Essays in Empirical Finance

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Doctoral Dissertation submitted to the faculty of Economics at the Universita' della Svizzera Italiana in partial fulfillment of the requirements for the degree of Doctor of Philosophy

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Under the supervision of Prof. Francesco Franzoni

Threat of Entry and Debt Maturity: Evidence from Airlines

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Abstract

This paper provides evidence for a causal effect of the threat of entry on capital structure in the airline industry. Building on the previous literature, the evolution of the main low cost air carriers' route network is used to identify routes where the probability of future entry dramatically increases. Empirical results show that when the most strategic routes are threatened, incumbents increase significantly debt maturity *before* low cost airlines start flying. Overall, my findings suggest that airlines respond to entry threats by lengthening the maturity of their debt for two reasons. First, airlines want to reduce liquidity risk. Second, the threat of entry limits incumbents' access to short-term bank debt.

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1 Introduction

The financial structure of firms has relevant implications for their ability to survive in competitive markets. For instance, a large literature explains that "deep-pocketed firms" will attempt to drive financially constrained competitors out of business (see, e.g., Telser (1966), Bolton and Scharfstein (1990)), while firms operating in tougher markets are more exposed to the risk of failing to rollover their debt at maturity (Diamond (1991)). A natural *ex ante* implication of this is that if firms anticipate tougher competition in the future, they should seek to adapt their financial structure today. However, empirical support for a causal effect of expected competition on financing choices is scarce at the very best.

This paper documents how the threat of entry affects corporate debt maturity decisions in the context of the American domestic airline industry. The choice of airlines as the main setting for such an analysis is driven by two considerations. First, domestic flights are (relatively) homogeneous products offered in a very competitive market. Second, it is empirically challenging to find a relation between corporate debt structure and competition. While competition may exhibit a trigger effect, debt and entry choices are endogenously determined and affected by other factors that weaken the empirical relation between the two. A domestic airlines setting provides rich data availability that makes it possible to identify a causal effect of expected competition on debt maturity choices.

Specifically, the main empirical challenge consists in identifying a setting in which incumbents can realize that the probability of entry has increased but their profitability has not yet been impacted, allowing them to have the necessary flexibility to change capital structure. In the airline industry, domestic flight data collected by the U.S. Department of Transportation make it possible to establish flight routes for each air carrier. In particular, building on Goolsbee and Syverson (2008), this paper looks at the evolution of the route network of the major low cost airlines in the United States. The focus is on situations where a low cost carrier begins to operate at one endpoint of a route (having already been operating out of the other endpoint), *but before it starts flying the route connecting the two endpoints*.

As an illustrative example, consider Southwest's entry into Washington Dulles International Airport. Southwest began to fly out of Dulles (IAD) in October 2006, with nonstop flights to four cities in its network, and one-stop service to several others. However, upon entering Dulles Airport, Southwest did not immediately start flying on the route Dulles (IAD)-Cleveland (CLE). Cleveland is also a Southwest airport: The airline flew between CLE and other airports, but not the CLE-IAD route. It is reasonable to expect that, after Southwest began to operate at both endpoints of the route, competing airlines would soon realize that the probability of Southwest entering the Dulles (IAD)-Cleveland (CLE) route had risen dramatically (in fact it started to fly the route in 2007).[1]

In particular, when a low cost airline starts operations out of both endpoints of a route, the probability that it will enter the route itself the year after increases disproportionally. Importantly, this is observable by incumbents (and potentially by lenders as well). This paper explores how the capital structure of incumbents changes in response to this threat. I find that airlines exposed to the threat of entry by low cost airlines significantly increase the proportion of long-term liabilities they hold, substituting short-term with long-term debt. This effect is significantly stronger when relatively more important routes in terms of passenger traffic are threatened. Conversely, I do not find an effect on leverage or on the overall level of debt.

In my analysis, I focus only on the threat posed by the main low cost airlines for three reasons. First, I find that the entry of a low cost carrier disrupts route profitability.

[1]This example is taken from Goolsbee and Syverson (2008).

Using a 10% random sample of all tickets sold by domestic airlines, I find that when a low cost airline actually starts flying on a route, average fares (adjusted for inflation) charged by all carriers operating on the same route drop by 6.4% on average. This number is particularly striking if one considers that the average profit margin in the airline industry is about 1%.[2] Conversely, the entry of legacy carriers has a much more contained effect on prices. Second, low cost airlines have expanded significantly in the last decade. Therefore, the entry in the second endpoint airport of a route increases significantly the probability that the low cost airline will enter the route itself soon (usually in year $t+1$ or $t+2$) forcing incumbents to change their capital structure quickly. Third, low cost carriers (mostly) do not enter into alliances or codeshare agreements with competing airlines. Therefore, they are regarded as competitors by incumbent airlines when they enter a new route.

The disruptive effect of low cost airlines' entry suggests that incumbents should anticipate actual entrance in order to adapt their financial structure before their profitability and cash flows are affected. My empirical findings indicate that incumbents respond to the threat of entry changing the structure of their debt. In particular, a one-standard deviation increase in the exposure to the threat of entry triggers an increase of 5.4% in the proportion of long-term debt held. This latter finding provides insight into the risk management strategy employed by airline companies. Longer debt maturity allows firms to reduce liquidity risk, i.e., the risk that lenders are unwilling to refinance when bad news arrives. When a firm is unable to rollover its debt, or to pay it back, it will have to pay potentially high restructuring costs (e.g., to liquidate assets, seek alternative sources of financing or renegotiate the debt). Therefore, from a firm's perspective it would be optimal to secure long-term financing before cutthroat competition affects its financial health in line with the theoretical predictions of Diamond

[2] See the IATA annual report at http://www.iata.org/about/documents/iata-annual-review-2013-en.pdf and "Why Airlines Make Such Meagre Profits?" The Economist - Feb 23rd 2014.

(1991) and Brunnermeier and Yogo (2009).

Consistent with such an explanation, I find my results to be stronger for financially constrained airlines since they are more exposed to liquidity risk. Additionally, I find evidence supporting the hypothesis that incumbents exposed to the threat of entry lose access to some segments of the debt market. Airlines finance themselves mainly with three types of long-term debt: bank debt, bonds (or similar financial instruments) and capital leasing. Threatened incumbents significantly reduce the proportion of bank debt they hold (while the proportion of capital leasing does not change significantly). This finding suggests that banks correctly anticipate low cost airlines' entry and limit their exposure to credit risk. Since bank debt has on average lower maturity than bonds, this finding suggests that also limited access to credit affects the observed increase in the debt maturity of threatened airlines. Conversely, I do not find evidence supporting alternative explanations such as those based on agency costs, strategic or signaling behaviors.

This paper contributes to three streams of literature. First, an extensive theoretical literature analyzes the optimal capital structure that firms should adopt to minimize liquidity risk.[3] In particular, Brunnermeier and Yogo (2009) argue that firms should secure long-term financing just before their financial conditions worsen. Long-term debt generally decreases a firm's ability to readjust its maturity structure quickly in response to changes in asset value. However, firms should trade off the costs of liquidity risk against the costs of reduced flexibility. Consistent with such a prediction, this paper shows that an increase in the probability of a future negative shock pushes incumbents to substitute short-term with long-term debt *before* the shock actually occurs. My result is also consistent with the evidence from Graham and Harvey (2001)'s extensive survey of 392 financial executives indicating that the cost of refinancing in "bad times"

[3]See, e.g., Morris (1976), Diamond (1991), Diamond (1993), and Brunnermeier and Yogo (2009).

is the second most important factor affecting the decision to issue long-term debt.

Second, a growing literature in finance explores empirically the effect of product market competition on payout policies (Grullon and Michaely (2007)), governance (Giroud and Mueller (2010) and Giroud and Mueller (2011)), innovation (Aghion, Bloom, Blundell, Griffith, and Howitt (2005)), leverage (MacKay and Phillips (2005), Banerjee, Dasgupta, and Kim (2008), and Xu (2012)), investments (Akdoğu and MacKay (2008) and Frésard and Valta (2012)), cash holdings (Morellec, Nikolov, and Zucchi (2013), He (2013)). The paper that is probably closer to mine in terms of its research methodology is Khanna and Tice (2000). In that paper, the authors study the effect of Wal-Mart's entrance in a local market on incumbents' choice to expand/retreat. However, the effect of competition on corporate debt maturity has not yet been explored. Moreover, all of the above papers look at the effect of competition on contemporaneous corporate policies or focus on exogenous shocks, such as cuts in import tariffs, that have an immediate effect on incumbent profitability. Conversely, my paper focuses on how incumbents change their capital structure ***before*** their profitability is affected.[4]

Finally, this paper speaks to the literature discussing strategic entry deterrence and accommodation. A large debate concerns whether deterrence actually makes sense, since it forces a firm to deviate from its optimal strategy before this is actually needed (i.e., before entry). My empirical finding that incumbents change debt structure before actual entry is broadly consistent with a series of papers supporting the deterrence argument (e.g., Dixit (1980); Aghion and Bolton (1987); and Milgrom and Roberts (1982a)).

The rest of the paper proceeds as follows. Section 2 develops the theoretical pre-

[4]Probably the only comparable paper in this regard is Hoberg, Phillips, and Prabhala (2014). In that paper the authors use product market fluidity to capture changes in rival firms' products relative to the firm's products. They find that fluidity decreases firm propensity to make payouts via dividends or repurchases and increases cash holdings, especially for firms with less access to financial markets. However, they do not explore the effect on debt maturity.

dictions on the relation between the threat of entry and capital structure. Section 3 describes the data used. Section 4 briefly outlines the empirical design. Section 5 presents the main empirical results. Section 5 provides additional results. Section 6 concludes.

2 Threat of Entry and Capital Structure

In a testimony before the Subcommittee on Aviation on September 2002 Donald J. Carty, American Airlines CEO, stated the following: "The challenge now for large network carriers like American is to revise our business model not only to deal with our old rivals, but (...) to prepare our company for long term success in an environment where *newer, lower cost competition represents a much bigger slice of the marketplace.*[5]"

Since 2002 JetBlue has increased by almost 10 times its route presence, Allegiant Air's network has increased by 100 times and Southwest Airlines has introduced about 2000 new routes becoming the largest low cost carrier in the world (see Figure 1). The rise of low cost carriers has intensified product market competition in an industry that was already extremely competitive. In particular, it is reasonable to expect that incumbents have adapted their financial structure to survive in a tougher environment. In this paper, I explore the effect of the threat of entry on financial decisions. The following predictions derive from previous theoretical and empirical work on product market competition and/or capital structure choices.

Prediction 1. Airlines exposed to the threat of entry decrease leverage

This prediction follows from Telser (1966), Bolton and Scharfstein (1990), Phillips (1991), Chevalier (1995), Zingales (1998) and Campello (2003). Telser (1966), Bolton and Scharfstein (1990) and Phillips (1991) derive theoretical predictions consistent with

[5]Testimony before the Subcommittee on Aviation, House Committee on Transportation and Infrastructure, September 24, 2002.

the hypothesis that high leverage firms are easily driven out of business. Chevalier (1995) shows that supermarket chains are more likely to enter into local markets where incumbents undertook LBOs, Zingales (1998) finds that highly leveraged truck companies were less likely to survive to the 1980 deregulation, Campello (2003) shows that leverage has a negative impact on sales growth in recession. Mixed empirical evidence is found in Phillips (1995) and Khanna and Tice (2000). Predictions consistent with the opposite argument, i.e., firms increase leverage to compete more aggressively, are derived in Brander and Lewis (1986), Maksimovic (1988), and Rotenberg and Scharfstein (1990).

Prediction 2. Airlines exposed to the threat of entry increase debt maturity

Several economic explanations would be consistent with the above prediction. First, an increase in debt maturity may be driven by agency costs. Myers (1977) argues that in the presence of unexercised investment options managers may reject profitable projects if a large part of the value created goes to debt holders. Firms can solve this problem by frequently renegotiating their debt (e.g., issuing debt with shorter maturity). Future competition shrinks firms' investment opportunity set, reducing the risk of rejecting profitable investment opportunities. This would encourage firms to issue more long-term debt. If the threat of entry captures a reduction in the value of investment options, I would expect to find no effect of the threat of entry on debt maturity after controlling for better proxies of growth prospects, i.e.,:

Prediction 2.1 The threat of entry has no effect on debt maturity after controlling for growth options

An alternative explanation consistent with prediction 2, would be that incumbents commit to long-term financing in order to increase their operational flexibility. For instance, managers may want to focus on competing more aggressively with the new entrants instead of spending time and resources to manage debt refinancing. If that is the case, an increase of long-term debt may also work as a threat to set predatory prices as a response to new entrants. Debt maturity is observable to new entrants and this may be enough to discourage them from entering a route if entry triggers a fall of prices below marginal costs (see, e.g, Areeda and Turner (1975) and Milgrom and Roberts (1982b)). Under this hypothesis I should observe stronger price cuts when new entrants enter into routes dominated by incumbents with more long-term debt:

Prediction 2.2 The price cut in response to entry increases in the debt maturity of the incumbents

From incumbents' perspective increasing debt maturity would also decrease liquidity risk. Firms operating in tougher markets are more exposed to the risk of being forced to inefficient liquidation when bad news arrives. This prediction follows from Diamond (1991), Diamond (1993), and Brunnermeier and Yogo (2009). In particular, Brunnermeier and Yogo (2009) predict that firms should tradeoff greater financial flexibility against lower liquidity risk costs before the financial health of the firm deteriorates. Under this hypothesis the response to the threat of entry should be driven by financially constrained firms, since those are on average more exposed to rollover risk:

Prediction 2.3 Debt maturity increases more in the threat of entry for financially constrained airlines

Yet, another possibility is that a change in the debt structure is enforced by lenders. In the presence of perfect information the cost of borrowing should reflect the higher credit risk for lenders associated to the threat of entry. Banks are probably the type of lender with the highest incentive to gather information on borrowers given their relatively higher exposure to each firm. Since bank debt has on average shorter maturity than bonds (see Custódio, Ferreira, and Laureano (2013)), a reduced access to bank debt would result in longer debt maturity.[6] In short:

Prediction 2.4 The proportion of bank debt decreases in the threat of entry

Alternative explanations are ruled out in Section 6.

3 Data

The sample used in my analysis is obtained from matching different data sources: Form 41 airlines data, the T-100 domestic market dataset, Compustat, and Capital IQ. The final sample covers the years from 2000 to 2013. The sample starts in 2000 since two of the main low cost airlines considered (Allegiant Air and JetBlue) started operations around that year. Additionally, Capital IQ data is only available from 2000.

3.1 Airlines financial data

All airlines in the United States are required to file reports (commonly referred to as form 41) including main balance sheet entries, employment data, fuel cost and consumption, and operating expenses. This study uses data collected by the Office of Airline Information of the U.S. Department of Transportation. Airlines operating domestic flights in the United States are also obliged to disclose data about all their flights to the Department. I match airlines' flights to other form 41 datasets using the variable "airline ID." Importantly, the sample is free from selection bias. The U.S. Department of Transportation makes data available for all operating and defunct airlines for the 2000-2013 period.

To gather financial data I match airlines by name to Compustat. This reduces significantly the sample since most of the airlines operating in the United States are

[6]The argument above assumes that banks are on average more informed than bondholders. However, the same result would hold true in the presence of perfect information if bondholders charge a lower price for the risk associated to the threat of entry because they can diversify it away in a large portfolio of assets.

private regional airlines that are not included in Compustat. However, financial data available for such air carriers are less detailed and several variables needed for my analysis are missing. To make sure that this selection is not affecting my results, in Section 6 I run similar regressions on the sample of all American domestic airlines using only the financial information provided by form 41 filings.

The final sample includes 26 passenger airlines for a total of 245 observations.[7] There airlines cover on average 81% of domestic passenger traffic. Results run on a wider sample of airlines unmatched to Compustat using financial data from form 41 include 138 passenger airlines and 794 observations. In my analysis, I consider as the main low cost airlines Southwest, JetBlue, Allegiant Air, and Frontier Airlines because they satisfy the following requirements: their entry has a disruptive effect on route profitability, double airport presence is a strong predictor of actual entry, they increased significantly their route network in the last decade.[8] Results obtained using broader or stricter definitions of low cost carriers are reported in the appendix.

3.2 Flight data

Data on flights are obtained from the T-100 domestic market dataset collected by the Department of Transportation. These data have an important conceptual difference with the T-100 domestic segment dataset. The former considers a route to be a "market" on the basis of its origin and destination airports, no matter how many stops occur in

[7]The airlines that make it into the final sample are: AirTran, Alaska Airlines, Allegiant Air, American Airlines, Big Sky Airlines, Continental, Delta, Era Aviation, ExpressJet, Frontier Airlines, Great Lakes Airlines, Hawaiian Airlines, JetBlue, Mesa Airlines, Midway Airlines, Northwest, Pinnacle, Republic Airlines, SkyWest, Southwest, Spernak, US Airways, United Airlines, Vanguard, Virgin.

[8]Codeshare agreements and alliances could potentially bias my results since incumbents may not react at all when the threat of entry arises from a "friendly" airline. However, such alliances are rare for low cost airlines. Southwest entered in a codeshare agreement with AirTran in 2013. JetBlue has several codeshare agreements with international carriers but none of these is included in my sample. Allegiant has no alliances or agreements with other companies. Frontier has a codeshare agreement with Great Lakes Airlines. However, dropping the "connected airlines" does not significantly alter the results.

between. The latter assumes that every stop breaks the flight into different markets, e.g., flights taking off from Boston Logan (BOS) for destination Santa Barbara (SBA) with one stop in Phoenix (PHX) are considered one market by the T-100 domestic market table, and two completely separate markets by the segment table (i.e., Boston [BOS] - Phoenix [PHX] and Phoenix [PHX] - Santa Barbara [SBA]). In the paper I present results using the first set of data. However, I obtain similar results using the T-100 domestic segment dataset.

Another important distinction is between airports and cities. Computing routes on the basis of airports assumes that two flights taking off from the same airport but landing in two different airports in the *same* city operate in completely different markets. Conversely, computing routes on the basis of cities assumes that travelers are indifferent to airports located in the same city.

Low cost airlines often do not operate in the main airport of a city but in a less busy (and sometimes more peripheral) one. For instance, Southwest Airlines does not fly from Chicago O'Hare, which is the main Chicago airport and one of the busiest airports in the world by number of takeoffs and landings. On the contrary, Southwest operates in Chicago Midway a smaller airport situated 8 miles from Chicago downtown. Therefore, in my analysis I determine routes on the basis of cities and not airports. For instance, I assume that the route from the Logan Airport in Boston to Chicago O'Hare would be affected if Southwest starts flying from Boston Logan to Chicago Midway.

My flight sample is complete in the sense that every single domestic flight that took off in the 2000-2013 period is recorded. The matching of flight data with airlines' financials is conducted by airline name as indicated above.

3.3 Main financial variables

The main variables of interest considered in my analysis are ***Leverage*** and ***Debt Maturity***. I focus on book leverage since I want to avoid that a variation in the market value of equity affects my results. For instance, if markets correctly value the effect of the threat of entry on the future cash flows of the incumbents this would decrease the denominator of the market leverage. As a result my results would suggest that incumbents ***increase*** leverage even when in reality they keep leverage constant. This problem is solved using book leverage. Summary statistics for ***Book Leverage*** are reported in Table 1. The median airline is extremely highly leveraged: around 40%. This number is about twice that reported by similar studies conducted on manufacturing firms (see, e.g., Xu (2012)).

Debt Maturity is computed as the non-current part of long-term debt minus the part of long-term debt maturing in either 2 or 3 years scaled by total debt. This measure follows the literature on corporate debt maturity (e.g., Barclay and Smith (1995); Custódio, Ferreira, and Laureano (2013)). Additionally, this measure better captures the response of airlines to increasing liquidity risk compared to proxies based on the average maturity of the debt instruments outstanding. In fact, when an incumbent is exposed to the threat of entry the best strategy would be to minimize the proportion of debt that will have to be refinanced when the low cost competitor actually enter the market.[9]

The median airline displays about 67% of long-term debt maturing in more than 3 years. This number is on average decreasing over time similar to other American industries (see Custódio, Ferreira, and Laureano (2013)). Results using alternative

[9]In particular, Diamond (1991) suggests that in equilibrium riskier firms should display intermediate levels of debt maturity. In fact, they want to avoid to refinance short-term debt too often but are excluded from the longest spectrum of debt maturity due to their riskiness. Consistent with this argument, in the empirical analysis I test whether firms minimize the proportion of debt instruments with the shortest maturities.

proxies are provided. Results are also provided for a larger sample of public and private airlines obtained using data from Form 41 financial filings. However, such data do not provide information on the actual maturity of long-term debt. Hence, similar to Titman and Wessels (1988) I define my proxy of debt maturity as non-current liabilities over total total liabilities.

Details on the construction of other financial variables are provided in the appendix. In my analysis I control for log *Sales* instead of *Size* since most of the variables are scaled by book assets and I want to minimize the risk of mechanical correlation between the variables. Summary statistics are reported in Table 1.

4 Empirical Design

The identification of an effect of entry on capital structure presents some empirical challenges including the following. First, the actual entry into a market is driven, among other things, by the debt structure of the incumbents (see, e.g., Chevalier (1995) and Lambrecht (2001)). There is rich theoretical and empirical support for the notion that highly leveraged incumbents with a relevant portion of their debt to roll over in the near future are less likely to respond aggressively to new entrants, e.g., starting a "price war." Hence, new firms are incentivized to enter markets dominated by firms having large debts with short maturities. At the same time incumbents may lengthen debt maturity and decrease leverage as a strategic response to entry. These two opposite effects may lead to biased estimates or cancel each other out when exploring the contemporaneous relationship between competition and debt.

Second, the identification of direct competitors is problematic. Widely used classification standards include Standard Industrial Classification (SIC) codes, the North American Industry Classification Standard (NAICS), and the Global Industry Classification Standard (GICS) system. However, Lewellen (2012) shows that traditional classification methods fail to properly map the product market space[10] (see also Clarke (1989) and Kahle and Walkling (1996) on the shortcomings arising from using standard industry classification methodologies). Furthermore, such identification standards allow for the construction of proxies for competition only at the aggregate industry level. It is, however, an unrealistic assumption that all firms in the same industry are exposed to the same degree of competition. Consistent with this claim, MacKay and Phillips (2005) show that the position of a firm within an industry is much more relevant than between-industry differences in explaining financial leverage.

In this paper I exploit the result, provided in Goolsbee and Syverson (2008), that Southwest's airport presence is a strong predictor of actual route entry.[11] Specifically, when Southwest enters the second endpoint airport of a route but not the route itself, the probability that it will enter the route "soon" increases dramatically (see Figure 2). In this paper I generalize this approach to the four major low cost airlines in the United States: Southwest Airlines, JetBlue, Allegiant Air, and Frontier Airlines.

Low-cost air carriers expanded their network significantly in my sample period, and for each one of them presence at both endpoint airports of a route rises significantly the probability of actual entry. I run probit regressions for the probability of a low cost carrier's actual entry into a route in year $t+1$, conditional on its presence at both

[10] As a general example consider two hypothetical restaurant chains, the first one operating only in New York City and the second only in California. The California restaurant chain will not compete directly with the restaurants in New York City because their customers are located in different states. Hence, the opening of a new shop or a price adjustment will probably have no effect on the policies of the "rival." However, traditional industry classification standards would typically group the two together in a broad "restoration" category. Similarly, two airlines operating in completely different locations would hardly influence one another. For instance, although they belong to the same industry, it is unlikely that the financial decisions of Sierra Pacific Airlines are influenced by the sales of Alaska Airlines, because they do not compete on any single route.

[11] Empirical work that has shown that endpoint airport presence is correlated with entry includes Berry (1992) and Peteraf and Reed (1994), while Bailey (1981) describes a case where this approach was used in antitrust policy. More broadly, the importance of airport presence is stressed in Borenstein (1989) and Borenstein (1990).

endpoints in year t. The sample of all possible routes is obtained from flight data.[12] The marginal probabilities are reported in Table 2 for entry in year $t+1$, $t+2$, and $t+3$ (time fixed effects are included and errors are clustered at the route level). Entry at the second endpoint of a route increases the probability of entry in the following year by 13% (Southwest), 8% (JetBlue), 13% (Allegiant) and 15% (Frontier). The marginal probabilities for entry in year $t+2$ are 2%, 8%, 4% and 4%, respectively. The marginal probabilities for entry in year $t+3$ are significantly smaller or not statistically significant. The marginal probability of entry conditional on presence at one endpoint airport only is also either significantly smaller or non-statistically significant.

These results suggest that incumbents can reasonably assess the probability of entry of a low cost airline. However, entry into a single route would hardly disrupt incumbents' profitability. Therefore, I aggregate such a measure of route threat at the airline/year level. Importantly, I need to give a different weight to different routes since routes with higher passenger traffic would be more important for an airline given the higher number of paying passengers and the strategic nature of the route (for instance, routes connecting to the hub have in general higher traffic). Data from the T-100 domestic market dataset allow me to have information on the exact passenger traffic for each airline/route/year. Hence, I define the threat of entry in the following way:

$$Threat\,of\,Entry_{i,t} = \sum_k \frac{Passengers_{k,i,t} I(ThreatenedRoute)_{k,i,t}}{Passengers_{k,i,t}} \tag{1}$$

where $Passengers_{k,i,t}$ is the number of passengers for airline i, in year t, flying on route k, while $I(ThreatenedRoute)_{k,i,t}$ is an indicator function that takes value of 1 if

[12] Following Goolsbee and Syverson (2008) I consider as potential routes only those where the low cost airline enters at some point. This approach rules out routes where the airline will never realistically enter. If I consider as potential routes all the routes in my sample, I would get smaller estimates but still positive and significant coefficients. For the purposes of this paper the exact probability of entry is however irrelevant. The only necessary conditions for my identification strategy to hold are that entry when the low cost carrier operates at both endpoints of a route is significantly more likely and that incumbents know this.

route k is under threat in year t and takes value of zero otherwise. The measure above goes from 0 to 1. A value of 0 indicates that no routes for airline i in year t are under the threat of entry. A value of 1 indicates that all routes are under threat. In my empirical analysis, I want to estimate the effect of such a threat on financial policies.

However, some other empirical concerns need to be addressed. In particular, both the decision of the low cost airline to enter the second endpoint of a route and the change in the financial policy of the incumbent may be driven by an omitted variable. Specifically, the main concern is that the profitability or the high passenger traffic of the incumbent is driving both its decision to change capital structure *and* the decision of the low cost carrier to enter the second endpoint airport of the incumbent's most profitable routes. To rule out such a concern it is important to control for incumbents' traffic and profitability in my regressions. Conversely, reverse causality does not seem to be an issue in this context since the change in capital structure of the incumbents (i.e., less leverage and longer maturity) makes it less convenient for potential entrants to choose to compete on the routes.[13] Hence, if there is an effect of the capital structure on the decision of entering the airport this would work against my findings. Therefore, I run the following regressions:

$$Leverage_{i,t} = \beta(Threat\,of\,Entry_{i,t}) + \gamma X_{i,t} + \theta_t + \vartheta_i + \varepsilon_{i,t}, \qquad (2)$$

$$Debt\,Maturity_{i,t} = \beta(Threat\,of\,Entry_{i,t}) + \gamma X_{i,t} + \theta_t + \vartheta_i + \varepsilon_{i,t}, \qquad (3)$$

where $Threat\ of\ Entry_{i,t}$ is defined as in equation (1) and captures the exposure of airline i in year t to the threat of entry, while $Leverage_{i,t}$ and $Debt\ Maturity_{i,t}$ are defined as in section 3. $X_{i,t}$ is a vector of time varying controls (including profitability

[13]Consistent with the previous argument, in unreported results I find that low cost airlines are less likely to enter into routes where incumbents have lower leverage and longer debt maturity.

and passenger traffic) and θ_t and ϑ_i are time and airline fixed. It is important that both time and airline dummies are included since my analysis focuses on within airline and cross-sectional variations in the threat of entry. Errors are clustered at the airline level. This may potentially lead to underestimate standard errors due to the limited number of clusters (26). To make sure this is not the case, I replicate my analysis using block bootstrapping to estimate standard errors. The results are reported in Section 6.

5 Empirical Results

This section presents the main empirical results of the paper. The first part addresses the channel through which capital structure is affected. Sections 5.2 and 5.3 present results for the effect of the threat of entry on leverage and debt maturity, respectively.

5.1 Entry and route profitability

To understand why incumbents respond to the threat of entry, I first have to document what are the effects of actual entry in my sample. To do so, I exploit the Domestic Airline Consumer Airfare Reports issued by the Department of Transportation. Average fares are computed using data from the Bureau of Transportation Statistics' Passenger Origin and Destination (OD) Survey, a 10% random sample of all airline tickets for U.S. carriers, excluding charter air travel. Fares are based on the total ticket value, which consists of the price charged by the airlines plus any additional taxes and fees levied by an outside entity at the time of purchase. Fares include only the price paid at the time of the ticket purchase and do not include other fees paid at the airport or on-board the aircraft. Averages do not include frequent-flyer or "zero fares" or a few abnormally high reported fares. The inflation adjustment is calculated using dollars for the most recent year of air fare data.

Low cost airlines' entry into a route has a disruptive effect on ticket prices.[14] Table 3 shows coefficients for average ticket prices regressed on a dummy variable that takes value of one when a low cost airline actually enters into a route (and until it stays in) and value of zero otherwise. More precisely, the dependent variable is: the average fare charged by air carriers operating on a given route recorded in the last quarter of the year. Results obtained using fares charged by only the largest carrier operating on the route are similar and are reported in the appendix. In my regressions I include time and route fixed effects and I cluster errors at the route level.

It seems clear that entry has a dramatic effect on the profitability of the route. Average fares drop by around 6% when a low cost airline starts operations on a route. More specifically, average fares drop by 5% when Southwest enters. The drop is 20%, 6%, and 4% for JetBlue, Allegiant and Frontier, respectively. I have no data on profit margins. However, external sources indicate that the average profit margin in the industry is around 1%.[15] Such a disruptive effect on route profitability suggests that airlines should try to preempt entry or, at the very least, seek to increase their financial flexibility in order to increase their chances of survival in a tougher market.

5.2 Threat of Entry and Leverage

A way to make a firm better suited for survival in a more competitive market would be to decrease the burden of debt: highly leveraged firms are easily pushed out of the market (Zingales (1998), less likely to expand (Khanna and Tice (2000)), and more likely to pass-up positive NPV projects (Myers (1977)). Additionally, new competitors prefer to enter markets dominated by high leveraged incumbents (Chevalier (1995)). The above

[14] The effects of Southwest's entry on prices are well known (see, e.g., Morrison (2001)). More generally, there is consensus concerning the notion that competition hurts firms' profitability (Tirole (2010)) and increases the riskiness of firms' cash flows (Raith (2003); Gaspar and Massa (2006); Irvine and Pontiff (2009)).

[15] See IATA annual report at http://www.iata.org/about/documents/iata-annual-review-2013-en.pdf

considerations suggest that a firm would be better off reducing leverage before new competitors enter the same market. Importantly, the threat of entry does not affect in any way incumbents' profitability (in unreported results I find the correlation between threat of entry and incumbents' profitability to be positive and non-statistically significant). Hence, threatened airlines would be better off changing their capital structure before competition actually affects their cash flows. Conversely, Brander and Lewis (1986), Maksimovic (1988), and Rotenberg and Scharfstein (1990) derive opposite predictions, e.g., firms should increase leverage under the threat of greater competition committing to a greater output stance.

Table 4 reports the coefficients estimated running specification (2). Threat of entry has the expected sign of the coefficient in the case of book leverage (consistent with prediction 1). However, I fail to reject the hypothesis that the coefficients are statistically different from zero (t-statistic of -0.94 in the full model specification). The results using market leverage are even more mixed (see columns from 4 to 6), however this is probably driven by the fact that the market value of the stock may already incorporate the effect of potential entry on future cash flows (which may work in the opposite direction).

The full model specification controls for $Sales$, $Profitability$, $Tangibility$, $Asset\ Maturity$, the log number of paying passengers, Tobin's Q, airline and time fixed effects. Coefficients have the expected signs, $Sales$ (used as a proxy of size) and $Tangibility$ are both positively and strongly correlated with $Leverage$ (as it should be according to previous literature see, e.g., Harris and Raviv (1991); Rajan and Zingales (1998)). Tobin's Q has the "wrong" sign in specification (3), but the sign flips if I drop airline dummies. Q has the expected negative sign in specification (6) (see, e.g., Myers (1977)). The trade-off theory predicts a positive relation between book leverage and profitability because higher profitability corresponds to higher benefits of debt and lower costs of financial distress. For market leverage, the tradeoff theory does not have a definite prediction since firm value also increases with profitability. Consistently, in my results a find a positive correlation between profitability and book leverage and non-statistically significant relation between profitability and market leverage.

Consistent with previous papers, my results suggest that there are multiple considerations that affect the relation between leverage and competition. Hence, the high heterogeneity in the response to expected competition leads to reject the prediction of a negative relation between the threat of entry and leverage.

Importantly, my setting is different from that of Xu (2012). In that paper the author estimates the impact of import reductions, instrumented by tariff cuts, on leverage. However, tariff reductions have an immediate negative effect on the profitability of domestic firms. Hence, Xu (2012) uses such reduction as an instrument for testing the impact of profitability on leverage. In my setting the threat of entry has no immediate effect on the profitability of incumbents (the correlation between threat of entry and profitability is positive even though not statistically significant). Therefore, in my analysis I simply rule out that expected competition has on average an effect on leverage. Results for the effect of actual entry on leverage are reported in section 6.

5.3 Threat of Entry and Debt Maturity

Firms borrow short-term to readjust their maturity structure more quickly in response to changes in asset values (Brunnermeier and Yogo (2009)), to attenuate the "debt overhang problem" (Myers (1977)), to signal to the market that they are underpriced (see, e.g., Flannery (1986)), or because a rat race among lenders leads toward shorter and shorter maturity (Brunnermeier and Oehmke (2013)), However, failure to rollover debt has a cost. In particular, subsequent to rollover failure firms will have to go through debt restructuring that can be costly for three reasons. First, owners of bonds are dispersed and difficult to locate (Buchheit and Gultai (2002)). Second, firms will have to seek more expensive sources of financing. Third, firms may be forced to liquidate assets at fire sale prices (Pulvino (1998); Shleifer and Vishny (2011)).

Hence, airlines under the threat of entry are potentially better off borrowing long-term to reduce liquidity risk costs. Additionally, the threat of increasing competition will also affect the investment opportunity set of incumbents or the willingness of lenders to provide further financing. This section explores the effect of the threat of entry on debt maturity and provides suggestive evidence on the economic drivers of such a result.

Table 5 shows the effect of the threat of entry posed by low cost carriers on corporate debt maturity. An increase of one-standard deviation in the threat of entry leads to a 5.4% increase in the proportion of long-term debt maturing after 3 years. This effect is significant at the 1% (t-statistic of 3.19 in specification (3)). Columns from 1 to 3 provide results including both airlines and time fixed effects but without controlling for the term spread (which would be collinear with the time dummies). In the specifications run in columns from 4 to 6, I include term spread and I drop the time dummies. Errors are clustered at the airline level, results obtained bootstrapping standard errors are provided in Section 6. The coefficients estimated for the threat of entry do not change dramatically in the different specifications. Controls have the expected signs: $Sales$ is positively correlated with debt maturity since bigger and more successful firms can borrow at longer maturities; $Profitability$, $Tangibility$, and $Asset\ Maturity$ have all positive coefficients (consistent with previous empirical work on debt maturity see, e.g., Barclay and Smith (1995), Guedes and Opler (1996), and Stohs and Mauer (1996)). However, they become not statistically significant when I include airline fixed effects, possibly because they do not display high within-firm variation. $Term\ Spread$ is negatively correlated with debt maturity since firms prefer to borrow short-term when short-term rates are relatively lower than long-term rates (i.e., when the yield curve has a more positive slope).

Tobin's Q is a first proxy of airlines' value of investment opportunities and, as expected, is negatively correlated with debt maturity (see Myers (1977)). However, the estimated coefficient for threat of entry is not affected by the inclusion of Q. This finding suggests that the effect of future competition on current debt maturity is not driven by the reduction in the value of the investment opportunities for the incumbent. Other proxies of investment opportunities are considered in Table 6.

A first concern with the previous results is however that the effect on debt maturity is not driven by new long-term debt but by some debt issues occurred in the past. To rule out such a possibility, I replicate my analysis using as dependent variable $\textit{Newly Issued Long-term Debt}$. This variable captures the amount of long-term debt that has just been issued (i.e., at time t) and it is scaled by the total amount of book assets to make sure that the result is not driven by the shrinking of the denominator. Results are reported in Table 6 (columns from 1 to 3). The estimated coefficients are lower than those reported in Table 5, since the denominator of the dependent variable is in general bigger, but the results suggest that airlines exposed to the threat of entry issue new long-term debt.

However, such results may be driven by failure to control for other important factors such as the exposure to oil price, the rating of the debt, the value of the collateral, the relations with employees, or the fact that some airlines are in distress.[16] Results in Table 6 account for such variables. In particular, a series of papers suggests that the liquidation value of the collateral may play a relevant role in the ability of a firm to finance itself (Benmelech (2008), Benmelech and Bergman (2009), and Benmelech and Bergman (2011)). In my sample I do not have information on the liquidation value of

[16] As an alternative proxy for *distress*, I use a dummy variable that takes value of one when an airline files for Chapter 11 protection and value of zero otherwise. Results are anyway similar and Chapter 11 airlines are actually a subset of the airlines in financial distress in my sample.

the collateral but I use the dollar value of total equipment owned (this number includes also leased planes) by the airline as a rough proxy of it. Consistent with Benmelech and Bergman (2009), I find a positive correlation between debt maturity and ***Equipment Owned***. Additionally, I find a negative and significant correlation between ***Debt Maturity*** and a trend variable. This finding is consistent with the average downward trend in the maturity of liabilities observed in most of American industries (see, e.g., Custódio, Ferreira, and Laureano (2013); Harford, Klasa, and Maxwell (2014)). Following Pulvino (1998) I additionally include as controls ***COST***, i.e., cost of goods sold over available seats, and ***LoadFactor***, computed as the the percentage of seats occupancy from 41 form filings times operative income before depreciation over the number of passengers. It is still debated in the literature whether measures such as Tobin's Q are flawed since they measure average rather than marginal firm prospects. The measures proposed by Pulvino (1998) capture firms' abilities to generate future cash flows. In particular, the former provides a measure of airlines' abilities to fill their planes with high-revenue passengers. The second provides a proxy of airlines' cost efficiencies. However, those variables are non-statically significant in my regressions. Estimated coefficients for other variables such as ***Fuel*** expenditures, the number of employees, the rating or the distress status are not statically different from zero as well.

The results presented above suggest that airlines under the threat of entry increase the proportion of long-term debt, substituting short-term debt with longer maturity debt instruments. In general, this result does not seem to be driven by a change of the investment opportunities of the incumbents since this effect survives to the inclusion of proxies such as ***Q***, ***Load Factor*** or ***COST***. An alternative explanation for this finding would be that airlines issue long-term debt so that they can divert resources that would otherwise go to service the debt (e.g., to pay it back) into maintaining lower prices. The choice of issuing long-term debt would therefore signal that the incumbent is committed to engage in a price war if actual entry occurs. Under this hypothesis, I should observe that prices are cut more aggressively when low cost airlines enter into routes dominated by incumbents holding more long-term debt. To test this prediction, I consider ***only*** observations at the route level for which I have entry of a low cost carrier in year ***t*** and financial data for ***all*** incumbents operating on the same route in year ***t***-1. Therefore, I regress the average price cut on the average previous year financial characteristics of incumbents operating in the same route weighted by passenger traffic. If the change in debt maturity were driven by strategic behaviors, I would expect to find a positive correlation between ***Debt Maturity*** and ***Price Cut***. However, this is not the case. I find a significant negative correlation between ***Leverage*** and ***Price Cut*** and a positive correlation between ***Cash Holdings*** and ***Price Cut*** suggesting that low leveraged and cash-rich firms are more likely to engage into price wars (consistent with Bolton and Scharfstein (1990), Chevalier (1995) and Frésard (2010)). However, I do not find a significant impact of ***Debt Maturity*** on prices. Similar results are found using ***Delta Debt Maturity*** instead of ***Debt Maturity***.

Another possible driver of the decision to reach for longer maturities may be rollover (or liquidity) risk. A capital structure that implies frequent debt rollover may lead to inefficient liquidation in a market characterized by tough price competition (Diamond (1991)). In this case I would expect to find that the firms with higher liquidation costs (e.g., firms that have more difficulties in finding alternative sources of financing) should display a stronger reaction to the threat of entry. In my analysis I assume that smaller and financially constrained firms have higher liquidation costs due to larger information asymmetries, reduced access to capital markets, and lack of internal sources of funding. Therefore, I split my sample in two using first ***Size*** (i.e., airlines with book value of assets below the median versus airlines with book value of assets above the median) and then the ***SA*** index developed by Hadlock and Pierce (2010) (I compare airlines with above median values of the *SA* index with airline below the median).[17]

Table 8 shows that my results on ***Debt Maturity*** are about 4 times stronger in the samples of small/financially constrained airlines. Conversely, even splitting the sample I do not find a significant effect for threat on entry on ***Leverage***. The debt maturity result is consistent with explanations based on the minimization of liquidity risk. Yet, another possibility (not mutually exclusive with liquidity risk based explanations) is that the effect of the threat of entry on debt maturity is the result of a limited access to credit markets. The relevant questions in this case are whether lenders realize that borrowers are potentially exposed to increasing competition in the future and whether they price their debt accordingly. If that were the case, I would expect banks to cut funding more severely in response to such a threat. In fact, banks are on average more exposed to each client than bondholders are (bondholders can include airlines' debt in a large diversified portfolio where the contribution of idiosyncratic risk to the overall portfolio's risk goes to zero) and they on average closely monitor their clients, which should decrease information asymmetries.

Therefore, I would expect banks to either charge a higher price for lending (i.e., making ***ceteris paribus*** more convenient for airlines to issue bonds) or to reduce risk through the collateral channel forcing an increase in the proportion of secured debt. Another possibility for the airline would be to change the proportion of capital leases. Under Section 1110 of U.S. bankruptcy code, capitalized leased obligations are essentially treated as "senior" debt. Under Section 1110, aircraft lessors are relieved from automatic stay provisions that affect most creditors during Chapter 11 proceedings; lessors have the right to seize "collateral" 60 days after the lessee violates the lease contract. Yet, the threat of entry implies that with high probability the market share

[17]The *SA* index is computed as a linear combination of ***Age***, ***Size***, and ***Size*** squared. Hadlock and Pierce (2010) show that such a measure is better suited in identifying financially constrained firms than alternative measures such as the ***KZ*** index.

of the incumbents is going to decrease in the future reducing the need to lease planes.

Results in Table 9 show the effect of the threat of entry on the proportion of bank debt, secured debt, and capital leasing, respectively. I fail to reject the null hypothesis of no effect for the threat of entry on secured debt and leasing possibly due to the limited sample size. However, the effect on bank debt is negative and significant. A one standard deviation increase in the threat of entry leads to a reduction of roughly 4% in the proportion of bank debt. This result suggests that lenders play a role in the change of debt structure that follows the threat of entry posed by low cost carriers.

Overall, my results show that the threat of entry affects debt maturity (but not leverage). Further analysis provides empirical evidence suggestive of explanations based on liquidity risk management and limited access to shorter-maturity bank debt.

6 Further results

6.1 Full sample results

Table 10 presents results using the full sample of airlines filing form 41 financial data. In particular, I replicate my analysis without matching form 41 data to Compustat. As a result the number of available variables is reduced. I define ***Debt Maturity*** as Non-current liabilities over Non-current liabilities plus current liabilities. ***Leverage*** is Total Liabilities over Total Assets. I control for log Total Assets instead of Log Sales (since the latter is not available); ***Profitability*** is Net Income over total assets; and ***Load Factor*** is computed as the percentage of seats filled times Net Income over passengers. Some observations display a value of liabilities significantly higher than the value of the assets. To avoid that extreme observations (e.g., severely distressed airlines) are biasing the analysis I simple drop observations for which the book value of the liabilities is greater than the book value of assets.

My sample now includes 138 passenger airlines for the time interval 1991-2013. As expected *Threat of Entry* is significantly lower before 2000 since Jetblue and Allegiant are not jet in the sample. Results are reported for the full sample (column 1), the time interval 2001-2013 (column 2), the time interval 1991-2000 (column 3), the full specification without time dummies but including *Term Spread* and *Trend* (column 4). In all specifications the coefficients estimated for the *Threat of Entry* are positive and significant. The economic magnitude is somehow smaller than that found in Table 5. However, this can be due to the fact that debt maturing in either 2 or 3 years is considered short-term debt in the specification run in Table 5 and long-term debt in the one run in Table 10. The coefficients estimated for the effect of the *Threat of Entry* on *Leverage* and *Cash Holdings* are not statistically significant (see columns 5 and 6).

6.2 Entry

Table 11 presents results for actual entry of low cost carriers on *Leverage* and *Newly Issued Long − term Debt*. I consider *Newly Issued Long − term Debt* instead of the standard definition of *Maturity* because the latter would be positively correlated with *Entry* even if long-term debt with maturity longer than 4 years were issued at time *t*-1. Conversely, the former measure captures the proportion of long-term debt issued when actual entry occurs. Low cost carriers are excluded from my analysis. I reject the hypothesis that actual entry triggers a change in the capital structure of the incumbents.

6.3 Cluster Bootstrap

Most of corporate variables display some form of cluster correlation. Bias in standard errors can be conveniently avoided with cluster-robust estimators. However, clustered standard errors can themselves be biased if the number of clusters is small. This is potentially the case in my analysis due to the limited number of matched airlines (26).

Donald and Lang (2007) show that Wald statistics obtained from standard methods such as OLS are not normally distributed when the number of clusters is small. Therefore, results are presented throughout the paper using a t-distribution with G-1 degrees of freedom (where G is the number of clusters). Additionally, Cameron, Gelbach, and Miller (2008) show that cluster bootstrap estimation can mitigate few-cluster bias (contrary to standard bootstrapping that only corrects for heteroskedasticity). This approach draws blocks of observations instead of single ones, in order to preserve the existing correlation structure within each block while using the independence across blocks to consistently estimate the standard errors.[18] Therefore, I construct 200 bootstrap samples drawing from 26 blocks (i.e., the different airlines) from the original sample. Results are presented in Table 12, estimated t-statistics are similar to those reported in Table 5.

6.4 Exit

Table 14 documents the effect of low cost airlines' exit from a route on debt maturity. Coefficients of *Exit* have a negative sign but they are not statistically significant. However, some caveats are in order. The four low cost airlines considered in the empirical analysis went through an impressive expansion in the last decade. Route exits in this period are rare. The variable *Exit*, which captures the percentage of routes for each incumbent from which low cost airlines are exiting the market, display extremely low mean (4%) and an even lower median (2.9%). Additionally, I cannot rule out that a (possible) debt maturity adjustment occurs at different times for different airlines, increasing the noise in my estimates. Finally, *Exit* is subjected to the same endogeneity concerns as the variable *Entry*.

[18] See also Giroud, Mueller, Stomper, and Westerkamp (2011) for an application in a finance setting.

7 Conclusion

The effect of competition on economic variables has been extensively debated. Several papers have shown that the competitive environment has major implications for corporate policies, and both empirical and theoretical work claims that the financial structure of firms influences how competition evolves. This paper looks for a causal effect of expected competition on financing choices. More specifically, the question addressed by this paper is whether firms react to the threat of competition by increasing corporate debt maturity.

The setting of this paper is the U.S. domestic airline industry. Today the role of competition has important implications, especially for airlines since the industry is becoming increasingly concentrated due to mergers, e.g., Delta-Northwest (2009), United-Continental (2010), Southwest-AirTran (2011), American Airlines-US Airways (2013) as well as alliances and codeshare agreements between companies that were competitors in the past.

However, airlines have some attractive features that make it possible to build a more precise identification strategy than similar studies based on all Compustat firms, and potentially to generalize some of the findings to other sectors. The largest part of the literature on competition focuses on broad proxies of industry sectors to identify competing firms and generally assumes that all firms within an industry are exposed to the same level of competition or to the same shocks. However, MacKay and Phillips (2005) indicate that most of the financial structure of firms is explained by within-industry differences. Additionally, the related literature looks at the effect of actual competition on corporate variables and not at the "threat" of future competition.

This paper proposes an identification strategy based on the threat of competition posed by low cost carriers network expansion, while it exploits data on flight routes to identify which airlines are actual competitors within the airline industry. I find competition to have strong implications for the maturity of corporate debt. Airlines exposed to tougher future competition increase the proportion of long-term liabilities and reduce the proportion of short-term ones. This result is driven by liquidity risk concerns and limited access to shorter-term bank debt. Overall, my findings support the claim that the financial structure has deep implications for the competitive environment and suggest that also potential future competition is considered when firms make financing choices.

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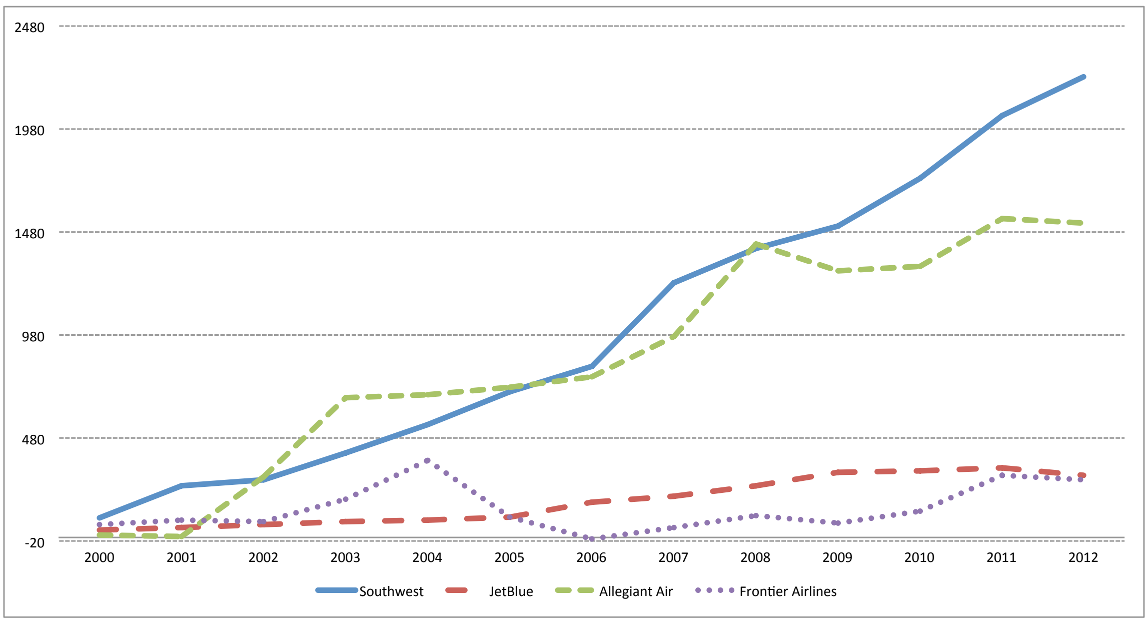

Figure 1: The rise of low cost airlines: This figure displays the cumulative number of new routes added by low cost carriers since 2000. Low cost carriers are Southwest Airlines, JetBlue, Allegiant Air and Frontier Airlines.

Table 1: Summary statistics

This table provides descriptive statistics for a sample of 26 domestic airlines in the years from 2000 to 2013. *Threat of Entry* measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. *Sales* is the total sales in thousand of dollars. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Q* is book assets plus market equity minus book equity over book assets.

	Mean	25th percentile	Median	75th percentile	Standard deviation
Threat of Entry	0.162	0.028	0.092	0.250	0.183
Book Leverage	0.402	0.255	0.395	0.532	0.222
Market Leverage	0.341	0.206	0.341	0.478	0.191
Maturity	0.593	0.507	0.665	0.761	0.253
Profitability	0.075	0.031	0.081	0.115	0.136
Tangibility	0.560	0.470	0.578	0.680	0.177
Asset Maturity	9.87	6.06	9.56	12.43	5.38
Q	1.343	1.019	1.173	1.448	0.564
Sales	6291	781	1970	11415	8012
Cash Holdings	0.130	0.050	0.100	0.196	0.107
New Long term debt	0.070	0.002	0.040	0.100	0.089
Bank debt	0.371	0.074	0.219	0.687	0.341
Secured debt	0.767	0.638	0.875	0.984	0.276
Capital leasing	0.081	0.012	0.039	0.099	0.132
Fuel	19.8	19.0	20.1	21.0	2.30
Rating	0.510	0.000	1.000	1.000	0.501
Collateral	14.21	12.63	14.27	15.89	1.85
Employees	21.57	3.61	8.92	37.25	24.33
Distress	0.257	0.000	0.000	1.000	0.438
Adjusted Load factor	0.184	0.026	0.092	0.186	1.041
COST	0.708	0.060	0.086	0.142	4.339

Table 2: Probability of Entry

This table presents the results from a probit regression in which the dependent variable takes the value of one if a low cost carrier entered into a route in year t+1, t+2, or t+3 conditional on being present at both endpoint airports (but not in the route itself) for the first time in year t. Marginal effects are reported. The routes considered are obtained from the T-100 Domestic Market database. Year fixed effects are always included. Errors are clustered at the route level. t-statistics are reported in parentheses.

	Probability of Entry in Year:		
	t+1	t+2	t+3
Entry at the second endpoint of the route for:			
Southwest Airlines	0.13	0.02	0.00
	(15.48)	(2.52)	(0.45)
JetBlue	0.08	0.08	0.01
	(5.22)	(5.31)	(0.65)
Allegiant Air	0.13	0.04	0.02
	(13.93)	(4.14)	(2.27)
Frontier Airlines	0.15	0.04	0.02
	(14.18)	(4.20)	(1.72)

Table 3: Low cost Airlines Entry and Route profitability

The dependent variable in the regressions is the log of the average route ticket prices. *Entry* is a dummy variable that takes value of one if at least one low cost airline operates on the route and takes value of zero otherwise. Results for only Southwest (or Jetblue, Allegiant, Frontier, respectively) are also reported. Average fares are adjusted for inflation and are obtained from the U.S. Department of Transportation Statistics' Passenger Origin and Destination (OD) Survey, a 10% sample of all airline tickets sold by U.S. carriers, excluding charter air travel. Average fares are average prices paid by all fare paying passengers. They cover first class fares paid to carriers offering such service but do not cover free tickets, such as those awarded by carriers offering frequent flyer programs. Time and route fixed effects are included and errors are clustered at the route level.

Dependent Variable:	**Log Ticket Price**				
	(1)	(2)	(3)	(4)	(5)
Entry any low cost Airline	-0.0639				
	(-9.33)				
Entry Southwest		-0.0474			
		(-6.30)			
Entry JetBlue			-0.2016		
			(-6.12)		
Entry Allegiant				-0.0639	
				(-4.72)	
Entry Frontier					-0.0373
					(-4.16)
Route Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y
Observations	75525	75525	75525	75525	75525
R-squared	0.8648	0.8642	0.8643	0.864	0.8638

Table 4: Does the Threat of Entry affect Leverage?

The dependent variables in the regressions are book leverage (columns 1 to 3) computed as total debt over total book assets, and market leverage (columns 4 to 6) computed as total debt over book assets plus market value of equity minus book value of equity. *Threat of Entry* measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers and is defined in section 4. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Paying Passengers* is log passengers. *Q* is book assets plus market value of equity minus book equity over book assets. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent Variable:	**Book Leverage**			**Market Leverage**		
	(1)	(2)	(3)	(4)	(5)	(6)
Threat of Entry	-0.0941	-0.0921	-0.0708	0.0131	0.0061	-0.0121
	(-0.88)	(-0.87)	(-0.68)	(0.19)	(0.09)	(-0.18)
Log Sales	-0.0008	0.0034	0.1022**	0.0885**	0.0761*	0.0794**
	(-0.02)	(0.05)	(2.09)	(2.09)	(1.96)	(2.32)
Profitability	0.3732***	0.3658**	0.3385***	-0.0874	-0.0611	-0.0463
	(2.97)	(2.40)	(2.90)	(-1.07)	(-0.78)	(-0.52)
Tangibility	0.4044*	0.4119*	0.6409***	0.5226***	0.4903***	0.4372***
	(1.85)	(1.91)	(2.94)	(4.05)	(3.59)	(3.05)
Asset Maturity	0.0053	0.0050	0.0004	-0.0008	0.0004	0.0008
	(1.10)	(1.19)	(0.10)	(-0.23)	(0.11)	(0.22)
Paying Passengers		-0.0057	0.0010		0.0236	0.0217
		(-0.15)	(0.05)		(1.31)	(1.31)
Q			0.0927**			-0.0547**
			(2.36)			(-2.42)
Airline Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	234	234	184	184	184	184
R-squared	0.596	0.596	0.810	0.855	0.857	0.866

Table 5: Does the Threat of Entry affect Debt Maturity?

The dependent variable in the regressions is Debt Maturity computed as non-current Long-term debt minus long-term debt maturing in 2 and 3 years over total debt. *Threat of Entry* measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Paying Passengers* is log passengers. *Q* is book assets plus market value of equity minus book equity over book assets. *Term Spread* is the difference between the yield on ten-year government bonds and the yield on three-month government bonds disclosed by the Federal Reserve. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent variable:	**Debt Maturity**					
	(1)	(2)	(3)	(4)	(5)	(6)
Threat of Entry	0.2813***	0.2823***	0.2964***	0.2113**	0.2097**	0.3740***
	(2.98)	(2.91)	(3.19)	(2.37)	(2.29)	(4.16)
Log Sales	0.1050*	0.1066**	0.1876**	0.0871*	0.0788	0.1120*
	(1.80)	(2.15)	(2.11)	(2.03)	(1.52)	(1.87)
Profitability	0.1188	0.1157	0.3482	0.0889	0.1016	0.2323
	(0.37)	(0.39)	(1.11)	(0.33)	(0.39)	(0.78)
Tangibility	0.0636	0.0663	0.2504	0.0436	0.0259	0.1774
	(0.18)	(0.18)	(0.76)	(0.16)	(0.09)	(0.71)
Asset Maturity	0.0051	0.0050	0.0005	0.0060	0.0064	0.0023
	(0.81)	(0.72)	(0.06)	(0.99)	(0.97)	(0.31)
Paying Passengers		-0.0022	-0.0327		0.0122	-0.0304
		(-0.05)	(-1.55)		(0.24)	(-1.51)
Q			-0.1016**			-0.0659
			(-2.14)			(-1.59)
Term Spread				-0.0207**	-0.0206**	-0.0242**
				(-2.15)	(-2.17)	(-2.33)
Airline Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	N	N	N
Observations	203	203	161	203	203	161
R-squared	0.634	0.634	0.710	0.614	0.614	0.686

Table 6: Robustness: Does the Threat of Entry affect Debt Maturity?

The dependent variables in the regressions are Debt Maturity, computed as non-current Long-term debt minus long-term debt maturing in 2 and 3 years over total debt, and *Newly Issued Long − term Debt*, computed as newly issued long-term debt over book assets. *Threat of Entry* measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Paying Passengers* is log passengers. *Q* is book assets plus market value of equity minus book equity over book assets. *Term Spread* is the difference between the yield on ten-year government bonds and the yield on three-month government bonds disclosed by the Federal Reserve. The other variables are defined in the appendix. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent Variable:	**Newly Issued Long-Term Debt**			**Debt Maturity**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Threat of Entry	0.1386***	0.1204*	0.0941*	0.2248**	0.2186**	0.2068**	0.2530***
	(2.88)	(2.05)	(1.95)	(2.53)	(2.69)	(2.52)	(3.68)
Log Sales	-0.0561**	-0.0323	-0.0355	0.1184	0.1498*	0.1683**	0.2498***
	(-2.21)	(-0.81)	(-1.40)	(1.16)	(2.06)	(2.34)	(3.91)
Profitability	0.1418**	0.1444*	0.1123	0.2194	0.1101	0.0736	-0.1255
	(2.44)	(1.81)	(1.51)	(0.80)	(0.43)	(0.30)	(-0.43)
Tangibility	-0.0522	-0.0157	-0.0037	-0.2258	-0.1386	-0.1875	-0.3231
	(-0.52)	(-0.15)	(-0.03)	(-0.99)	(-0.52)	(-0.70)	(-1.60)
Asset Maturity	0.0044	0.0025	0.0015	0.0010	-0.0001	-0.0010	0.0013
	(1.38)	(0.60)	(0.33)	(0.09)	(-0.01)	(-0.09)	(0.15)
Paying Passenegrs	0.0179*	0.0166	0.0124	-0.0840**	-0.0736*	-0.2099*	-0.2242*
	(1.74)	(1.39)	(0.76)	(-2.66)	(-1.82)	(-1.79)	(-2.05)
Q		-0.0155	-0.0114	-0.0186	0.0017	-0.0020	-0.0118
		(-1.14)	(-0.80)	(-0.28)	(0.02)	(-0.03)	(-0.16)
Fuel				-0.2568	-0.2587	-0.1113	-0.1208
				(-0.85)	(-0.91)	(-0.44)	(-0.68)
Rating				0.3469	0.3405	0.3541	0.3060
				(1.38)	(1.37)	(1.37)	(1.30)
Equipment Owned				0.1546**	0.1364**	0.1716***	0.1906**
				(2.25)	(2.40)	(3.35)	(2.89)
Employees					-0.0285	0.0363	-0.0616
					(-0.22)	(0.25)	(-0.55)
Distress					-0.0791	-0.0650	-0.0676
					(-0.87)	(-0.68)	(-1.03)
Load Factor						0.0517	0.0097
						(0.38)	(0.08)
COST						-0.3454	-0.2018
						(-0.65)	(-0.41)
Term Spread			0.0014				-0.0141
			(0.26)				(-1.06)
Trend							-0.0328***
							(-3.37)
Airline Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	N	Y	Y	Y	N
Observations	234	184	184	146	146	146	146
R-squared	0.405	0.378	0.296	0.756	0.760	0.763	0.752

Table 7: Does long Debt Maturity lead to Price Wars?

The dependent variable in the regressions is ***Price Cut*** computed as minus the change of average ticket price for a given route. The observations are at the route-year level. Only routes/year for which there is entry of at least one low cost airline are included. Only observations for which financials for all carriers operating on the same route in the previous year are available are included. ***Leverage*** is the average leverage of incumbents in year t-1, ***Maturity*** is the average debt maturity of incumbents in year t-1, and ***Cash Holdings*** is the average cash holdings of incumbents in year t-1. All regressions include an intercept (not reported). t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent variable:		**Price Cut**	
	(1)	(2)	(3)
Leverage	-0.0796**	-0.0827**	-0.0788**
	(-2.30)	(-2.32)	(-2.22)
Maturity		-0.0142	-0.0040
		(-0.37)	(-0.10)
Cash			0.2889**
			(2.12)
Observations	392	392	392
R-squared	0.013	0.014	0.025

Table 8: Are results driven by Financially Constrained Airlines?

The dependent variables in the regressions are ***Book Leverage*** and ***Debt Maturity***. Airlines are divided between financially constrained (book assets below annual median, or ***SA*** Index above annual median) and financially unconstrained (book assets above year median, or ***SA*** Index below annual median). ***SA*** Index is defined as in Hadlock and Pierce (2010). ***Threat of Entry*** measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. ***Log Sales*** is the log of dollar sales. ***Profitability*** is operative income before depreciation over book assets. ***Tangibility*** is Property, Plat and Equipment over book assets. ***Asset Maturity*** is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. ***Paying Passengers*** is log passengers. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Proxy of financial constraints	**Size**				**SA**			
Dependent Variable:	**Lev**		**Mat**		**Lev**		**Mat**	
Financially Constrained	Y	N	Y	N	Y	N	Y	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Threat of Entry	-0.0596	0.1402	0.3501**	0.0754	-0.1497	0.0833	0.3317**	0.0868
	(-0.34)	(1.16)	(2.26)	(0.56)	(-0.80)	(1.20)	(2.13)	(1.03)
Log Sales	0.0329	-0.0217	0.0600	0.1069	-0.0352	0.0314	0.1308	0.1207**
	(0.28)	(-0.36)	(0.79)	(1.20)	(-0.28)	(1.03)	(1.54)	(2.72)
Profitability	0.2797	0.3502	0.0467	-0.1862	0.3175	0.4096	0.0857	-0.2789
	(1.27)	(0.66)	(0.21)	(-0.41)	(1.18)	(0.89)	(0.38)	(-1.03)
Tangibility	1.0185***	0.0024	1.0549**	-0.8478*	0.9026***	-0.5633	0.8081	-1.5842***
	(5.23)	(0.01)	(2.25)	(-1.87)	(3.64)	(-1.10)	(1.55)	(-3.25)
Asset Maturity	-0.0045	0.0035	-0.0202	0.0069	-0.0031	0.0092	-0.0087	0.0166**
	(-0.79)	(0.38)	(-1.60)	(0.88)	(-0.52)	(1.43)	(-0.67)	(2.72)
Paying Passengers	0.0458	0.0793	0.0010	0.0384	0.0808	-0.0285	-0.0045	0.0148
	(1.26)	(0.96)	(0.02)	(0.69)	(1.65)	(-0.28)	(-0.07)	(0.20)
Airline Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	117	117	89	114	114	115	87	111
R-squared	0.704	0.619	0.806	0.514	0.734	0.714	0.806	0.650

Table 9: Does the Threat of Entry affect Debt Composition?

The dependent variables in the regressions are the proportion of bank debt, secured debt, and capital leasing, respectively. *Threat of Entry* measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Paying Passengers* is log passengers. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent variable:	**Bank Debt**		**Secured Debt**		**Capital Leasing**	
	(1)	(2)	(3)	(4)	(5)	(6)
Threat of Entry	-0.2938**	-0.2072*	0.1527	0.2004	-0.1326	-0.1333
	(-2.22)	(-1.94)	(1.09)	(1.44)	(-1.33)	(-1.51)
Sales	-0.0538	0.0098	0.0184	0.0653	-0.0084	0.0354
	(-0.97)	(0.17)	(0.29)	(1.03)	(-0.09)	(0.68)
Profitability	0.1277	-0.0457	-1.0656***	-1.1518***	-0.2649	-0.2888
	(0.58)	(-0.21)	(-3.85)	(-4.32)	(-1.41)	(-1.76)
Tangibility	-0.7574***	-0.6052**	-0.3949*	-0.2928	-0.2416***	-0.1831**
	(-3.04)	(-2.43)	(-1.75)	(-1.50)	(-3.87)	(-2.49)
Asset Maturity	0.0085*	0.0030	0.0180**	0.0138**	0.0053	0.0047
	(1.99)	(0.62)	(2.79)	(2.40)	(0.95)	(1.22)
Paying Passengers		-0.1018*		-0.0780**		-0.1046
		(-1.77)		(-2.64)		(-1.51)
Airline Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	141	141	174	174	110	110
R-squared	0.876	0.888	0.744	0.753	0.836	0.850

Table 10: Full sample results

The dependent variables in the regressions are ***Debt Maturity*** computed as non-current Liabilities over non-current Liabilities plus current Liabilities; ***Leverage*** computed as total Liabilities over total assets; ***Cash Holdings*** computed as total cash over total assets.
Threat of Entry measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. ***Size*** is the log of total assets. ***Profitability*** is net income over book assets. ***Paying Passengers*** is log passengers. ***Load Factor*** is Load Factor*(Net Income/Passengers). ***Term Spread*** is the difference between the yield on ten-year government bonds and the yield on three-month government bonds disclosed by the Federal Reserve. Financial data are taken from Form 41 financial filings. The sample contains 138 different airlines. ***Time interval*** indicates the year included in the sample (e.g., 91-13 indicates that years from 1991 to 2013 are considered). Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent variable:	**Debt Maturity**				**Leverage**	**Cash Holdings**
Time interval:	91-13	01-13	91-00	91-13	91-13	91-13
	(1)	(2)	(3)	(4)	(5)	(6)
Threat of Entry	0.2207***	0.2067**	0.2111**	0.2063***	0.0586	0.0571
	(2.81)	(2.26)	(2.01)	(4.44)	(0.78)	(1.09)
Size	0.1349***	0.1682***	0.1720***	0.1380***	0.0044	-0.0534***
	(4.26)	(3.05)	(6.93)	(4.34)	(0.16)	(-3.58)
Profitability	0.0013	-0.0458	0.1575	0.0053	-0.0065	0.0648
	(0.02)	(-1.07)	(1.16)	(0.10)	(-0.17)	(1.26)
Load Factor	-0.1047	-1.8895**	0.2132	-0.3095	0.1224	-0.3142
	(-0.22)	(-2.07)	(0.78)	(-0.62)	(0.45)	(-0.95)
Paying Passengers	-0.0326*	-0.0598**	-0.0408**	-0.0330**	-0.0011	0.0031
	(-1.94)	(-2.27)	(-2.38)	(-2.08)	(-0.08)	(0.38)
Term Spread				-0.0035		
				(-0.49)		
Trend				-0.0058*		
				(-1.89)		
Airline Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	N	Y	Y
Observations	794	452	342	794	794	782
R-squared	0.761	0.842	0.787	0.746	0.614	0.641

Table 11: Does Actual Entry affect Debt Policies?

The dependent variables in the regressions are *Book Leverage* and *Newly Issued Long−term Debt*. *Entry* measures the percentage of routes where entry actually occurs. Low cost airlines are dropped. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Paying Passengers* is log passengers. *Q* is book assets plus market value of equity minus book equity over book assets. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent Variable:	**Leverage**		**Newly Issued Long-term debt**		
	(1)	(2)	(3)	(4)	(5)
Entry	-0.0946	0.1122	0.2634	0.2890	0.1740
	(-0.21)	(0.37)	(1.20)	(1.22)	(0.65)
Sales	-0.0196	0.0959	-0.0488*	-0.0662*	-0.0521**
	(-0.17)	(1.34)	(-1.78)	(-1.99)	(-2.24)
Profitability	-0.7805	-0.9132***	0.1456**	0.1750**	0.1474*
	(-1.35)	(-3.10)	(2.55)	(2.59)	(2.14)
Tangibility	0.5658	0.7916**	-0.0154	-0.0496	-0.0063
	(1.27)	(2.41)	(-0.17)	(-0.48)	(-0.06)
Asset Maturity	-0.0136	-0.0180**	0.0034	0.0046	0.0020
	(-1.33)	(-2.63)	(1.13)	(1.48)	(0.45)
paying Passengers	-0.0149	0.0135		0.0244*	0.0124
	(-0.27)	(0.49)		(1.81)	(0.80)
Q		0.3374***			-0.0100
		(5.95)			(-0.69)
Term Spread					0.0057
					(1.03)
Airline Fixed Effects	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	N
Observations	234	184	234	234	184
R-squared	0.558	0.841	0.379	0.388	0.280

Table 12: Bootstrapped standard errors

The dependent variable in the regressions is Debt Maturity computed as non-current Long-term debt minus long-term debt maturing in 2 and 3 years over total debt. *Threat of Entry* measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Paying Passengers* is log passengers. *Q* is book asset plus market value of assets minus total common/ordinary equity over book assets. *Term Spread* is the difference between the yield on ten-year government bonds and the yield on three-month government bonds disclosed by the Federal Reserve. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are obtained through block bootstrapping with 26 blocks and 200 replications. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent variable:	**Debt Maturity**					
	(1)	(2)	(3)	(4)	(5)	(6)
Threat of Entry	0.2813***	0.2823***	0.2964***	0.2113**	0.2097**	0.3740***
	(3.07)	(2.65)	(2.88)	(2.58)	(2.40)	(4.08)
Log Sales	0.1050*	0.1066	0.1876*	0.0871*	0.0788	0.1120*
	(1.95)	(1.63)	(1.65)	(1.77)	(1.36)	(1.71)
Profitability	0.1188	0.1157	0.3482	0.0889	0.1016	0.2323
	(0.31)	(0.28)	(0.72)	(0.26)	(0.29)	(0.67)
Tangibility	0.0636	0.0663	0.2504	0.0436	0.0259	0.1774
	(0.22)	(0.15)	(0.50)	(0.15)	(0.08)	(0.65)
Asset Maturity	0.0051	0.0050	0.0005	0.0060	0.0064	0.0023
	(0.67)	(0.54)	(0.04)	(1.01)	(1.04)	(0.30)
Paying Passengers		-0.0022	-0.0327		0.0122	-0.0304
		(-0.03)	(-0.46)		(0.22)	(-0.65)
Q			-0.1016			-0.0659
			(-1.63)			(-1.61)
Term Spread				-0.0207**	-0.0206**	-0.0242**
				(-2.26)	(-1.97)	(-2.47)
Airline Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	N	N	N
Observations	203	203	161	203	203	161
R-squared	0.634	0.634	0.710	0.614	0.614	0.686

Table 13: Other Variables

The dependent variables in the regressions are ***Cash Holdings***, ***Investment***, ***Asset Growth*** and ***Equity Issuance***, respectively. ***Threat of Entry*** measures the percentage of routes under the threat of entry by low cost carriers weighted by the number of passengers. ***Log Sales*** is the log of dollar sales. ***Profitability*** is operative income before depreciation over book assets. ***Tangibility*** is Property, Plat and Equipment over book assets. ***Asset Maturity*** is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. ***Paying Passengers*** is log passengers. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent variable:	Cash Holdings (1)	Investment (2)	Asset Growth (3)	Equity Issuance (4)
Threat of Entry	-0.0045	0.0689	0.6669	0.2810
	(-0.08)	(1.56)	(1.71)	(0.78)
Log Sales	-0.0138	-0.0782***	-0.1065	-0.2228
	(-0.73)	(-4.37)	(-0.84)	(-1.36)
Profitability	0.2947***	-0.0492	3.2968	0.3391
	(4.57)	(-0.52)	(1.67)	(0.89)
Tangibility	-0.2642***	-0.0338	-1.3080**	-1.1402
	(-2.90)	(-0.37)	(-2.42)	(-1.57)
Asset Maturity	0.0039	0.0055	0.0669***	0.0236
	(1.37)	(1.60)	(3.03)	(1.62)
Paying Passengers	0.0006	0.0096	0.0616	0.0765
	(0.05)	(0.90)	(0.52)	(0.97)
Airline Fixed Effects	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Observations	234	234	228	228
R-squared	0.698	0.642	0.357	0.209

Table 14: Does Exit affect Debt Maturity?

The dependent variables in the regressions are Debt Maturity (columns 1 and 2) and Newly Issued Long-term debt (columns 3 and 4). *Exit* measures the percentage of incumbent's i routes left low cost airlines. *Log Sales* is the log of dollar sales. *Profitability* is operative income before depreciation over book assets. *Tangibility* is Property, Plat and Equipment over book assets. *Asset Maturity* is current assets over current assets plus Property, Plat and Equipment times current assets over cost of goods sold, plus Property, Plat and Equipment over current assets plus Property, Plat and Equipment times Property, Plat and Equipment over depreciation and amortization. *Paying Passengers* is log passengers. *Q* is book assets plus market value of equity minus book equity over book assets. Accounting variables are winsorized at the 1% level. All regressions include an intercept (not reported) and year and airline dummies where specified. Errors are clustered at the airline level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1%, respectively.

Dependent Variable:	**Debt Maturity**		**Newly Issued Long-term debt**	
	(1)	(2)	(3)	(4)
Exit	-0.4630	-0.4131	-0.1875	-0.0495
	(-0.92)	(-1.49)	(-0.86)	(-0.36)
Log Sales	0.0956	0.0647	-0.0443	-0.0425**
	(1.49)	(1.55)	(-1.64)	(-2.07)
Profitability	0.0637	0.0672	0.1268*	0.1022
	(0.17)	(0.20)	(2.01)	(1.59)
Tangibility	0.1113	0.0757	-0.0157	-0.0181
	(0.29)	(0.25)	(-0.16)	(-0.21)
Asset Maturity	0.0030	0.0039	0.0032	0.0028
	(0.45)	(0.66)	(0.99)	(0.85)
Term Spread		-0.0122		0.0031
		(-1.21)		(0.69)
Airline Fixed Effects	Y	Y	Y	Y
Time Fixed Effects	Y	N	Y	N
Observations	192	192	222	222
R-squared	0.617	0.597	0.399	0.339

A Appendix

Table A.1: Description of variables

This table provides a detailed description of the variables used. Airline characteristics are from Compustat and form 41 filings. Debt structure variables are from Capital IQ. Size, equipment owned and sales are in million dollars, passengers and employees are in thousand people.

Variable	Definition
Size	Total assets
Sales	Log of sales
Total Debt	Debt in current liabilities + Long-term debt
Threat of Entry	See Section 4
Profitability	Operating income before depreciation / Total assets
Tangibility	Net property, plant and equipment (PPENT) / Total assets
Asset Maturity	(Current Assets/(Current Assets+PPENT)*(Current Assets/Cost of goods sold)+ +(PPENT/(Current Assets+PPENT)*(PPENT/Depreciation and amortization)
Paying passengers	Log passengers
Cash Holdings	Cash/Total assets
Fuel	Fuel expenditure for domestic flights over book assets
Rating	Dummy = 1 if a firm is rated by S&P
Equipment Owned	Log dollar value of equipment owned (including leased planes)
Employees	Log employees
Distress	Dummy = 1 if firm's value of total liabilities is greater than total value of assets
Load Factor	Load factor from 41 filings * * (Operating income before depreciation / Passengers)
COST	Cost of goods sold/Available seats
Term Spread	yield on ten-year government bond - - yield on three-month government bonds
Q	(book assets + market value of equity - book equity)/ book assets
Book Leverage	Total Debt/Total Assets
Market Leverage	Total Debt/(Total Assets + Market Value of Equity - Book Value of Equity)
Debt Maturity	Ratio of long-term debt (DLTT) - - debt maturing in two and three years (DD2+DD3) to total debt

Are Star Funds really Shining? Cross-trading and Performance Shifting in Mutual Fund Families

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Abstract

This paper exploits institutional trade level data to study cross-trading activity inside mutual fund families. Cross-trades are opposite trades matched between siblings (i.e., funds belonging to the same fund family) without going to the open market. We find that large fund families with weak governance and high within family size dispersion cross-trade more and are more likely to misprice their cross-trades. Additionally, we find that cross-trades are used to increase the performance of the most valuable siblings (on average by 2.5% per annum) at the expense of the less valuable funds. More restrictive governance policies introduced as a consequence of the late trading scandal were effective in reducing the amount and the mispricing of cross-trades.

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1 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[1]. This conflict of interest can be magnified 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. Specifically, using a unique institutional trade-level dataset we examine the cross-trading activity inside mutual fund families and its consequence on performance. Cross-trades are transactions where buy and sell orders for the same stock coming from the same fund family are offset by the broker without going into the open market. Cross-trades are permitted under rule 17a-7 of the U.S. Investment Company Act and can be beneficial for mutual fund investors since they reduce trading costs and commissions. However, unfairly priced cross-trades are illegal and potentially shift performance between the two parties involved in the trade.

Previous literature has provided evidence of illegal performance shifting consistent with cross-trading. However, due to data availability previous papers infer potential cross-trading activity from quarterly holdings data[2] (see e.g. Gaspar, Massa, and Matos (2006), Goncalves-Pinto and Sotes-Paladino (2010)) or indirectly from return level data (see Chaudhuri, Ivkovich, and Trzcinka (2012)) with controversial findings. In contrast, from our institutional trade-level dataset provided by Ancerno we identify cross-trades as trades executed within the same fund family, in the same stock, with the same volume, the same execution price, the

[1] There is a significant literature suggesting that money manager opportunistically try to present a "rosier" version of reality to their investors, see, e.g., Lakonishok, Shleifer, Thaler, and Vishny (1991), Sias and Starks (1997), Ben-David, Franzoni, Landier, and Moussawi (2013) on window dressing practices.

[2] Using quarterly holdings it is not possible to distinguish whether two funds trading the same stock in opposite directions are trading during the same day or in different months. Hence, the resulting proxies of cross-trading activity are upward biased.

same execution date and the same execution time but in opposite trade directions. Thus, we provide a significantly more precise proxy for cross-trading activity. Additionally, having the cross trades' execution prices we can directly assess any impact on performance.

We begin our empirical analysis studying the determinants of cross-trading activity and find supporting evidence for the hypothesis that cross-trading is used to shift performance across different funds. First, cross-trading activity is significantly higher in fund families with weak governance. Second, in line with the argument that a big difference in product sizes would allow to move performance from big to small products at low cost (Chaudhuri, Ivkovich, and Trzcinka (2012)) we find that cross-trading activity increases when there are large size differences between funds in the family. Third, consistent with the incentive of creating "star funds" stressed in Nanda, Wang, and Zheng (2004) cross-trading activity is increasing in the intra-family dispersion of returns. Besides testing the cross-sectional determinants of cross-trading activity we also study the time-series determinants. 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 fund families. Hence, if cross-trading was primarily used to illegally shift performance across funds, it should decrease after 2004. Our results suggest that indeed cross-trading activity decreased significantly after 2004.

Families are only able to shift performance via cross-trades when the execution prices of the trades deviate significantly from the market price at the time of order execution. In the next step we therefore compare execution prices of cross-trades to the volume weighted average execution price of the day (VWAP). We find that cross-trades in our sample are often mispriced, displaying execution prices up to 2% away from VWAP. Furthermore, the families that cross-trade the most are also more likely to cross-trade at prices far away from the VWAP. Finally, the requirement to employ a compliance officer pushed the execution prices of cross-trades significantly towards the VWAP implying a lesser degree of performance redistribution across funds.

Our aforementioned results are suggestive of performance shifting at the mutual fund family level. However, our findings about the mispricing of cross-trades are consistent with two different strategies. First, in line with Goncalves-Pinto and Sotes-Paladino (2010), Bhattacharya, Lee, and Pool (2012), Schmidt and Goncalves-Pinto (2012) families can shift performance via cross-trades in order to smooth performance across different funds in the family. Such a strategy would help low value funds that suffer because of investor redemptions at the expense of high value siblings[3]. We refer to such a strategy as performance smoothing. Second, in line with the incentive of fund families to enhance the performance of the most valuable funds (see Guedj and Papastaikoudi (2005), Gaspar, Massa, and Matos (2006), and Evans (2010)) fund families can use cross-trades to play favorites, increasing the performance of high value funds while hurting the performance of the less valuable funds.

To distinguish between the two different strategies we study mutual fund returns employing an empirical strategy motivated by the seminal paper of Gaspar, Massa, and Matos (2006). In particular, we study the differences in risk-adjusted returns between funds having a high value for the fund family and funds having a low value for the fund family and test whether the amount of cross-trading activity has a significant impact on this difference. Following the literature (see, e.g., Bhattacharya, Lee, and Pool (2012)) we define high-value funds as funds with flows in the top tercile of the fund family flow distribution and low value funds as funds with flows in the bottom tercile. We regress their spread in performance on the percentage of cross-trading within their family conditional of being in the same investment style and controlling for differences in fund size, past performance and past flows plus other family level controls. We find that an increase by one standard deviation in within family cross-trading increases the gap in the alphas between high value and low value funds by 22

[3]We refer to "high value" ("low value") siblings to indicate funds that we conjecture to be particularly important (unimportant) for the family, e.g., because they are able to attract high (low) flows or charge high (low) fees.

basis points per month (51 bps if we consider the spread in raw returns). Additionally, we use mutual fund fees as a sorting variable instead of flows (consistent with Gaspar, Massa, and Matos (2006)) and find similar results. Finally, we replace the level of cross-trading with the monthly average mispricing of cross-trades in the family as our independent variable of interest and obtain results in line with our previous tests.

Our analysis is motivated by a recent legal action of the Security and Exchange Commission against Western Asset Management. The investment firm allegedly executed the sell side of cross transactions at the highest current independent bid price available for the securities. By cross trading securities at the bid, rather than at an average between the bid and the ask, Western favored the buyers in the transactions over the sellers, even though both were advisory clients of Western and owed the same fiduciary duty. As a result, Western deprived its selling clients of approximately $6.2 million. According to the SEC Western's cross-trading violations were caused in large part by its failure to adopt adequate policies and procedures to prevent unlawful cross-trading[4].

Hence, to make sure our results are really driven by opportunistic practices, we explore how time-series and cross-sectional differences in family governance affect our results. We find performance shifting to be almost 10 times less effective after 2003 when the new SEC regulation was implemented. Furthermore, performance shifting via cross-trades is significantly stronger in fund families with weak family governance.

Overall, our results indicate that fund families exploit cross-trades to improve the performance of high value funds at the expenses of low value siblings. This finding is consistent with the incentive of families to improve the performance of the best funds in order to attract new inflows. 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 vein mutual fund complexes desire to attract flows

[4]See administrative proceeding No. 3-15688 of January 27, 2014. Similar evidence is provided by the SEC case against BNY Mellon, administrative proceeding No. 3-14191 of January 14, 2011.

to the family to collect more fees. Increasing returns of sibling funds at the expense of a less expensive fund is optimal if we take into account the findings of Sirri and Tufano (1997) 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.

The incentive for fund families to play favorite is stressed in Gaspar, Massa, and Matos (2006). The authors empirically document that favorite funds (e.g., high-fee funds) outperform less valuable funds. While Nanda, Wang, and Zheng (2004) show empirically that one fund in the family outperforming the rest of the market has a significant positive impact in terms of fund flows on all other funds in the family. Thus, strategically shifting performance to create one "star" fund in the family can be rational from family perspective despite simultaneously decreasing the returns for some fund investors.

This paper makes two contributions to the literature. First, a large debate in this field concerns whether siblings help or exploit funds in the same families that suffer because of money redemptions. Cross-trading is probably the easiest way for equity funds to shift performance from or to other siblings. However, mutual funds are required to publish their holdings at a quarterly frequency. Hence, previous literature was forced to estimate imprecise proxies of cross-trading activity out of low-frequency data. As a consequence, other papers find controversial results. In this paper we exploit high-frequency transaction data to build a reliable proxy of cross-trading activity. Our finding supports the hypothesis that performance is shifted from low value funds to the most valuable siblings in the family despite fiduciary duties would demand to treat all funds equally.

Second, we show that cross-trading has an enormous impact on the ability of funds to generate "alpha". We find that cross-trading boosts on average the risk-adjusted performance of top funds of roughly 1.0% per year (causing an equivalent loss for the least important funds) compared to funds belonging to families that display no cross-trading activity. Additionally, this artificially constructed performance is "pure alpha" since it is uncorrelated to any risky factors. The mutual fund literature (as well as mutual fund clients) heavily relies on past alpha as a proxy of a fund manager's skill. However, our results suggest that a large fraction of alpha has nothing to do with skill but is simply an effect of performance redistribution. Consistently, the constraint to cross-trading activity that has followed the new regulation introduced after the late trading scandal may contribute to explain the decreased "ability" of fund managers to generate risk-adjusted performance documented in the last decade (see, e.g., Pastor, Stambaugh, and Taylor (2014)).

This paper proceeds as follows. Section 2 describes the data we used. In Section 3 we document cross-trading activity. Section 4 disentangles between the cooperation and the favoritism hypotheses. Section 5 presents additional robustness checks. Section 6 concludes.

2 Data

For our analysis we compile data from four different sources. First, we use the CRSP Survivor Bias Free US Mutual Fund Database to obtain mutual fund returns and characteristics. Second, we use the MFLinks table provided by WRDS. Third, we use a table provided by WRDS linking management companies from SEC 13F filings to mutual funds reporting their holdings in the Thomson Reuter's S12 holdings database. Finally, we use institutional trade-level data provided by Abel Noser Solutions/ANcerno, a consulting firm that works with institutional investors to monitor their trading costs.

2.1 Mutual Fund Data

Our dataset construction starts with a merge between the CRSP database, the MFLinks table and information concerning the management companies. The merge with the MFLinks table allows us to aggregate mutual fund information across different share classes and deletes all funds not trading in equities. Furthermore, it provides an identifier to match management companies to the mutual funds. After the merging of the datasets we impose two filters. As the focus of our analysis is on mutual fund families we exclude families with less than three family members. The requirement to have at least three funds trading in equities is driven by our empirical methodology and is explained later. Additionally, we impose a minimum number of return observations for a fund to be included in our sample. 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 compute Carhart (1997) four factor alphas. To ensure reliable estimates we require a fund to have at least a 3-year return history. Finally, we focus on data between 1999 and 2010 where the ANcerno data is available to us.

Besides mutual fund alphas, we obtain several other variables important for our analysis from the CRSP Mutual Fund Database and the Thomson holdings data. On the fund level we obtain a mutual fund's size, its fees and its flows. Following Gaspar, Massa, and Matos (2006) we compute fees as 1/7(frontload+rearload)+expense ratio. For the flows we follow the literature (e.g. Coval and Stafford (2007)) and compute them as

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

where TNA are the total net assets under management and ret is the monthly return of fund i in month t. On the family level we obtain the family size, the intra-family return dispersion and the intra-family size dispersion. Family size is the defined as the sum of the individual funds' assets. For intra-family return dispersion we follow Nanda, Wang, and Zheng (2004) and compute it as

$$ReturnDispersion_{ft} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\alpha_{it} - \bar{\alpha}_{ft})},$$

where α_{it} is the four-factor alpha of fund i in month t and $\bar{\alpha}_{ft}$ is the mean of four-factor adjusted returns of all siblings within family f in month t. The variable ***Size Dispersion*** is defined as the difference between the size of the largest and the smallest fund in the family scaled by the average size of the funds in the family. Additionally, we compute the variable ***Siblings*** as the natural log of the number of equity funds belonging to the same family f in month t. Finally, we use Thompson Reuters investment objective codes to identify the investment style for each fund.

2.2 Institutional Trading Data

We obtain trade-level data from Abel Noser Solutions/ANcerno, a consulting firm that works with institutional investors to monitor their trading costs. This database contains a detailed record of *all* executed trades since the client started reporting[5]. Previous research has shown that ANcerno institutional clients constitute approximately 8% of the 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)).

The data is collected at the trade level and contains several variables useful for our investigation: stock identifier (*cusip*), *tradedate*, execution price, execution time, volume traded, side of the trade (i.e., buy or sell). This information is sent to Ancerno by its different clients. The identity of the clients is thereby always anonymized. Importantly, while the client is anonymized the family (called manager in Ancerno) is not. Ancerno for a limited period of time has provided a separate table including a *managercode* and a *managername* and the variables to link them to the trades. This allows us to match the Ancerno data with the CRSP Mutual Fund Database.

In particular, we hand-match fund families from ANcerno to 13f/S12 by name. There are few papers which use the management company identifier provided by ANcerno to match it with 13f companies, e.g., Franzoni and Plazzi (2012), Jame (2012). However, previous papers focused only on Hedge Funds while this is the first paper to match ANcerno to mutual fund

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

families reporting to 13f.

Our matched database spans the time interval from 1999 to 2010 and covers families including 35% to 45% of the funds in the CRSP database. Unfortunately, ANcerno did not provide us with unique fund identifies. Whether it is possible to identify funds at all using ANcerno data is debatable (from our conversations with the ANcerno support team it seems that this is not possible). Therefore, we keep all the variables we obtain from ANcerno at the family level. Recently, ANcerno has decided not to provide family identifiers anymore. Hence, our data series stops at the end of 2010, since we are not able to match trades with fund families after that date.

Our main variable of interest computed from the ANcerno data is the amount of cross-trading taking place inside a mutual fund family. A cross-trade is a transaction where a buy and a sell order for the same stock coming from the same fund family is conducted by the broker without going through the open market. We identify cross-trades in our database as transactions occurring i) in the same family ii) in the same stock, iii) at the same time, iv) at the same price and having the v) the same volume in opposite directions. Figure 1 plots average commission costs for all the trades in ANcerno and the trades we identify as cross-trades. The commissions paid for cross-trades are about 1/10th of the other trades since the broker has not to look into the open market for an opposite trade but simply to record it. This result suggests that our methodology is correct. This identification solves the main concern about the cross-trade definition used in other papers based on quarterly snapshots (see e.g. Gaspar, Massa, and Matos (2006)). Using our approach, opposite trades recorded in the same quarter but occurring on different days are *not* considered as cross-trades. Therefore, our main explanatory variable $CT_{i,t}$ is computed as the dollar volume of cross-trades executed by family f in month t over its total dollar volume of trades in the same month.

2.3 Summary Statistics and Additional Variable Definitions

Table 1 presents summary statistics over time. Panel A shows the sample of mutual funds before matching the families with Ancerno data. The average number of funds per month ranges from a maximum of 1799 to a minimum of 775. These funds are managed by between 225 and 135 different mutual fund management companies. The average and median mutual fund size significantly increases over time. While the average fund size was around USD 1 billion in 1999 it increased to nearly USD 1.9 billion in 2010.

Matching our sample of mutual funds to the ANcerno data decreases our sample size significantly. On average our matched sample contains between 20% and 25% of the mutual fund families from Panel A. Having between 36 and 49 families and 357 and 709 different mutual funds provides however a sample sufficient to conduct our empirical tests. Importantly, our sample is biased toward large families since the smallest families are less likely to buy ANcerno's services (this bias has been recognized also by previous studies see, e.g, Puckett and Yan (2011)). In particular, our final sample contains observations from 8 out of the 10 largest mutual fund families is the United States[6]. However, since the top 10 families hold around 70% of the assets managed by the whole mutual fund industry, the bias toward larger institutions does not seem to compromise the validity of our analysis.

Table 2 presents summary statistics for the variables used in our empirical tests. Panel A shows fund level variables and Panel B displays family level variables. in total we match 206 families out of which 127 cross-trade at least one time. The most important variable for our analysis is the cross-trading variable ***CT***. In total we classify 732434 separate trades as cross-trades The average monthly cross-trading volume per family is 0.0135% of the total monthly trading volume. This number is small, but mainly driven by the fact that a large fraction of families are not engaging in any cross-trade activity. For more than 75% of all our family-month observation the variable ***CT*** is equal to zero.

Panel B of Table 2 also contains the so far undefined variable ***Weak Governance***. In

[6]Given the non-disclosure agreement we signed with ANcerno we are forbidden to reveal the exact names of the management companies contained in our sample.

several of our tests we study the relationship between cross-trading and the governance of the mutual fund family. For this purpose we search in the Internet and in the SEC filings whether a family was involved in any kind of SEC litigation. Panel B of Table 2 shows that 36.8 of all our observations comes from families involved in a SEC investigation.

3 Empirical Results

3.1 The cross-section of cross-trades

Cross-trading is the practice where buy and sell orders for the same stock coming from the same fund family are offset by the broker without going through the open market. Cross-trades are permitted under rule 17a-7 of the U.S. Investment Company Act provided that i) such 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[7] is calculated by averaging the highest and lowest current independent bid and offer price determined on the basis of a reasonable inquiry. Yet, some discretion may be in order when determining the "current market price[8]".

This section studies how family characteristics and time-series variation in mutual fund industry regulations affect cross-trading activity. In particular, if cross-trades are used to shift performance, we would expect the following variables to be correlated with a family's cross-trading activity.

Previous literature suggests that fund proliferation is used as a marketing strategy to attract new clients (Massa (2003)) and a large number of funds in a family allows families to manage their funds like internal capital markets shifting performance across funds with similar holdings and investment styles. The first explanatory variable used in our analysis is

[7]E.g., municipal securities.

[8]From our talks with compliance officers and professionals in large fund families, we understand that the pricing of cross- 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 recorded execution price strongly deviates from the average between the bid and the ask.

therefore the number of funds in a family (***Siblings***). We also include a mutual fund family's size in our regressions (***Family Size***). The high correlation of ***Family Size*** and ***Siblings*** (above 90%) potentially creates problems due to multicollinearity concerns.

The next variable we use is ***Weak Governance***, a dummy equal to 1 for families involved in a SEC litigation case and equal to zero otherwise. We conjecture that families having been engaged in suspicious practices in the past are on average more likely to lack the necessary control mechanisms to detect and avoid illegal cross-trading activity.

Chaudhuri, Ivkovich, and Trzcinka (2012) argue that an asymmetry of "product" size allows to take away relatively minor performance from larger funds to enhance substantially the performance of smaller funds. In line with this argument we include the variable ***Size Dispersion*** in our regressions.

Nanda, Wang, and Zheng (2004) empirically show that a strategy of some mutual fund families is to start a large number of funds with different strategies to increase the chances to create a "star fund", i.e., a fund whose performance ranks high among its peers. Such families have on average a higher intra-family return dispersion (***Return Dispersion***). We conjecture that families following the aforementioned strategy are also more likely to use cross-trades in order to increase the performance of specific funds in the family.

Finally, we study governance not only in the cross-section, but also in the time-series. An exogenous change in the regulatory environment forcing management companies to improve their governance was triggered by the late trading scandal. On September 3, 2003 the New York State Attorney General Eliot Spitzer announced the issuance of a complaint claiming that several mutual fund firms had arrangements allowing trades that violated terms in their funds' prospectuses, fiduciary duties, and securities laws. Subsequent investigations showed that at least twenty mutual fund management companies, including some of the industry's largest firms, had struck deals permitting improper trading (McCabe (2009)).

As a consequence of the scandal, in 2004 the SEC adopted new rules requiring fund families to adopt more stringent compliance policies. In particular, Rule 38a-1 under the

Investment Company Act of 1940 required each fund to appoint a chief compliance officer responsible for administering the fund's policies and procedures. Additionally, compliance officers have to report directly to the board of directors to increase their independence. The compliance date of the new rules and rule amendments was October 5, 2004. From our talks with compliance officers at one of the largest management companies, we understood that one of the main tasks of the compliance officer is to check that the execution price of the cross-trades is within a "reasonable" range from the mid price of the day.

This regulatory change makes it, on the one hand, more difficult for fund families to misprice cross-trades. On the other hand, if performance shifting was the main rationale for crossing trades within the family, the new regulation reduces the incentive for cross-trading activity. To capture a potential decrease in cross-trading activity we define a dummy variable equal to one for observations after 2003

Table 3 presents results from pooled regressions of cross-trading activity on the above-mentioned variables. Observations are at the month-family level and all standard errors are clustered at the time level. In columns (1)-(6) of Table 3 we first run univariate regressions using the different family characteristics and, to capture the regulatory change in 2004, the dummy equal to one for observations after 2003. Our results indicate that families with many siblings, weak governance, high size and return dispersion, and a large family size have exhibit significantly higher cross-trading activity. This result is in line with the hypothesis that mutual fund families use cross-trades to actively shift performance between different funds in the family. Additionally, the average amount of cross-trading significantly drops (by roughly 8.4 basis points) after the late trading scandal. Hence, the new compliance policy was effective at the very least in limiting the amount of cross-trading activity.

In column 7 we run multivariate regressions. While most of the coefficients stay significant and have similar magnitudes as in the univariate regressions, the effect of *Siblings* on the amount of cross-trading becomes ambiguous. The estimated coefficient is positive and significant in column 1. After controlling for other family characteristics however, the sign changes in column 7. This finding is probably driven by the high correlation between ***Siblings*** and ***FamilySize***.

In Figure 2 we plot the average amount of cross-trading across time. The figure shows clearly that the decrease in cross-trading is not a trend but starts around the late trading scandal. In particular, cross-trading activity drops significantly after the new regulation's compliance date.

3.2 The Pricing of Cross-Trades

Cross-trading is legal when it occurs at reasonable market prices and does not benefit one counterparty over the other. Conversely, cross-trading shifts performance when one party buys (or sells) at a discount (or at a premium). In Table 4 we regress the absolute percentage deviation of the execution price from the VWAP on family characteristics. If cross-trades were correctly priced we should not observe significant deviations from the VWAP. Additionally, family characteristics should not matter on how cross-trades are priced. Here only one leg of the cross-trades is included in the sample, e.g., only the buy side (since the sell side of the cross-trades is executed at the same price, running our regressions only on the sell side would give exactly the same results). In our regressions we use the same explanatory variables as before. We do not include stock level controls since characteristics that normally have an effect on the execution price (such as stock illiquidity, price impact, past return) should be of no importance when the trade is not executed in the open market. Our regressions are now at the trade level and include ***only*** cross-trades. Day fixed effects are included and errors are clustered at the day level.

Almost all variables that predict a larger amount of cross-trading activity also predict higher mispricing in the execution price. Families with weak governance, more assets to manage, and large fund size dispersion execute cross-trades at prices far away from the average of the market during the day for that particular stock (the coefficient of ***Return Dispersion*** is however not significantly different from zero). This result strongly suggests that cross-trades executed within such families “move” performance. Additionally, after the late trading scandal, the average deviation from the VWAP drops by 36 basis points (see also Figure 3). Results in this section suggest that cross-trading shifts performance between funds. However, we cannot tell whether cross-trades are use to shift performance to the most valuable funds or smooth performance across all funds in the family.

4 Star funds, cross-trading and performance shifting

4.1 Methodology

In this section we explore whether fund families use mispriced cross trades as a tool for shifting performance toward the most valuable funds or smooth performance across the family.

On the one hand, the work of Nanda, Wang, and Zheng (2004) suggests that there is a clear incentive for a mutual fund family to improve the performance of good performing funds with high inflows. Nanda, Wang, and Zheng (2004) find that funds rated as “star” funds by the popular Morningstar rating experience significant inflows and they have a positive spill-over effect on other funds in the family. Specifically, also other funds in the family have higher inflows when there is one “star” fund in the family. On the contrary, a bad performing fund in the family does not seem to have any negative effect on the flows to rest of the family. Flows are of particular importance in the mutual fund industry since revenues are usually a fixed part of the asset under management, i.e., performance fees are uncommon (Haslem (2010)). Hence, in order to maximize fees at the family level performance shifting via cross-trades can be an optimal strategy for a fund family.

On the other hand, cross-trades can be used by the family to provide liquidity to under-performing funds to decrease the performance consequences of large investor redemptions. This strategy would be optimal when a severe underperformance of a fund has a negative impact on the other members of the family that is greater than the cost of providing coinsurance. Goncalves-Pinto and Sotes-Paladino (2010), Bhattacharya, Lee, and Pool (2012) and

Schmidt and Goncalves-Pinto (2012) provide support for this hypothesis.

The two alternative hypotheses mentioned above have opposite empirical predictions. According to the favoritism hypothesis, cross-trading should increase the gap in the performance between the most important funds and the least important funds in the family. Conversely, the performance smoothing hypothesis predicts that cross-trading reduces the spread in their performance. Importantly, according to the law cross-trading could decrease trading costs and, hence, improve funds' performance. However, it should not be systematically correlated with the gap in the performance between high and low value funds.

It is important to highlight again that due to the structure of our data we are not able to identify the funds on both sides of a cross-trade, i.e. we are not able to pinpoint which funds in the family are trading with each other. Our empirical strategy is therefore first to define groups of funds inside a family which we hypothesize are likely to benefit or suffer from cross-trading if a fund family strategically shifts performance. Afterwards, we test whether the difference in their returns correlates with cross-trading activity drawing from the methodology of Gaspar, Massa, and Matos (2006).

Specifically, in our main tests we rank funds according to their monthly flows (see, e.g., Bhattacharya, Lee, and Pool (2012)). The reason for ranking funds according to their flows is intuitive. Funds with outflows are liquidity demanders and funds with inflows are the natural liquidity suppliers. On the one hand, under a performance smoothing family strategy the liquidity suppliers can buy at inflated prices securities from the liquidity demanding funds thereby increasing the performance of the outflow funds while decreasing their own performance. On the other hand, the liquidity supplying funds can buy at deflated prices securities from the liquidity demanding funds increasing the performance of the inflow funds. Besides ranking funds according to their flows, in some of our tests we also rank funds according to their fees following Gaspar, Massa, and Matos (2006).

Having ranked the funds, we sort them inside a family into terciles[9]. Funds that display

[9]Using quintiles gives similar results.

intermediate flows are discarded. From the two extreme terciles we construct pairwise combinations of funds from the top and the bottom terciles and we compute the spread in their style adjusted performance (4-factor alpha). In order to control for style effects we impose as an additional restriction that the funds operate in the same investment style.

For instance, consider a family having 6 funds with the same investment style and assume that in month t, the funds have all different flows. This implies a ranking from 1 to 6 and two funds in each tercile. For our analysis we discard the funds ranked third and fourth and we build the return spread from the remaining funds. Specifically, the observations in our final sample are the difference of performance between fund 5 and fund 1; fund 5 and fund 2; fund 6 and fund; fund 6 and fund 2.

To understand whether cross-trading smoothes performance across the family or shifts performance to the most valuable funds, we regress the spread in performance between funds in the top tercile and bottom tercile on different measures of cross-trading activity controlling for family characteristics and observable differences between the two funds. Formally,

$$Spread_{i,j,t} = \beta(CT_{f,t}) + Controls_{i,j,t} + \theta_t + \varepsilon_{i,j,t},$$

where $spread$ is the difference between the high value fund i and the low value fund j's raw performance (or 4 factor alpha) in month t conditional on having the same investment style and belonging to the same fund family. θ_t are month fixed effects and $CT_{f,t}$ is the cross-trading measure.

The average $spread$ will be positive since on average funds with higher flows (fees) outperform funds with lower flows (fees). However, under the null hypothesis of no strategic interaction, we should not expect a statistically significant correlation between the spread in performance and CT. Under the favoritism hypothesis we should expect a positive correlation between the spread and CT (i.e., favoritism increases the performance of the high value funds at the expense of the low value siblings). Under the performance smoothing hypothesis we should expect a negative coefficient (i.e., families smooth performance, decreasing the gap in performance between high and low value funds).

4.2 Favoritism versus Performance Smoothing

In Table 5 we study the effect of cross-trading activity on the performance spread between high flow and low flow funds inside each family. We report results for the spread in style adjusted returns (columns 1-4) and for the spread in 4-factor alphas (columns 5-8). All of our regressions include time fixed effects and we cluster errors at the time level[10].

The correlation between ***CT*** and ***spread*** is positive and strongly significant. This result suggests that cross-trades favor the high inflow funds at the expenses of low inflow funds inside the family and does not support the performance smoothing hypothesis. Controlling for a number of control variable does change the results qualitatively. In column 2 and 6 we include ***Family Size*** in the regressions to control for the significant relation between cross-trading and family size[11]. In columns 3 and 7 we include a number of fund level controls. Specifically, to ensure that our results are not driven by differences in characteristics between the two funds in a spread portfolio we include their size difference (Δ***Size***), their return difference in the previous month (Δ***Returns***) and the their flow difference in the previous month (Δ***FLow***). The results suggest that fund level differences are of no statistical importance. Finally, we also include the family level variables ***Size Dispersion*** and ***Return Dispersion*** in the regressions. Columns 4 and 8 suggest that ***Size Dispersion*** and ***Return Dispersion*** not only have a positive impact on cross-trading activity, but also independently predict a higher difference in returns between high value funds and low value funds.

We consider different specifications of our main test. First, instead of using the cross-trading activity ***CT*** as a regressor we use the value-weighted mispricing of cross-trades. Potentially, our previous results would be consistent also with a big spread in performance

[10]Clustering errors at the fund pair level or including fund-pair fixed effects does not influence the results.

[11]We use family size and not the number of siblings. Using ***Siblings*** as a regressor does not change the results.

between high and low value siblings triggering higher cross-trading activity. In order to show that cross-trades have a causal effect on the performance spread, we want to show that a higher mispricing of the cross-trades is associated with a larger performance gap. To obtain this explanatory variable we first compute the mispricing of each cross-trade as the difference between the execution price and the VWAP of the day. Afterwards we aggregate the mispricings for each family in each month by weighting the different cross-trades by their dollar size. Hence, a family whose cross-trades are on average priced far away from the VWAP have a higher value of our variable "value-weighted mispricing". The results in Table 6 suggest a positive effect of value-weighted mispricing on the performance spread between high flow funds and low flow funds. Again, this results supports the hypothesis of a family strategy which shifts performance to the most valuable funds.

Second, we sort funds according to their fees instead of their flows. Gaspar, Massa, and Matos (2006) argue that high fee funds are more valuable to the family as they generate more fee income. Hence, families can use cross-trades to increase the performance and the subsequent flows of high fee funds. And indeed, the results in Table 7 support this hypothesis. Although the results are economically weaker, there is a statistically significant relationship between the amount of cross-trading inside the family and the performance spread between high fee funds and low fee funds inside a mutual fund family.

Overall, our empirical results are consistent with the hypothesis that mutual fund families use cross-trades to shift performance to their most valuable funds. In families where cross-trading activity is high, the spread in performance between popular and unpopular funds is greater.

In the next section we study whether the performance implications of cross-trading vary systemically with proxies for fund governance in the time-series and cross-section.

4.3 Governance

Drawing from our analysis in Section 3 we study in this section the impact of differences in mutual fund governance on the performance spread between high value funds and low value funds. We start by analysing the impact of the regulatory change due to the mutual fund late trading scandal.

In Table 8 we therefore divide the sample into a pre-2003 period and a post-2003 period and run our analysis separately on the two different samples. The results in Table 8 show that the coefficients for the effect of ***CT*** on the spread of the performance between high and low value funds are 10 times smaller after the late trading scandal and not statistically significant. Figures 2 and 3 show that the amount of cross-trading as well as the mispricing of cross-trades dropped significantly after the scandal (i.e., it is not just a trend). Interestingly, the mispricing of the cross-trades increases again around the financial crisis. This finding suggests that the value of shifting performance to "rescue" the important funds in the family during the crisis was higher than the cost of "being caught".

In particular, concerning the anecdotal evidence reported in the introduction about the legal action of the Security and Exchange Commission against Western Asset Management, the SEC discovered that most of the (allegedly) illegal cross-trading activity took place during the financial crisis. This seems consistent with our findings.

In Table 9 instead of analysing the relation between mutual fund governance changes in the time-series and the performance spread, we examine cross-sectional differences in governance using our previously defined variable ***Weak Governance***. Columns 1 to 4 show results for the sample of mutual funds where the value of ***Weak Governance*** is equal to 1, whereas columns 5 to 8 show results for the sample of mutual funds where the value of ***Weak Governance*** is equal to 0. Consistent with the hypothesis that predation is stronger in families where governance is weak, we find our results to be entirely driven by sample of mutual funds with weak governance.

5 Robustness

In this section we provide additional evidence supporting the validity of our results. A potential issue with our results in Table 5 is that, given that the distribution of the ***CT*** variable is highly skewed, the correlation between ***CT*** and ***spread*** could be driven by some outliers. To rule out this concern in Table 10 we replicate our empirical design using as main explanatory variable a dummy variable taking value of 1 when there is at least a cross trade in family f and month t, and equal to zero otherwise . We find the gap in performance between high and low value funds to be 42 basis points (17 basis point considering risk-adjusted returns) higher in families that cross-trade. This excludes that our results are driven by outliers.

Another potential problem with our main methodology explained in Section 4 arises from using as dependent variable in our regressions the spread in the performance between high value and low value funds. In this way we cannot rule out that the correlation between ***CT*** and the performance spread is driven only by one of the two parties of the transaction. If that was the case, our results would be inconsistent with performance shifting through cross-trading.

Hence, in Table 11 we replicate our regressions without matching funds. In particular, all funds are divided in terciles according to the distribution of flows in the current month. Funds displaying intermediate flows in month t are dropped. Hence, we create two separate sub-samples. The first one containing only high-flow funds, the second one only low-flow funds. In this way each sample contains only funds with relatively similar contemporaneous flows.

Using this alternative methodology we do not need to impose that a family has at least three funds to be included in our sample. Hence, our sample is much bigger containing 206 fund families and 1397 funds.

Results in columns 1 and 2 suggest that the performance of high value funds positively correlates with the amount of cross-trades executed within their own family. Coefficients reported in column 3 and 4 show that the performance of low value funds is negatively correlated with the amount of cross-trades. Importantly coefficients are almost symmetric. This result is consistent with the hypothesis that performance is shifted from outflow to inflow funds through cross-trading.

Additionally, in Table 12 we replicate the results reported in Table 5 using lagged ***CT*** as the main independent variable. Results stay unchanged. This finding relaxes concerns about reverse causality bias. In particular, we want to rule out that a high spread in performance triggers cross-trading activity. Consistent with a causal effect of ***CT*** on performance, our results do not change when we explore the effect of past cross-trading activity on present spread.

6 Conclusion

In this paper, we explore the extent of cross-trading activity in mutual fund families and its impact on fund performance. Previous proxies of cross-trades used in the literature rely on quarterly holdings which makes a precise identification of cross-trades impossible. To overcome this issue we exploit institutional trade level data provided by Ancerno. In order to consider two opposite trades as a cross-trade, we require that the trades come from funds belonging to the same fund family, are in the same stock, involve the exact same quantity of shares traded, and share the same execution day, time and price. That provides us with a much more reliable identification of cross-trades in mutual fund families.

Using this measure, we document that cross-trading activity is particularly high in large and weak governance families with high fund size dispersion and before 2003. The same families that cross-trade more are also more likely to cross-trade at prices unfairly far from the VWAP of the day (up to a deviation of 2% per trade). This mispricing has a significant impact on performance. We find that "star" funds performance in family that cross-trade is boosted by 2.5% per year (1% risk adjusted), while the performance of the less valuable funds is reduced by the same amount. Since average monthly risk-adjusted performance in our sample is slightly negative and non-statistically different from zero, this behavior has obviously important implications for fund ranking, fund selection and fund manager evaluation.

Mutual fund families have a fiduciary duty to treat all their clients equally. Using cross-trading activity to favor the most valuable siblings makes economic sense since outperforming funds attract disproportionate flows and have spillover effects on the other affiliated funds. However, this practice breaches fiduciary duties toward investors since severely hurts the performance of the less valuable funds in the family. Additionally, our results suggest that fund alphas significantly misrepresent the real ability of fund managers to create value for their investors. Studies on fund manager skill as well as investors choosing where to allocate their money should consider the extent of cross-trading activity and its impact on performance in their analyses. Finally, we find that governance is highly effective in reducing unfair cross-trading activity. In particular, both cross-sectional and time series variations in family governance suggest that better governance is associated with less cross-trading and lower mispricing.

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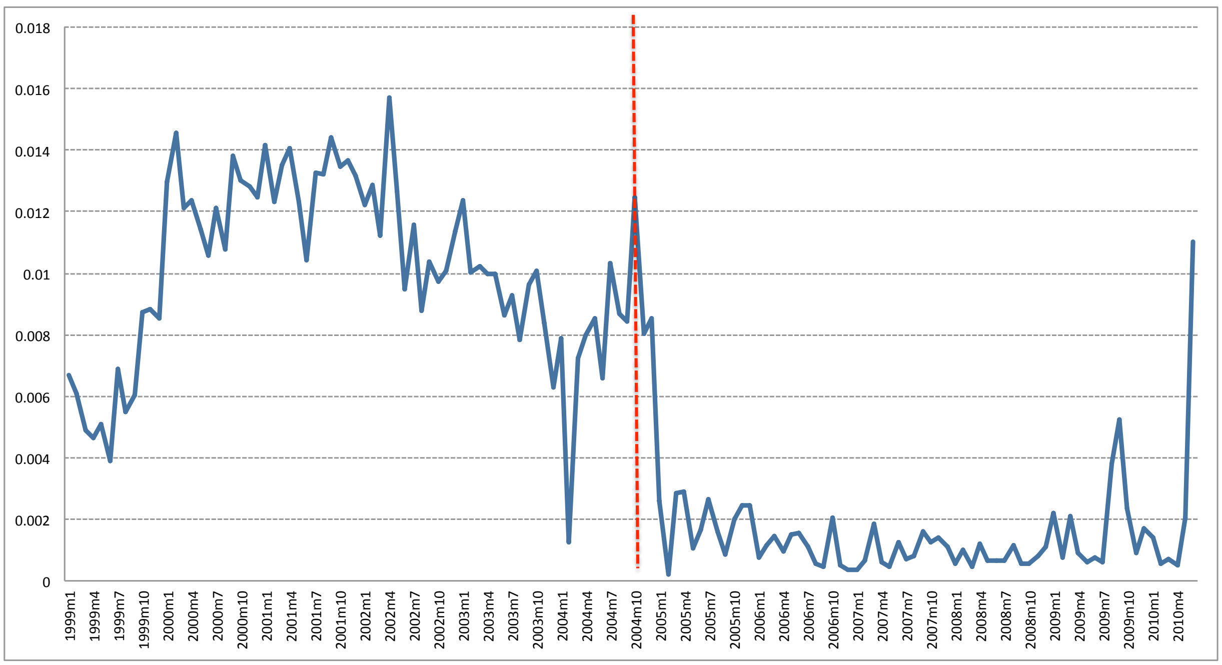

Figure 2: Amount of cross-trading activity over time. Cross trading is computed for each family f in month t as the dollar amount of cross traded positions scaled by its monthly total trading volume in USD. SEC rules 38a-1 and 206(4)-7 and the amendments to rule 204-2 became effective on February 5, 2004, while the designated compliance date was October 5, 2004 (see the red vertical line). Average values are plotted for each month weighting the amount of cross-trading by the number of funds belonging to a particular family.

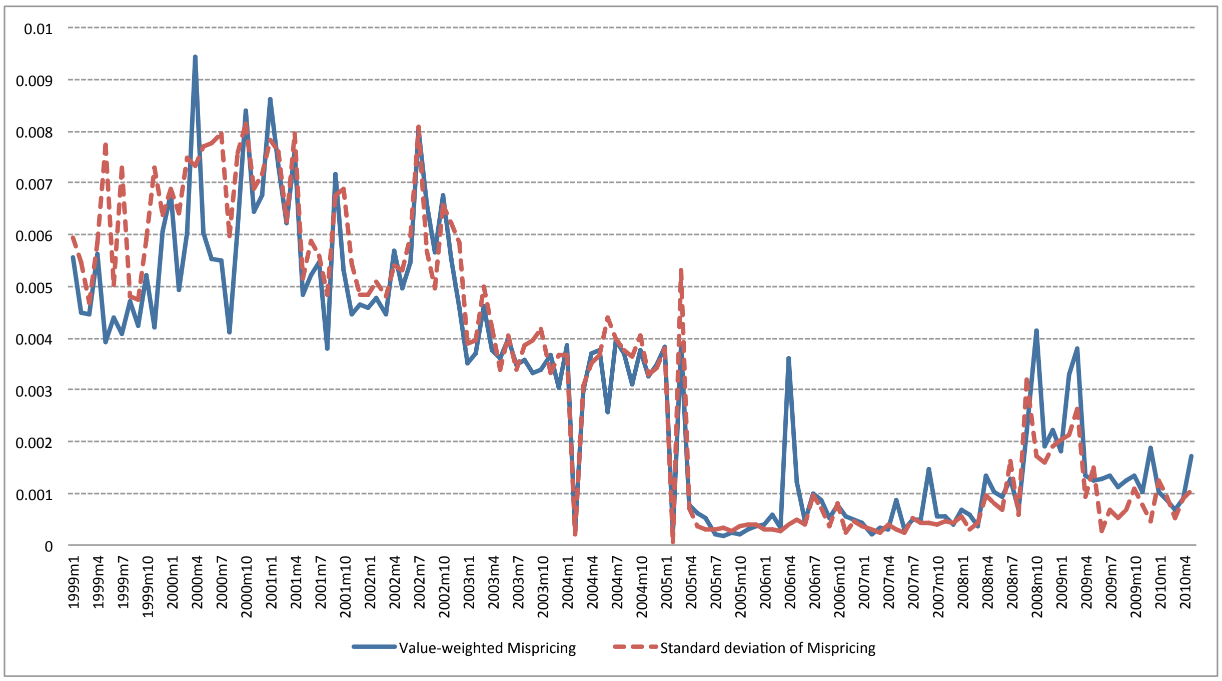

Figure 3: Mispricing of cross-trades over time. Mispricing is defined as the absolute deviation of a cross-trade's execution price from the volume-weighted average price of the day (VWAP). The blue straight line represents mispricing weighted by the dollar volume of the trade, the red dashed line represents the standard deviation of mispricings giving the same weight to each cross-trade. Average values are plotted for each month weighting the amount of cross-trading by the number of funds belonging to a particular family

Table 1: Summary Statistics

This table provides summary statistics over time for the CRSP Mutual fund database and the CRSP-Ancerno matched sample. All the variables are annual averages of monthly averages. Funds is the number of funds, Fund Size and Family Size are measured in USD millions, Families is the number of families, Siblings is the number of funds in a family.

CRSP Mutual Fund Database							
		Fund Size				**Family Size**	
Year	**Funds**	**Mean**	**Median**	**Siblings**	**Families**	**Mean**	**Median**
1999	1789	1082	115	8	224	8647	1402
2000	1799	1285	140	9	223	10387	1634
2001	1698	1136	142	8	213	9061	1463
2002	1634	1005	135	8	205	8031	1341
2003	1542	1012	145	8	195	7995	1312
2004	1457	1324	193	8	185	10403	1718
2005	1370	1525	212	8	177	11785	1929
2006	1297	1718	231	8	167	13334	2193
2007	1187	2050	277	8	155	15658	2534
2008	1138	1805	239	8	150	13679	2200
2009	971	1426	201	8	144	9608	1617
2010	775	1897	266	8	135	10921	1813
Ancerno-Crsp Match							
1999	619	1846	148	14	46	24715	2529
2000	709	1842	163	14	55	23779	3094
2001	587	1729	178	15	43	23806	2636
2002	655	1615	191	14	48	21924	3142
2003	666	1493	197	14	49	20139	3289
2004	638	1953	274	14	49	25656	4109
2005	611	2097	339	13	49	26484	4385
2006	579	2271	370	13	46	28816	4373
2007	541	2629	445	13	42	33841	7143
2008	498	2370	403	14	38	31321	7604
2009	451	1771	354	13	38	20929	5015
2010	357	2362	491	13	36	23175	5442

Table 2: Summary Statistics for fund-level and family-level regression

This table provides summary statistics for the pooled sample. Panel A shows fund level variables and Panel B family level variables. Size is fund size measured in USD millions, Excess return is fund return minus the risk-free rate, Alpha is the risk-adjusted return using the Carhart (1997) four factor model, Fees are annual fund fees defines as $\textbf{\textit{ExpenseRatio}} + 1/7 * (\textbf{\textit{FrontLoad}} + \textbf{\textit{RearLoad}})$, Flow is monthly flow defined as $\frac{AUM(t) - AUM(t-1)*(1+ret)}{AUM(t-1)}$, ***CT*** is the family volume of cross-trades in USD divided by the family's monthly trading volume in USD. ***Siblings*** is the number of funds in the family, ***Weak Governance*** is a dummy variable equal to 1 if the family was involved in a litigation for practices potentially hurting mutual fund clients at any point in time, ***Size*** dispersion is the size difference between the largest and the smallest fund in the family divided by the average fund size in the family, ***Return Dispersion*** is the monthly cross-sectional return standard deviation inside the family, ***Family Size*** is assets under management of the family in USD millions.

	Mean	**Stdev**	**Percentiles**				
			10	**25**	**50**	**75**	**90**
Panel A: Fund Level Summary Statistics							
Size	1,688	5,687	9.600	44.90	222.7	940.5	3,379
Excess Return	0.00168	0.0554	-0.0641	-0.0258	0.00435	0.0321	0.0626
Alpha	0.000233	0.0231	-0.0229	-0.00990	-0.000330	0.00953	0.0238
Fees	0.0134	0.00647	0.00580	0.00910	0.0128	0.0177	0.0221
Flow(t)	0.00291	0.0606	-0.0360	-0.0170	-0.00492	0.0100	0.0419
Panel B: Family Level Summary Statistics							
CT	0.00143	0.00950	0	0	0	0	0.000135
Return Dispersion (t-1)	0.0167	0.0115	0.00549	0.00893	0.0142	0.0216	0.0304
Siblings(t-1)	11.20	14.01	3	4	7	13	23
Family Size(t-1)	18,141	58,443	190.3	582.9	2,334	9,248	35,894
Size Dispersion(t-1)	3.827	2.938	1.207	1.919	2.976	4.736	7.734
Weak Governance	0.368	0.482	0	0	0	1	1

Table 3: The cross-section of cross-trading activity

This table presents results of cross-sectional regressions studying the relationship between monthly cross-trading activity, fund family characteristics and time-series changes in the mutual fund regulation. The dependent variable is a family's monthly volume of cross-trades in USD divided by the family's monthly trading volume in USD. ***Siblings*** is the (log) number of funds in the family, ***Weak Governance*** is a dummy variable that takes value one if a family was involved in a litigation for practices potentially hurting mutual fund clients at any point in time, ***Size*** dispersion is the lagged size difference between the largest and the smallest fund in the family divided by the average fund size in the family, ***Return Dispersion*** is the lagged monthly cross-sectional return standard deviation inside the family, ***Family Size*** is the log of assets under management of the family in USD millions in month ***t***-1, ***Post***2003 is a dummy variable equal to one after 2003. Standard errors are clustered at the month level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Siblings	0.00294***						-0.00185***
	(16.62)						(-9.025)
Weak Governance		0.00192***					0.000781***
		(8.938)					(4.140)
Size Dispersion			0.00111***				0.00145***
			(17.26)				(13.93)
Return Dispersion				0.0570***			0.0125*
				(6.142)			(1.664)
Family Size					0.00103***		0.000113*
					(17.47)		(1.661)
Post2003						-0.000843***	
						(-5.819)	
Constant	-0.00457***	0.000721***	-0.00283***	0.000481***	-0.00665***	0.00186***	-0.00177***
	(-12.67)	(9.145)	(-11.47)	(3.108)	(-14.38)	(16.40)	(-5.339)
Time Fixed Effects	Y	Y	Y	Y	Y	N	Y
Observations	9,343	9,343	9,343	9,184	9,329	9,343	9,170
R-squared	0.070	0.019	0.127	0.014	0.058	0.002	0.135

Table 4: The cross-section of mispricing

This table presents results of cross-sectional regressions studying the relationship between the mispricing of cross-trades, fund family characteristics and time-series changes in mutual fund regulation. **Only** cross-trades are included. The dependent variable is the mispricing of a cross-trade defined as the absolute deviation of a cross-trades execution price from volume-weighted average price of the day (VWAP). ***Siblings*** is the (log) number of funds in the family, ***Weak Governance*** is a dummy variable that takes value one if a family was involved in a litigation for practices potentially hurting mutual fund clients at any point in time, ***Size*** dispersion is the lagged size difference between the largest and the smallest fund in the family divided by the average fund size in the family, ***Return Dispersion*** is the lagged monthly cross-sectional return standard deviation inside the family, ***Family Size*** is the log of assets under management of the family in USD millions in month ***t***-1, ***Post***2003 is a dummy variable equal to one after 2003. Standard errors are clustered at the month level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Siblings	0.0007***						-0.0005
	(8.37)						(-1.21)
Weak Governance		0.0014***					0.0012***
		(7.42)					(3.52)
Size Dispersion			0.0001***				0.0001*
			(7.67)				(1.80)
Returns Dispersion				0.0487***			-0.0062
				(3.57)			(-0.34)
Family Size					0.0003***		0.0002**
					(7.17)		(2.41)
Post 2003						-0.0036***	
						(-13.20)	
Constant	0.0061***	0.0079***	0.0072***	0.0073***	0.0057***	0.0105***	0.0061***
	(18.55)	(65.63)	(35.08)	(16.87)	(13.16)	(65.72)	(9.08)
Time Fixed Effects	Y	Y	Y	Y	Y	N	Y
Observations	366,217	366,217	366,217	366,147	366,217	366,217	366,147
R-squared	0.216	0.216	0.216	0.215	0.216	0.032	0.216

Table 5: Favoritism versus Performance Smoothing

This table presents results for regressions of ***spread*** on ***CT*** and controls. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. ***spread*** is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. ***CT*** is computed as the percentage of cross-trades in family f in month t. The independent variables are: ***FamilySize***, the natural log of the lagged assets under management of the family; Δ*Size*, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; Δ*Returns*, the difference in funds' i and j lagged returns; *Size Dispersion*, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; ***Returns Dispersion***, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.2749***	0.1796***	0.1777***	0.1464***	0.1712***	0.0971***	0.0956***	0.0640***
	(8.88)	(5.62)	(5.44)	(4.13)	(9.63)	(5.07)	(5.04)	(2.92)
Family Size		0.0021***	0.0021***	0.0011***		0.0017***	0.0017***	0.0007***
		(9.14)	(8.65)	(3.81)		(8.35)	(8.80)	(2.96)
Δ*Size*			-0.0006*	-0.0006*			-0.0002	-0.0002
			(-1.95)	(-1.95)			(-1.63)	(-1.63)
Δ*Returns*			0.0215	0.0187			0.0025	-0.0000
			(0.33)	(0.29)			(0.12)	(-0.00)
$\Delta Flows$			-0.0164**	-0.0165**			-0.0142***	-0.0143***
			(-1.99)	(-2.00)			(-2.99)	(-3.01)
Returns Dispersion				0.2821***				0.2523***
				(4.10)				(5.25)
Size Dispersion				0.0003*				0.0003**
				(1.75)				(2.40)
Constant	0.0071***	-0.0145***	-0.0142***	-0.0119***	0.0050***	-0.0118***	-0.0116***	-0.0089***
	(11.24)	(-5.98)	(-6.01)	(-4.97)	(13.81)	(-5.68)	(-5.78)	(-5.09)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	106,220	106,123	105,734	105,640	106,220	106,128	105,734	105,640
R-squared	0.121	0.125	0.125	0.127	0.057	0.062	0.064	0.066

Table 6: Mispricing of cross-trades and fund returns

This table presents results for regressions of *spread* on *Value − weightedMispricing* and controls. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. *Value − weightedMispricing* is computed as the tradesize weighted average of absolute deviations of cross-trades' execution prices from volume-weighted average prices in family f in month t. The independent variables are: *FamilySize*, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; *Sizedispersion*, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; *ReturnDispersion*, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value weighted Mispricing	1.3713***	0.6379***	0.6236***	0.4434***	0.8499***	0.3134***	0.3123***	0.1819*
	(7.71)	(4.36)	(4.31)	(3.58)	(6.92)	(2.92)	(2.92)	(1.89)
FamilySize		0.0031***	0.0031***	0.0006*		0.0022***	0.0022***	0.0004*
		(11.70)	(11.31)	(1.90)		(11.55)	(12.07)	(1.88)
$\Delta Size$		-0.0005*	-0.0006*	-0.0006*			-0.0002	-0.0002
		(-1.72)	(-1.86)	(-1.88)			(-1.55)	(-1.56)
$\Delta Returns$			0.0232	0.0185			0.0038	0.0002
			(0.35)	(0.28)			(0.17)	(0.01)
$\Delta Flows$			-0.0173**	-0.0172**			-0.0146***	-0.0146***
			(-2.09)	(-2.08)			(-3.06)	(-3.06)
Returns Dispersion				0.3076***				0.2606***
				(4.30)				(5.35)
Size Dispersion				0.0008***				0.0006***
				(5.41)				(5.54)
Constant	0.0079***	-0.0236***	-0.0230***	-0.0109***	0.0055***	-0.0171***	-0.0168***	-0.0084***
	(13.30)	(-8.06)	(-8.13)	(-4.65)	(13.37)	(-8.23)	(-8.41)	(-4.83)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	109,233	109,128	108,739	108,645	109,233	109,141	108,739	108,645
R-squared	0.107	0.121	0.119	0.123	0.047	0.059	0.061	0.065

Table 7: Sorting on fees

This table presents results for regressions of *spread* on *CT* and controls. Each observation is obtained from the pairwise combinations of high-fee funds with low- fee funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of high-fee fund i (i.e., funds with fees in the top tercile of family f in a given month t) minus low-fee fund j's return (4-factor alpha), i.e., funds with fees in the bottom tercile of family f in a given month t. Funds with fees in the intermediate tercile are dropped. *CT* is computed as the percentage of cross-trades in family f in month t. The independent variables are: *FamilySize*, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; *Sizedispersion*, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; *ReturnDispersion*, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.0399	0.0478*	0.0422	0.0497*	0.0345**	0.0394***	0.0382**	0.0334*
	(1.54)	(1.83)	(1.53)	(1.73)	(2.55)	(2.61)	(2.51)	(1.96)
FamilySize		-0.0002	-0.0003*	-0.0001		-0.0001	-0.0001	-0.0003
		(-1.19)	(-1.92)	(-0.28)		(-0.80)	(-1.09)	(-1.33)
$\Delta Size$			-0.0003	-0.0003			-0.0001	-0.0001
			(-1.48)	(-1.52)			(-0.91)	(-0.89)
$\Delta Returns$			0.0393	0.0392			0.0203	0.0203
			(0.53)	(0.53)			(0.88)	(0.88)
$\Delta Flows$			0.0003	0.0003			-0.0021	-0.0022
			(0.03)	(0.03)			(-0.45)	(-0.46)
Returns Dispersion				0.0701				0.0300
				(1.05)				(0.58)
Size Dispersion				-0.0002				0.0001
				(-1.36)				(0.48)
Constant	0.0006	0.0024	0.0031**	0.0010	-0.0003	0.0008	0.0011	0.0016
	(1.24)	(1.48)	(2.15)	(0.65)	(-1.17)	(0.58)	(0.78)	(1.20)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	108,350	108,330	107,833	107,739	108,350	108,330	107,833	107,739
R-squared	0.023	0.023	0.025	0.025	0.019	0.019	0.020	0.020

Table 8: Late Trading Scandal

This table presents results for regressions of ***spread*** on ***CT*** and controls for different sub-samples. Specifically, the sample is divided into a pre 2003 period and a post 2003 period. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. ***spread*** is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. $CT_{t,f}$ is computed as the percentage of cross-trades in family f in month t. The independent variables are: ***FamilySize***, the natural log of the lagged assets under management of the family; Δ***Size***, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; Δ***Returns***, the difference in funds' i and j lagged returns; ***Sizedispersion***, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; ***ReturnDispersion***, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Pre Late Trading Scandal				**Post Late Trading Scandal**			
	Spread of Style adj. returns		Spread of 4-factor alpha		Spread of Style adj. returns		Spread of 4-factor alpha	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.2273***	0.2040***	0.1359***	0.1065***	0.0330	0.0278	0.0135	0.0104
	(5.69)	(3.63)	(6.08)	(2.70)	(0.83)	(0.67)	(0.39)	(0.28)
Family Size	0.0014***	0.0013***	0.0009**	0.0006**	0.0025***	0.0011***	0.0021***	0.0007**
	(3.21)	(3.10)	(2.66)	(2.40)	(10.24)	(2.75)	(9.05)	(2.02)
Δ*Size*	-0.0009*	-0.0009*	-0.0003	-0.0003	-0.0001	-0.0001	-0.0001	-0.0001
	(-1.79)	(-1.81)	(-1.63)	(-1.67)	(-0.79)	(-0.73)	(-0.52)	(-0.47)
Δ*Returns*	0.0145	0.0132	0.0076	0.0065	0.0349	0.0303	-0.0115	-0.0166
	(0.16)	(0.14)	(0.28)	(0.25)	(0.67)	(0.58)	(-0.29)	(-0.42)
$\Delta Flows$	-0.0144	-0.0147	-0.0119*	-0.0122*	-0.0194***	-0.0194***	-0.0173**	-0.0174**
	(-1.12)	(-1.14)	(-1.82)	(-1.85)	(-2.81)	(-2.81)	(-2.55)	(-2.56)
Returns Dispersion		0.2848***		0.2245***		0.1792**		0.2298***
		(2.71)		(2.66)		(2.57)		(3.52)
Size Dispersion		-0.0001		0.0001		0.0005***		0.0004**
		(-0.18)		(0.39)		(2.97)		(2.53)
Constant	-0.0056	-0.0103**	-0.0042	-0.0068**	-0.0192***	-0.0123***	-0.0161***	-0.0095***
	(-1.31)	(-2.49)	(-1.18)	(-2.12)	(-7.33)	(-4.01)	(-6.58)	(-3.71)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	51,351	51,333	51,351	51,333	54,383	54,307	54,383	54,307
R-squared	0.141	0.142	0.066	0.067	0.067	0.069	0.056	0.059

Table 9: Governance

This table presents results for regressions of ***spread*** on ***CT*** and controls for different sub-samples. Specifically, the sample is divided into a sample of weak governance families and a sample of strong governance families. A mutual fund family is assumed to have weak governance if it was involved in a legal litigation at any point in time. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. ***spread*** is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. $CT_{t,f}$ is computed as the percentage of cross-trades in family f in month t. The independent variables are: ***FamilySize***, the natural log of the lagged assets under management of the family; Δ***Size***, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; Δ***Returns***, the difference in funds' i and j lagged returns; ***Sizedispersion***, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; ***ReturnDispersion***, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

Governance	**Weak**				**Strong**			
	Spread of Style adj. returns		Spread of 4-factor alpha		Spread of Style adj. returns		Spread of 4-factor alpha	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.1911***	0.1561***	0.1911***	0.1561***	0.0127	0.0050	0.0289	0.0237
	(5.21)	(4.18)	(5.21)	(4.18)	(0.36)	(0.14)	(0.84)	(0.66)
Family Size	0.0022***	0.0005	0.0022***	0.0005	0.0013***	0.0017***	0.0005***	0.0008***
	(6.61)	(1.15)	(6.61)	(1.15)	(4.92)	(4.84)	(3.09)	(3.68)
Δ*Size*	-0.0006*	-0.0006*	-0.0006*	-0.0006*	-0.0004**	-0.0004**	-0.0001	-0.0001
	(-1.79)	(-1.81)	(-1.79)	(-1.81)	(-2.10)	(-2.07)	(-1.03)	(-0.99)
Δ*Returns*	0.0214	0.0189	0.0214	0.0189	0.0221	0.0217	0.0088	0.0079
	(0.33)	(0.29)	(0.33)	(0.29)	(0.32)	(0.31)	(0.45)	(0.40)
$\Delta Flows$	-0.0214**	-0.0216**	-0.0214**	-0.0216**	-0.0024	-0.0021	0.0025	0.0027
	(-2.26)	(-2.28)	(-2.26)	(-2.28)	(-0.33)	(-0.30)	(0.66)	(0.72)
Returns Dispersion		0.4224***		0.4224***		0.0487		0.1137**
		(4.57)		(4.57)		(0.74)		(2.12)
Size Dispersion		0.0004**		0.0004**		-0.0004*		-0.0004**
		(2.07)		(2.07)		(-1.78)		(-2.21)
Constant	-0.0149***	-0.0098***	-0.0149***	-0.0098***	-0.0071***	-0.0094***	-0.0016	-0.0049**
	(-4.78)	(-3.13)	(-4.78)	(-3.13)	(-2.71)	(-3.25)	(-1.14)	(-2.55)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	77,522	77,490	77,522	77,490	28,212	28,150	28,212	28,150
R-squared	0.142	0.143	0.142	0.143	0.069	0.069	0.029	0.030

Table 10: Alternative proxy

This table presents results for regressions of *spread* on CTD and controls. CTD is a dummy variable that takes value one when a family cross-trade in month t and zero otherwise. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. Families with less than 3 funds are dropped as well. The independent variables are: *FamilySize*, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; *Sizedispersion*, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; *ReturnDispersion*, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT Dummy	0.0125***	0.0051***	0.0050***	0.0042***	0.0077***	0.0023**	0.0023**	0.0017**
	(7.78)	(4.31)	(4.27)	(4.01)	(7.02)	(2.42)	(2.46)	(2.00)
Family Size		0.0032***	0.0032***	0.0004		0.0023***	0.0023***	0.0004
		(12.45)	(11.58)	(1.35)		(11.73)	(12.04)	(1.57)
$\Delta Size$		-0.0005*	-0.0005*	-0.0006*			-0.0002	-0.0002
		(-1.68)	(-1.83)	(-1.90)			(-1.51)	(-1.59)
$\Delta Returns$			0.0232	0.0186			0.0035	-0.0001
			(0.35)	(0.28)			(0.16)	(-0.00)
$\Delta Flows$			-0.0177**	-0.0172**			-0.0149***	-0.0146***
			(-2.13)	(-2.08)			(-3.10)	(-3.06)
Returns Dispersion				0.3168***				0.2671***
				(4.49)				(5.56)
Size Dispersion				0.0009***				0.0006***
				(5.48)				(5.23)
Constant	0.0079***	-0.0245***	-0.0238***	-0.0104***	0.0055***	-0.0174***	-0.0171***	-0.0083***
	(12.67)	(-8.32)	(-8.23)	(-4.32)	(13.11)	(-8.24)	(-8.34)	(-4.66)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	106,220	106,123	105,734	105,640	106,220	106,128	105,734	105,640
R-squared	0.107	0.121	0.120	0.124	0.046	0.059	0.061	0.065

Table 11: Alternative methodology

This table presents results for regressions of *excess returns* and *alphas* on *CT* and controls. Each month funds are sorted in three terciles on the basis of their contemporaneous flows. Funds displaying intermediate flows are discarded. Regressions are ran separately for funds with flows in the top tercile (Inflow funds) and in the bottom tercile (Outflow funds). The independent variables are: ***Siblings*** the log of the number of funds in family f in month t, ***FamilySize***, the natural log of the lagged assets under management of the family; ***FundSize***, the natural log of the lagged fund i total assets under management; ***PastFlows***, fund i lagged flows; ***PastReturns***, fund i lagged returns; ***Sizedispersion***, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; ***ReturnDispersion***, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Inflow funds		Outflow funds	
	ex. rets	alpha	ex. rets	alpha
	(1)	(2)	(3)	(4)
CT	0.0841***	0.0418***	-0.0694***	-0.0386***
	(3.69)	(2.98)	(-3.70)	(-2.70)
Family Size	0.0002	0.0003***	-0.0003	-0.0001
	(1.00)	(3.23)	(-1.65)	(-0.62)
Fund Size	-0.0000***	-0.0000***	-0.0000	0.0000
	(-3.73)	(-4.09)	(-0.63)	(0.53)
Returns Dispersion	0.1117*	0.0839**	-0.0606	-0.0594**
	(1.67)	(2.49)	(-1.19)	(-2.25)
Size Dispersion	0.0000	0.0001	-0.0001	-0.0001
	(0.27)	(1.19)	(-0.71)	(-1.59)
Past Flows	-0.0052	0.0006	-0.0078	-0.0022
	(-0.61)	(0.18)	(-0.97)	(-0.47)
Past Returns	0.0761	0.0375*	0.0331	0.0057
	(0.88)	(1.66)	(0.54)	(0.34)
Constant	0.0016	-0.0026**	0.0030*	0.0005
	(0.75)	(-2.47)	(1.91)	(0.61)
Observations	36,403	36,403	35,442	35,442
R-squared	0.633	0.088	0.659	0.083

Table 12: Lagged Cross Trading

This table presents results for regressions of ***spread*** on lagged ***CT*** and controls. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. ***spread*** is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. ***CT*** is computed as the percentage of cross-trades in family f in month $t-1$. The independent variables are: ***FamilySize***, the natural log of the lagged assets under management of the family; Δ***Size***, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; Δ***Returns***, the difference in funds' i and j lagged returns; ***Size Dispersion***, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; ***Returns Dispersion***, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Excess returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged CT	0.2711***	0.1799***	0.1751***	0.1414***	0.1711***	0.0995***	0.0981***	0.0671***
	(8.81)	(5.70)	(5.56)	(4.17)	(9.66)	(5.25)	(5.24)	(3.08)
Family Size		0.0021***	0.0022***	0.0010***		0.0016***	0.0017***	0.0006***
		(9.21)	(8.72)	(3.49)		(8.05)	(8.46)	(2.80)
Δ*Size*		-0.0005*	-0.0006**	-0.0006**			-0.0002*	-0.0002*
		(-1.86)	(-2.01)	(-2.01)			(-1.77)	(-1.78)
Δ*Returns*			0.0113	0.0084			-0.0019	-0.0045
			(0.17)	(0.13)			(-0.09)	(-0.20)
$\Delta Flows$			-0.0168**	-0.0170**			-0.0143***	-0.0144***
			(-2.04)	(-2.06)			(-2.99)	(-3.01)
Returns Dispersion				0.2874***				0.2541***
				(4.03)				(5.20)
Size Dispersion				0.0003*				0.0003**
				(1.97)				(2.27)
Constant	0.0070***	-0.0145***	-0.0144***	-0.0116***	0.0049***	-0.0114***	-0.0113***	-0.0087***
	(11.01)	(-5.98)	(-6.05)	(-4.79)	(13.43)	(-5.46)	(-5.58)	(-4.96)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	104,746	104,649	104,264	104,176	104,746	104,654	104,264	104,176
R-squared	0.120	0.126	0.124	0.125	0.057	0.062	0.063	0.065

Do Underpriced Firms Innovate Less?

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Abstract

This paper finds that stock underpricing triggers underinvestment in research. To identify underpricing, I build on previous literature on liquidity induced trading pressure to develop an exogenous proxy of mispricing. This measure is based on funds that underperform because of their over-exposure to an economically distressed industry and are forced to sell stocks of healthy firms in unrelated industries for liquidity reasons. As a consequence price drops below fundamentals and firms respond decreasing innovation activity. The main empirical explanation which is consistent with this finding is that underpriced firms prefer to divert resources from R&D into buying back their own shares at a discount, in particular when financially constrained and held by impatient shareholders.

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1 Introduction

There is little doubt that innovation is one of the main driving forces of economic growth, and that private firms contribute substantially to the investment in the research needed to nurture innovation activity. Yet our knowledge about the determinants of a firm's decision to invest in Research and Development (R&D) is still limited. In fact, incentives of managers in private firms are not necessarily set to produce the optimal level of innovation. On the one hand, managers are evaluated on a short-term basis (Porter 1992). On the other hand, altough R&D spending generates abnormal operating performance in the long-run, the market is slow to fully incorporate R&D value into prices (Eberhart, Maxwell, and Siddique 2004). This paper analyzes how price affects a firm's research spending decision and more specifically it tests whether stock underpricing dampens innovation activity.

My analysis provides evidence for a causal effect of the trading pressure induced by institutional investors suffering liquidity shocks on R&D. The identification strategy exploits the underperformance in the reported return over assets (ROA) of a particular industry as an exogenous event that triggers outflows in the funds over-exposed to that industry. These funds suffer higher investor-redemptions than their peers and are forced to liquidate non-distressed stocks (i.e., stocks that are unrelated with the distressed industry and display better than average fundamentals). Fund Trading Pressure (FTP) pushes these stocks below their fundamental value and triggers a decrease in R&D spending.

The choice to use as an instrument a real shock in an industry which is economically unrelated to the treatment group allows to study how R&D spending is set because of a completely external event, ruling out the possibility that the change in firm policy is motivated by reasons internal to the firm. In particular, stocks subject to FTP at least once in a year display an average cumulative annual return of -5.5% (versus 19% of the rest of the sample), while they have better economic fundamentals and greater past and future returns (i.e., they outperform in year $t-1$ and $t+1$). Such a large drop in valuation may force managers to rethink their firm's strategy, possibly exploiting temporary mispricing to implement firm policies that create value, while pushing the stock price back to its fundamental value.

What policies do underpriced firms favor? Previous literature documents that when market valuation is low, firms are more reluctant to issue shares and more likely to buy them back. In fact, timing share repurchases create value for shareholders and it is the main reason why managers start repurchasing programs (see, e.g., Ikenberry, Lakonishok, and Vermaelen (1995), Brav, Graham, Harvey, and Michaely (2005), Chan, Ikenberry, and Lee (2007), Peyer and Vermaelen (2009)). I test and find evidence supporting the hypothesis that underpriced firms divert resources from R&D into buying back cheap shares in an attempt to "time the market", i.e., exploit downward price pressure to buy their own shares at a discount and earn from the reversal to fundamentals.

In short, underpricing has a negative effect on research[1] which is magnified by the fact that managers prefer to repurchase instead of issuing shares to finance innovation. Consistent with this argument, I find that the reduction in R&D spending is significantly more severe for financially constrained firms. Using the "AS index" proposed by Hadlock and Pierce (2010), I classify firms in the two subsamples of the 33% most financially constrained and 33% less financially constrained firms and I find that the reduction of R&D spending triggered by stock underpricing in the first subsample is about 10 times greater than the one in the second subsample.

Despite underinvesting in innovation may dampen long-run performance, this choice may still be optimal when investors are not willing to wait for the research value to be fully incorporated into prices. In particular, I show that the substitution between R&D and share repurchases is driven by firms mostly held by impatient

[1] Recent anecdotal evidence which supports this result is offered by a New York Time article which reports that Pfizer after a prolonged stock underperformance has decided to cut its research budget and buy back an additional $5 billion worth of its own stock and that this is an increasing tendency among American corporations (New York Times, November 21, 2011).

investors (i.e., investors with high churn ratio). This result is consistent with the short-horizon of impatient investors. In fact, impatient investors often do not hold the stock long enough in their portfolio to fully acquire the benefits of R&D spending (or to bear the cost of less innovation). Therefore, they will be better off when firm policies are short-term oriented. Similarly, a manager will prefer to shift resources for buying back shares from R&D[2] since its value is systematically overlooked by investors[3] while, for instance, investors take into account capital investments when they price stocks (Polk and Sapienza 2009).

This paper relates to a recent body of literature that documents a real (causal) effect of different proxies of stock underpricing on firm policies. Polk and Sapienza (2009) measure mispricing using discretionary accruals, while Baker, Stein, and Wurgler (2003) rely on Tobin's Q to study the effect of mispricing on investments. Gao and Lou (2011) use price pressure resulting from flow induced trading and look at stock issuance. Khan, Kogan, and Serafeim (2012) and Edmans, Goldstein, and Jiang (2012) use Coval and Stafford's measure of flow induced mispricing to study respectively SEOs and takeover probabilities. Hau and Lai (2012a) measure mispricing in non-financial fire sales of mutual fund exposed to losses in their financial holdings during the 2007-2008 crisis to look at the effect on investments and employment.

However, all previous measures of mispricing have some limitations since they are noisy proxies of mispricing[4] (Polk and Sapienza (2009) and Baker, Stein, and Wurgler

[2]Empirical confirmation that R&D is regarded as "less important" is found also by Almeida, Fos, and Kronlund (2013) although in a different setting: the authors show that firms use buybacks (and decrease R&D) to meet EPS forecasts.

[3]There is increasing empirical evidence that markets do not account or misvalue R&D spending when price is determined (see Eberhart, Maxwell, and Siddique (2004), Hirshleifer, Hsu, and Li (2012), and Cohen, Diether, and Malloy (2013)).

[4]See Hau and Lai (2012a) for a detailed discussion.

(2003)), fail to properly account for endogeneity[5] (Gao and Lou (2011), and to a lesser extent Khan, Kogan, and Serafeim (2012) and Edmans, Goldstein, and Jiang (2012)), or are limited to a specific period with unusual market conditions (Hau and Lai 2012a). Conversely, the identification proposed in this paper generalizes the idea presented in Hau and Lai (2012a) allowing to expand it outside the financial crisis. Interestingly, using this improved identification methodology the effect of mispricing on investments is found to be much weaker than the one on R&D spending.

This paper relates to two other streams of literature: the first studies the increase in the correlation between assets due to liquidity shocks, the second investigates the impact of institutional ownership on corporate decisions. The first area comprises studies about financial contagion like Jotikasthira, Lundblad, and Ramadorai (2012), which shows that a liquidity shock to funds domiciled in developed countries and investing in emerging countries can be propagated to foreign markets through forced selling of emerging market stocks. Similar is also the result in Anton and Polk (2013), which illustrates that common active mutual fund ownership increases stock return correlation when some of the funds suffer a liquidity shock. However, differently from those papers, my identification strategy starts a step earlier, investigating what is the cause of the liquidity shock in order to disentangle between the distressed stocks that caused the outflows in the first place and "good stocks" that are suffering because of FTP.

For what concerns the second stream of literature, there is widespread consensus that institutional investor holdings have some influence on firm policies. Parrino, Sias, and Starks (2003) find that institutional ownership is negatively related to the probability of forced CEO turnover, while Aghion, Van Reenen, and Zingales (2013) explain that managers of firms that have larger institutional investor ownership have more

[5]Previous literature assumes that fund flows are exogenous or random. This is hardly the case when firm economic conditions or policy choices are incorporated into the price. In fact, fundamental stock movements cause inflows or outflows in the funds holding the stock, consistent with a large empirical evidence showing that investors chase returns.

incentives to invest in R&D since they face lower risk of being fired if the research does not pay out. Evidence of the effect of institutional ownership on payout policies, and in particular share repurchases, is more controversial. Grinstein and Michaely (2005) find that institutions buy companies that regularly repurchase shares and avoid firms that do not pay dividends. However, they do not find that institutional holdings or a concentration of holdings have any impact on payout policies. Conversely, Desai and Jin (2011) argue that firm managers adapt their payout policies to the preferences of their institutional shareholders. Coherent with their result, this paper finds that underpriced firms on average decrease R&D spending and boost share repurchases when shareholders are impatient. Consistent with this evidence, Gaspar, Massa, Matos, Patgiri, and Rehman (2013) show that payout policies are influenced by investors impatience.

Summing up, this paper contributes to the current debate adding the following results. Firstly, it shows that R&D spending is severely affected by a firm's stock underpricing. This real effect of underpricing is mainly due to firms attempt to time the market, shifting resources from research into repurchasing underpriced securities. The choice to forgo research projects that would create positive value in the future is rational when investors prefer short-term value creation[6]. Coherently, this paper finds that the substitution between R&D spending and share repurchases is driven by firms held by impatient investors. Financial constraints also play a major role in determining the decrease in R&D.

Secondly, this paper proposes a measure of stock mispricing that addresses more carefully the issue of exogeneity to firm conditions respect to alternative measures proposed by the literature. An increasing number of papers[7] use fund liquidity induced trades as an exogenous event to study firm policies. However, there is plenty of evidence that investors chase returns, suggesting that funds holding ex-ante the best (worst) performing assets will receive the highest (lowest) inflows. More specifically,

[6]See the theoretical model in the Appendix.

[7]See for instance Khan, Kogan, and Serafeim (2012) and Edmans, Goldstein, and Jiang (2012).

previous fire sale measures do not identify the cause of the fund liquidity shock that is assumed to be random or exogenous. However, this is not true if investors rationally anticipate fund performance (see also Hau and Lai (2012a) and Hau and Lai (2012b)) or if the outflows are caused by fund holdings in distressed stocks.

Finally, this paper finds that profitability shocks originated at the firm level have an influence on the policy choices of apparently unrelated firms through the trading pressure of institutional investors holding both stocks. This result contributes to explain how real shocks are transmitted through the financial markets, connecting otherwise unrelated firms.

The remainder of the paper proceeds as following: Section 2 describes the data used, Section 3 illustrates the methodology adopted to identify distressed funds and compute FTP. In Section 4, empirical results are provided, showing evidence that FTP has a negative effect on R&D spending and a positive effect on buybacks. The last part of Section 4 addresses how financial constraints and investor impatience influence R&D spending when a firm is underpriced. Section 5 provides additional evidence on the robustness of the results, while Section 6 concludes.

2 Data

Fund information is collected from Thomson Financial/CDA Spectrum and CRSP Mutual Funds and linked using the MFLINKS tables. Mutual fund holdings and institutional investor holdings come from Thomson Financial/CDA and fund returns from CRSP. Index, international, municipal bond, fixed income and balanced funds are excluded.

Table 1 reports the number of funds, fund families and fund average size, quarterly flows and returns for each year in the sample. In total the database contains 21 years (1990-2010), 2943 funds and 500 fund families. $\boldsymbol{Holdings}$ and $\boldsymbol{\Delta Holdings}$ are quarterly variables while returns are at monthly frequency. Hence, the quarterly return is computed as the cumulative return of the three monthly returns in a given quarter. Fund flows are computed following Coval and Stafford (2007):

$$Flow_{j,t} = \frac{TNA_{j,t} - (1+r_t) * TNA_{j,t-1}}{TNA_{j,t-1}}$$

where $TNA_{j,t}$ are the assets under management of fund j in quarter t and r are quarterly returns. Flow observations below -0.7 or above 2 are eliminated from the sample similarly to Lou (2012) and Coval and Stafford (2007). In this way the average $Flow$ in the sample is 3.8% per quarter and the median is 0%. Logarithm of $Size$ and $FamilySize$ are used and the variables are lagged one month to avoid endogeneity issues. All the other fund variables are from CRSP Mutual Fund Database.

To compute investor impatience, I rely mainly on the stock churn ratio[8] computed as in Yan and Zhang (2009) and lagged one year (to avoid that the churn ratio is influenced by the firm's policy):

$$CR_{j,t} \equiv \frac{min(ABuy_{j,t}, ASell_{j,t})}{\sum_{i=1}^{N} \frac{S_{j,i,t}P_{i,t} + S_{j,i,t-1}P_{i,t-1}}{2}}$$

Where $ABuy_{j,t}$ and $ASell_{j,t}$ are respectively institution j's aggregate purchase and sale for quarter t, while $P_{i,t}$ is stock i's price in quarter t and $S_{j,i,t}$ the number of stock i held by institution j in quarter t. Stock level churn ratio is computed summing across different institutions the number of stocks held at the beginning of the quarter weighted by institution's churn ratio[9].

[8]This measure of churn ratio is computed very similarly to Gaspar, Massa, and Matos (2005). The main difference is that Yan and Zhang (2009) use the minimum of aggregate purchase and sale, whereas Gaspar, Massa, and Matos (2005) use the sum of aggregate purchase and sale. The advantage of the former measure over the latter is that it minimizes the impact of investor cash flows on portfolio turnover. However, the correlation between the two is above 90%.

[9]I alternatively (as robustness) define impatience on the basis of stock turnover computed as the average of the total monthly volume traded in stock i over share outstanding lagged one year (similarly to Polk and Sapienza (2009)) and I find similar results.

For what concerns firm data, the sample used in this paper contains 8616 firms divided in 223 industries identified with the first three digits of the SIC code[10]. All observations are obtained from Compustat North America. Companies incorporated outside of the United States are dropped. Financial companies and utility companies are dropped as well. Only companies living at least 8 years (25% of the age distribution) are kept in the sample in order to avoid that results are driven by young tech start-ups that disappear from the sample in a few years[11] and do not buy back shares.

ROA is used to measure the profitability of a firm/industry. $E[ROA]$ for an industry is computed as the equally weighted ROA of all the firms with the same first 3-digit SIC code in the corresponding quarter of the year, e.g., if the ROA of the automotive industry for the first quarter of year 2009 has to be compared to $E[ROA]$, the latter will be computed as the average ROA for all automotive firms using only the first quarters of the whole time series (i.e., observations of automotive firms from quarters 2, 3 and 4 will be dropped in order to account for seasonal differences). Equally weighting is used instead of value weighting in order to reduce the probability to capture idiosyncratic shocks affecting only a few large firms and not the majority of the firms in that industry. Nonetheless, even in an industry that is underperforming the average ROA there will be some firms with good financial returns[12]: therefore when the whole industry is considered, an additional filter based on the stock returns will be applied (see below). All variables are winsorized at the 1% level and their construction is described in the Appendix.

Table 2 reports descriptive statistics for the whole sample of firms (column 1), firms with (underpriced) stocks affected by Fund Trading Pressure (FTP), defined as the

[10] An alternative approach would be to use Fama and French industries but since their categories are much broader this would reduce the number of different industries and the analysis would be less precise.

[11] Anyway including also younger firms leave the main results unchanged.

[12] Even though the equally weighted ROA is below the average of its distribution some observations may fall into the right tail because of idiosyncratic features.

forced sales of funds exposed to the distressed industry[13] (column 2), and whether the difference between the two is statistically significant (column 3). Firms in the FTP-Sample repurchase more stocks and spend less in R&D as a percentage of their previous year dollar book assets[14]. Moreover, they have higher ROA and better past stock performance (the annual difference is 7.8%) than the average firm in the sample. They also display on average more cash holdings, bigger size (measured as book value in dollars), and less leverage even though the difference is not statistically significant. The fact that FTP stocks have better fundamentals and better past performance is the result of a rational choice of mutual fund managers to sell well-performing, liquid stocks in order to limit the price impact of their forced trades[15].

As pointed out, firms subject to FTP display better ROA than the average firm in the sample. In unreported results, I also find that these firms have a level of ROA that is statistically greater than several benchmarks (i.e., they have better ROA than other firms in the same industry, firms from other industries during the same year, and firms in the same industry and the same year). This finding rules out the possibility that the underperformance of FTP stocks is due to an economic connection with the distressed industry rather than to mutual funds forced sales.

2.1 Identifying underperforming industries

As a first step industries that are less profitable (in terms of ROA[16]) than their average in a particular quarter are identified[17]computing their Industry Performance:

$$DROA_{s,t} = ROA_{s,t} - E[ROA_s]$$

[13]See below.

[14]Alternative scaling measures are provided in Section 5.

[15]More on this in Section 3.

[16]The choice of using ROA instead, for example, of ROE is due to the fact that this variable is reasonably exogenous, since it does not depend on stock movements.

[17]As an alternative identification strategy, I computed the Industry Performance as $DROA_{s,t} = \frac{ROA_{s,t} - E[ROA_s]}{\sigma_{ROA_{s,t}}}$. However, the results look qualitatively similar.

Where *s* represents the industry identified from the first 3 digits of the SIC code obtained from Compustat, and *t* is the time indicator. ***DROA*** is strongly correlated with contemporaneous stock returns (see Figure 1). This is not surprising since in efficient markets the price should be equal to the sum of the discounted cash flows shareholders will receive (see, e.g., Chen, Da, and Zhao (2013)) and a diminished return on asset reflects lower cash flows from the firm to the investor in the future. An alternative approach would be to identify directly distressed firms from the difference between ROA and expected ROA, the advantage of controlling for the industry is that it allows to exclude from the treatment group firms belonging to a distressed industry and, as such, subject to similar economic conditions and shocks. I define the bottom 10% of ***DROA*** distribution as distressed industries[18]. Deviation from average ROA is a very persistent measure, which is strongly correlated over time. This is due to the fact that a reduction in the profitability of an industry depends on several factors that are usually long-lasting, such as a drop in the customer demand, increase in the cost of raw materials, increase in the production cost, augmented competition or simply the fact that an industry has reached its mature stage. As a consequence the price of distressed stocks starts to decrease before the event quarter (i.e., the one with the lowest ***ROA***, computed as difference between ***ROA*** and the average ***ROA*** of the industry) and keeps decreasing afterward (see Figure 1).

3 Fund trading pressure

The literature offers several examples of price divergence from fundamental value due to limits of arbitrage[19], investor bounded rationality[20], and liquidity shocks[21]. Very commonly used in the literature of contagion through mutual fund trading is the price

[18] Only the bottom 10% is considered in order to account only for the most severe situations. However, the choice of different thresholds give qualitatively similar results.

[19] See Shleifer and Vishny (1997).

[20] E.g., Hong and Stein (1999)

[21] E.g., Coval and Stafford (2007).

pressure due to liquidity shocks with an identification *à la* Coval and Stafford (2007). Unfortunately, this approach raises some concerns about endogeneity since both returns cause flows and flows cause returns. Hence, Coval and Stafford (2007) result would be also consistent with rational investors anticipating poor fund performance[22].

This paper takes a different approach to identify price swings due purely to trading pressure: it computes price pressure motivated by liquidity needs of distressed funds exposed to totally unrelated firms in economic distress. This approach resembles the one proposed in Hau and Lai (2012b), in which the financial crisis is used as an exogenous event that triggers pressure on non-financial stocks, but has two advantages: first, it is computable for the whole data sample (and not only for the financial crisis period, i.e., 2007-2009) and second, it identifies as stocks affected by FTP companies that have better than average fundamentals (while, on the contrary, during the crisis most of the firms were suffering also because they were exposed to the financial sector). In particular, the fact that FTP firms have better economic fundamentals than comparable firms rules out the possibility that the price pressure of their stock is due to economic contagion from the distressed industry.

When a shock hits only (or mainly) a specific industry, the funds that are exposed the most to that industry in terms of stock holdings underperform the others. Hence, there is a high chance that those funds will suffer investor redemptions. High outflows will force fund managers to liquidate not only distressed stocks but also healthy ones. This is likely to happen for three reasons. Firstly, this will allow a fund to realize lower losses since healthy stocks will usually sell at a lower discount than distressed ones if markets are reasonably efficient[23]. Secondly, this behavior is consistent with the "disposition effect", i.e., the tendency of investors to sell winners too early and hold on to losers (e.g., Frazzini (2006)). Thirdly, it may be efficient from a tax perspective to realize capital gains in periods of widespread distress when their investors are realizing losses (Hau and Lai (2012a)).

[22]See also Hau and Lai (2012b).

[23]Table 2 shows that FTP-stocks had higher than average cumulative returns in the previous year.

In order to identify underpriced stocks, I need first to detect the funds that are selling for liquidity reasons, using a more exogenous measure than $outflows$[24]. In order to do so, I compute the ***Exposure*** of a fund to the distressed industries in the following way:

$$Exposure_{j,t} = \sum_i w_{i,t-1} * (-Return_{i,t})$$

where w is the dollar weight of the holdings of fund j in stock i only if i belongs to a distressed industry (w would otherwise be equal to zero). ***Return*** is the quarterly return[25] of stock i in quarter t. For instance, if in quarter t the automotive industry is in distress and fund j holds 10% of its portfolio in an automotive company which has a return of -1%, ***Exposure*** would be 0.001. The higher is the exposure[26] of a fund, the higher will be the loss due to loading on the distressed industries. Among exposed funds, i.e., funds with ***Exposure*** in the top decile, the median ***Exposure*** is equal to 1.3% and the average is 2%. Exposed funds have average flows of roughly 5% less than non-exposed ones (see also Figure 2).

Moreover, in Table 4, it is shown that ***Exposure*** is negatively correlated with fund flows. This allows me to condition a fund's sales of non-distressed stocks to the exposure to the distressed ones (i.e., while previous literature uses simply unconditional flows) overcoming the endogeneity issue. Therefore, funds with high ***Exposure*** will be forced to liquidate good stocks into the market, exercising downward price pressure.

My measure of mispricing will be necessarily biased toward stocks significantly held by mutual funds. This is not a big concern since institutional holdings are tilted toward bigger and liquid stocks that are more representative of the market. However, in Section 5 I replicate my analysis using propensity score matching in order to leave in

[24]Stock prices depressed by unconditional outflows can be due to funds holding bad performing companies.

[25]Using 4-factor alpha instead of stock return gives similar results.

[26]Funds with more than 90% of their portfolio holdings concentrated in a single industry are dropped, in order to avoid to consider mutual funds that specialize only in that industry.

the control sample only observations with similar stock characteristics. Fund trading pressure is computed in the following way:

$$FTP_{i,t} = \frac{\sum_j ((\Delta Holdings_{j,i,t}) \big| (Exp_{j,t-1} > Pctile(90th) \cap (i \notin DistressedIndustry_t)))}{SharesOutstanding_{t-1}}$$

Where $\Delta Holdings_{j,i,t-1}$ is the change in holdings of stock i during quarter t of fund j. $FTP_{i,t}$ aggregates the selling of the 10% of the (distressed) funds with the highest $Exposure$ to the distressed industry (i.e., $Exposure_{j,t}$>90th percentile). This measure is similar in spirit to Coval and Stafford (2007) with an important exceptions: distressed stocks (i.e., stocks of companies belonging to an underperforming industry) are excluded *a priori*, making sure that the underperformance is not due to fundamentals[27].

Underpriced stocks are defined as those in the bottom 15% of the FTP distribution (those that are more heavily sold by distressed funds). However, results using 10% or 20% thresholds look qualitatively similar.

Figure 1 illustrates what happens to FTP stocks. Consistent with results in Section 2, these stocks display better than average returns until distressed funds unload them into the market because they need liquidity. During the distress quarter they reach a cumulative average abnormal return[28] of around -6%, reverting their trend in the following quarters. In total, FTP stocks trade at a discount for 7-8 quarters, suggesting that would be optimal for their managers to boost share repurchases.

Compared to the results in Coval and Stafford (2007), fire sale stocks drop less (the lowest cumulative returns reached is -6% versus -14% in Coval and Stafford), while they stay mispriced for a shorter period. This difference is due to the fact that

[27]The issue that distressed funds are potentially selling these stocks because firms are decreasing R&D is addressed computing ex-ante which stocks a distressed fund is more likely to sell due to portfolio composition *before* the distress occurs.

[28]Cumulative average abnormal returns are computed as the average of quarterly stock returns minus the average equally weighted return of stocks held by mutual funds in the previous quarter, similarly to Khan, Kogan, and Serafeim (2012) and Coval and Stafford (2007).

in the identification used in this paper, distressed firms are *a priori* excluded. On the contrary, in Coval and Stafford (2007) distressed stocks are included when associated to large outflows in the mutual fund industry[29].

Figure 1 shows also cumulative abnormal returns for distressed stocks, identified as stocks of firms in the bottom 15% of the ***ROA*** distribution[30]. Distressed stocks start to drop some quarters before and keep underperforming after the distressed quarter. The fact that their underperformance does not trigger immediately fund trading pressure is consistent with the possibility of fund managers to meet early redemption using their internal cash buffer (estimated around 4% on average by previous research[31]). The protracted poor performance of distressed stocks suggests that profitability drops at the industry level are long-lasting and correlated over time.

However, the main difference in the pattern of distressed stocks and stocks suffering because of FTP is what happens after the event quarter. Distressed stocks keep underperforming the benchmark since their ability to generate revenues stays below expectations. Conversely, stocks affected by price pressure revert their pattern after the quarter in which exposed funds sell them the most. This is what we should expect since these stocks are not affected by any fundamental shocks and exposed funds, having already unloaded their holdings into the market, cannot induce further downward price pressure. Hence, the non-fundamental price pressure is gradually absorbed until the price reverts to its fundamental value.

The downward price pressure computed in this section is non-fundamental because it is induced by a fundamental shock originated in a different industry. One could argue that the same shock could hit a different industry to a lesser extent or that the underperformance of the supposedly good stocks is due to an economic connection between the distressed industry and the industry to which the underpriced firm

[29]Distressed stock holdings trigger outflows since investors are more likely to withdraw their money when a fund underperforms.

[30]The bottom 10% (or 20%) stocks display a similar pattern.

[31]Yan (2006).

belongs. There are two main replies to this objection: first, after the event quarter the price completely reverts to its original level in a relatively short time (this would not happen if the shock is fundamental, the price after the drop should stay at the bottom of the graph in Figure 1[32]). Second, as it has been pointed out already in Section 2, stocks in the FTP sample have better than average fundamentals, i.e., in all specifications these firms display earnings over book assets greater than or equal to the benchmark suggesting that these companies are economically healthy.

Hence, findings in this section are consistent with a price drop due to FTP that is non-fundamental. Next section will use FTP as an exogenous shock to a firm's price, and will test whether this influences R&D spending.

4 Empirical findings

4.1 Underpriced stocks and underinvestment in R&D

Table 4 reports results from regressing *ShareRepurchases* on $FTPD_{i,t}$, a dummy that takes value one if a firm is in the bottom 15% of the FTP distribution[33] in year t, and control variables. Coefficients are estimated running OLS regressions including time fixed effects and either firm or industry fixed effects. Errors are clustered both at the firm and at the year level. The variable $FTPD_{i,t}$ aims at capturing the effect on R&D of mispricing due to mutual fund trading pressure. Differently from similar literature, firm belonging to distressed industries are ex ante excluded by the treatment group, assuring that the effect on R&D in not due to deteriorating fundamentals.

Across all columns of Table 4 coefficients of Fund Trading Pressure range from -0.39% to -0.85% and are significant at the 1% level when firm fixed effects are included. This result documents an economically significant effect of stock underpricing on research spending. As an additional robustness test, results are replicated using

[32]Similarly to the distressed stocks.

[33]Results using 10% or 20% thresholds are qualitatively similar.

propensity score matching in order to keep for each observation in the treatment group only the most similar observation in the control group according to a selection of variables (e.g., industry, size, past returns, ROA). The regressions are also replicated excluding all year-firm observations for which R&D spending is equal to zero to make sure that they are not biasing the analysis. In both cases results are economically and statistically stronger (see Section 5).

Control variables have the expected signs: large and profitable firms spend proportionally less in R&D (the companies that spend proportionally more in R&D are small tech companies). Large cash availability at the beginning of the year means that a firm can spend more in research, and higher Tobin's Q is generally associated with better investment opportunities and, therefore, with higher R&D spending. Conversely, past stock returns and volatility do not play a clear role in explaining R&D at time t.

The negative effect of FTP on R&D is a economically relevant and surprising result. In fact, Aghion, Van Reenen, and Zingales (2013) show that institutional ownership on average fosters firm innovation. However, results in this section suggests that institutional investors' induced mispricing[34] has a negative effect on research spending. This result survives also including institutional ownership from 13F as a control. Therefore, my findings suggest that on average institutional ownership has a positive effect on research spending, *unless* outflows force funds to induce downward price pressure on the stock.

Concluding, contemporaneous stock movements seem relevant in determining research spending. This result expands a body of literature that highlights the effect of stock mispricing on several firm variables. However, a potential concern in the interpretation of the result is that distressed fund managers may choose to liquidate stocks of firms that are decreasing R&D (i.e., there is potentially a reverse causality

[34]Using S12 I am able to compute only mispricing induced by mutual fund outflows. Hence, my measure of mispricing is by construction tilted toward stocks significantly held by mutual funds.

bias). To make sure that there is a causal effect of stock underpricing on firm R&D a measure of expected fund trading pressure (E[FTP]) is computed. This variable does not rely on actual sales but on the holdings of the distressed funds before the distress (conditionally to the requirement that stocks do not belong to the distressed industry) assuming that a distress fund is more likely to sell a stock that was already in its portfolio before the distress period. Results obtained using this alternative identification are qualitatively similar (see Section 5).

4.2 Underpriced stocks and buybacks

A sharp decrease in research spending triggered by underpricing suggests that a firm has either less financial resources available or is diverting the resources that would otherwise go to R&D into a different investment opportunity (or both). A source of variation in the investment opportunity set of a firm is caused by the stock underpricing. When a firm's stock is underpriced, managers will be more reluctant to issue stocks at a discount (Khan, Kogan, and Serafeim 2012) and may find it convenient to boost buybacks, increasing the value of the company.

Table 5 presents OLS regression results for the effect of $\boldsymbol{FTPD}$ on annual share repurchases[35]. The coefficients of $\boldsymbol{FTPD}$ are always positive and significant at the 1% level. The result provides strong evidence that some of the financial resources of underpriced firms are transferred into buybacks. However, the marginal effect of $\boldsymbol{FTPD}$ on share repurchases is smaller in absolute value than the one on R&D (the increase in buybacks explains roughly half of the decrease in R&D spending). Is this difference explained by the fact that underpriced firms are more reluctant to issue shares to finance R&D since they are already buying their stocks back?.

To answer this question, I test how the incentive to cut research changes based on firm's financial constraints. In fact, firms that do not depend on external financing

[35]Results are replicated dropping firm-year observations when the dependent variable is equal to zero, and stay qualitatively similar.

may simply boost share repurchases using internal resources without affecting their research spending. Hence, I would expect to see a stronger reduction of R&D spending in financially constrained firms. To investigate the importance of financial constraints, I employ the AS index[36] proposed by Hadlock and Pierce (2010). The authors show that a measure based solely on age and size does a better job in identifying financially constrained firms and is more robust and exogenous than the KZ index (Kaplan and Zingales 1997).

Table 6 repeats the analysis in Table 4 for the two subsamples[37] of the 33% most financially constrained and unconstrained firms. Coherent with a negative effect on research also due to a greater difficulty to secure external financing, coefficients of $FTPD$ for the most financially constrained firms are roughly ten times the value of those for the most unconstrained ones (-1.8% versus -0.2%). However, to a lesser degree some negative effect on research spending is also found in unconstrained firms. This suggests the presence of a (much weaker) substitution effect between R&D and share buybacks also in these firms. However, the fact that this result is strongly driven by financially constrained firms rules out the possibility that underpriced firms display lower R&D spending for some alternative firm specific reasons. Underpriced firms that are unlikely to get funding from external sources are forced to cut expenses to be able to buy back shares, and the type of expense that is more affected by this decision is the one in research.

Concluding, results in this section provide evidence that underpriced firms reduce share issuance and boost buybacks to the detriment of R&D spending, and that this is driven by financially constrained firms.

[36] The index is calculated as $(-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age)$.

[37] Using 20% or 40% as threshold yields qualitatively similar results.

4.3 Impatient investors and short term firm policies

Why do firm managers prefer to buy back underpriced shares instead of investing in R&D? There are two possible explanations that are consistent with this finding. First, repurchasing discounted shares is simply more profitable. Hence, a manager would always maximize shareholders wealth diverting resources from research into repurchases. Second, buying back discounted shares is more valuable than R&D when investors are impatient. Mounting evidence is suggesting that R&D spending is not rewarding in the short-term[38]. Moreover, investors are becoming increasingly impatient and managers are often evaluated on quarterly results. Therefore, when shareholders are focused on the short-term, it may be optimal to divert resources from R&D into buying back underpriced shares. According to this second explanation short-term investors maximize their utility when value is rapidly incorporated into the price, therefore they neglect long-term investment opportunities since they discount future cash flows at a higher rate. Similarly, managers may divert resources from R&D at a low cost since shareholders do not penalize them for doing so.

Table 7 provides evidence for the effect of $\boldsymbol{FTPD}$ on R&D for firms held by impatient versus patient investors. The first three columns report results for the 33% of firms held by the most impatient investors (i.e., those mostly held by the investors with the highest churn ratio), while the last three columns display the coefficients for the subsample of the 33% of firms held by the most patient investors. Consistent with the predictions of a simple theoretical model in which managers maximize the utility of a representative impatient investor (see Appendix), results show that firms for which the price is pushed below fundamentals display a 0.34% lower R&D spending than similar firms when held by impatient investors. Conversely, firms held by the most patient investors display an effect of FTP on R&D which is statistically non-different from zero.

[38]See Hirshleifer, Hsu, and Li (2012), Cohen, Diether, and Malloy (2013), and Eberhart, Maxwell, and Siddique (2004).

Overall, results in this section are consistent[39] with the hypothesis that managers working for firms held by impatient shareholders rationally focus firm's financial resources into shorter-term policies.

5 Robustness tests

5.1 Expected Fund Trading Pressure

Results in Section 4 provides evidence of a causal effect of FTP on research. The methodology proposed allows to identify underpriced stocks without running into the risk that the drop in the price is due to firm fundamentals. However, the evidence presented does not exclude the possibility that distressed fund managers prefer to liquidate firms that are decreasing R&D. This is probably not true since previous literature documents that investors overlook R&D and prefer to hold firms that are increasing buybacks (like the firms in my treatment group).

However, this section provides an identification of expected fund trading pressure which is exogenous to fund managers' preferences on which stock to sell.

$$E[FTP_{i,t}] = \frac{\sum_j((Shares_{j,i,t-1})\big|(Exp_{j,t-1}>Pctile(90th)\cap(i\notin DistressedIndustry_t)))}{SharesOutstanding_{t-1}}$$

Where $Shares_{j,i,t-1}$ are the holdings in stock i at the end of period $t-1$ of fund j entering into a distressed situation in t. $E[FTP_{i,t}]$ aggregates the selling of the 10% of the funds with the highest $Exposure$ to the distressed industry (i.e., $Exposure_{j,t}$>90th percentile). This measure computes in which stocks the portfolios of distressed funds are more concentrated (provided that they do not belong to the distressed industry) before the distress. These stocks are more likely to be liquidated when a fund needs liquidity compared to stocks that funds do not hold yet, or hold in a small quantity.

[39]However, potentially there can be a reverse causality bias if impatient investors anticipate stock mispricing and firm short-term policies. Results in Section 4.3 merely illustrate correlation between impatient investor holdings and firm short term focus and do not claim any causality.

Table 8 shows that the effect of E[FTP] on R&D is negative and significant. However, the statistical significance is lower since this measure of mispricing is necessarily more imprecise.

5.2 Subsamples

Table 9 replicates results in Table 4 dividing the whole sample in two decades (1990-2000, 2001-2010) to make sure that the result is not driven by particular market conditions or is changing over time. Coefficients for the ***FTPD*** dummy suggest that the negative effect on R&D was slightly stronger in the 1990-2000 decade. However, the result is robust and survives over time (all coefficients are significant at the 1% level).

5.3 Propensity score matching

Another potential issue is that distressed fund managers pick stocks with characteristics correlated to lower R&D when they decide to sell because they need liquidity. The underlying assumption in investigating the effect of the underpricing on the firm policies is that fund managers choice is quasi-random. However, from Section 3 we know that distressed fund managers are more likely to sell stocks that outperformed in the past and have better than average fundamentals. To overcome this concern, Table 10 replicates the main results matching the control sample on the main characteristics of the treatment group (i.e., industry, size, past-returns, ROA). A logistic regression is run in order to find which observation in the control group is the most likely to end up in the treatment group according to similarity in the control variables and only this observation is kept as control (i.e., for each underpriced firm I have a non-mispriced firm with similar characteristics). However, results look qualitatively similar.

5.4 Different scaling of R&D

Table 11 replicates results in Table 4 scaling R&D expenditures over market value instead of book value, to make sure that the result is not driven by the choice of the denominator. However, results look qualitatively similar.

6 Conclusions

Economic development is driven and sustained by innovation activity. However, firms find more convenient to underinvest in research in order to have more resources to buy back shares when their stock is underpriced. This paper proposes a methodology to identify underpricing which is exogenous to firm characteristics (differently from the liquidity induced sales *à la* Coval and Stafford (2007) commonly used in the literature), and finds that underpricing triggers a reduction in research spending.

The identification proposed exploits the economic distress of an industry, identified by a decrease in the average profitability (ROA), to show that over-exposed funds (i.e., funds with holdings concentrated in that industry) sell stocks of healthy firms in unrelated industries, driving down their price. This channel is relatively new since most of the literature focuses on the transmission of "pure liquidity" shocks, assuming that they are random (while this is not necessarily true) and presents the advantage of being more exogenous. Moreover, the fact that firms with stocks affected by fund trading pressure have better than average fundamentals rules out the possibility that the stock underperformance is due to an economic connection with firms in the distressed industry.

A growing body of literature is focusing on describing the influence of mutual funds on the real economy and this paper aims at contributing to the ongoing debate. In particular, this paper shows that a firm's stock underpricing has a real effect on R&D spending because, on average, underpriced firms prefer to substitute R&D with share repurchases. This effect is particularly strong for financially constrained firms and firms held by impatient investors. The choice to decrease the resources dedicated to R&D is consistent with a growing literature on limited investor attention that shows that investors overlook or are not able to assess the importance of research spending. Hence, such a strategy can be rational especially when shareholders are impatient (i.e., they have a high churn ratio).

Concluding, the choice to shift resources that would otherwise go into R&D happens because R&D is considered a relatively "flexible" expense. In fact, markets overlook its real contribution to value creation and do not penalize managers for undermining firm future innovation potential. The negative effect of underpricing on research is particularly strong for firms held by impatient investors. Dividing observations in two subsamples of firms held by shareholders with the highest and the lowest churn ratio, I find that the result is driven by the former group. This is consistent with recent empirical evidence suggesting that the value of R&D is slowly impounded into prices. Moreover, empirical results provide evidence consistent with the hypothesis that impatient investors foster short-term firm strategies.

7 Appendix A: Construction of the Variables

R&D spending is R&D spending over book assets at the beginning of the year.

Share Repurchases is dollar share repurchases over book assets at the beginning of the year.

Cash is Cash over Book Assets available at the beginning of the year.

FTPD is a dummy variable that takes value one if in at least one quarter of the year ***FTP*** was below the 10th percentile of its distribution.

Leverage is long-term liabilities over book assets at the beginning of the year.

TQ is Tobin's Q computed as the sum of market equity and book assets less book equity, deferred taxes, and investment tax credits over book assets.

ROA is EBITDA over book assets at the beginning of the year.

Size is the log of book assets.

Past Stock Returns is the cumulative return of the stock in year $t-1$.

Past Stock Volatility is the standard deviation of stock monthly returns in year $t-1$.

8 Appendix B: Theoretical framework

This section presents a simple model that explains why managers maximize the utility of impatient shareholders passing up valuable research projects in order to buy back underpriced securities. The setup and intuition behind the model follow closely Stein (1996) and Polk and Sapienza (2009).

I consider an underpriced firm that can allocate its capital K either to research, R, or to repurchase shares for an amount $K-R$. K is given and comprises the dollar amount of all available internal resources. R is continuous and homogeneous and decided by the manager. The stock underpricing, α_t, depends on the mispricing level $\alpha \geq 0$ and is gradually corrected at a rate $p \geq 0$, i.e., $\alpha_t = \alpha * e^{-pt}$.

Shareholders face a liquidity shock that force them to sell their shares at time $t+u$. The arrival of the liquidity shock, q_j, follows a Poisson process with mean arrival rate $q_j \in [0, \infty)$. q_j increases with investor's impatience (i.e., high q_j indicates high impatience, while low q_j means that the investor is patient[40]). The research pays with probability π an amount $log(R)$, which increases slowly over time at a rate $i < q$, since the value of research is progressively incorporated into the price, and pays 0 with probability $1-\pi$. The cost of research is R.

A rational manager who wants to maximize the utility of a representative investor j at time zero will solve the following problem:

$$MAX\ U_j^t \equiv \int_{t=0}^{\infty} \left[\pi log(R) e^{it} + (K-R)(1+\alpha * e^{-pt})\right] q_j e^{-q_j t} dt - (R - R_0)$$

That is, investor's utility is a function of the value generated by the innovation (i.e., the outcome of the investment in research) and the value generated by repurchasing mispriced stocks. If the mispricing of the stock is zero ($\alpha = 0$), buying back shares does not increase shareholder's wealth. Similarly, if the probability of the innovation is zero ($\pi = 0$), to invest in R&D decreases the utility of the investor. In fact, investing in

[40]In this model an impatient investor is defined as an investor j who is forced to liquidate the stock soon, as in Polk and Sapienza (2009).

R&D may have a negative expected value, either because the innovation probability is low (π is small) or because the liquidity shock is expected to occur soon (q_j is high[41]). It is assumed that the value generated by the stock after $t+u$, i.e., after the investor exits her position, does not increase her utility. The optimal level of investment in research will therefore be:

$$R^* = \frac{q\pi}{(q-i)\left(2+\frac{\alpha q}{p+q}\right)}$$

Hence, the higher the mispricing the greater will be the incentive of the manager to divert resources from research into buying back shares. More importantly, this incentive will increase with j's investor impatience. Conversely, research spending increases with the innovation rate, i, the probability of a successful outcome, π, and the speed of the price reversal, p.

As expected, if the probability of the innovation to occur is zero ($\pi = 0$) all money will go into buybacks. Conversely, when the mispricing is zero, the optimal level of research still depends on π and q_j. However, for $\pi = 1$ and i that approaches q_j the investment in research will spike (and buybacks will fall toward zero), suggesting that the investor is better off patiently investing in R&D and waiting for the innovation to create value in the long-run.

Summing up, the optimal strategy for a rational manager who maximizes investor j's utility will be to focus on buying back underpriced shares when investors are impatient (q_j is high), while investing more in research when they are patient (q_j is low).

[41] The net value of the innovation at the initial stage $t = 0$ is negative even if $\pi = 1$, i.e., $log(R) - R < 0$, since its value is slowly incorporated into the price. Hence, the investor needs to hold the stock for a sufficiently long period for the investment in R&D to become convenient.

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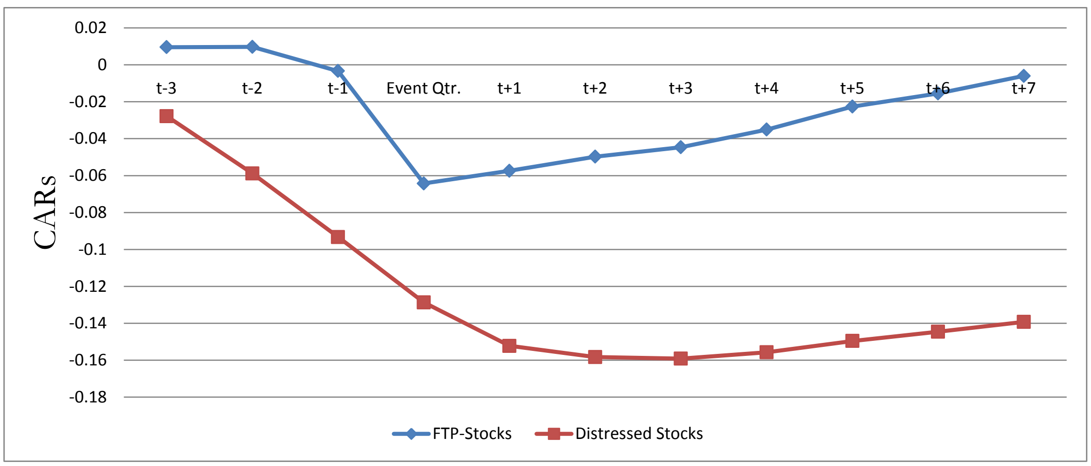

Figure 1: Cumulative Average Abnormal returns from three quarters before to five quarters after a "distress quarter". Distress quarter is defined as a quarter in which either a stock is in the bottom 15% of the FTP (Fund Trading Pressure) distribution, or in the bottom 15% of the *DROA* distribution (i.e., it is a distressed stock). Abnormal returns are computed as quarterly stock returns minus the equally weighted returns of quarterly mutual fund holdings (similarly to Coval and Stafford (2007)).

Table 1: **Fund summary statistics**

This table reports fund sample statistics at the annual level. Only equity funds that invest in domestic stocks are included (Inv. Obj.=2, 3, 4, or missing provided that the fund reports to S12). The assets under management (TNA) are in million dollars. Qtr. Flow and Qtr. Return are respectively the annual average among quarterly fund flows defined as in Section 3 and quarterly fund returns.

Year	N. Funds	N. Families	TNA	Qtr. Flows	Qtr. Returns
1990	812	243	301	0.03	-0.01
1991	893	264	356	0.07	0.07
1992	1018	289	424	0.10	0.02
1993	1216	314	518	0.11	0.04
1994	1462	351	539	0.06	0.00
1995	1622	373	594	0.06	0.06
1996	1781	400	706	0.07	0.04
1997	2000	431	772	0.07	0.05
1998	2219	469	835	0.04	0.03
1999	2299	464	889	0.03	0.07
2000	2303	459	1013	0.02	0.00
2001	2136	443	855	0.02	-0.01
2002	2031	436	787	0.01	-0.04
2003	1861	418	897	0.01	0.07
2004	1692	402	1149	0.00	0.03
2005	1612	383	1340	0.00	0.02
2006	1514	364	1513	-0.01	0.03
2007	1444	353	1723	-0.02	0.02
2008	1347	342	1374	-0.01	-0.11
2009	1283	326	1254	-0.01	0.08
2010	1189	320	1464	-0.01	0.04

Table 2: **Firm summary statistics**

This table reports firm annual sample statistics. All firms not incorporated in the US are excluded. Utilities and financial companies are excluded as well. FTP Sample includes firms affected by Fund Trading Pressure in a given year. Column 3 reports whether for each firm variable the difference between the full sample and the FTP sample is statistically significant at the 10% (*), 5% (**), or 1% (***). Variable construction is explained in the Appendix. The sample goes from 1990 to 2010.

Variable	Full Sample (1)	FTP Sample (2)	Difference (1) - (2)
Book Assets	1688	1888	
Share Repurchases	0.0144	0.0239	***
R&D	0.0971	0.0870	***
ROA	0.0551	0.1024	***
Cash	0.1347	0.1383	
Leverage	0.2427	0.2123	
Tobin's q	2.4359	2.0172	
Stock Return(t-1)	0.1791	0.2577	***
Stock Volatility(t-1)	0.1652	0.1628	

Table 3: **Exposure and flows**

This table reports coefficients from an OLS regression of mutual fund *Flows* on fund *Exposure* and control variables. *Exposure* is the exposure of a fund to the distressed industries computed as $Exposure_{j,t} = \sum_i w_{i,t-1} * (-Return_{i,t})$. *Size* is the log of assets under management, *FamilySize* is the log of assets under management at the family level, *Exp.Ratio* and *TurnoverRatio* are respectively the expenses and the turnover of a fund. Errors are clustered at the fund level. The observations have quarterly frequency. The data sample goes from 1990 to 2010.

Dep.Variable: Fund Flows	(1)	(2)	(3)	(4)
Dist.Industry_Exposure	-0.244***	-0.259***	-0.254***	-0.258***
	(-7.57)	(-6.86)	(-6.64)	(-3.53)
Fund Size			0.001	-0.001
			(0.79)	(-0.50)
Family Size			-0.006	0.030**
			(-0.82)	(2.07)
Exp. ratio				0.014***
				(4.32)
Turnover ratio				0.002
				(0.73)
Lag(Returns)				0.407***
				(13.10)
Lag(Flows)				0.000**
				(2.42)
Constant	0.017***	-0.031***	-0.028***	-0.040***
	(13.77)	(-19.08)	(-5.03)	(-2.58)
Style Fixed Effect	N	Y	Y	Y
Time Fixed Effect	N	Y	Y	Y
Observations	44,246	41,581	41,479	17,641
R-squared	0.008	0.041	0.040	0.064

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Do underpriced firms spend less in R&D?

This table reports coefficients from a linear regression of *R&D* spending over book assets at the beginning of the year on *FTPD* and controls. *FTPD* is a dummy variable that takes value one if the price of the stock was subject to *FTP* for at least one quarter in year t, and zero otherwise. Time, industry, and firm fixed effects are included when indicated. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable: Annual R&D Spending over Book Assets	(1)	(2)	(3)	(4)
FTPD	-0.0085***	-0.0056***	-0.0039**	-0.0054***
	(-6.77)	(-4.57)	(-2.40)	(-4.38)
Size		-0.0207***	-0.0053***	-0.0199***
		(-19.26)	(-13.97)	(-18.79)
ROA		-0.0113***	-0.0456***	-0.0103***
		(-4.28)	(-9.92)	(-3.86)
Cash		0.0194***	0.1217***	0.0169***
		(3.56)	(21.46)	(3.07)
TQ		0.0064***	0.0082***	0.0062***
		(12.77)	(10.89)	(10.73)
Past Stock Returns			-0.0028**	0.0015*
			(-2.47)	(1.90)
Past Stock Volatility			0.0689***	-0.0023
			(8.52)	(-0.36)
Constant	0.0810***	0.1882***	0.0640***	0.1825***
	(42.65)	(28.13)	(15.64)	(26.69)
Time Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	N	N	Y	N
Firm Fixed Effects	Y	Y	N	Y
Observations	37,945	36,869	36,166	36,166
R-squared	0.743	0.768	0.503	0.772

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: **Do underpriced firms boost buybacks?**

This table reports coefficients from a linear regression of dollar share repurchases over book assets at the beginning of the year on $FTPD$ and controls. $FTPD$ is a dummy variable that takes value one if the price of the stock was subject to FTP for at least one quarter in year t, and zero otherwise. Time, industry, and firm fixed effects are included when indicated. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable: Annual Share Repurchases over Book Assets	(1)	(2)	(3)	(4)
FTPD	0.0029***	0.0022***	0.0026***	0.0021***
	(4.10)	(3.05)	(3.25)	(2.89)
Size		0.0028***	0.0032***	0.0024***
		(9.86)	(27.01)	(8.00)
ROA		0.0038***	0.0102***	0.0043***
		(7.69)	(12.32)	(7.80)
Cash		0.0151***	0.0199***	0.0166***
		(8.75)	(13.04)	(9.27)
TQ		0.0003***	0.0015***	0.0004***
		(2.93)	(9.27)	(3.05)
Past Stock Returns			-0.0000	0.0003
			(-0.16)	(1.30)
Past Stock Volatility			-0.0340***	-0.0207***
			(-15.63)	(-9.86)
Constant	0.0182***	-0.0022	-0.0003	0.0038*
	(20.96)	(-1.15)	(-0.22)	(1.80)
Time Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	N	N	Y	N
Firm Fixed Effects	Y	Y	N	Y
Observations	51,116	49,707	48,823	48,823
R-squared	0.329	0.333	0.117	0.339

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Do financially constrained firms decrease R&D more?**

This table reports coefficients from a linear regression of *R&D* spending over book assets at the beginning of the year on *FTPD* and controls. *FTPD* is a dummy variable that takes value one if the price of the stock was subject to *FTP* for at least one quarter in year t. Financially constrained firms are defined on the basis of the AS index (see Section 4). Firms in the bottom 33% of the AS distribution are considered financially unconstrained, firms in the top 33% of the distribution are considered financially constrained. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable:	**Financially Constrained**		**Financially Unconstrained**	
Annual R&D Spending over Book Assets	(1)	(2)	(3)	(4)
FTPD	-0.0232***	-0.0175**	-0.0017	-0.0022**
	(-3.18)	(-2.54)	(-1.59)	(-1.98)
Size		-0.0245***		-0.0048***
		(-8.32)		(-3.28)
ROA		0.0028		0.0015
		(0.32)		(0.17)
Cash		0.0122		0.0327***
		(1.21)		(3.22)
TQ		0.0068***		0.0082***
		(6.58)		(7.56)
Past Stock Returns		-0.0015		0.0009
		(-0.94)		(1.27)
Past Stock Volatility		0.0060		-0.0261***
		(0.58)		(-2.70)
Constant	0.1940***	0.2174***	0.0391***	0.0628***
	(14.57)	(14.21)	(35.70)	(5.36)
Time Fixed Effects	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y
Observations	10,165	9,673	13,523	12,634
R-squared	0.749	0.781	0.765	0.780

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: **Do impatient firms decrease R&D more?**

This table reports coefficients from a linear regression of *R&D* spending over book assets at the beginning of the year on *FTPD* and controls. *FTPD* is a dummy variable that takes value one if the price of the stock was subject to *FTP* for at least one quarter in year t. The header "Impatient Investors" (columns 1, 2, and 3) indicates firms that are in the highest 33% "impatience" percentile. Conversely, the header "Patient Investors" (columns 4, 5, and 6) indicates firms that are in the lowest 33% "impatience" percentile. Impatience is computed on the average churn ratio of investors who held the stock in year $t-1$, as explained in Section 2. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable: Annual R&D Spending over Book Assets	**Impatient Investors** (1)	(2)	(3)	**Patient Investors** (4)	(5)	(6)
FTPD	-0.0037***	-0.0048**	-0.0034**	-0.0121*	0.0077	-0.0070
	(-2.58)	(-2.57)	(-2.37)	(-1.76)	(0.88)	(-1.06)
Size		-0.0062***	-0.0158***		-0.0075***	-0.0128***
		(-9.34)	(-8.25)		(-5.34)	(-5.30)
ROA		-0.0534***	-0.0246***		-0.0475***	-0.0045
		(-5.83)	(-4.04)		(-7.00)	(-1.06)
Cash		0.0810***	0.0225**		0.1304***	0.0128
		(8.82)	(2.32)		(12.62)	(1.18)
TQ		0.0096***	0.0074***		0.0078***	0.0064***
		(11.52)	(8.99)		(5.82)	(5.43)
Past Stock Returns		-0.0029**	0.0004		-0.0057***	-0.0019
		(-2.44)	(0.39)		(-3.20)	(-1.32)
Past Stock Volatility		0.0737***	-0.0272**		0.0540***	-0.0004
		(5.00)	(-2.41)		(4.54)	(-0.05)
Constant	0.0640***	0.0729***	0.1691***	0.1217***	0.0719***	0.1442***
	(35.49)	(10.97)	(11.68)	(14.89)	(5.92)	(11.60)
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	N	Y	N	N	Y	N
Firm Fixed Effects	Y	N	Y	Y	N	Y
Observations	12,386	11,736	11,736	10,533	9,964	9,964
R-squared	0.795	0.540	0.818	0.778	0.474	0.806

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Expected Fund Trading Pressure and R&D

This table reports coefficients from a linear regression of *R&D* spending over book assets at the beginning of the year on $E[FTPD]$ and controls. $E[FTPD]$ is a dummy variable that takes value one if a stock is likely to be subject to FTP for at least one quarter in year t, and zero otherwise (construction is described in Section 5). Time, industry, and firm fixed effects are included when indicated. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable: Annual R&D Spending over Book Assets	(1)	(2)	(3)	(4)
E[FTPD]	-0.0057***	-0.0031**	-0.0040**	-0.0025*
	(-4.22)	(-2.33)	(-2.39)	(-1.90)
Size		-0.0195***	-0.0063***	-0.0187***
		(-19.23)	(-18.60)	(-18.57)
ROA		-0.0083***	-0.0332***	-0.0088***
		(-4.74)	(-12.99)	(-4.80)
Cash		0.0154***	0.1239***	0.0140***
		(3.17)	(26.17)	(2.81)
TQ		0.0062***	0.0076***	0.0060***
		(14.31)	(13.21)	(12.11)
Past Stock Returns			-0.0026***	0.0016**
			(-2.78)	(2.27)
Past Stock Volatility			0.0452***	-0.0072
			(6.36)	(-1.32)
Constant	0.0867***	0.1834***	0.0793***	0.1787***
	(46.70)	(30.31)	(20.71)	(28.53)
Time Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	N	N	Y	N
Firm Fixed Effects	Y	Y	N	Y
Observations	48,800	47,606	46,487	46,487
R-squared	0.773	0.793	0.494	0.797

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: **Subsamples**

This table reports coefficients from a linear regression of *R&D* spending over book assets at the beginning of the year on *FTPD* and controls. *FTPD* is a dummy variable that takes value one if the price of the stock was subject to *FTP* for at least one quarter in year *t*, and zero otherwise. Time, industry, and firm fixed effects are included when indicated. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample is split in observations from 1990 to 2000 and from 2001 to 2010.

Dep.Variable:	**1990-2000**			**2001-2010**		
Annual R&D Spending over Book Assets	(1)	(2)	(3)	(4)	(5)	(6)
FTPD	-0.0076***	-0.0074***	-0.0066***	-0.0046***	-0.0047***	-0.0045***
	(-3.63)	(-3.45)	(-3.09)	(-3.29)	(-3.43)	(-3.30)
Size		-0.0078***	-0.0071***		-0.0252***	-0.0244***
		(-4.28)	(-3.85)		(-12.46)	(-12.01)
ROA		-0.0074*	-0.0072*		-0.0047	-0.0061
		(-1.94)	(-1.94)		(-1.08)	(-1.19)
Cash		0.0035	0.0035		0.0163**	0.0140*
		(0.37)	(0.35)		(2.15)	(1.85)
TQ		0.0056***	0.0054***		0.0073***	0.0076***
		(8.05)	(6.73)		(9.41)	(8.09)
Past Stock Returns			0.0001			-0.0001
			(0.05)			(-0.17)
Past Stock Volatility			0.0163			-0.0066
			(1.59)			(-0.87)
Constant	0.0903***	0.1156***	0.1080***	0.0879***	0.2181***	0.2138***
	(54.10)	(12.12)	(10.86)	(49.62)	(18.12)	(17.43)
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	18,505	17,997	17,700	19,440	18,872	18,466
R-squared	0.805	0.813	0.815	0.804	0.823	0.827

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: **Propensity Score Matching**

This table reports coefficients from a linear regression of *R&D* spending over book assets at the beginning of the year on $FTPD$ and controls. $FTPD$ is a dummy variable that takes value one if the price of the stock was subject to FTP for at least one quarter in year t, and zero otherwise. Time, industry, and firm fixed effects are included when indicated. The control group keeps only observations that are the most similar to each observation in the treatment group (i.e., a logit regression is run on industry dummies, size, past returns, Tobin's Q, and ROA). The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable: Annual R&D Spending over Book Assets	(1)	(2)	(3)	(4)
FTPD	-0.0085***	-0.0074***	-0.0063**	-0.0076***
	(-3.20)	(-3.03)	(-2.46)	(-3.11)
Size		-0.0176***	-0.0066***	-0.0175***
		(-5.01)	(-7.05)	(-4.93)
ROA		-0.0157*	-0.0345***	-0.0161*
		(-1.76)	(-3.05)	(-1.78)
Cash		0.0047	0.0804***	0.0035
		(0.27)	(6.09)	(0.21)
TQ		0.0073***	0.0082***	0.0069***
		(7.35)	(6.10)	(6.72)
Past Stock Returns			-0.0022	0.0021
			(-1.15)	(1.31)
Past Stock Volatility			0.0800***	0.0003
			(4.12)	(0.02)
Constant	0.0677***	0.1708***	0.0724***	0.1700***
	(18.27)	(7.23)	(7.49)	(6.83)
Time Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	N	N	Y	N
Firm Fixed Effects	Y	Y	N	Y
Observations	6,375	6,355	6,355	6,355
R-squared	0.826	0.841	0.514	0.841

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: R&D scaled on market value

This table reports coefficients from a linear regression of *R&D* spending over market value at the beginning of the year on $FTPD$ and controls. $FTPD$ is a dummy variable that takes value one if the price of the stock was subject to FTP for at least one quarter in year t, and zero otherwise. Time, industry, and firm fixed effects are included when indicated. Control variables are described in the Appendix. The observations have annual frequency. Errors are clustered both at the firm and the time level (two-dimensional clustering). The data sample goes from 1990 to 2010.

Dep.Variable: Annual R&D Spending over Market Value	(1)	(2)	(3)	(4)
FTPD	-0.0088***	-0.0055***	-0.0058***	-0.0051***
	(-9.36)	(-6.05)	(-5.21)	(-5.68)
Size		-0.0219***	-0.0059***	-0.0206***
		(-23.13)	(-19.88)	(-21.45)
ROA		-0.0058***	-0.0188***	-0.0044***
		(-3.97)	(-7.60)	(-2.85)
Cash		-0.0297***	0.0223***	-0.0240***
		(-7.71)	(5.85)	(-6.20)
TQ		-0.0039***	-0.0051***	-0.0035***
		(-9.91)	(-10.98)	(-8.07)
Past Stock Returns			-0.0068***	-0.0059***
			(-7.30)	(-7.62)
Past Stock Volatility			0.0692***	0.0122**
			(10.82)	(2.29)
Constant	0.0694***	0.2087***	0.0963***	0.2018***
	(49.24)	(35.44)	(30.44)	(32.78)
Time Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	N	N	Y	N
Firm Fixed Effects	Y	Y	N	Y
Observations	26,141	25,340	24,828	24,828
R-squared	0.658	0.693	0.354	0.703

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1