1 if the initiation took place after Global Research Analyst Settlement (after 2003) The following controls are included:*Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Market Cap* - the log of market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. Unit of analysis is manager-recommendation. Robust standard errors clustered on a stock-level are reported in parentheses. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets.

	(1) NetBuyer	(2) NetTrades
post-GRAS	**-0.295***** **(-21.73)** **[-0.12/-0.12]**	**-0.127***** **(-6.98)**
Manager Size	0.041*** (11.18)	0.020*** (4.05)
Frequent Trader	0.014*** (3.71)	0.007 (1.30)
logMcap	-0.034*** (-8.78)	-0.021*** (-3.85)
Unaffiliated Upgrade	0.051** (2.35)	0.045 (1.48)
Unaffiliated Downgrade	-0.022 (-1.33)	-0.027 (-1.10)
Event-day Return	0.084 (0.57)	-0.022 (-0.11)
7-day Cumulative Return	0.115* (1.66)	0.246** (2.29)
Constant	-0.050 (-0.38)	0.018 (0.10)
Observations	47684	47684
pseudo R^2	0.019	
R^2		0.003

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.10: **Has tipping increased since Global Research Analyst Settlement (GRAS)?**

This table reports OLS regression estimates of the equation 1.3: $NetTrades_{m,i,t} = a + \beta\text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, separately for the periods before and after GRAS, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i. Unit of analysis is manager-recommendation. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the event, scaled by the average trading volume for the manager in non-event period [-36;-6] days. *Best Client* denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation;*Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of the market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. The sample includes only "Strong Buy" and "Buy" initiations. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009.

	(1) After GRAS	(2) Before GRAS
Best Client	**0.111*****	**0.052***
	(2.86)	**(1.74)**
Manager Size	0.026***	0.020**
	(4.50)	(2.08)
logMcap	0.000	-0.023**
	(0.06)	(-2.16)
Analyst Coverage	-0.054**	-0.033
	(-2.44)	(-1.31)
Upgrade	0.039	0.067
	(0.93)	(1.56)
Downgrade	-0.020	-0.029
	(-0.58)	(-0.81)
Event-day Return	0.038	0.025
	(0.11)	(0.10)
3-day Cumulative Return	0.389	0.086
	(1.39)	(0.45)
Constant	-0.346	0.309
	(-1.42)	(0.82)
Observations	27074	20651
R^2	0.008	0.007

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: **Trades in recommended stocks by market capitalization groups**

This table reports OLS estimates of the equation 1.3:
$NetTrades_{m,i,t} = a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}$
for three market capitalization groups of recommended stocks. Unit of analysis is manager-recommendation. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the initiation scaled by the average trading volume by for the manager in non-event period [-36;-6] days. *Best Client* denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Market Cap* - the log of the market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. Unit of analysis is manager-recommendation. The sample includes only "Strong Buy" and "Buy" initiations. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009.

	Dependent variable: NetTrades		
	SMALL-CAP	MID-CAP	LARGE-CAP
Best Client	**0.182****	**0.048**	**0.083****
	(2.45)	**(1.27)**	**(2.48)**
Manager Size	0.082***	0.031***	0.010
	(5.17)	(3.16)	(1.62)
Analyst Coverage	-0.024	-0.067***	-0.023
	(-0.63)	(-2.70)	(-0.83)
Upgrade	0.045	-0.014	0.083**
	(0.43)	(-0.25)	(2.21)
Downgrade	-0.149*	-0.001	-0.019
	(-1.66)	(-0.03)	(-0.62)
Event-day Return	-0.414	-0.177	0.413
	(-1.02)	(-0.59)	(1.20)
7-day Cumulative Return	0.251	0.406*	-0.021
	(0.67)	(1.67)	(-0.08)
Constant	-2.548***	-0.679*	0.150
	(-4.36)	(-1.79)	(0.57)
Observations	6384	15431	25912
R^2	0.041	0.019	0.010

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.12: **Broker size and pre-announcement trading**

This table reports probit model estimates of the equation 1.8: $NetTrades_{m,i,t} = a + \beta \text{Large Broker}_{b,t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and OLS estimates of the equation 1.7: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta \text{Large Broker}_{b,t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i.Unit of analysis is manager-recommendation.The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading dollar volume in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the initiation scaled by the average trading volume by for the manager in non-event period [-36;-6] days. The explanatory variable *Large Broker* is a dummy variable equal to 1 if the broker employs more than 30 analysts in a given year and 0 otherwise. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; $Upgrade/Downgrade$ - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets.

	(1) NetBuyer	(2) NetBuyer	(3) NetTrades	(4) NetTrades
Large Broker	**0.022***	**0.031****	**0.041****	**0.045****
	(1.66)	**(2.37)**	**(2.32)**	**(2.53)**
	[0.008/0.008]	**[0.012/0.012]**		
Manager Size		0.047***		0.021***
		(11.31)		(3.73)
Frequent Trader		0.004		0.000
		(0.96)		(0.03)
logMcap		-0.037***		-0.019***
		(-8.16)		(-2.91)
Upgrade		0.051**		0.047
		(2.31)		(1.51)
Downgrade		-0.031*		-0.027
		(-1.77)		(-1.05)
Event-day Return		0.166		0.150
		(1.01)		(0.72)
7-day Cumulative Return		0.075		0.227**
		(0.99)		(2.05)
Constant	0.178	-0.231	0.233	0.127
	(1.45)	(-1.17)	(1.48)	(0.49)
Observations	43194	43193	43194	43193
pseudo R^2	0.027	0.033		
R^2			0.008	0.009

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.13: **Broker size and pre-announcement trading by "best clients"**

This table reports OLS estimates of the equation of the equation 1.3 separately for large (more than 30 analysts) and small brokers: $NetTrades_{m,i,t} = a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and probit model estimates 1.4: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i. Unit of analysis is manager-recommendation. The dependent variable *NetBuyer* equals 1 if the manager's net directional trading volume (in shares) in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable *NetTrades* is the net directional dollar volume in the recommended stock 5-day period before the event, scaled by the average trading volume for the manager in non-event period [-36;-6] days. *Best Client* denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of the market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. The sample includes only "Strong Buy" and "Buy" initiations. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets. Marginal effects at means/average marginal effects are reported in square brackets.

	LARGE BROKERS (1) - (4)				SMALL BROKERS (5) - (8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NetBuyer	NetBuyer	NetTrades	NetTrades	NetBuyer	NetBuyer	NetTrades	NetTrades
Best Client	**0.295***** **(12.57)** **[0.111/0.115]**	**0.246***** **(10.05)** **[0.092/0.096]**	**0.080***** **(2.89)**	**0.061**** **(2.12)**	**0.089** **(1.49)** **[0.034/0.035]**	**0.058** **(0.97)** **[0.022/0.023]**	**0.104** **(1.42)**	**0.088** **(1.21)**
Manager Size		0.033*** (5.52)		0.013* (1.74)		0.051*** (9.15)		0.024*** (3.02)
Frequent Trader		0.014** (2.41)		0.001 (0.16)		-0.007 (-1.24)		-0.002 (-0.21)
logMcap		-0.038*** (-6.04)		-0.021** (-2.40)		-0.032*** (-5.06)		-0.015* (-1.69)
Upgrade		0.043 (1.45)		0.041 (0.99)		0.066** (2.11)		0.061 (1.39)
Downgrade		-0.051** (-2.12)		-0.041 (-1.16)		-0.018 (-0.76)		-0.019 (-0.53)
Event-day Return		-0.083 (-0.36)		-0.117 (-0.39)		0.390* (1.65)		0.405 (1.38)
7-day Cumulative Return		-0.100 (-1.00)		-0.079 (-0.54)		0.277** (2.43)		0.572*** (3.55)
Constant	-0.011 (-0.07)	-0.072 (-0.26)	0.252 (1.22)	0.402 (1.14)	0.431** (2.24)	-0.104 (-0.37)	0.235 (1.00)	-0.049 (-0.13)
Observations	22273	22273	22273	22273	20921	20920	20921	20920
pseudo R^2	0.035	0.039			0.029	0.035		
R^2			0.011	0.012			0.012	0.014

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.14: **Initiations by All-star analysts and pre-announcement trading**

This table reports probit model estimates of the equation 1.10: $NetTrades_{m,i,t} = a + \beta\text{All-Star}_{a,t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and OLS estimates of the equation 1.9: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta\text{All-star}_{a,t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i.Unit of analysis is manager-recommendation.The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading dollar volume in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the initiation scaled by the average trading volume by for the manager in non-event period [-36;-6] days. The explanatory variable *Allstar* is a dummy variable equal to 1 if the recommending analyst is an All-star analyst defined by II rankings, and 0 otherwise. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *3-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 3-day window before the event period. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets.

	(1) NetBuyer	(2) NetBuyer	(3) NetTrades	(4) NetTrades
All-star	**-0.004**	**0.008**	**0.037**	**0.042**
	(-0.16)	**(0.37)**	**(1.24)**	**(1.37)**
Manager Size		0.047***		0.021***
		(11.30)		(3.73)
Frequent Trader		0.004		0.000
		(0.96)		(0.03)
logMcap		-0.036***		-0.018***
		(-8.05)		(-2.82)
Upgrade		0.051**		0.047
		(2.32)		(1.52)
Downgrade		-0.031*		-0.027
		(-1.79)		(-1.08)
Event-day Return		0.170		0.148
		(1.04)		(0.70)
7-day Cumulative Return		0.078		0.228**
		(1.02)		(2.06)
Constant	0.193	-0.226	0.252	0.135
	(1.57)	(-1.15)	(1.61)	(0.52)
Observations	43194	43193	43194	43193
pseudo R^2	0.027	0.032		
R^2			0.008	0.009

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.15: **Initiations by All-star analysts and pre-announcement trading of "best clients"**

This table reports OLS estimates of the equation 1.10 separately for Allstar and non-Allstar analysts: $NetTrades_{m,i,t} = a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t} + \epsilon_{m,i,t}$, and probit model estimates 1.9: $P\{NetBuyer_{m,i,t} = 1\} = \Phi(a + \beta \text{Best Client}_{m,b(i),t} + Controls_{m,i,t}) + \epsilon_{m,i,t}$, for a given investment manager m in the 5-day period before analyst coverage initiation for the stock i. Unit of analysis is manager-recommendation. The dependent variable $NetBuyer$ equals 1 if the manager's net directional trading volume (in shares) in the 5-day period before the initiation is positive, and equals 0 otherwise. The dependent variable $NetTrades$ is the net directional dollar volume in the recommended stock 5-day period before the event, scaled by the average trading volume for the manager in non-event period [-36;-6] days. *Best Client* denotes manager who was allocated shares in at least 25% of IPO deals underwritten by the broker in the 3 years preceding the initiation. The following controls are included: *Manager Size* - the log of the manager's stock holdings as reported in 13f filings in the quarter preceding a recommendation; *Frequent Trader* is a dummy variable equal to 1 if the manager was in the top 1st decile by their trading frequency in ANcerno and 0 otherwise; *Market Cap* - the log of the market capitalization of the recommended stock 1 month before the event; *Analyst Coverage* - number of analysts covering the stock; *Upgrade/Downgrade* - dummy equal to 1 if there was an upgrade/downgrade by another broker in the 3-day window before and during the event period, and 0 otherwise; *Event-day Return* - the net of the market return for the stock i (value-weighted CRSP stocks) on the recommendation day; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) in the 7-day window before the event period. The sample includes only "Strong Buy" and "Buy" initiations. Robust standard errors clustered on a stock-level are reported in parentheses. Monthly time effects are included. The sample period is January 1999 to December 2009. Marginal effects at means/average marginal effects are reported in square brackets. Marginal effects at means/average marginal effects are reported in square brackets.

	ALL-STAR (1) - (4)				NON-ALLSTAR (5) - (8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NetBuyer	NetBuyer	NetTrades	NetTrades	NetBuyer	NetBuyer	NetTrades	NetTrades
Best Client	**0.437***** **(8.53)** **[0.161/0.171]**	**0.400***** **(7.36)** **[0.146/0.156]**	**0.174***** **(2.80)**	**0.181***** **(2.74)**	**0.217***** **(9.19)** **[0.083/0.085]**	**0.178***** **(7.43)** **[0.068/0.070]**	**0.067**** **(2.43)**	**0.048*** **(1.71)**
Manager Size		0.024* (1.85)		0.009 (0.50)		0.044*** (10.02)		0.020*** (3.39)
Frequent Trader		0.012 (0.93)		-0.007 (-0.36)		0.002 (0.50)		0.000 (0.03)
logMcap		-0.020 (-1.33)		0.006 (0.31)		-0.037*** (-7.88)		-0.019*** (-2.78)
Upgrade		0.174** (2.57)		0.112 (1.22)		0.039* (1.67)		0.044 (1.34)
Downgrade		-0.032 (-0.61)		0.104 (1.36)		-0.032* (-1.73)		-0.046* (-1.70)
Event-day Return		-0.244 (-0.49)		0.033 (0.05)		0.199 (1.13)		0.145 (0.65)
7-day Cumulative Return		-0.791*** (-2.80)		-0.885** (-2.35)		0.142* (1.80)		0.313*** (2.74)
Constant	-0.273 (-1.02)	-0.544 (-0.95)	0.260 (0.69)	-0.068 (-0.10)	0.243* (1.75)	-0.054 (-0.26)	0.232 (1.34)	0.162 (0.57)
Observations	4327	4327	4335	4335	38859	38858	38859	38858
pseudo R^2	0.057	0.061			0.029	0.034		
R^2			0.043	0.046			0.008	0.010

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Predation versus cooperation in mutual fund families

in collaboration with Alexander Eisele and Gianpaolo Parise [1]

2.1 Summary

This paper asks how funds belonging to the same fund family (siblings) trade when another affiliated fund enters into a distress situation caused by severe investors' redemptions. We test two alternative hypotheses: funds cooperate easing the cost of distress or siblings predate the out-of-favor fund to their own advantage. Our results indicate that in large fund families performance is shifted from distressed funds to the most valuable siblings. Conversely, we do not find any evidence of strategic interaction in small fund families. To provide a better identification, we also use the introduction of new compliance regulation in 2004 as an exogenous shock. Finally, using proprietary trading data, we find cross-trades to be the main source of performance redistribution.

[1] Eisele is at University of Lugano. Parise is at Swiss Finance Institute and University of Lugano.

2.2 Introduction

Delegated portfolio management creates a principal-agent problem because the fund investor (principal) can only imperfectly monitor the fund manager (agent), and their incentives are not necessarily aligned[2]. This conflict of interest can be enhanced when a fund is not a standalone entity, but belongs to a mutual fund family. In particular, affiliation with a mutual fund family implies that a portfolio manager is first of all working for the family and not for the fund's investors.

In this paper we study how the tension between fund interests, family interests and shareholder interests impacts a fund family's performance distribution when one fund in the family faces severe financial distress in the form of investor redemptions. A fund who falls out of favor with investors often experiences large capital outflows forcing it to engage in asset sales with significant price impact. When a fund's distress affects other members of the family, siblings (i.e., non-distressed funds in the same fund family) may, on the one hand, cooperate with the distressed fund to reduce the price impact of its trades. Thus, the mutual fund family smooths performance across its funds. On the other hand, siblings may exploit the forced sales to their own advantage and harm the distressed fund. Hence, the mutual fund family can allow or encourage performance shifting from the distressed fund to other funds in the family. This paper examines the empirical relevance of these two different possibilities and asks whether siblings cooperate with or predate the distressed fund.

In our analysis we differentiate between small and large families. Internal markets of large fund families provide the necessary environment (several funds with similar holdings and strategies) and incentives to promote strategic interaction between funds. Furthermore, the previous literature suggests that in the biggest families strategic behaviors in order to achieve higher performance are common (see, e.g., Kempf and Ruenzi (2008), Nanda, Wang, and Zheng (2004)). Finally, stock holdings of funds belonging to large families are usually more concentrated (Pollet and Wilson (2008)). This suggests that potential spillover-effects due to

[2]See, for example, the literature on "window dressing" (e.g., Lakonishok, Shleifer, Thaler, and Vishny (1991)).

distress-induced sales are more relevant because of a lesser degree of portfolio's diversification. In contrast, we do not expect much strategic interaction to take place in small families.

We start our empirical analysis by comparing the performance of distressed funds in large versus small mutual fund families. Our empirical findings indicate that distressed funds belonging to large complexes suffer more than distressed funds in small ones[3]. Conditional on having quarterly outflows below the 10th percentile of the sample distribution we estimate a more than 1% lower (risk-adjusted) quarterly return for funds belonging to a large family compared to funds belonging to a small one after controlling for fund size and other fund characteristics. Relying on this result, we reject the "cooperation" hypothesis. If other funds help the distressed siblings, the performance of a distressed fund belonging to a large family should be relatively higher. However, this result may be due some other differences between large and small families that we are not taking into account. In order to ensure that our results are not endogenous or driven by an omitted variable bias and to better understand the channels underlying this relationship, we conduct several further tests.

First, we exploit an exogenous shock. At the beginning of 2004, the U.S. Securities and Exchange Commission (SEC) made several amendments to industry regulations, as a response to the "late trading scandal". Among the new requirements, fund families were asked to employ a compliance officer and to enforce compliance policies. We hypothesize that the presence of a compliance officer dampened any unlawful behavior inside the fund families. Thus, if siblings of a distressed fund take unfair advantage of a distressed fund, this effect would be weaker after 2003 (on the contrary, if siblings were helping the distressed funds the cost of distress will be higher from 2004). We find that the negative effect of belonging to a large family conditional on experiencing quarterly outflows below the 10th percentile of the sample distribution drops from around -1.6% quarterly before 2004 to -0.6% afterward, suggesting that the new regulation had a major effect in protecting distressed funds.

[3] Chen, Hong, Huan, and Kubik (2004) show that belonging to a large family is beneficial for the performance of a fund. We find that this is true on average, however this relation reverts when a fund enters into distress.

Second, we study the effect of mutual fund distress on the performance of the siblings. If performance is transferred from the distressed funds, we would expect other funds in the family to benefit. And indeed, we find that mutual funds in large families outperform their peers on average by 0.26% per quarter, when there is at least one family member in distress. We furthermore find a clustering of this extra performance among the non-distressed funds charging the highest fees inside the family. We interpret this result as evidence for strategy coordination at the family level. High-fee funds are the most valuable funds in the family and enhancing their performance brings the highest benefit to the fund complex. Conversely, we do not find any performance transferred to index and less valuable funds.

Third, we use high-frequency trading data provided by ANcerno. Using this data allows us to distinguish between the channels used by the fund family to shift performance among the funds. We propose two channels a fund family can use to shift performance from the distressed member. First, the fund family can allow or encourage front-running as presented in the seminal paper of Brunnermeier and Pedersen (2005). Thus, family members with an overlap in their holdings with the distressed fund are granted preferential and illegal access to information concerning the amount and timing of forced sales of the distressed fund. Using this information the non-distressed family members can liquidate their positions before the distressed fund to avoid the negative performance impact of the forced liquidations. Second, drawing on the idea of Gaspar, Massa, and Matos (2006), fund families can engage in cross-trading activities. Specifically, the family can force the distressed fund to absorb the poor performing positions of the siblings and to sell them the best performing ones. Additionally, the price of the cross trades can be set at a disadvantage for the distressed funds.

Although we are at a significant advantage using the high-frequency dataset, a direct test of the front-running channel is not possible using our data. We are however able to test the second channel directly. Our empirical strategy is therefore to construct a proxy for the second channel and to examine whether it can fully explain the inferior performance of distressed funds in large families. As a first glance on our results, Figure 1 plots the time series of cross-trading activity inside large mutual fund families defined as the dollar amount of cross-trades divided by the total net assets of a mutual fund family. We can observe that the average cross-trading activity was reduced significantly around the regulatory change in 2004. Specifically, we observe three significant drops: corresponding to the first SEC inquiries (Q3, 2003); the introduction of the new regulations (Q1, 2004), and in the quarter after the deadline for fund families to be compliant was reached (Q1, 2005). After 2004 the amount of cross trading activity fell to less than 0.5% of the total assets under management, before partially recovering during the financial crisis. Since all our results are economically and statistically stronger when cross-trading activity is high, our main candidate to explain the performance shifting is cross-trading[4] among funds in the same family.

And indeed, we estimate a negative impact of the amount of cross-trading activity inside a family on the performance of distressed funds and a positive effect on the returns of the siblings. After controlling for the effect of cross-trading, the negative impact of belonging to a large family on the performance of the distressed fund becomes insignificant. Hence, the front-running channel appears to be less relevant. Additional results suggest that distressed funds act as "waste bins", buying from the siblings poor-performing and less liquid positions and selling to them well-performing liquid ones. Furthermore, cross trades in large distressed families are settled at a discount to the buy-side on the value weighted average price (VWAP) of the day. This evidence is consistent with siblings profiting from unfair pricing of the trades in which distressed funds are the counter parties. This result holds after controlling for trade and stock characteristics.

Overall, our findings suggest that funds take advantage of their distressed siblings and this strategy is coordinated at the family level. Moreover, our evidence points towards cross-trading as the main channel of performance redistribution. But what is the rationale for this strategy? There are three main motives that influence a fund family to pursue such a strategy. First, families may want to improve the performance of the best funds in order to attract new inflows. Nanda, Wang, and Zheng (2004) show empirically that a star fund (i.e., a fund within the 5% top

[4]This strategy is sometimes dubbed "parasite-trading" by professionals, especially when cross-trades are used to enhance the performance of a fund at the disadvantage of another. Cross trading is permitted by the law under some conditions (see below). However, it is forbidden when one side of the transaction is negatively affected at the advantage of the other. Yet in the last twenty years there has been a number of major enforcement actions involving cross-trading activity (see Casavecchia and Tiwari (2013)).

funds in a month for average return) attracts disproportional inflows to all funds in the family. However, there is no impact of a bad-performing fund on the flows to the other funds in the family. Second, a large fund family has an incentive to fire low performing managers to increase its credibility (Gervais, Lynch, and Musto (2005)). Coherent with this prediction, we find significantly higher probability for a fund manager to be replaced after severe investors' outflows when she is working for a large family. Hence, it is economically convenient to leave the distressed fund with less valuable positions that the new manager will liquidate anyway (Jin and Scherbina (2011)). Third, directing flows into funds generating high-fees increase the overall profit of the family. According to Chevalier and Ellison (1997), the shape of the flow-performance relationship serves as an implicit incentive contract for mutual funds. Mutual funds earn their fees based on their assets under management and this creates incentives for them to attract new assets to manage. In the same vain mutual fund complexes desire to attract flows to the family to collect more fees. Increasing returns of sibling funds at the expense of a distressed fund is optimal if we take into account the findings of Sirri and Tufano (1998) showing that an improvement in the return of a good fund disproportionally attracts new inflows, while on the contrary, the outflows of the worst performing funds are less affected by a further drop in performance.

Our results contribute to an increasing amount of literature studying the strategic interactions inside mutual fund families. In their seminal paper Gaspar, Massa, and Matos (2006) find that performance is shifted from low-fee funds to high-fee funds within the same family. We find performance shifting from distressed funds (irrespectively of their fees) to non-distressed high-fee funds in large families. Moreover, we find that high-fee funds outperform only when there is at least one distressed fund in the same family and we find that the returns of low-fee siblings are neither improved nor worsened by the cross-trading activity. In line with Gaspar, Massa, and Matos (2006) we find cross-trading to be the main channel of performance shifting. However, we complement their result by studying cross-trades using high frequency data which allow for a more precise identification of cross-trading activity. Our results are consistent with the incentive structure of large fund families that benefit from "winner picking".

The evidence on mutual fund family support for distressed funds is mixed. On the one hand, drawing on Gaspar, Massa, and Matos (2006) the support of distressed funds seems unlikely. On the other hand, Bhattacharya, Lee, and Pool (2012) show that funds of funds provide liquidity to distressed funds by increasing their share in the affiliated distressed funds. However, our findings are not necessarily inconsistent with theirs. In particular, Bhattacharya, Lee, and Pool (2012) argue that funds of funds help only in situations of temporary liquidity needs, while we look at the most severe distress situations. Our results suggest that other funds in the family, beyond providing no support, predate the distressed funds.

Finally, our work contributes to a series of papers showing that families increase the performance of their most strategic funds, but do not provide clear answers concerning the channels of performance redistribution, e.g., Guedj and Papastaikoudi (2005) and Evans (2010). Using high frequency data, we suggest that cross trading activity among sibling funds is the most relevant channel and we study how it allows to boost fund performance.

The rest of the paper proceeds as follows. Section 2 presents data and summary statistics; Section 3 shows and discusses empirical results obtained using return data at the fund level; Section 4 provides results using transaction level data; Section 5 rules out alternative explanations and Section 6 concludes.

2.3 Data

2.3.1 CRSP Mutual Fund Data

For our empirical analysis we merge mutual fund data from the CRSP Survivor Bias Free US Mutual Fund Database with mutual fund holdings data from CDA/Spectrum. Our sample period spans from 1990 to 2010. We focus on the time after 1990 when the number of merged funds increases significantly. From the CRSP mutual fund database we obtain data on monthly returns, the fund family name and several characteristics commonly used in the literature like fund size and expense ratio. All our analysis is done on a quarterly frequency. Therefore, we cumulate the returns in CRSP to get quarterly returns. The CDA/Spectrum database provides us with mutual fund stock holdings on a quarterly reporting frequency. After merging the two databases we apply several filters to the data.

First, holdings in the CDA/Spectrum database are most complete for domestic open-end equity mutual funds. Therefore, following the literature we only include funds with investment objectives “Aggressive Growth", “Growth", “Growth & Income" or missing in the Spectrum Database. Second, the CRSP mutual fund database often includes several share classes of one fund. All the share classes however are managed by the same manager and the same portfolio is underlying them. To avoid double counting we eliminate duplicates and aggregate the fund-level variables across different share classes. Third, the focus of our analysis is on mutual fund families. Hence, we require that a fund reports its management company. Furthermore, we exclude families with less than three family members. The last filter we impose concerns the number of return observations. In our empirical analysis our dependent variables are raw returns as well as risk-adjusted returns. For the risk adjustment we have to run time-series regressions at the fund level. To ensure reliable estimates we require a fund to have at least 3-year return history.

Table 1 shows the descriptive statistics of our final dataset. Panel A shows summary statistics by year and Panel B for the pooled sample. Panel A focuses on the number and size of funds and families over time whereas Panel B provides information concerning quarterly net return, alphas, size, siblings, flows, family size and fees. In 1990 our sample spans 648 funds belonging to 140 distinct families. The peak concerning the number of funds is reached in 2000 with 2142 funds belonging to 317 families. The average mutual fund in our sample has USD 1.13 billion total net assets (TNA). The size distribution is however significantly skewed with the median of the distribution being just USD 156.8 million. Consistent with previous literature the average and median mutual fund underperform their benchmark. When returns are adjusted for exposures to the three Fama and French (1993) factors and the Carhart (1997) momentum factor, the mutual funds generated an average (median) alpha of -0.115% (-0.169%) quarterly. Row 5 of Table 1 reports quarterly mutual funds. We follow the literature (e.g. Coval and Stafford (2007)) and compute flows as

$$FLOW_{it} = \frac{TNA_{it} - (1 + ret_{it})TNA_{it-1}}{TNA_{it-1}},$$

where TNA are the total net assets and ret is the quarterly return of fund i in quarter t. To mitigate the influence of outliers, we follow Coval and Stafford (2007) and exclude observation with $FLOW_{it} > 2$ and $FLOW_{it} < -0.7$. The $FLOW_{it}$ variable is important in our analysis because we use it to define a fund in distress. The mean quarterly flow in our sample period is 3.6% and the median is 0.0078%.

2.3.2 ANcerno Data

We obtain trade-level data from Abel Noser Solutions/ANcerno, a consulting firm that works with institutional investors to monitor their equity trading costs. This database contains a detailed record of *all* executed trades since the client started reporting[5]. Previous research has showed that ANcerno institutional clients constitute approximately 8% of total CRSP daily dollar volume (Anand, Irvine, Puckett, and Venkataraman (2012)) and that there is no survivorship or backfill bias (see, e.g, Puckett and Yan (2011)).

Potential selection biases are due to the fact that clients reporting to ANcerno are on average bigger than average institution reporting to 13F filings. Moreover, since reporting is discretionary we would expect the database to understate the real amount of "controversial" trades if any ex-ante selection is happening. However, given that ANcerno data is not used for any regulatory purpose, and from now on the identity of the trading institution is not provided to third parties, it is not clear whether a fund family has an incentive to misreport or not to buy ANcerno services if any wrongdoings are happening.

The data is collected at the trade level and contains several variables useful for our investigation: stock identifier (*cusip*), *tradedate*, execution price, volume traded, side of the trade (i.e., buy or sell). Importantly, thanks to manager identification files provided by ANcerno, we could map the trades to the trading fund family.

[5]Examples of other empirical studies using ANcerno include Chemmanur, He, and Hu (2009), Anand, Irvine, Puckett, and Venkataraman (2012).

The *managercode* variable was shortly made available by ANcerno and recently was scrubbed and back-cleaned. Hence, we have an edge in analyzing the trading behavior around a fund's distress over previous or contemporaneous research that either use quarterly snapshots (e.g., Schmidt and Goncalves-Pinto (2012) and Gaspar, Massa, and Matos (2006)) or cannot rely on the family identification. In particular, we hand-match fund families from ANcerno to 13f/S12 by name[6]. Once we have the link between our main database and ANcerno, we can rely on our previous identification of large and distressed families (see previous section). Our matched database spans the time interval from 1999 to 2010 and covers roughly 15% of the initial database. Unfortunately, we were not provided by ANcerno of unique fund identifiers. Hence, all our trade-level analysis is conducted at the family level.

Our main variable of interest computed from ANcerno is $cross-trades$. $Cross-trades$ are computed as a dollar amount of positions cross-traded by family f in quarter q over the total dollar equity holdings of family f at the end of quarter $q-1$ where the prices are lagged to overcome endogeneity. We define as a cross-trade the minimum of total dollar purchases and total dollar sales requiring that i) the trades occur in the same stock, ii) the trades occur within the same family, iii) the trades occurs during the same day[7]. This identification solves the main concern about the cross-trade definition used in other papers based on quarterly snapshots. Using our approach, opposite trades recorded in the same quarter but occurring in different days are *not* considered cross-trades[8].

Summary statistics of cross trades are presented in Table 2. Our matched sample includes 192 mutual fund families, for a total of roughly 45 million mutual fund trades, out of which we identify less than 2% of them to be cross-trades (802,087).

[6]There are few papers which use our same management company identifier provided by ANcerno see, e.g., Franzoni and Plazzi (2012), Jame (2012) and Nefedova (2012).

[7]ANcerno provides also time-stamps indicating the time at which the trade was executed. However, this variable is not always precise and the execution time of several trades is randomly assigned either at the beginning or at the end of the trade day. Hence, we do not use this variable in our main analysis. However, as robustness we computed a proxy of cross-trades requiring also that the execution time of the buy side trade is the same as the sell side trade. This variable has a 70% correlation with our main variable.

[8]There is mounting evidence that mutual funds intra-quarter trading activity is positively correlated with performance (Puckett and Yan (2011), Kacperczyk, Sialm, and Zheng (2008)). Hence, the choice to assume that mutual funds trade only once per quarter seems overly-simplistic and inaccurate.

To analyze pricing of the identified cross trades, we construct the dependent variable *Trading Cost* as the difference between execution price of a trade and the daily VWAP of a stock as a % of VWAP (volume-weighted average value across manager-stock-day). Table 2 shows sample summary statistics for the trading costs and associated control variables. The mean trading cost for sell transactions in the sample equals 0.032%, it amounts to 0.04% for buy transactions.

2.4 Evidence at the fund level

2.4.1 Predation versus cooperation

Are severe liquidity shocks of one fund in a mutual fund family absorbed by other fund members? Or do other funds in the family take advantage of the forced liquidations of other funds in the family? In this section we test the cooperation against the predation hypotheses by examining the performance of distressed funds.

The cooperation hypothesis suggests that liquidity shocks of one fund are absorbed by other funds in the family and the capability to absorb liquidity shocks increases with the number of siblings in the fund family. A higher number of siblings increases the size of the internal capital market and decreases the cost of providing liquidity for a single fund as the costs are split among more parties. Hence, the cooperation hypothesis predicts that the performance of a distressed fund in a large fund family is better than the performance of a distressed fund in a small family keeping all else equal. On the contrary, the predation hypothesis predicts that the performance of distressed funds in large families is worse than in a small family.

The first step in our analysis is to define whether a fund is in distress and whether it belongs to a large or a small family. These definitions are clearly arbitrary to some extent. To make our results the least susceptible to data mining we follow the previous literature and replicate our results using different cut-off points. Similar to Bhattacharya, Lee, and Pool (2012) we classify a fund as "distressed" when its flows are below the 10th percentile of the distribution of quarterly flows[9]

[9]The results stay qualitatively the same using more severe thresholds.

which is around −8.9% in our sample. Similar to Kempf and Ruenzi (2008) we classify a mutual fund family as *Large* when it has more than 20 members, which corresponds to roughly the 75th percentile of the distribution of the number of funds per family. However, using the mean, the median, or simply the number of siblings per quarter-family do not alter our results.

Using our definition of distress we only keep distressed funds[10] in our sample and run the following Fama and MacBeth (1973) cross-sectional regressions of (risk-adjusted) returns on the dummy *Large* and other control variables as in the equation below 2.1:

$$Return_{i,t} = a + \beta Large + controls + \epsilon_{i,t}, \tag{2.1}$$

where the control variables are lagged size, fees, lagged flows and lagged returns of a fund. The dependent variable in our regressions are either raw returns or risk-adjusted returns[11]. To compute risk-adjusted returns we run every month a time-series regression of mutual fund excess returns on the three Fama and French (1993) factors and the Carhart (1997) momentum factor. The risk-adjusted return in month t is then defined as the constant of the time-series regression plus the residual.

Columns 1 to 4 of Table 3 suggest a significant and negative impact of family size on the (risk-adjusted) performance of the distressed fund. Belonging to a large family on average decreases the (risk-adjusted) returns during the distress quarter by (1.1%) 1%. This result is in stark contrast with the cooperation hypothesis[12]. However, a concern with the results presented in Table 3 is that since funds in large families are on average larger, their sales are bigger and have higher price impact that would justify a higher cost of distress. The inclusion of fund size

[10] Note that keeping only the distressed funds or using the full sample and including a dummy equal to 1 when a fund is in distress yields the same result. Restricting the sample to distressed funds is however more convenient in terms of interpreting the results.

[11] Using other risk-adjustments like 1 factor or 3 factor model does not change the results.

[12] Additionally, in the Appendix we test what is the probability for a fund manager to be replaced in the quarter *after* the distress. Schmidt and Goncalves-Pinto (2012) conjecture that other fund managers co-insure the distress manager so that he will reciprocate in case they will need liquidity in the future. However, we find that consistent with Gervais, Lynch, and Musto (2005) fund managers are likely to be replaced in the quarter after the distress and that this firing/substitution policy is significantly stronger in large families.

as a control addresses this problem. If the relation between size and returns is however not linear, this control will not be enough. In the Appendix we divide all funds in four bins according to their size and we rerun our regression for each bin in order to compare funds in large families only with funds in small families that have similar size. Interestingly, our result holds true for each bin, but it is statistically and economically stronger for funds in the second and third bins, i.e., for the medium size distressed funds, suggesting that the negative effect due to belonging to a large family is somehow weaker for the largest funds in our sample. Hence, we rule out the possibility that higher cost of distress for funds in large families is due to a larger fund size.

The results in Table 3 are particularly interesting because the literature suggests a positive relation between $FamilySize$ due to for example increasing returns to scale in research and administrative tasks (see Chen, Hong, Huan, and Kubik (2004) and Nanda, Wang, and Zheng (2004)). However, we show that this relation completely reverts when a fund enters into distress. Columns 5 to 8 of Table 2 replicate the analysis including as independent variable $FamilySize$ in place of $Large$. The number of siblings and the AUM (assets under management) at the mutual fund family level are highly correlated. Therefore using $Large$ or the AUM of the fund family should yield similar results. And indeed, the effect of $FamilySize$ on returns is negative and significant in all specifications. Therefore, despite advantages of belonging to a large family, a higher number of siblings seem to hurt severely the performance of a fund when it enters into a distress situation.

We interpret results in Table 3 as evidence against the hypothesis of cooperation in large fund families, since distressed funds do not have any advantage in having several siblings[13]. Moreover, since we conjecture that the main reason to provide liquidity to a distressed fund is to avoid negative spillover effects, we construct a variable that captures the intersection between stocks sold by the distressed fund in quarter q and the stocks held by the siblings at the beginning of the same quarter. We would expect that, if siblings intervene to dampen the effect of the price pressure of the forced sales that could damage their own portfolios, this

[13]In unreported results we also look at the performance of high-fee distressed funds to see if they are helped or enjoy some advantage when in distress compared to the low-fee distressed funds. However, we find that this is not the case.

"overlap" variable will be positively correlated with the returns of the distressed fund. On the contrary, we find that in large families portfolio similarity with the siblings hurt severely the returns of the distressed fund which is consistent with the predation hypothesis but not with cooperation (see Appendix).

2.4.2 Changes in compliance rules of investment companies

Concerns regarding our results are reverse causality and omitted variable bias. Although we control for a host of characteristics there can be unobserved systematic differences between large and small fund families leading to an omitted variable bias. The reverse causality concern when using contemporaneous flows as a right hand variable in mutual fund return regressions is carefully discussed in Edelen (1999). It emerges in our empirical design because flows are measured at a low (quarterly) frequency. Specifically, returns in the earlier part of the quarter can cause flows in the later part of the quarter. If belonging to a large family does not have an effect on the flow performance relationship, the reverse causality problem will not impact our results. For a given performance in the earlier part of the sample funds in large and small families experience similar outflows, which should ceteris paribus have a similar impact on the performance in the rest of the quarter assuming the effect of family size is zero. The empirical results of Huang, Wei, and Yan (2007) however suggest that funds in larger fund families have higher inflows for a given performance. Hence, for a flow below our threshold of -8.9% in the later part of the quarter a fund in a large family needs to have significantly lower performance in the earlier part of the quarter.

To address the aforementioned concerns, in this section we conduct a quasi-natural experiment. In the second half of 2003, several large fund families were involved in the so called "Late Trading Scandal[14]". The accused mutual fund families allowed special clients to trade mutual fund shares after 4pm at which time the closing price of mutual fund shares is determined. Hence, the favored clients were allowed to profit from new information arriving in the markets. Late trading not only benefited the favored clients, but also harmed other mutual fund investors

[14] From 2003 to 2006, 25 fund families settled allegations of illegal trading that included market timing and late trading (See McCabe (2009) and Zitzewitz (2006)).

as it implied excessive trading. As a reaction to the scandal, the Securities and Exchange Commission (SEC) amended the Investment Company Act and the Investment Advisers Act significantly to guarantee a better protection of mutual fund shareholders. Mutual fund families were required to "adopt and implement written policies and procedures reasonably designed to prevent violation of the federal securities laws" and to appoint a chief compliance officer independent by the fund management[15]. These new rules were intended to force mutual fund families to implement effective compliance policies in order to prevent fund managers from engaging in controversial practices. Hence, under the new regulatory framework, we would expect any illegal or improper trading activity to weaken due to improved internal monitoring.

On the one hand, the cooperation hypothesis predicts a stronger negative effect of flows on mutual fund returns after 2003 as the internal capital market is less effective. On the other hand, the predation hypothesis predicts a weaker effect of flows on mutual fund returns as any controversial performance shifting practices are less likely to occur due to more intense internal monitoring. The results in Table 4 are obtained using Fama-MacBeth regressions as it is the empirical approach most commonly used in the mutual fund literature (e.g., Bhattacharya, Lee, and Pool (2012) and Chen, Hong, Jiang, and Kubik (2013)). To estimate the effect of the regulatory change we have to employ however pooled OLS regressions (since our regulatory change dummy would be collinear with the constant if we run separate cross-sectional regressions for each quarter). For robustness, column 1 and 2 of Table 4 repeats our baseline results using pooled OLS regressions with time-fixed effects and standard errors clustered at the fund level. The results suggests that changing the empirical methodology leaves the results unchanged. In column 3 we include a $Post2003$ dummy and an interaction term between between the $Large$ dummy and the $Post2003$ dummy. The $Post2003$ dummy is equal to one beginning in January 2004. Officially the amendments to the Investment Company Act were introduced February 2004 and mutual fund companies had to comply from the beginning of October 2004. Although not legally binding we argue that mutual funds probably reacted immediately to the changes due to the intense pressure

[15]See rule 38a-1 under the Investment Company Act of 1940, rule 206(4)-7 under the Investment Advisers Act of 1940, and amendments to rule 204-2 under the Advisers Act.

from the SEC on mutual funds during this time[16]. Results in Table 4 show that the coefficients of $Large \times Post2003$ are positive and significant at the 1% level (coefficients range from 0.83% to 1%). Hence, distressed funds in large families benefited significantly from the new regulation. However, the marginal effect of belonging to a large family is still negative and survives after 2003, even though statistically and economically reduced (to less than -0.60% quarterly).

We interpret these results as evidence for controversial trading practices which were dampened through a successful intervention by the regulatory body. The evidence is inconsistent with the cooperation hypothesis and consistent with the hypothesis of families taking advantage of funds hit by severe outflows. One can argue the $Post2003$ is picking up other events or a trend. We control however for time-fixed effect which should alleviate these concerns[17]. In the next section we study the performance of the funds affiliated with the distressed fund. Any reverse causality concerns are not present for this group of funds.

2.4.3 Performance redistribution

The predation hypothesis predicts a positive effect of at least one distressed fund in the family on non-distressed funds. If performance is redistributed from the distressed funds to the siblings, we will expect the siblings to generate superior returns. To examine the relation between a distress situation in the family and the performance of affiliated funds we run the following Fama and MacBeth (1973) regression after excluding the distressed funds from the sample[18]:

$$Return_{i,t} = a + \beta \text{Distress\_Family} \times Large + controls + \epsilon_{i,t}, \tag{2.2}$$

where the control variables are the lagged size, lagged family size, lagged flows and the lagged returns of a fund. Results in Table 5 show that siblings in large families on average outperform other non-distressed funds of a 0.24% per quarter when there is at least a distressed fund in the same family. To better isolate the

[16]Anyway using a post-2004 dummy yields similar results.
[17]Moreover, evidence in Figure 1 is consistent with our explanation.
[18]We show that this does not affect the result in the Section 5.

effect of having a distressed fund in the family, the analysis is replicated using propensity score matching. The results are reported in Table 11 Section 5 and look qualitatively similar.

Our empirical results confirm that, consistent with the predation hypothesis, performance is redistributed in large fund families and this creates value for non-distressed funds. However, this evidence does not tell us whether performance is redistributed equally to all healthy siblings or fund families "play favorites". An optimal strategy from a family's perspective would be to boost the performance of the most valuable funds, e.g., those that charge higher fees[19] as suggested by Gaspar, Massa, and Matos (2006).

Results in Table 6 display the effect of the interaction between siblings ($DistressFamily$ dummy) and funds with fees above the median of the family ($HighFees$ dummy) for small (columns 1 and 2) and large families (columns 3 and 4). In large families the most valuable funds outperform when there is at least a fund in distress. High-fee siblings in large families display a quarterly (risk-adjusted) return of (0.58%) 0.62% when there is at least a distressed fund in the family. Moreover, consistent with predation happening only in large families, in small families excess and abnormal returns are not statistically different from zero. Hence, the predatory behavior does not happen randomly or because of geographical proximity of fund managers. On the contrary, it is consistent with a rational strategy at the family level with the objective to boost the performance of the funds that are more profitable from a family perspective[20]. Conversely, in small families high-fee funds do not outperform when a fund in the same family enters into a distressed situation.

The last four columns (5 to 8) of Table 6 include also the interaction between Index-funds and $DistressFamily$. In this case our time-series is shorter since the index fund identifier is available in CRSP only since 1999. However, the corresponding coefficients are negative and never statistically significant. Hence, coherent with

[19]We do not look whether large funds enjoy the same artificially inflated performance because, despite being clearly important to the family, it is far more difficult to boost their performance especially when the distressed fund is small.

[20]The largest majority of the mutual fund industry charges fixed fees or fees based on the assets under management and not performance based fees (see, e.g., Haslem (2010)). Hence, we would expect funds that charge higher commissions to be the most valuable for fund families when their performance attracts new assets.

a predatory strategy that aims at maximizing the overall profit from fees, performance is not shifted to Index funds which are usually considered non-strategic funds. Conversely, the coefficients of the interaction between $DistressFamily$ and $HighFees$ stay positive and significant.

Figure 2 plots quarterly four-factor alpha for distressed funds, low-fee siblings and high-fee siblings in large families around the distress quarter. The pattern we observe clearly indicates that high-fee siblings' performance is boosted *only* during the distress of another fund in the family. Afterward, the performance of distressed funds, low-fee siblings and high-fee siblings becomes indistinguishable. This suggests that a fund is predated only when investors are already leaving. In fact, predatory behaviors unfairly hit the returns of a fund manager. This strategy may be however optimal if a fund manager is going to be replaced anyway (see results in the Appendix) and the underperformance has no negative spillover effects. In particular, our results suggest that most of the performance redistribution does not occur between low-fee funds and high-fee funds but between distressed funds (irrespectively of their fees) and non-distressed high-fee funds. In fact, Figure 2 and Table 6 show clearly that non-distressed low-fee funds are completely unaffected from the performance shifting that is happening within their own fund family.

Concluding, evidence in this section shows that headquarters or management in large fund families shift performance in an internal mutual fund market. In this way, a fund family can arbitrarily pick "winners" and "losers". Consistent with a rational strategy that maximizes profit from the fees paid by the investors, the returns of high-fee funds are boosted while those of distressed funds are worsened.

2.5 Evidence from fund trades

The previous sections suggest a reallocation of performance from distressed funds to other funds in the family. In particular the most valuable non distressed-funds profit from the distress of other funds in the family. However, the channel of performance shifting is so far unclear. In this section we examine the intra-family trading during periods when at least one of the funds in the family is in distress.

Using high-frequency data provided by ANcerno we are able to differentiate between two alternative channels available to the family to shift performance among the funds.

The first channel is front-running. In the seminal paper of Brunnermeier and Pedersen (2005) informed traders liquidate positions ahead of forced asset sales by distressed traders. Thus, they avoid the negative performance impact resulting from the price pressure of the fire sales and they are able to buy back the assets at a discount after the distressed trader finished its liquidations. Information concerning the asset sales of a distressed fund is inside information and therefore illegal. Nevertheless, empirical results (see, e.g., Massa and Rehman (2008)) suggest that there are significant amounts of potentially illegal information flows inside financial conglomerates. We therefore conjecture that fund families can allow their most valuable to exit common positions *before* the distressed fund. Through this behavior the performance of the valuable fund is protected or even enhanced when it profits from buying back the position at a discount at a later point.

The second channel is cross-trading. Gaspar, Massa, and Matos (2006) find evidence consistent with performance shifting from low-value funds to high-value funds in the family using quarterly holdings data. We conjecture and test whether fund families transfer performance through cross-trades from funds facing large outflows to well-performing funds. We would expect that a distressed fund, being anyway forced to trade due to the outflows, sells for example its well-performing positions at a discount to other funds in the family.

Although the high frequency data gives us an advantage compared to previous literature, we cannot construct proxies for both mentioned channels. The reason is that we are not able to identify distressed funds inside the family, which is crucial to conduct direct tests for the front-running hypothesis. We are however able to identify with high precision the cross-trades inside the family. Hence, our empirical strategy is to study the effect of cross-trading on the performance of the distressed fund and to examine whether controlling for cross-trades fully explains the underperformance of distressed funds in large families compared to small families.

2.5.1 Cross trading activity and fund performance

Cross-trades are trades where the buyer and the seller are both funds belonging to the same family[21]. They are permitted under rule 17a-7 of the U.S. Investment Company Act provided that i) transactions involve securities for which market quotations are readily available, ii) transactions are effected at the independent current market prices of the securities, and iii) the "current market price" for certain securities[22] is calculated by averaging the highest and lowest current independent bid and offer price determined on the basis of a reasonable inquiry. Despite strict regulation on cross-trades however, fund managers may use some discretion in setting the price.[23]

The sharp decrease in cross trading activity in large families after the regulatory change in 2004 plotted in Figure 1 suggests that such activity may play a major role in explaining the underperformance of distressed funds in large families and the weakening of the effect after 2004. We formally test this hypothesis including the amount of cross-trading inside the fund family in a multivariate regression. Table 5 reports results from pooled OLS regressions of (risk-adjusted) returns on the amount of cross-trading, *Large*, an interaction term between the amount of cross-trading and *Large* as well as other controls used in the previous results. We run regressions for both distressed funds (columns (1) to (4)) as well as siblings (columns (5) to (8)). All specifications include time fixed effects and errors are clustered at the fund level. In this part of the paper we use OLS instead of Fama-Macbeth regressions since our sample is smaller and distressed situations are sparse over time. In fact, we include in our sample only observations obtained from the intersection of CRSP, 13F, and ANcerno.

Our results indicate that the amount of cross-trades negatively (positively) affects the returns of distressed funds (siblings). Moreover, the coefficient of *Large* for distressed funds turns positive and non-significant. This suggests that the

[21] Cross trades computation is defined in Section 3.

[22] E.g., municipal securities.

[23] From our talks with compliance officers and professionals in large fund families, we understand that the pricing of such trades is considered one of the most relevant and critical compliance issues. Yet these trades are usually checked only with a delay and a cross trade is considered "suspicious" only if the price deviates significantly, far more than the bid-ask spread, from the current market price.

whole underperformance of distressed funds in large families is explained by cross-trading activity. Similarly, the whole siblings' outperformance in large families is explained by the interaction of $Large$ and CT. Hence, the performance shifting we documented in the previous sections seems to be entirely due to cross-trading activity. Front-running activity, if happening, does not significantly affect fund performance on a large scale. Consistent with our previous results, we do not find cross-trading to significantly improve or worsen the performance of funds in small families.

This result is to the best of our knowledge the most direct empirical evidence that cross-trading is shifting performance between funds.

2.5.2 Cross-trades under the magnifying glass

In this section we take a closer look at the cross-trades inside mutual fund families and examine two ways through which cross-trades reallocate performance across funds. First, distressed funds can buy the positions the siblings want to sell and sell them what they want to buy. Second, distressed funds can sell these positions at a discount. Both of these strategies artificially increase the performance of the funds trading with the distressed fund.

Since we cannot identify distressed funds from ANcerno, we use S12 snapshots to see for which positions distressed funds belonging to family f, during quarter t are net buyers or net sellers[24]. Once we have identified which stocks the distressed fund is trading, we compute cross-trades from ANcerno that involve those stocks. For instance, if fund j in family f is a net seller of IBM in quarter 1, we consider all cross-trades in in family f and quarter 1 in which one party is selling IBM (and symmetrically the other party is buying IBM in the same day). Therefore, we can disentangle in which cross-trades distressed funds are more likely selling or buying[25].

[24]Since we do not have fund identifiers, we cannot infer distressed funds' trades directly from ANcerno. However, it is unlikely that distressed funds execute many round-trip trades during the distress quarter.

[25]It is of course possible that the distressed fund is selling IBM but does not participate to the family cross-trade for which IBM is on the sell-side simply because it is another fund that is selling. However, we find cross-trading to disproportionally increase in the stocks concentrated in the portfolios of the distressed funds when a family is in distress.

In unreported results we find that distressed funds are more likely to be on the sell side than on the buy side of a cross-trade. This is however intuitive as distressed funds are forced to sell due to severe outflows. Hence, we run probit regressions to estimate the probability that the distressed fund is on the buy side of the transaction on the basis of stock characteristics (only cross-trades are included). Results in Table 8 suggest that distressed funds in large families are more likely to be on the buy side of a cross-trade for relatively illiquid and underperforming positions, i.e., distressed funds are more likely to buy from the siblings "bad stocks" and more likely to sell to the siblings "good stocks". Conversely, stock characteristics do not influence whether a distressed fund buys or sells in small families. This evidence suggests that distressed funds in large families act as "waste bins" absorbing the underperforming positions that other funds want to sell. At the same time they sell well-performing liquid positions to the siblings.

Since trading is a zero-sum game, it is not surprising that one party is losing because of the transaction while the other is gaining from it. However, the fact that distressed funds systematically take the wrong side of the transaction with the siblings suggests that this may be one of the key explanations of our results. Such a pattern could also be explained by the lack of skills of distressed fund managers that are systematically outguessed by their colleagues. However, we do not find a similar result to hold for distressed fund managers in small families. Therefore, this result would be also consistent with the (unlikely) scenario of distressed fund managers in large families to be more unskilled than distressed fund managers in small families.

As a second step, we examine the pricing of cross-trades. Since on a daily basis we are not able to distinguish whether distressed funds are selling or buying, we assume that distressed funds are on the sell side of the cross-trade and siblings are on the buy side. This is of course a simplification, since we know that distressed funds may be net buyers for some positions. However, we believe it is a reasonable assumption since distressed funds are forced to sell by heavy investors' redemptions. Hence, we expect them to be on average more often on the sell side of the cross-trades compared to the siblings.

We construct the trading cost measure (*Trading Cost*) as a dollar volume-weighted average of the execution prices across all prices for the same stock, day and trading manager with respect to the volume-weighted average price (VWAP) for the same stock and day. We calculate our measure as a percentage of the VWAP. VWAP benchmark is often used by both academics and professionals for evaluating trading performance (for example, see Puckett and Yan (2011)). This measure shows how well the trade is performed with respect to the market. We compute trading costs of sell transactions. For more intuitive interpretation of the results we multiply the measure by -1. Positive trading cost means the trade performed worse than the market on that particular day.

Our empirical prediction related to the pricing of the cross trades is as follows. Given that distressed funds are expected to take mostly sell side of cross trade transactions, then the trading cost measure for the sell side of the cross trades should capture the cost borne by distressed funds. Therefore, we expect a positive coefficient on our *Distress Family* dummy for sell-side transactions.

We test our empirical prediction using the following OLS regression model:

$$TradingCost_{m,s,t} = a + \beta \text{Distress Family}_{m,q} + Controls_{m,s,t} + \epsilon_{m,s,t}, \qquad (2.3)$$

where *Trading Cost*$_{m,s,t}$ is the trading cost for the manager m, stock s and trade t. Explanatory variable *Distress Family*$_{m,q}$ dummy is defined for each manager m and quarter q. Table 9 presents results from OLS regressions of the *Trading Cost* variable on the *Distress Family.* Following the existing literature (see, e.g., Keim and Madhavan (1997)) we include stock and trade characteristics. Only transactions identified as cross trades are included in the analysis. Time fixed effects are included and observations are clustered at the stock level. The coefficient on the *Distress Family* for the group of large families is positive and significant (0.03%). This result is consistent with funds in large (distressed) families buying the positions from funds in the same family at a (daily) discount. In small families the coefficient is insignificant. Overall, our results suggest that distressed funds transfer value to other members in the family both because they sell at a discount to their siblings and because they take the "wrong" side in the cross-trades.

2.6 Alternative explanations and Robustness checks

In this section we discuss and address other possible explanations for our results and presents additionally robustness tests.

2.6.1 Truncated return distributions

One potential concern with the results in Table 5 is due to the choice of excluding distressed funds from our siblings sample. It can be argued that by excluding distressed funds we are truncating the mutual fund returns' distribution only for distressed families (even though the cut-off threshold is the the same for all families, i.e., around -9%). As an effect we are artificially shifting up the average performance of the affiliated funds only in families where there is at least a fund in distress. In this case the positive and significant coefficient of the $Distress\_Family$ dummy only captures the mechanical effect of truncating the return distribution for some families.

To rule out this explanation we run again our regressions leaving in the sample only funds which have positive flows (see Table 10). In this way we tilt the distribution of the returns upward in the same way for distressed and not distressed families. We find that running the regression from Table 5 using only funds with positive flows makes our result stronger. Hence, inflow funds from distressed families are performing better than inflow funds that are not connected with a distressed fund. Therefore, we can exclude this type of mechanical relation between the $Distress\_Family$ dummy and mutual fund returns.

2.6.2 Dispersion of investment strategies in large mutual fund families

An alternative explanation for our results is that a larger return dispersion inside large mutual fund families is generating extreme funds' performance. Nanda, Wang, and Zheng (2004) suggest that it can be rational for a fund family to choose a strategy that yield returns with zero or even negative correlation between funds. In this way the family maximizes the odds that one of their funds is reporting very high returns. Under this scenario the significant relation between $Distress\_Family$ and returns would be driven by the choice to minimize similar portfolio holdings.

To address this concern we first replicate our results including the variable cs_σ, which is the average cross-sectional standard deviation of fund alphas within the same family using the previous 12 months of data. If larger dispersion in investment styles or contrarian strategies are the drivers of our result, we should expect the variables $Distress\_Family$ or $Distress\_Family\&Large$ to be subsumed by cs_σ. We see that this is not the case (results are showed in the Appendix).

2.6.3 Propensity score matching

In addition we replicate our analysis of siblings' returns constructing a matched sample in which we match siblings to other funds on selected fund and family characteristics, i.e., the size of the fund, the size of the family, and the investment style. After that we compare returns in the "treatment" and "control" samples. Results look qualitatively similar to Table 5, suggesting that the result is not driven by potential selection bias.

Further tests and tables are included in the Appendix

2.7 Conclusions

The strategic interactions inside mutual fund families have recently attracted the attention of a growing stream of literature. This paper rigorously studies such strategic interactions when one of the funds in the same family is in financial distress due to significant investor redemptions. Our results suggest that the performance of distressed funds in large families is economically and statistically lower when a fund belongs to a large fund family where strategic interaction is more likely to occur. Corroborating the results for the distressed funds, we furthermore find an increase of the performance of the non-distressed funds inside the family which is particularly pronounced among the most valuable funds. We interpret these results as evidence that mutual fund families strategically shift performance in order to maximize the value to the family but not the value for the individual funds' investors.

Our documented evidence calls into action regulatory bodies. And indeed, although for different reasons the regulatory body intervened in the aftermath of the late trading scandal by enforcing stricter compliance rules for mutual fund companies. In line with our argumentation, we report a positive effect of the regulatory intervention on the performance of distressed funds in large mutual fund families. To the best of our knowledge our paper is the first to document the effect of the new compliance rules on the performance of mutual funds.

To explore the channels of performance shifting, we use trade level data from ANcerno. Our results indicate that cross-trading activity within large families decreases the performance of the distressed funds and pumps up the returns of the siblings. This happens because i) distressed funds systematically take the wrong side of the cross-trades and ii) because cross-trades look improperly priced. Conversely, cross-trading does not shift performance in small families.

Our results appear particularly striking because within-family fund performance is on average strongly correlated, since affiliated funds have access to the same research analysis and many families have a prescribed investment style (Elton, Gruber, and Green (2007)). However, we show that cross-trading increases fund returns' variability producing artificially "star" and "dog" funds. The economic implications of such a result are many. First, we show that the organizational structure in large fund families produce an incentives distortion, magnified by the additional level of (family) interests besides those of the fund manager and the investor. Conversely, this agency problem does not occur when a few funds are organized in small fund families. Second, since investors buy outperformers (Nanda, Wang, and Zheng (2004), Frazzini and Lamont (2008)) the predation strategy leads to sub-optimal investors' money allocation. Families artificially pump up the returns of high-fee funds, as a consequence dumb money will flow to

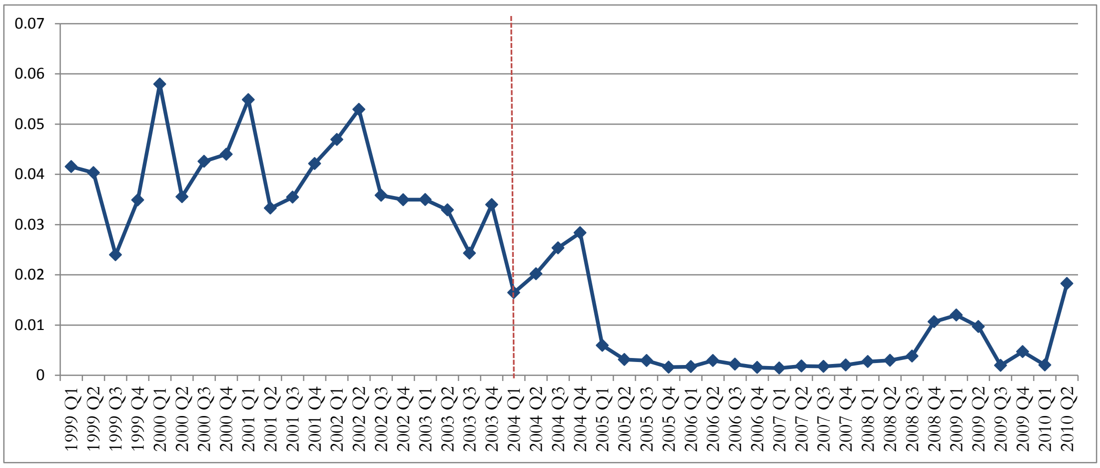

FIGURE 2.1: Amount of cross-trading over time. Cross trading is computed as the dollar amount of cross traded positions for family f in quarter q, scaled by dollar holdings at the beginning of the quarter. SEC rules 38a-1 and 206(4)-7 (introduction of chief compliance officer independent from fund management) and the amendments to rule 204-2 (advisers must maintain copies of their compliance policies and procedures and copies of any records documenting the adviser's annual review of those policies) became effective on February 5, 2004 (see red line), while the designated compliance date was October 5, 2004 (fourth quarter 2004). Only large families are included. Observations have quarterly frequency.

unskilled fund managers. This result has a similar effect to other window dressing policies common in the money management industry (e.g., Ben-David, Franzoni, Landier, and Moussawi (2013)). Third, investors holding shares of distressed funds in large families will pay an additional cost of distress, besides the one due to poor fund selection, because of predatory practices. Fourth, we show that the regulatory change in 2004 was effective in, at least, mitigating the negative effects of incentives distortion.

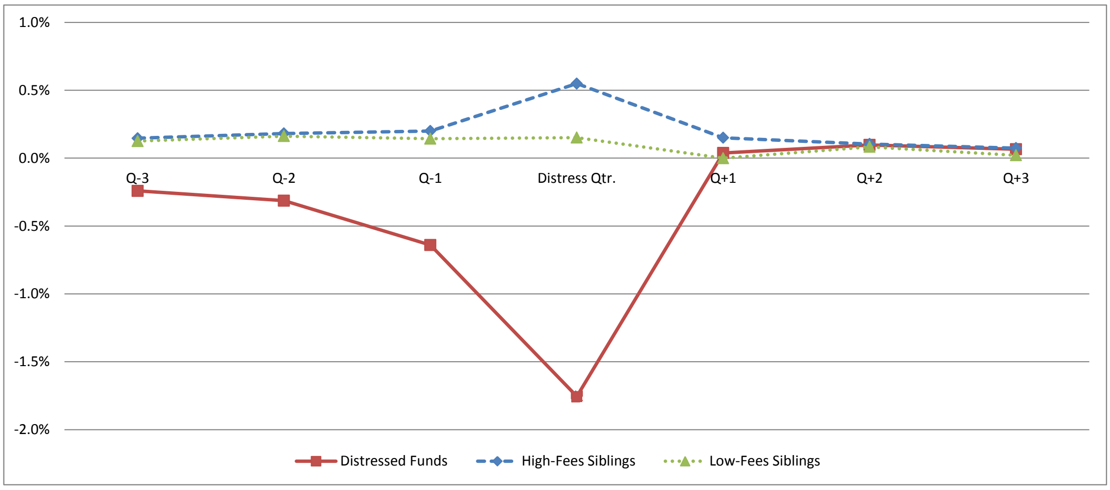

FIGURE 2.2: Abnormal returns around the distress of a fund. Distressed funds are funds for which the quarterly flows are below the 10th percentile of the flow distribution in the distress quarter. High-Fee Siblings are non-distressed funds that charge above median fees and belong to families with at least a distressed fund during the distress quarter. Low-Fee Siblings are non-distressed funds that charge below median fees and belong to families with at least a distressed fund during the distress quarter. The graph shows abnormal (non-cumulative) returns computed using 4-factor alpha from 3 quarters before to 3 quarters after the distress quarter. Only large families are included.

TABLE 2.1: **Summary Statistics CRSP Mutual Fund Database**

This table presents summary statistics for our sample of US domestic equity mutual funds. Panel A shows summary statistics by year and Panel B presents pooled summary statistics. In Panel A No. of funds is the number of unique funds in the sample; No. of families is the number of unique families; Fund TNA are total net assets under management reported by CRSP survivorship-bias-free mutual fund database; Family TNA are the total net assets of all US domestic equity mutual funds inside a family. In Panel B Return is the quarterly excess return in %; Alpha is the quarterly 4 factor alpha in %; Size is Fund TNA in million USD; Siblings is the number of funds per family; Flow is quarterly flow in % and Fees are the total fees (expense ratio+1/7 of the front load fees)

Panel A: Summary Statistic by Year

Year	**No. Funds**	**No. Families**	**Fund TNA (mln USD)**		**Family TNA (mln USD)**	
			Mean	**Median**	**Mean**	**Median**
1990	648	140	333	86.4	5489.2	1249.6
1991	708	151	370.3	91	6538.9	1283.7
1992	850	174	445.6	98	8339.22	1331.9
1993	1076	203	500.8	96	10901.9	1483.3
1994	1273	229	520.1	94.6	12967.2	1697.6
1995	1439	251	558.1	95.8	15101.4	1873.1
1996	1628	276	669.8	104.4	19277.4	2239.1
1997	1838	295	770.4	107	23769.4	2524.5
1998	2032	317	873.2	108.2	28700.7	2966.6
1999	2125	317	964.6	97.3	35492.9	3289.8
2000	2142	317	1148.6	121.4	41877.6	4148.8
2001	2029	304	1011.6	121	35569.9	3835.3
2002	1948	292	908.9	116.9	31562	3486.8
2003	1849	281	926.2	123	31702.5	3436
2004	1730	270	1221.5	170.2	41055	4243.5
2005	1648	257	1417	189.5	46383.6	4557.1
2006	1548	249	1600.2	209	51680	4910.7
2007	1464	237	1882.2	237.2	59403	5565.2
2008	1385	226	1648.4	199.2	51588.1	4630.8
2009	1310	220	1252.6	160.1	37122.8	3656
2010	1223	209	1553.1	215.9	45384.5	5582.3

Panel B: Pooled Summary Statistics

	Mean	**Stdev**	**25th Pct.**	**Median**	**75th Pct.**
Return	1.292	10.06	-3.210	1.534	6.301
Alpha	-0.112	4.067	-1.876	-0.169	1.525
Size	1130	4480	40.14	156.8	615
Siblings	18.12	23.40	5	11	19
Flow	3.631	18.86	-3.482	0.00780	5.386
Familysize	37296	99782	1172	4345	16025
Fees	1.366	0.672	0.930	1.339	1.816

Table 2.2: **Cross-trades summary statistics**

This table presents summary statistics for our cross-trades data computed using ANcerno database. The data covers the period 1999-2010.

Number of families	192				
Number of manager-quarters	74,611				
Number of cross-trades	802,087				
	Mean	**S.D.**	**25th**	**Median**	**75th**
Trading Cost (Sells)	.00032	.0093	-.0026	.00019	.0033
Trading Cost (Buys)	.00040	.0096	-.0028	.00019	.0034
Sell Volume mgr-stock-day	62,803	240,009	700	4,310	30,900
Sell Volume (% of shrout)	.00021	.0013	0.000	.000011	.000084
Buy Volume mgr-stock-day	57,622	218,921	600	3,600	26,828
Buy Volume (% of shrout)	.00019	.0013	0.000	0.000	.000076
Market Cap (in billions)	37	61	4.2	14	39
Amihud ratio	.0068	.087	.00039	.00096	.0028
Big	.34	.47	0	0	1
1/P	.042	.23	.015	.023	.038
Past 7-day return	.0012	.063	-.026	-.00013	.028

TABLE 2.3: **Is the cost of distress higher in large families?**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. **Only** distressed funds are included. The independent variables are: *Large*, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FamilySize*, the natural log of the lagged assets under management of the family; *FundSize*, the natural log of the lagged fund's total assets under management; *Fees*, the expense ratio plus 1/7th of the front load; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns		4-factor alpha		Excess returns		4-factor alpha	
Large	-0.0132***	-0.0103***	-0.0121***	-0.0113***				
	(-4.84)	(-3.66)	(-5.66)	(-4.42)				
Family Size					-0.0032***	-0.0024***	-0.0024***	-0.0023***
					(-5.51)	(-4.11)	(-5.41)	(-4.48)
Fund Size		-0.0010*		0.0000		-0.0004		0.0007
		(-1.81)		(0.09)		(-0.62)		(1.27)
Fees		-0.3163**		-0.2863**		-0.3061**		-0.3020***
		(-2.27)		(-2.36)		(-2.20)		(-2.66)
Past Flows		-0.0153**		-0.0119*		-0.0146*		-0.0134*
		(-2.13)		(-1.94)		(-1.97)		(-1.98)
Past Returns		0.0126		0.0282		0.0135		0.0317
		(0.30)		(0.99)		(0.33)		(1.21)
Constant	0.0048	0.0103	-0.0077***	-0.0051	0.0275**	0.0247**	0.0090***	0.0086**
	(0.51)	(1.22)	(-5.73)	(-1.44)	(2.48)	(2.61)	(2.76)	(2.11)
Observations	7,832	7,714	7,832	7,714	7,831	7,714	7,831	7,714
R-squared	0.049	0.230	0.044	0.180	0.053	0.233	0.042	0.179

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: **How did the regulatory change influence predatory behaviors?**

This table reports results for OLS regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. **Only** distressed funds are included. The independent variables are: *Post*2003, a dummy which takes the value of one for years after 2003 and, and zero otherwise; *Large*, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FamilySize*, the natural log of the lagged assets under management of the family; *FundSize*, the natural log of the lagged fund's total assets under management; *Fees*, the expense ratio plus 1/7th of the front load; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. Time fixed effects are included in all specifications and errors are clustered at the fund level. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ex. returns	4-fctr alpha	Excess returns		4-factor alpha	
Post2003			0.0150	0.0150	0.0014	0.0044
			(0.79)	(0.78)	(0.07)	(0.24)
Post2003×Large			0.0100***	0.0098***	0.0085***	0.0083***
			(3.03)	(2.94)	(3.09)	(2.99)
Large	-0.0119***	-0.0089***	-0.0163***	-0.0159***	-0.0127***	-0.0123***
	(-6.02)	(-5.23)	(-6.09)	(-5.75)	(-5.42)	(-5.21)
Fund Size	-0.0009*	-0.0003		-0.0009*		-0.0003
	(-1.87)	(-0.87)		(-1.90)		(-0.89)
Fees	-0.2553*	-0.2981***		-0.2144		-0.2634**
	(-1.83)	(-2.80)		(-1.52)		(-2.47)
Past Flows	-0.0175***	-0.0100***		-0.0173***		-0.0098***
	(-3.84)	(-2.99)		(-3.77)		(-2.92)
Past Returns	0.1009***	0.0377***		0.1009***		0.0376***
	(4.97)	(2.81)		(4.98)		(2.81)
Constant	0.0141***	-0.0021	0.0441**	0.0456**	-0.0119	-0.0119
	(4.06)	(-0.82)	(2.38)	(2.36)	(-0.66)	(-0.64)
Observations	7,714	7,714	7,832	7,714	7,832	7,714
R-squared	0.672	0.087	0.666	0.672	0.083	0.089

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.5: **Are siblings outperforming during the distress quarter?**

table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. Distressed funds are **not** included. The independent variables are: *DistressFamily*, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with quarter flows below the 10th percentile), and zero otherwise; *Large*, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FamilySize*, the natural log of the lagged assets under management of the family; *FundSize*, the natural log of the lagged fund's total assets under management; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)
	Excess returns		4-factor alpha	
DistressFamily×Large	0.0045**	0.0038***	0.0035***	0.0024**
	(2.38)	(2.65)	(2.80)	(2.19)
Large	0.0012	-0.0014	0.0015**	-0.0001
	(1.04)	(-1.22)	(2.10)	(-0.12)
DistressFamily	0.0006	0.0005	0.0004	0.0004
	(0.75)	(0.68)	(0.89)	(0.87)
Fund Size		-0.0007**		-0.0004**
		(-2.30)		(-2.53)
Family Size		0.0008***		0.0007***
		(4.46)		(4.88)
Past Flows		0.0042		0.0053***
		(1.29)		(3.14)
Past Returns		0.0890*		0.0677***
		(1.81)		(3.00)
Constant	0.0145	0.0059	-0.0004	-0.0069***
	(1.55)	(0.70)	(-0.38)	(-3.57)
Observations	74,739	73,394	74,739	73,394
R-squared	0.013	0.157	0.011	0.079

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.6: **Are high-fee siblings/index funds outperforming during the distress quarter?**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. Distressed funds are **not** included. The independent variables are: $High - Fees$, a dummy variable which takes value one if a fund charges fees (computed as expense ratio plus 1/7th of the front load) above the median of its family; $Index$, a dummy variable which takes value one if a fund is an Index Fund and zero otherwise; $DistressFamily$, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with quarter flows below the 10th percentile), and zero otherwise; $FamilySize$, the natural log of the lagged assets under management of the family; $FundSize$, the natural log of the lagged fund's total assets under management; $PastFlows$, quarterly fund flows in the previous quarter; $PastReturns$, quarterly fund returns in the previous quarter. The sample is split in two sub-samples: one for small families (columns 1, 2, 5, and 6) and one for large families (columns 3, 4, 7 and 8). The frequency of the observations is quarterly. The sample goes from 1990 to 2010 for columns from (1) to (4) and from 1999 to 2010 for columns from (5) to (8).

	Small Family		**Large Family**		**Small Family**		**Large Family**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns	4-factor alpha	Excess returns	4-factor alpha	Excess returns	4-factor alpha	Excess returns	4-factor alpha
DistressFamily*Index					-0.0011	-0.0008	-0.0025	-0.0006
					(-0.98)	(-1.18)	(-1.44)	(-0.34)
Index					-0.0012	-0.0016	0.0007	-0.0011
					(-0.82)	(-1.28)	(0.70)	(-1.03)
DistressFamily*High-Fees	0.0008	0.0008	0.0062***	0.0058***	-0.0002	-0.0003	0.0074**	0.0072***
	(0.93)	(0.93)	(2.74)	(2.78)	(-0.17)	(-0.32)	(2.54)	(3.10)
High-Fees	0.0012	0.0003	-0.0010	-0.0008	0.0033**	0.0013	-0.0033	-0.0033*
	(1.16)	(0.52)	(-0.61)	(-0.72)	(2.25)	(1.66)	(-1.12)	(-1.75)
DistressFamily	0.0003	0.0002	-0.0012	-0.0016	0.0004	0.0002	-0.0025	-0.0025
	(0.41)	(0.42)	(-0.75)	(-1.43)	(0.39)	(0.31)	(-0.93)	(-1.24)
Fund Size	-0.0004	-0.0002	-0.0008*	-0.0004	-0.0004	0.0002	-0.0002	0.0002
	(-1.26)	(-1.01)	(-1.75)	(-1.25)	(-0.97)	(0.78)	(-0.37)	(0.79)
Family Size	0.0004	0.0004**	0.0021***	0.0017***	0.0005	0.0003	0.0017***	0.0013***
	(1.53)	(2.23)	(4.89)	(4.58)	(1.48)	(1.31)	(2.89)	(2.72)
Past Flows	0.0053	0.0068***	0.0010	0.0018	0.0060	0.0096***	0.0022	0.0007
	(1.62)	(3.45)	(0.18)	(0.39)	(1.12)	(3.09)	(0.25)	(0.11)
Past Returns	0.0837*	0.0601***	0.1072**	0.0850***	0.0867	0.0373	0.0910	0.0550
	(1.67)	(2.67)	(2.22)	(2.99)	(1.15)	(1.21)	(1.28)	(1.63)
Constant	0.0078	-0.0048**	-0.0069	-0.0164***	-0.0016	-0.0048**	-0.0143	-0.0153***
	(0.89)	(-2.58)	(-0.97)	(-3.75)	(-0.13)	(-2.16)	(-1.62)	(-3.36)
Observations	56,779	56,779	16,615	16,615	36,876	36,876	12,560	12,560
R-squared	0.161	0.077	0.213	0.139	0.183	0.081	0.207	0.111

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.7: **How does cross-trading influence fund performance?**

This table presents results for pooled OLS regressions of excess and 4-factor abnormal fund returns on family characteristics and controls. The independent variables are: CT the amount of assets cross-traded over the total family holdings at the beginning of the quarter; , $Large$, a dummy which takes value one if the family has more than 20 funds, and zero otherwise; $FamilySize$, the natural log of the lagged assets under management of the family; $FundSize$, the natural log of the lagged fund's total assets under management; $PastFlows$, quarterly fund flows in the previous quarter; $PastReturns$, quarterly fund returns in the previous quarter; $Fees$, the expense ratio plus 1/7th of the front load; $PastFlows$, quarterly fund flows in the previous quarter. Distressed funds (columns 1, 2, 3, and 4) indicate funds that experience flows below the 10th percentile. Siblings (columns 5, 6, 7, and 8) sub-sample includes only funds in distressed families for which flows are above the 10th percentile. Only families that we are able to match between 13F, CRSP, and ANcerno are included. The frequency of the observations is quarterly. The sample goes from 1999 to 2010.

	Distressed Funds				**Siblings**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns		4-factor alpha		Excess returns		4-factor alpha	
CT	0.0033	0.0023	-0.0005	-0.0017	0.0022	0.0027	0.0018	0.0027**
	(1.10)	(0.66)	(-0.20)	(-0.57)	(1.20)	(1.42)	(1.55)	(2.18)
CT×Large	-0.3493***	-0.3429***	-0.1917**	-0.1850**	0.0994**	0.0589*	0.1192***	0.0873***
	(-3.15)	(-3.10)	(-2.11)	(-2.02)	(2.51)	(1.66)	(4.73)	(3.36)
Large	0.0046	0.0038	0.0023	0.0026	0.0006	-0.0009	-0.0014	-0.0027*
	(0.95)	(0.71)	(0.55)	(0.60)	(0.32)	(-0.41)	(-1.00)	(-1.79)
Fund Size		-0.0008		0.0003		-0.0015***		-0.0007**
		(-0.72)		(0.42)		(-3.21)		(-2.07)
Fees		-0.1030		-0.2227				
		(-0.26)		(-0.77)				
Past Flows		-0.0009		-0.0072		0.0071		0.0063
		(-0.07)		(-0.68)		(1.07)		(1.50)
Past Returns		0.0098		0.0131		0.1182***		0.0638***
		(0.19)		(0.33)		(4.88)		(3.72)
Family Size						0.0013**		0.0011**
						(2.31)		(2.47)
Constant	-0.0013	0.0048	-0.0092***	-0.0080	0.0059***	0.0021	-0.0016*	-0.0080**
	(-0.46)	(0.51)	(-4.32)	(-1.23)	(3.24)	(0.42)	(-1.70)	(-2.29)
Observations	993	987	993	987	5,923	5,885	5,923	5,885
R-squared	0.714	0.716	0.114	0.118	0.716	0.723	0.066	0.077

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.8: **Are distressed funds used as "waste bins"?**

This table presents results for probit regressions. The dependent variable is equal to one when a distressed fund is a net buyer for stock i in quarter q, and zero if it is a net seller (this identification comes from S12). **Only** cross trades AND distressed families are included. $Qtr.ExcessReturns$ are quarterly (contemporaneous) stock returns in excess of the risk-free; $4-factor-alpha$ are quarterly (contemporaneous) stock returns adjusted using the 4-factor model proposed in Carhart (1997). $Amihud'sIlliquidity$ is stock illiquidity in quarter $q-1$; $StockVolatility$ is intra-quarter daily return volatility computed in quarter $q-1$. Columns 1 and 2 include only cross-trades happening in small families (less than 20 equity funds). Columns 3 and 4 include only cross-trades happening in large families (more than 20 equity funds). Observation frequency is daily. Time fixed effects are included in all specifications and errors are clustered at the stock level. The sample goes from 1999 to 2010.

	Large Family		**Small Family**	
	(1)	(2)	(3)	(4)
Qtr. Excess Returns	-0.1449**		-0.0793	
	(-2.02)		(-0.63)	
4-factor alpha		-0.1507*		-0.0538
		(-1.69)		(-0.35)
Amihud's Illiquidity	3.5802***	3.5179**	0.3931	0.3855 *
	(3.88)	(3.82)	(0.70)	(0.68)
Stock Volatility	0.1656	0.1570	0.3087	0.2710
	(1.07)	(1.01)	(0.99)	(0.83)
Constant	-0.0677	-0.0800	-0.4364***	-0.4413***
	(-0.48)	(-0.57)	(-3.95)	(-3.97)
Observations	7,734	7,734	3,962	3,962

Robust z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 2.9: **Trading cost of cross trades in distress**

This table reports OLS estimates of the equation 2.3: $TradingCost_{m,s,t} = a + \beta DistressFamily_{m,q} + Controls_{m,s,t} + \epsilon_{m,s,t}$, for a given investment manager m, stock s and trade t. The dependent variable *Trading Cost*$_{m,s,t}$ is the difference between execution price of a trade and the daily VWAP of a stock as a % of VWAP (we compute the volume-weighted average value across manager-stock-day). Explanatory variable *Distress Family*$_{m,q}$ is a dummy equal 1 whenever a family m has at least one distressed fund in a given quarter q. The following controls are included: *Trade Volume* is the volume of the transaction normalized by shares outstanding; *1/P* is the ratio of 1 over price of the traded stock from the previous day; *Amihud ratio* is the Amihud illiquidity ratio for the traded stock in the previous month; *Mkt Cap* - the log of market capitalization of the traded stock 1 month before the event; *7-day Cumulative Return* - the cumulative net of the market return (value-weighted CRSP stocks) for the stock in the 7-day window before the trading day. The sample includes only cross trades. Robust standard errors clustered on a stock-level are reported in parentheses. Year time effects are included. The sample period is from January 1999 to December 2010.

	Large Family		**Small Family**	
	(1)	(2)	(3)	(4)
Distress Family	0.00031***	0.00031***	0.00003	0.00003
	(2.72)	(2.66)	(0.97)	(0.86)
Trade Volume		-0.01360		0.02069
		(-0.82)		(0.90)
1/P		-0.00005		-0.00024
		(-0.10)		(-1.58)
Amihud ratio		0.00043*		0.00015
		(1.88)		(0.92)
Mkt Cap		-0.00002		-0.00010***
		(-1.08)		(-9.54)
7-day Cum Return		0.00044		0.00070
		(0.81)		(0.98)
Constant	0.00050	0.00087*	0.00047***	0.00284***
	(1.47)	(1.74)	(3.89)	(10.06)
Observations	272716	272716	529371	529371
R^2	0.00033	0.00038	0.00014	0.00047

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.10: **Truncation of the fund flow distribution**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. **Only** funds with positive quarterly flows are included (i.e., flow>0). The independent variables are: $DistressFamily$, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with quarter flows below the 10th percentile), and zero otherwise; $Large$, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; $FamilySize$, the natural log of the lagged assets under management of the family; $FundSize$, the natural log of the lagged fund's total assets under management; $PastFlows$, quarterly fund flows in the previous quarter; $PastReturns$, quarterly fund returns in the previous quarter. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)
	Excess Returns		4-factor alpha	
DistressFamily×Large	0.0070**	0.0050**	0.0077***	0.0058***
	(2.57)	(2.42)	(4.37)	(3.71)
Large	0.0022	-0.0010	0.0008	-0.0014
	(1.18)	(-0.61)	(0.78)	(-1.38)
DistressFamily	0.0020*	0.0013	0.0011	0.0006
	(1.90)	(1.22)	(1.46)	(0.80)
Size		-0.0012***		-0.0008***
		(-2.87)		(-3.61)
Family Size		0.0015***		0.0013***
		(5.61)		(7.15)
Flows(t-1)		-0.0079***		-0.0026
		(-2.78)		(-1.55)
Returns(t-1)		0.1194**		0.0841***
		(2.40)		(3.64)
Constant	0.0211**	0.0089	0.0037**	-0.0059***
	(2.21)	(1.02)	(2.62)	(-2.91)
Observations	35,038	33,988	35,038	33,988
R-squared	0.026	0.178	0.024	0.102

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.11: **Propensity score matching**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. Distressed funds are **not** included. Only funds matched to funds in distressed families (based on *Large*, *FundSize*, and investment style) are included as the control group. The independent variables are: *DistressFamily*, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with quarter flows below the 10th percentile), and zero otherwise; *Large*, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FamilySize*, the natural log of the lagged assets under management of the family; *FundSize*, the natural log of the lagged fund's total assets under management; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)
	Excess returns		4-factor alpha	
DistressFamily×Large	0.0044**	0.0034**	0.0037***	0.0024**
	(2.08)	(2.30)	(2.91)	(2.24)
Large	0.0013	-0.0015	0.0013*	-0.0004
	(0.94)	(-1.46)	(1.85)	(-0.78)
Siblings	0.0010	0.0006	0.0005	0.0004
	(1.10)	(0.74)	(0.92)	(0.83)
Fund Size		-0.0009***		-0.0005**
		(-2.82)		(-2.45)
Family Size		0.0011***		0.0009***
		(4.18)		(4.13)
Past Flows		0.0037		0.0046**
		(1.11)		(2.52)
Past Returns		0.0825		0.0650***
		(1.66)		(2.83)
Constant	0.0141	0.0049	-0.0005	-0.0075***
	(1.52)	(0.58)	(-0.43)	(-3.60)
Observations	50,315	49,500	50,315	49,500
R-squared	0.018	0.165	0.015	0.087

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

.1 Appendix

TABLE A.1: **Are similar portfolio holdings hurting distressed funds?**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. **Only** distressed funds are included. *Overlaps* is computed as the fraction of the affiliated funds aggregated portfolio at time $t-1$ invested in the positions the distressed funds are selling at time t. The independent variables are: *Large*, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FamilySize*, the natural log of the lagged assets under management of the family; *FundSize*, the natural log of the lagged fund's total assets under management; *Fees*, the expense ratio plus 1/7th of the front load; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)
	Excess returns		4-factor alpha	
Large×Overlaps	-0.0412***	-0.0428**	-0.0308***	-0.0331**
	(-2.86)	(-2.59)	(-2.67)	(-2.40)
Large	-0.0061	-0.0019	-0.0067*	-0.0034
	(-1.31)	(-0.37)	(-1.93)	(-0.79)
Overlaps	0.0058	0.0008	0.0111**	-0.0027
	(0.80)	(0.10)	(2.26)	(-0.36)
Size		-0.0009		0.0004
		(-1.52)		(0.55)
Fees		-0.3335**		-0.2821**
		(-2.29)		(-2.19)
Past Flows		-0.0115		-0.0083
		(-1.52)		(-1.31)
Past Returns		-0.0029		0.0122
		(-0.07)		(0.41)
Constant	0.0039	0.0096	-0.0091***	-0.0066
	(0.39)	(1.05)	(-5.32)	(-1.58)
Observations	7,018	6,931	7,018	6,931
R-squared	0.092	0.276	0.078	0.221

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.2: **Percentiles of Fund Size and Cost of Distress**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. All funds are divided in four bins according to fund size in quarter $q-1$. **Only** distressed funds are included. The independent variables are: *Large*, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FamilySize*, the natural log of the lagged assets under management of the family; *FundSize*, the natural log of the lagged fund's total assets under management; *Fees*, the expense ratio plus 1/7th of the front load; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. The frequency of the observations is quarterly. The sample goes from 1990 to 2010.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns				4-factor alpha			
Fund Size Ptcile	1	2	3	4	1	2	3	4
Large	-0.0077**	-0.0129***	-0.0137***	-0.0127**	-0.0065***	-0.0121***	-0.0060*	-0.0092**
	(-2.42)	(-3.71)	(-3.26)	(-2.40)	(-2.66)	(-4.07)	(-1.91)	(-2.48)
Fund Size	-0.0020	-0.0028	-0.0115***	-0.0013	-0.0002	0.0004	-0.0073**	-0.0007
	(-1.09)	(-0.84)	(-2.67)	(-0.61)	(-0.17)	(0.16)	(-2.47)	(-0.39)
Fees	-0.2989	-0.4647**	-0.2275	0.6662	-0.3804**	-0.2643	-0.1872	-0.2404
	(-1.38)	(-2.15)	(-0.70)	(1.25)	(-2.34)	(-1.61)	(-0.72)	(-0.67)
Past Flows	-0.0161***	-0.0155**	-0.0267**	-0.0071	-0.0089*	-0.0089*	-0.0157	-0.0099
	(-2.68)	(-2.07)	(-2.04)	(-0.21)	(-1.90)	(-1.71)	(-1.56)	(-0.47)
Past Returns	0.0671**	0.1256***	0.1235***	0.1247*	0.0137	0.0562**	0.0439	0.0683
	(2.00)	(3.29)	(3.09)	(1.82)	(0.69)	(2.25)	(1.52)	(1.48)
Constant	0.0152**	0.0246	0.0788***	0.0121	-0.0011	-0.0060	0.0362*	0.0014
	(2.22)	(1.53)	(2.94)	(0.65)	(-0.22)	(-0.53)	(1.92)	(0.10)
Observations	2,924	2,329	1,646	815	2,924	2,329	1,646	815
R-squared	0.670	0.684	0.696	0.692	0.086	0.124	0.122	0.177

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: **Are distressed fund managers more likely to be replaced in large fund families?**

This table reports results for probit regressions where the dependent variable is a dummy that takes value one if the fund manager of fund j in quarter $t+1$ is different from the fund manager of fund j in quarter t, and zero otherwise. *DistressedFund* is a dummy that takes value one if quarterly fund flows are below the 10th percentile of our fund flow distribution. *Large* is a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; *FundSize*, the natural log of the lagged fund's total assets under management; *Fees*, the expense ratio plus 1/7th of the front load; *PastFlows*, quarterly fund flows in the previous quarter; *PastReturns*, quarterly fund returns in the previous quarter. Fund manager data are obtained from CRSP Mutual Funds. Time fixed effects are included in all specifications and errors are clustered at the fund manager level. The sample goes from 1999 to 2010.

	(1)	(2)	(3)
DistressedFund	0.2335***	0.1765***	0.1558***
	(9.58)	(7.21)	(6.36)
DistressedFund×Large	0.1287**	0.1180**	0.1088**
	(2.55)	(2.32)	(2.13)
Large	-0.0389	-0.0148	-0.0102
	(-1.42)	(-0.57)	(-0.40)
Fund Size		-0.0632***	-0.0551***
		(-13.40)	(-10.38)
Fees			8.6666***
			(4.28)
Past Returns			-0.0661
			(-0.39)
Past Flows			-0.2067***
			(-3.22)
Constant	-1.3429***	-0.9938***	-1.1492***
	(-13.60)	(-9.78)	(-12.26)
Observations	54,888	54,865	54,371

Robust z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.4: **Cross sectional dispersion in returns**

This table presents results for Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund characteristics and controls. Distressed funds are **not** included. The independent variables are: $CS(\sigma)$ the within family cross sectional quarterly return dispersion computed as in Nanda, Wang, and Zheng (2004); $DistressFamily$, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with quarter flows below the 10th percentile), and zero otherwise; $Large$, a dummy which takes the value of one if a fund belongs to a family constituted by more than 20 equity funds, and zero otherwise; $FamilySize$, the natural log of the lagged assets under management of the family; $FundSize$, the natural log of the lagged fund's total assets under management; $PastFlows$, quarterly fund flows in the previous quarter; $PastReturns$, quarterly fund returns in the previous quarter.

	(1)	(2)	(3)	(4)
	Excess returns		4-factor alpha	
Large × DistressFamily	0.0040**	0.0037**	0.0035***	0.0027**
	(2.09)	(2.57)	(2.73)	(2.29)
Large	0.0010	-0.0012	0.0012*	-0.0000
	(0.88)	(-1.12)	(1.81)	(-0.05)
DistressFamily	0.0004	0.0003	0.0002	0.0003
	(0.50)	(0.45)	(0.42)	(0.56)
$CS(\sigma)$	0.0998**	0.0433	0.0493*	0.0226
	(2.04)	(1.11)	(1.79)	(0.99)
Fund Size		-0.0007**		-0.0004**
		(-2.27)		(-2.59)
Family Size		0.0008***		0.0007***
		(4.07)		(4.82)
Past Flows		0.0047		0.0055***
		(1.53)		(3.25)
Past Returns		0.0859*		0.0669***
		(1.76)		(3.00)
Constant	0.0124	0.0060	-0.0013	-0.0066***
	(1.48)	(0.75)	(-1.29)	(-3.42)
Observations	74,419	73,166	74,419	73,166
R-squared	0.025	0.165	0.019	0.084

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: **Under which conditions a cross-trade is more likely to occur?**

This table reports results for probit regressions where the dependent variable is a dummy that takes value one if a trade meets our requirements to define a cross trade (i.e., there is at least another trade happening within the same family, during the same day, in the same stock but in an opposite direction), and zero otherwise. **Only** trades of large families are included. $DistressedFundHoldings$ is the percentage of the share outstanding held by distressed funds in the family at the beginning of the quarter; $Laggedalpha$ is stock 4-factor alpha in quarter $q-1$; $Amihud'sIlliquidity$ is stock illiquidity in quarter $q-1$; $StockVolatility$ is intra-quarter daily return volatility computed in quarter $q-1$. Time fixed effects are included in all specifications and errors are clustered at the stock level. The sample goes from 1999 to 2010.

	(1)	(2)	(3)
Distressed Fund Holdings	4.3812***	3.3484***	3.6811***
	(22.84)	(21.03)	(21.91)
Lagged alpha		0.2238***	0.2456***
		(6.23)	(6.54)
Amihud's Illiquidity		-2.2688***	-3.0768***
		(-14.00)	(-15.25)
Stock Volatility		-0.2308***	-0.0701
		(-4.00)	(-1.03)
Constant	0.2437***	0.0643***	0.3184***
	(5.28)	(3.66)	(6.85)
Observations	39,952	39,947	39,947

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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