# Trading Out of Sight: An Analysis of Cross-Trading in Mutual Fund Families[☆]

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Alexander Eisele[a], Tamara Nefedova[b], Gianpaolo Parise[c,*], Kim Peijnenburg[d]

[a]*UBS Asset Management, Stockerstrasse 64, 8098, Zurich, Switzerland*
[b]*Université Paris-Dauphine, Place du Maréchal de Lattre de Tassigny, 75775, Paris, France*
[c]*EDHEC, 393 Promenade des Anglais, 06200, Nice, France*
[d]*CEPR and EDHEC, 393 Promenade des Anglais, 06200, Nice, France*

**Abstract**

This paper explores how mutual fund groups set the price of in-house transactions among affiliated funds. We collect a data set of four million equity transactions and compare the pricing of trades crossed internally (cross-trades) with that of twin trades executed with external counterparties. While cross-trades should reduce transaction costs for both trading parties, we find that the price of cross-trades is set strategically to reallocate performance among sibling funds. Furthermore, we provide evidence that a large number of cross-trades is backdated. We discuss the implications for the literature on fund performance and the current regulatory debate.

*Keywords*: Mutual fund families, Cross-trades, Performance-shifting, Monitoring, Backdating, Transfer Pricing
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*gianpaolo.parise@edhec.edu

## 1. Introduction

Equity trading has been increasingly moving to private and less regulated markets both in the United States and elsewhere (see, e.g., Degryse et al., 2015). A portion of this off-exchange trading occurs within mutual fund families. In fact, fund families are allowed to offset opposite trades of affiliated funds in an internal market, a practice commonly known as "cross-trading." A growing number of papers explicitly or implicitly assume that these internal transactions are used opportunistically to the advantage of the overarching fund family. For example, previous literature posits that cross-trades strategically reallocate performance from low- to high-value funds (Gaspar et al., 2006), from outsourced to in-house funds (Chuprinin et al., 2015), from mutual funds to hedge funds (Del Guercio et al., 2018), and from large to small and successful financial products (Chaudhuri et al., 2017). However, the current literature lacks any direct evidence of *how* this performance reallocation is achieved.

There are potentially different ways in which cross-trades influence fund performance. First, cross-trades can be used to reduce the transaction costs and commissions borne by both trading funds. In this regard, Rule 17a-7 of the U.S. Investment Company Act establishes that cross-trades should be executed at market prices to benefit both trading parties. Second, cross-transactions can be used in a coordinated family-level effort to avoid asset liquidations at fire-sale prices. Liquidity-constrained funds can sell assets internally at a full price rather than externally at a fire-sale discount. Finally, the opacity of this internal market allows some discretion in setting a price that may favor one trading party and penalize the other. As an illustrative example, in the midst of the 2008 financial crisis, Western Asset Management (allegedly) transferred \$6.2 million to favored funds by systematically pricing cross-trades at the highest bid price available rather than at the average between the bid and the ask price.[1]

This paper asks two related questions: Are cross-trades strategically priced on average? Can monitoring policies imposed by the regulator curb the opportunistic use of cross-trades? The answer to these questions is important for three reasons. First, it sheds light on whether cross-trades are mostly used to transfer performance or as a tool to minimize transaction costs and improve liquidity management. Second, it contributes to the ongoing debate on the optimal degree of regulation of alternative trading venues. Third, it offers evidence on the incentive structure of fund conglomerates and helps to explain documented regularities in fund performance.

The main limitation encountered by previous papers addressing cross-trading stems from the fact that mutual funds only disclose their portfolio holdings at the *end* of each

[1] "SEC Fines Western \$21 Million for Defrauding Clients" January 27, 2014 *Bloomberg*.

quarter, while what happens *during* the quarter remains unseen. This makes it virtually impossible to reliably identify cross-trades from regulatory disclosure filings. As a further empirical challenge, no information on the pricing of these transactions is publicly available. Therefore, most of the conclusions in the literature to date are necessarily drawn indirectly, by looking at the performance of funds that are ex ante more likely to benefit from cross-trading activity.

In this paper, we overcome these limitations by using a database of 12 years of trade-level equity transactions from a large number of U.S.-domiciled mutual funds. Data on these trades were collected by ANcerno (also known as Abel Noser Solutions), one of the leading trading cost consulting firms in the United States. Using ANcerno's data, this paper is the first to precisely identify and study cross-trades. Specifically, we identify cross-trades as mirror transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) in the same minute of the same day,[2] v) at the same price, but vi) traded in opposite directions. Having detailed information on both cross-trades and open market trades, we are able to explore whether (and under what conditions) cross-transactions are strategically priced.

Our empirical strategy is as follows. First, we compute for each transaction the *Effective Spread*, which is the *unsigned* percentage difference between the execution price and the average between the bid and the ask price at execution. Intuitively, the effective spread measures the difference between the execution price of a trade and the fundamental value that would be available in the absence of transaction costs. Second, we test whether the effective spread is larger or smaller for cross-trades vis-à-vis similar trades executed on the open market. Under the null hypothesis that cross-trades are mostly used to limit transaction costs, we should find a significantly *lower* effective spread for such trades, as the lower transaction costs should allow a fund to trade near (or exactly at) the mid price. By contrast, if cross-trades are used to shift performance among trading parties via strategic pricing, we should find a *higher* effective spread than that of similar open market trades. In fact, a higher effective spread reallocates performance in a zero-sum game in which there is a "winner" (the fund that is buying cheap or selling expensive) and a "loser" (the fund that is buying expensive or selling cheap).

A challenge to our identification arises from the fact that the choice to cross-trade is not random, but is presumably influenced by the cost of trading on the open market. In our tests, we therefore regress the effective spread of each trade on a cross-trade dummy and *stock*×*family*×*time* fixed effects. In this way, we compare the effective spread of cross-

[2] We cannot look at higher frequencies since ANcerno reports the execution time at minute precision. As not all time-stamps in ANcerno are reliable, we exclude from the analysis all the transactions for which the reported execution time might be incorrect.

trades with that of open market trades in the same stock, by the same fund family, and executed in the same time interval (i.e., within the same stock-family-time group).

Furthermore, we explore the effects of an exogenous increase in monitoring imposed by the regulator. In 2004, new rules entered into force after an investigation uncovered widespread malpractice in the industry, known as the "late trading scandal." The new rules have increased the autonomy of compliance units, also forcing fund families to appoint independent chief compliance officers who can be held personally liable for trading violations by the monitored funds. One of the main consequences of the new regulation was that of intensifying the control by compliance officers over cross-trades, thereby limiting the scope for opportunistic pricing practices. We run a difference-in-difference analysis in which we exploit this regulatory change to assess the effect on the pricing of cross-trades vis-à-vis similar open market trades.

Our analysis yields three main findings. First, our paper shows that cross-trades are on average strategically priced when monitoring is weak. While cross-trades are permitted under the assumption that they will be used to minimize transaction costs, we find that on average these trades display a 42 basis points *higher* effective spread than that of twin open market trades. This implies that the execution price of these transactions deviates systematically more from the mid price compared to similar transactions executed in public exchanges. This result is reversed however when monitoring by compliance units is enhanced in 2004, as the effective spread of cross-trades becomes 3 basis points *lower* than that of open market trades. Hence, our results suggest that cross-trades are mostly used to strategically reallocate performance when monitoring is weak, while they are priced with less or no discretion when strong monitoring policies are in place. Furthermore, we find that strategic pricing intensifies under bad market conditions.

Second, we provide evidence that cross-trades are "backdated." The price of cross-trades appears to be retroactively set to either the highest or the lowest price of the day, i.e., those prices that shift the largest performance among trading counterparties. In particular, we find that cross-trades are four times more likely to be executed *exactly* at the highest or the lowest price of the day than similar open market trades. This suggests that cross-trades are often executed *after* the market closes and backdated to the moment of the day when the price was the most extreme.

Finally, we explore the relation between fund characteristics and the pricing of cross-trades.[3] We find that high-fee funds, young funds, and funds experiencing temporary

[3]We obtain the identity of the fund families in our sample from ANcerno. However, the identity of the individual funds reporting to ANcerno is commonly anonymized in the data. For a limited number of funds, we are able to overcome this issue by matching ANcerno's clients with Thomson Financial/CRSP funds on the basis of the similarity in their trading behavior when aggregated at a quarterly frequency (similar to, e.g.,

liquidity shortfalls systematically cross-trade at advantageous prices with respect to the market benchmark. By contrast, funds experiencing persistent outflows are systematically on the losing side of cross-trades. Taken together, these findings indicate that cross-trades are on average priced in such a way that performance is reallocated from persistently distressed funds to funds that are either highly valuable from a fund family's perspective or in need of temporary liquidity injections.

Our paper contributes to the literature on fund family strategies by adding three main novel findings and by confirming a previous finding with better data and an improved identification. In particular, i) we are the first to show that cross-trades are mispriced on average and to document the existence of backdating practices in the industry. Previous papers establish that cross-trades absorb the fire sales of funds that lack liquidity, thereby buffering their cost of distress (see, e.g., Goncalves-Pinto and Schmidt (2013) and Chuprinin et al., 2015). We are the first to show that strategic pricing is a key economic channel through which cross-trades affect performance. This finding indicates that the subsidization via cross-trades goes beyond buffering the effects of occasional liquidity shortfalls. Relatedly, ii) we argue that fund family incentives change over the business cycle, as strategic pricing intensifies when market conditions worsen. iii) We provide novel evidence that compliance policies are effective in curbing opportunistic pricing strategies. This last result has implications for studies that attempt to identify strategic behaviors at the fund family level. In fact, the extent of other opportunistic policies should also be dampened by the introduction of compliance officers in 2004. Finally, our paper confirms the existence of fund family favoritism (first documented in Gaspar et al. (2006)) using actual cross-trade data and an exogenous shock. Gaspar et al. (2006) state that their analysis is "limited by the level of information disclosure to which mutual fund activities are subject." We confirm their main conclusion using intra-quarter trade-level data.

As a second set of contributions, our paper adds to the literature on mutual fund performance.[4] Previous papers have shown that i) fund managers are able to beat benchmarks only in bad market states,[5] ii) young funds outperform old funds (e.g., Evans, 2010), and iii) changes in end-of-quarter snapshots of portfolio holdings account for a relatively small fraction of fund performance (Kacperczyk et al., 2008; Puckett and Yan, 2011; and Anand et al., 2012). While we do not argue that cross-trading is the only driver behind these

Agarwal et al., 2012). This procedure is described in detail in Online Appendix C.

[4]Specifically, our results add to the literature on the incentives of mutual funds and mutual fund families. See, e.g., Carhart et al., 2002; Massa, 2003; Nanda et al., 2004; Guedj and Papastaikoudi, 2005; Evans, 2010; Bhattacharya et al., 2013; Wu et al., 2016; Casavecchia and Tiwari, 2016; Evans et al., 2018; Del Guercio et al., 2018; and Goncalves-Pinto and Sotes-Paladino, 2018.

[5]Evidence that mutual funds deliver abnormal performance only or mostly during downturns can be found in Sun et al. (2009); Glode (2011); Kosowski (2011); and Kacperczyk et al. (2016).

empirical facts, our results do suggest that it plays a role in explaining them. In fact, we find that: i) there is more strategic pricing of cross-trades in bad market states, ii) young funds systematically benefit from cross-trading, and iii) a significant portion of trade performance is explained by the choice of the trading venue (internal versus open markets), which is unreported in the end-of-quarter filings. Overall, we posit that studies that explore the determinants of risk-adjusted performance likely overstate the role of fund managers' skill in generating returns before 2004, especially during market downturns.

Finally, our work provides insights into the current regulatory debate. A large (and growing) portion of equity trades is today executed in dark pools, internalizers, and other opaque venues. The growth of off-exchange trading has spurred a debate on the implications for investors. For example, asset managers argue that crossing trades internally reduces significantly transaction and fire-sale costs. From a welfare perspective, this argument views the increasing reliance on alternative venues as beneficial. By contrast, regulators have recently raised concerns about the risks posed by firms crossing client orders internally "too often."[6] In this regard, we provide evidence that, when adequately monitored by compliance officers, cross-trades are effective in dampening fire-sale and trading costs in bad market states, thereby benefiting the final investors. By contrast, inadequately monitored cross-trades unfairly penalize some investors, even when careful pricing rules are in place.

## 2. Data and Identification of Cross-Trades

### *2.1. Trade-Level Data*

We obtain trade-level data for the period from January 1, 1999, to December 31, 2010, from ANcerno. ANcerno is a consulting firm that provides services for measuring the quality of trade execution to institutional investors. Client institutions send batches of data with equity trades. ANcerno claims that for the specific period covered by a batch *all* equity trades are reported. We cannot test whether some clients strategically misreport cross-trades. However, this would presumably bias our results against finding evidence for mispricing, as opportunistic fund families would tend to disclose only/mostly cross-trades that are correctly priced. Previous research has shown that ANcerno's clients constitute approximately 8% of the total CRSP daily dollar volume (Anand et al., 2012) and that the data do not suffer from survivorship or backfill bias (see, e.g, Puckett and Yan, 2011).[7]

[6]See, e.g., "Esma Warns of Potential Loophole in New Share Trading Rules" February 15, 2017 *Financial Times*.

[7]An increasing number of papers rely on ANcerno data. Recent examples include, e.g., Chemmanur et al., 2009; Chemmanur et al., 2010; Brown et al., 2013; and Ben-Rephael et al., 2017.

The data set contains several variables that are useful for our analysis. Namely, for each execution ANcerno reports information on the CUSIP and ticker symbol of the stock, the execution time at minute precision, the execution date, the execution price, the side (i.e., buy or sell), the number of shares traded, the commissions paid, whether the trade is part of a larger order, and a number of trade-level benchmarks to evaluate the quality of the execution. We match trades from ANcerno with stock characteristics from CRSP, and with the best bid and ask prices available at the moment of execution from TAQ.

We are able to link fund families to their trades using additional information provided by ANcerno. For a limited period of time, in 2010, ANcerno provided its academic subscribers with a separate identification table including the names of the management company (fund family) to whom the trading funds are affiliated. This set of identification files is, however, subscription specific: the sample used in this study is constructed using the fullest set of files, to which earlier and later ANcerno subscribers do not have access (see Hu et al., 2018 for a discussion of this point).

ANcerno includes not only mutual fund families but also other institutional investors. To restrict our sample to mutual fund families, we match the management companies included in ANcerno to those listed in Thomson Financial S12 by name. As an illustrative example, we match the trades from PIMCO in ANcerno to PIMCO information from Thomson Financial.[8] A detailed explanation of the construction of the database is included in Online Appendix B.

Importantly, it is challenging to match individual mutual funds with their trades. In most cases, ANcerno does not disclose the name of the specific fund within the fund family for which the trades are available. To provide an illustrative example, with the ANcerno data it is easy to link a specific trade to PIMCO (the fund family) but not trivial to match it to the PIMCO Total Return Fund (a specific fund within PIMCO). We are able to overcome this problem for a limited number of funds (see the discussion in Online Appendix C).

The final number of mutual fund families in our sample is 266. In particular, our matched sample contains around 50% of the mutual fund families managing equity funds that report information to Thomson Financial in the same period. However, our sample is tilted toward large institutions because small families are less likely to rely on ANcerno's services (see Puckett and Yan, 2011 for a discussion of this issue). This may induce a bias,

[8]We cannot report the names of the fund families included in our sample, because of our non-disclosure agreement with ANcerno. We base our examples on PIMCO because most of the mutual funds affiliated with this fund family trade bonds instead of equity, which implies that, in any case, they would not be included in our sample. Therefore, all examples involving PIMCO are only for illustrative purposes and do not reflect actual information in our data.

as ANcerno's clients are likely to pay lower transaction costs on average. Furthermore, as mutual funds are not obliged to report to ANcerno, we cannot rule out the presence of selection bias. We overcome this issue by comparing trades *within* the same fund family. For instance, we compare cross-trades from PIMCO to trades on the open market also from PIMCO. We cannot however generalize our findings to (usually smaller) fund families for which we do not have information.

To make computation feasible we extract a random sample of 10% of ANcerno's trades, after cross-trades are identified on the entire sample (this approach is not uncommon in the literature see, e.g., Ben-David and Hirshleifer, 2012). We find similar results on alternative random samples of 1% and 5% of the trades, respectively. More information on the ANcerno database, the variables contained, and our data construction procedure is presented in Online Appendices B and C.

### *2.2. Identifying Cross-Trades*

Using the trade-level data, this paper is the first to precisely identify cross-trades. A cross-trade is a transaction in which the buy side and the sell side are matched within the same fund family, without going through a public exchange. We identify cross-trades as mirror transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) in the same minute of the same day, v) at the same price, but vi) traded in opposite directions. For instance, a *buy* trade of 1,000 Apple shares executed on January 2, 2010, 10:05 a.m., at $101.58 is classified as a cross-trade only if we have in our sample a corresponding *sell* trade of 1,000 Apple shares coming from the same fund family executed on January 2, 2010, 10:05 a.m., at $101.58. While it is possible that two mirror trades are executed on the open market instead of being crossed internally, it is however unlikely (as the affiliated funds would unnecessarily pay transaction costs and commissions).

To check the reliability of our matching procedure, we compare information on commission costs for the trades that we classify as open market trades and those that we classify as cross-trades. Cross-trades should exhibit no (or extremely low) commissions, as the broker does not need to find a third party willing to enter the opposite transaction and is not exposed to any inventory risk (although in rare cases a commission may be due for bookkeeping services). Figure 1 reports the percentage of trades for which no commissions are paid. We find that no commissions are paid for more than 98% of the trades that we classify as cross-trades. Overall, this suggests that we are identifying cross-trades with high precision.

Most related papers attempt to measure cross-trades using quarterly or semiannual snapshots of stock holdings. Specifically, a common assumption is that cross-trades are equal to the minimum of total buys and total sells of the same stock, by funds in the same fund family, within a quarter or a semester (see, e.g., Gaspar et al., 2006; Goncalves-Pinto and Schmidt, 2013; and Chuprinin et al., 2015). This methodology leads to consider *all* opposite trades as cross-trades even if occurring on different days of the same quarter. Alternatively, a number of papers focus on the N-SAR disclosure by fund families on whether any cross-trades were made during the year (see, e.g., Casavecchia and Tiwari, 2016; Del Guercio et al., 2018). Such disclosure, however, does not provide any information on when funds cross-traded, how often, and at what prices.

Our identification procedure overcomes the main limitation of previous proxies used in the literature. Through our approach, we ensure that opposite trades recorded in the same quarter but occurring on different days/times and having different sizes and prices are not considered as cross-trades. According to our calculations, estimating cross-trades from quarterly changes in portfolio holdings leads to a roughly threefold overestimation of the percentage of dollar volume that is cross-traded (12% versus 4% in our sample). Our approach allows us to provide the first accurate estimate of the actual extent of cross-trading.

Importantly, time-stamps in ANcerno are often not reliable (see, e.g., Choi et al., 2017). In particular, around 50% of the trades in ANcerno exhibit an execution time between 16:00 and 16:59 (4:00 and 4:59 pm), which is clearly unrealistic.[9] Our contact at ANcerno has indicated that, when the exact execution time is not reported by a client, ANcerno replaces it with an arbitrary time-stamp. In the beginning of our sample, this arbitrary time-stamp for missing execution times is 16:00, in the middle of our sample 16:10, and, at the end, 16:20. This is potentially an issue for our analysis because we could be flagging as cross-trades mirror trades that, while being executed at different times, display the same execution time (arbitrarily chosen) in ANcerno. To make sure that time-stamp misreporting does not bias our estimates, we restrict our analysis to only those trades with time-stamps that differ from 16:00, 16:10, and 16:20. This excludes about half of the observations in our sample and leaves us with 4,865,337 trades. In any case, the results are qualitatively similar if we do not apply this filter (see Table A5 in the Online Appendix).

### *2.3. Effective spread and choice of the benchmark*

Rule 17a-7 of the U.S. Investment Company Act establishes that cross-transactions should occur at the "current market price" of the security. Specifically, this current market price should be the last sale price or, alternatively, the average of the highest current independent bid and lowest current independent offer. As a more general rule, cross-trades

[9]While in ANcerno there is also an unrealistically high number of trades executed exactly at 9:00, this issue is resolved when we restrict our sample to ANcerno trades from mutual fund families only.

should occur only if they are beneficial to both parties and should never take place if a better price for one party is available in a public exchange.

As the main benchmark, we focus on the midpoint between the best ask and the best bid at the moment of execution. We rely on this benchmark for three reasons. First, the spread between the execution price and the midpoint is commonly used in the literature as a proxy for the difference between the price of a security and its fundamental value (e.g., Lee, 1993), which is what we attempt to gauge in our analysis. Second, different from benchmarks based on realized trades (e.g., the last sale), the midquote price does not incorporate realized transaction costs. Third, past Security and Exchange Commission (SEC) investigations mostly relied on this price as the reference point to assess potential violations of Rule 17a-7 (see, e.g., the administrative proceedings No. 3-15688 and 3-17567). We obtain the midpoint from the NYSE Trade and Quote (TAQ) database. We clean the quotes using the procedure advised in Holden and Jacobsen (2014). As transactions in ANcerno are reported at minute precision, we take the average of all the best bids in each trading minute from TAQ and the average of all the best asks in the same minute. We define the mid price as the average between the (average) best bid and best ask in each minute.

While the regulator specifies that cross-trades should be executed at the current market price, it is not immediately evident that this is indeed the "fairest" price. For instance, a large (fire-)sale of an illiquid asset would presumably trade in the open market at a discount with respect to the midpoint. This implies that the buy side would be better off purchasing the asset on the open market rather than internally at the midpoint. Yet, to cross-trade at a discounted price would unfairly penalize the seller, as, if the trade is not driven by new information, the price of the asset should ultimately revert to its original fundamental value, regardless of the potential price impact at the moment of the trade. In sum, if market prices fully reflect all available information, the midpoint at the moment of the transaction represents the fair value of the asset.

In Section 6, we present results using a number of alternative benchmark prices including respectively i) the last sale price, ii) a benchmark that accounts for the (estimated) price impact of the trade, iii) the volume-weighted average price of the day (VWAP), iv) the volume-weighted average price from placement of the order to the execution of the trade, and v) the closing price of the day. Alternatively, to assess whether cross-trades are strategically priced, we also test whether the execution price of cross-trades is more likely to be exactly equal to the highest or the lowest price of the day (i.e., the prices that reallocate the largest performance across trading parties). This allows us to be agnostic about the correct benchmark.

We define our main dependent variable, effective spread ($ES$), as the absolute value of the difference between the execution price of a trade and its benchmark price scaled by the benchmark price itself:

$$ES_{f,i,t} = \frac{|P_{f,i,t} - M_{i,t}|}{M_{i,t}}, \tag{1}$$

where $P_{f,i,t}$ is the execution price of a transaction executed by fund family $f$, in stock $i$, at execution time $t$ at minute precision. $M_{i,t}$ is the benchmark price of stock $i$ at execution time $t$ (the midpoint between the best bid and the best ask for most of our tests). We winsorize $ES$ at the 1% level to account for misreporting and outliers. Our results are similar however without this adjustment. We calculate the effective spread for both open market trades and cross-trades in an analogous way.

Consideration of the *absolute* value of the deviation from the benchmark is the correct approach in our setting, as we are interested in the deviation from the benchmark price *per se*, regardless of whether positive or negative. A spread for a cross-trade that is positive and significantly higher than that of similar trades executed in the open market implies the presence of another cross-trade for which the spread is negative and significantly lower. For instance, for each cross-trade with a positive spread of 0.05, there will be another cross-trade with a spread of -0.05 (the other side of the trade). Consequently, if we calculated the average of the signed spreads of these two cross-trades, we would mechanically obtain a value of 0. This would erroneously suggest that the cross-trades are traded exactly at the benchmark price.

Intuitively, our measure captures the spread between the execution price of a trade and its fundamental value. Cross-trades should exhibit a significantly smaller spread than similar open market trades, as they are intended to minimize transaction costs. Consequently, their effective spread should be zero or very close to zero. By contrast, a large spread would indicate that performance is reallocated between the two cross-traders, as it suggests that the execution price is either "too high" or "too low."

### *2.4. Fund-level information*

Identifying the exact mutual fund that trades is challenging with our data, as ANcerno anonymizes its clients' identity. However, we can, to some extent, circumvent this limitation by matching funds with standard mutual fund databases (such as Thomson Reuters S12 and CRSP) on the similarity of their trading behavior once aggregated at a quarterly level. To give an illustrative example, if the net quarterly changes in holdings of a fund affiliated with PIMCO (as reported by Thomson Reuters (S12)) exactly match the net quarterly changes in holdings of a client affiliated with PIMCO in ANcerno, there is a very high probability that the two funds are the same (this procedure is similar to that applied by, e.g., Agarwal et al., 2012 and is described in detail in Online Appendix C). This procedure allows us to match with high likelihood 53 funds. A limitation of this approach is, however, that, due to the small number of matched funds, our results are not necessarily generalizable to the whole mutual fund industry. Furthermore, the subset of matched funds is in all likelihood nonrandom. Therefore, we do not rely on this fund matching for most of the analyses of the paper, but only for one fund-level analysis (see Table 6 in Section 5.5 of the paper).

Once we match a set of cross-trades with the cross-trading funds, we can estimate which type of funds are systematically on the winning (losing) side of cross-trades. To that end, we compute the *signed* effective spread as:

$$SES_{f,i,t} = \frac{P_{f,i,t} - M_{i,t}}{M_{i,t}} \times (-Side), \tag{2}$$

where $Side$ is the side of the trade: 1 for buys, -1 for sells. Intuitively, a positive $SES$ indicates a gain with respect to the benchmark price (the fund is buying at a discount or selling at a premium). By contrast, a negative $SES$ indicates a loss (the fund is buying at a premium or selling at a discount).

## 3. Hypotheses

Fund families, motivated by overall profit maximization, can cross-trade to improve the trade execution of all funds or subsidize a subset of valuable ones. Family strategies that favor some funds at the expense of others are optimal when the gain of the favored funds in terms of additional dollar fees outweighs the loss of the penalized funds. In the following, we present our hypotheses:

$H_0$. **Cost reduction.** Our null hypothesis is that mutual fund families offset internally opposite transactions of affiliated funds to reduce trading costs and commissions. There is no overall family strategy to improve the performance of some funds at the expense of others. This implies that the main reason to cross-trade is to maximize the return earned by all investors. Therefore, the assets are exchanged internally at the market price, as established by Rule 17a-7 of the Investment Company Act.

We propose two alternative hypotheses. In particular, Chuprinin et al. (2015) argue that there are two possible channels through which cross-trades can be used to subsidize affiliated funds. First, cross-trading may affect performance if used to absorb fire sales by funds in distress that lack liquidity. Second, cross transactions may be executed at opportunistic prices. We frame our alternative hypotheses accordingly:

$H_1$. **Fire sale absorption:** Cross-trades are used to benefit distressed funds by mitigating the cost of liquidity-induced fire sales, thereby buffering their cost of distress. This hypothesis follows from the theoretical work that analyzes the equilibrium price of asset sales when liquidity disappears, thereby increasing the cost of selling (Scholes, 1972 and Shleifer and Vishny, 1992; see Coval and Stafford, 2007 for an empirical analysis). In the context of fund families, cross-trades are an ideal way to absorb liquidity-induced trades. Under a coordinated strategy, high-value funds facing outflows are helped by low-value funds taking the opposite side of their transactions, thereby mitigating the impact of distress on performance.[10] Importantly, this strategy can reallocate performance between funds *even if the price complies with Rule 17a-7*, as the transaction executed on the market could have a significant price impact, which is avoided by the cross-trade. Empirically, this hypothesis implies that cross-trades are executed at better prices than comparable market trades, especially when liquidity in the market is scarce.

$H_2$. **Strategic pricing:** Subsidization is achieved by opportunistically pricing cross-trades. We develop the theoretical arguments underpinning this hypothesis by relying on the literature on transfer pricing (e.g., Hirshleifer, 1956; Alles and Datar, 1998) and tunneling (e.g., Johnson et al., 2000; Bertrand et al., 2002). The transfer pricing literature derives theoretically how an organization with a divisional structure should set the price of an asset transferred across divisions to maximize the profit achieved by the organization as a whole. The tunneling literature posits that majority shareholders may use transfer pricing to their own advantage, looting firms where they have lower cash flow rights at the expense of minority shareholders.[11] One of the key predictions of transfer pricing models is that the price of an asset exchanged among divisions will deviate from the market price when this is beneficial to the organization as a whole (Hirshleifer, 1956). In the context of our paper, we view a mutual fund family as a multi-divisional organization, which establishes the pricing rule for internal exchanges of assets among different divisions (i.e., the affiliated mutual funds). Sibling funds should exchange assets internally at market prices under the assumption of efficient markets and absent any strategic behavior. However,

[10]Performance shifting via cross-trades can be coordinated in a number of ways. In the following, we assume that the fund family has complete control over the cross-trading activity of affiliated funds. This assumption is akin to that in Stein (1997) regarding the role of corporate headquarters in reallocating resources among competing divisions. Alternatively, it is fairly common that the same fund manager or team is in charge of multiple funds. This makes it straightforward to use cross-trading to inflate the performance of the most expensive/valuable fund (possibly even if the fund family is unaware of that). Furthermore, coordination can take place between two fund managers in charge of different funds that could enter into a tit-for-tat agreement whereby repeated interactions facilitate one fund accepting a worse price than that available on the open market (see Goncalves-Pinto and Schmidt, 2013). In our empirical analysis, we are however unable to pinpoint the prevalent coordination mechanism.

[11]As an example, Johnson et al. (2000) discuss the case of Marcilli, an Italian machinery maker 51-percent owned by Sarcem, a Swiss company. Sarcem allegedly underpaid for products bought from Marcilli and resold them at a premium. As a result, the Swiss manufacturer was pocketing an immediate profit at the expense of the profitability of the Italian company. We test whether similar dynamics are present within mutual fund families.

from a family perspective, an incentive to price cross-trades strategically arises when the additional benefit accruing to the fund cross-trading at the advantageous price more than compensates for the loss of the penalized fund. This is commonly the case in mutual fund families, as the heterogeneity in fund characteristics usually implies that some funds are relatively more valuable than others from a group's perspective. In that case, the pricing of cross-trades can be used as a tunneling device to reallocate performance across affiliated funds. The fund that buys at a premium (sells at a discount) subsidizes its counterparty.

To disentangle between the hypotheses above, we explore how cross-trades are priced. Importantly, the economic incentive for cross-trading may change over time and different incentives likely coexist. For instance, the same fund family might pursue a subsidization strategy by using some cross-trades to buffer the market impact of fire sales, and some to shift performance by mispricing the exchanged assets. In our empirical analysis, we attempt to identify what the *prevalent* economic incentive is. To that end, we formulate a set of testable restrictions regarding the pricing of cross-trades that should be validated under the strategic pricing hypothesis ($H_2$) and should not be validated under the cost reduction ($H_0$) and the fire sale absorption ($H_1$) hypotheses.[12] Empirically, cost-reduction or fire sale absorption strategies should both minimize the spread between the execution price of the cross-trade and the benchmark market price. By contrast, strategic pricing should magnify it. The first restriction follows:

- *H2-a: The execution price of the cross-traded asset differs from its market price.*

Fund families face a trade-off, as tunneling performance may have legal and reputational costs. Fund groups should therefore price cross-trades strategically only when the expected reward exceeds the expected cost. Notably, the expected cost is going to be higher if cross-trades are validated by an independent monitor, as an opportunistic price is more likely to be spotted and sanctioned. We exploit an exogenous increase in the independence of compliance officers imposed by the SEC to explore the implications on transfer prices (see details in Section 4.2). We would expect that independently monitored cross-trades are not (or are significantly less) strategically priced:

- *H2-b: In the presence of stronger monitoring the cross-traded asset is transferred at a price closer to its market price.*

For the subset of cross-trades that are actually mispriced, we should expect the prices to deviate even more from market prices when performance reallocation is more valuable. To the best of our knowledge, the mutual fund literature to date has not explicitly tested whether fund family incentives are time varying. However, it is a common assumption that investors have a higher marginal utility of consumption in bad times. If investor

[12] In Online Appendix A, we present a simple theoretical framework that derives more formally analogous restrictions.

flows are more sensitive to performance when investors value performance the most, flow-performance sensitivity (FPS) should be higher in bad times.[13] In turn, if the differential in FPS between sibling funds is higher in bad times, it becomes relatively more advantageous to boost the performance of high-FPS funds in busts than in booms.[14] This argument implies that, in the presence of weak or absent monitoring, cross-trades should exhibit larger effective spreads in downturns:

- *H2-c: If strategically priced, the price of a cross-traded asset should deviate more from its market price in downturns.*

Under the strategic pricing hypothesis, cross-trades should be priced to benefit the most profitable funds from a family's perspective. The revenues of mutual fund families derive from the sum of the total fees charged by their funds. In this regard, sibling funds differ among each other in two important aspects: the magnitude of the fees charged and the responsiveness of their investor base to performance. From a fund family's perspective, the optimal strategy to maximize dollar fees is to inflate the performance of the funds that charge the highest fees and have the highest FPS. At the same time, the revenues of the family are reduced relatively little if the performance of cheap and low-FPS funds is deflated, as their investors pay lower fees and are less likely to pull their money out. Therefore, we should have that:

- *H2-d: High-FPS funds and high-fee funds cross-trade at advantageous prices. Low-FPS funds and low-fee funds cross-trade at disadvantageous prices.*

We explain how we test empirically these restrictions in Section 4.1 below.

## 4. Research design

### *4.1. Testing strategy*

In this section, we explain how we test the empirical implications of our hypotheses. Restriction H2-a requires that the price of cross-trades presents a spread with respect to the benchmark price. We define as the main benchmark, $M$, the mid price of the stock at the time of execution. We then assess whether the effective spread of cross-trades, $ES$, is larger than the effective spread of similar open market trades (see Figure 2). Cross-trades

[13] Support for the assumption that flows should be more responsive to performance in bad times is provided by Glode (2011) and Schmalz and Zhuk (2018). The former paper posits that fund managers exert greater effort to maximize investors' utility in bad market states, the latter argues that bad market states are more informative of the value of assets and asset managers. The empirical evidence on time-varying FPS is mixed and ultimately is affected by the model used to compute abnormal returns and the definition of downturns (see, e.g., Franzoni and Schmalz, 2017 and Starks and Sun, 2016).

[14] This testable restriction is formally derived in Online Appendix A under the assumption that the FPS during bad times is $\xi$ times the FPS in good times, with $\xi \geq 1$ equal for all sibling funds.

should exhibit on average a *lower* effective spread than that of similar open market trades, as they should allow the cross-trading funds to minimize transaction costs. Therefore, the analysis is performed at the trade level focusing on the effective spread, $ES_{f,i,m}$, of each transaction executed by family $f$, in stock $i$, at time $m$. We consider $m$ at the monthly level to ensure that each cross-trade in our sample has several twin open market trades in the same family-time-stock group. We also present results defining $m$ at the daily level (this forces us to discard several cross-trades for which we do not have valid control observations, i.e., open market trades executed by the same fund family, in the same stock, *during the same day*).

Our empirical approach is the following. Assume that the effective spread of a trade may be decomposed into:

$$ES_{f,i,m} = \beta_0 + \beta_1 \times CT_{f,i,m} + \eta_{f,i,m}, \tag{3}$$

where $CT_{f,i,m}$ is a variable that takes a value of 1 if the trade is crossed internally and 0 if it is executed on the open market, and $\beta_1$ measures the average difference in effective spreads between cross-trades and open market trades. $\eta_{f,i,m}$ represents a time-varying *unobservable* component of the effective spread that depends, for instance, on the type of stock traded, the characteristics of the fund family, and the conditions of the market. Notably, ignoring the unobservable component and estimating the main coefficient of interest with OLS regressions will yield a biased coefficient $\beta_1^{OLS}$ if $Corr(CT_{f,i,m}, \eta_{f,i,m}) \neq 0$. If the choice to cross-trade is not random but influenced by market conditions or stock characteristics, $CT_{f,i,m}$ and $\eta_{f,i,m}$ will be correlated and the OLS estimate will be biased. To overcome this problem, we add $time \times stock \times family$ fixed effects, $\beta_{f,i,m}$, in our estimation of equation (3):

$$ES_{f,i,m} = \beta_{f,i,m} + \beta_1^{FE} \times CT_{f,i,m} + \epsilon_{f,i,m}. \tag{4}$$

The fixed-effect approach allows us to test whether cross-trades exhibit systematically different spreads from those of open market trades in the *same* stock, by the *same* fund family, and executed in the *same* month. Since the comparison is, therefore, within stock-family-time groups, all time-varying stock and fund family characteristics, as well as time-varying market conditions are absorbed by the fixed effects. Importantly, in this way we estimate $\beta_1^{FE}$ out of twin trades executed in different venues (open versus internal market), as all cross-trades without at least one twin open market trade in the same stock-family-time group are collinear with the $time \times stock \times family$ fixed effects and therefore do not enter into the estimation. In other words, the control group is composed of twin open market trades executed by i) the same fund family, ii) in the same stock, and iii) in the same month as the cross-trades (we consider alternative control groups in the Online Appendix).

As $ES_{f,i,m}$ is always positive by construction, we should find $\beta_1^{FE} > 0$ if the effective spread of cross-trades is, on average, greater than that of open market trades. By contrast, we should find $\beta_1^{FE} < 0$ if the effective spread of cross-trades is, on average, smaller than that of open market trades.[15]

Alternatively, we test restriction H2-a by assessing whether the price of cross-trades is opportunistically decided ex post. This empirical approach allows us to avoid to take a stance on what the "correct" benchmark price is. An optimal strategy from a fund family's perspective would be that of setting the price of cross-trades retroactively equal to the price of the day that shifts the greatest performance (which is the highest or lowest price of the day). In order to test whether fund families backdate cross-trades, we construct a variable—*HighLow*—that takes a value of 1 if the execution price of a trade is *exactly* equal to either the highest or the lowest price of the day, and takes a value of 0 otherwise. If trades are crossed internally only when, by chance, two sibling funds want to execute opposite transactions, cross-trades and open market trades should display similar probabilities of being executed exactly at the highest or lowest price of the day. In other words, under the null hypothesis of cost reduction, we should obtain a non-significant coefficient when regressing $HighLow$ on $CT$.

We explore whether strongly monitored cross-trades are more fairly priced (restriction H2-b) using a similar approach. In 2004, new security laws increased the independence of compliance units in charge of monitoring the execution prices of cross-trades (details follow in the next section). Hence, we test whether the regulatory change in 2004 has a causal impact on the effective spread of cross-trades. Specifically, we run a difference-in-difference specification in which we compare the difference between the effective spread of cross-trades before and after 2004 (treatment group) vis-à-vis the effective spread of open market trades before and after 2004 (control group). Open market trades are the ideal control group in this case, as they should not be affected by the appointment of compliance officers (or should be affected to a lesser extent).

We test whether cross-trades are more likely to be strategically priced in market downturns (restriction H2-c) by comparing how the difference between the effective spread of cross-trades and open market trades changes in good and bad market states. To conduct our analysis, we focus on three measures of market stress. Specifically, we consider a stock market downturn indicator which takes a value of 1 if the cumulative market performance in a three-month window is below -5%, the CBOE volatility index (VIX), and a measure of financial uncertainty proposed by Jurado et al. (2015).

[15]For brevity, we omit the subscripts of the variables in the rest of the paper. All specifications in the text refer to asset $i$ traded by fund family $f$ during minute $t$ of month $m$ or day $d$. The unit of observation is at the transaction level.

Finally, we test whether high-fee funds and high-FPS funds are more likely to cross-trade at advantageous prices (restriction H2-d). As FPS is notoriously hard to estimate at the fund level (fund-level flow-performance sensitivities are quite noisy), we consider fund characteristics that are known to relate to FPS. In particular, we focus on fund age and liquidity needs, as young funds and funds that suffer temporary liquidity shortfalls typically display high FPS (Chevalier and Ellison, 1997 and Coval and Stafford, 2007), whereas funds with persistent liquidity demands exhibit relatively lower FPS (Sirri and Tufano, 1998; Bhattacharya et al., 2013). To that end, we estimate the relation between the *signed* effective spread and fund characteristics on cross-trades only. A positive (negative) correlation indicates that a specific type of fund tends to cross-trade at better (worse) prices.

### *4.2. Changes in compliance policies*

We test empirical restriction H2-b by exploring the role of regulatory induced monitoring on the pricing of cross-trades. To this end, we exploit a regulatory change in the aftermath of the "late trading scandal" as an exogenous source of variation in the intensity of monitoring. On September 3, 2003 the New York State Attorney General announced the issuance of a complaint claiming that several mutual fund firms had arrangements allowing trades that violated the terms of their funds' prospectuses, their fiduciary duties, and general securities laws. Subsequent investigations showed that at least 20 mutual fund management companies, including some of the industry's largest firms, had struck deals permitting improper trading (see, e.g., Zitzewitz, 2006; McCabe, 2009; Anton and Polk, 2014). Notably, most of the violations involved late-trading practices, while none of the funds under scrutiny were charged with improper cross-trading.

As a reaction to the late trading scandal, a new set of rules was introduced in October 2004 requiring fund families to implement more stringent compliance policies to prevent violations of federal securities laws (see, in particular, Rule 38a-1 under the Investment Company Act and Rule 206(4)-7 under the Investment Advisers Act). Among the new rules, there are three requirements that are likely to limit the scope for pricing cross-trades opportunistically. *First*, before 2004 compliance officers were directly employed by the fund management, whereas since October 2004 compliance officers have to respond only to the board of directors, which, in most cases, includes a majority of independent directors (or a "super majority" of 2/3rd).[16] This, in turn, has significantly increased the independence of the "monitors." *Second*, the chief compliance officer can be held personally liable for wrongdoings by the monitored fund, thereby creating a strong incentive to report suspicious cross-trading activity. *Third*, the SEC has increased the requirements

[16]See, for instance, "Understanding the role of mutual fund directors" ICI, 1999.

and its control over reporting and monitoring procedures. In the Adopting Release of Rule 38a-1, the SEC stresses that compliance officers should put in place procedures to *monitor for circumstances that may necessitate fair value prices* which clearly speaks to the cross-trade pricing issue.[17]

The new regulatory framework intensifies the monitoring on fund managers and fund families.[18] Hoffman et al. (2008) conduct a survey on compliance officers and mutual fund board members, concluding that Rule 38a-1 has significantly increased compliance officers' independence, thereby improving mutual fund governance. This appears particularly important as, before 2004, compliance officers lacked independence. As an example, in the majority of fund firms involved in the late trading scandal, the compliance staff spotted and reported trading violations. However, company officials systematically overruled any compliance staff's efforts to limit late trades. Hoffman et al. (2008) argue that the late trading scandal might not have happened had Rule 38a-1 been already in place. In short, the new regulatory environment provides a setting in which pricing cross-trades opportunistically is comparatively more difficult.

## 5. Empirical results

### *5.1. The cross section of (cross-)trade pricing*

This section compares the pricing of cross-trades with that of trades executed on public exchanges. As a preliminary analysis, we report average characteristics for the two different types of trades in Table 1. Column (1) reports the average trade and stock characteristics for the sample of cross-trades, Column (2) for the sample of open market trades, and Column (3) for the difference between the two. In line with the strategic pricing hypothesis, we find that cross-trades exhibit a significantly higher effective spread than open market trades (1.23% versus 0.50%), and are almost five times more likely than open market trades to be executed at either the highest or the lowest price of the day.

The higher effective spread of cross-trades could also arise from differences between the stocks traded in the open market and those exchanged internally. Table 1 indicates that cross-traded stocks tend to be more liquid and have a larger market capitalization, which is likely due to the fact that these stocks account for the greatest overlap in the portfolios of sibling funds. The wide presence across fund portfolios increases the scope for cross-trading. Also, cross-traded stocks exhibit more volatility. This is driven by the fact that

[17] According to our talks with employees at one of the largest fund families, the task of monitoring the execution price of cross-trades is generally among the main responsibilities of compliance officers.

[18] See, e.g., "The New Compliance Rule: An Opportunity for Change" Lori A. Richards speech at Mutual Fund Compliance Programs Conference, Washington, DC June 28, 2004.

stocks are more likely to be cross-traded when they experience high volatility on the open market. We also find that cross-trades are significantly cheaper in terms of commissions paid to the broker (no commissions are paid on 98% of cross-trades, see Figure 1) and larger, both in terms of number of traded shares and dollar trade size. In our sample, cross-trades are less than 1% of all trades but account for more than 4% of the entire trading volume in dollars. The latter result is of interest in itself. A growing literature posits that sophisticated investors profit from trading around large orders of mutual funds (see, e.g., Shive and Yun, 2013 and van Kervel and Menkveld, 2017). Our results suggest that the costs of such "predatory trading" might be mitigated by the fact that mutual funds tend to trade their largest positions off-market.

To formally test whether the pricing of cross-trades is different from that of open market trades, we estimate the difference in effective spreads, $ES$, in a multivariate framework. The number of observations is kept constant across specifications, to simplify the comparison of the coefficients. Column (1) of Table 2, Panel A indicates that cross-trades present a 73 basis points higher effective spread than open market trades when we do not include any control or fixed effect (this estimate is statistically significant at the 1% level). The estimated coefficient decreases to 44 basis points when we include stock, family, and time fixed effects to account for aggregate fluctuations in effective spreads and for time-invariant differences across stocks and families (see Column 2). Column (3) shows that our estimate is robust to the inclusion of time-varying controls. Column (4) also adds quadratic terms for all the control variables to account for potential nonlinearities. Overall, the coefficients of interest are very similar across specifications, thereby suggesting that differences in trade size and time-varying stock characteristics do not explain why cross-trades and open market trades are priced differently.

Column (5) presents the results using our preferred specification, which includes triple interaction fixed effects ($time \times stock \times family$). The coefficient of $CT$ reported in Column (5) measures the average difference in effective spreads between cross-trades and open market trades in the *same* stock, by the *same* fund family, and executed at the *same* time (time in this specification is defined at the monthly level, results including day fixed effects are presented in Panel B). All time-varying stock and family characteristics are absorbed by the fixed effects. The rationale for this specification lies in the fact that fund managers may systematically choose to cross-trade when expected transaction costs on the open market are higher. Furthermore, the higher effective spread may arise from unobservable differences between cross-trades and open market trades. By using this specification, we restrict the control group to only twin trades. The estimated effect of cross-trading on the effective spread is 42 basis points, and is significant at the 1% level. This result validates restriction H2-a, as it indicates that cross-trades are strategically priced on average. According to Rule 17a-7, cross-trades should minimize effective spreads but, instead, exhibit significantly larger spreads from benchmark prices than similar open market trades do. Importantly, as cross-trades are zero-sum games, strategically priced transactions necessarily reallocate performance among trading parties. While in all likelihood cross-trades occur both to reduce transaction costs and to shift performance via strategic pricing, the latter incentive appears to dominate on average.

The difference in effective spreads between cross-trades and open market trades is economically significant. The 42 basis point higher effective spread of cross-trades corresponds to 84% of the average effective spread of trades in ANcerno (which is 50 bps) and is twice the average bid-ask spread for the stocks in our sample obtained from CRSP (21 bps). Furthermore, the higher spread also amounts to four times the average commission per dollar paid on open market trades (11 bps).[19] Overall, our results indicate that the choice of trading venue (open versus internal market) has large economic implications for the return of a trade.

Panel B of Table 2 provides additional results and a battery of robustness tests. Column (1) includes only trades by fund families that have been investigated by the SEC for violations of trading regulations, while Column (2) includes only trades by fund families that have never been investigated. We consider this as a proxy of governance, as Dimmock and Gerken, 2012 show that past regulatory and legal violations predict investment fraud. We find that only the cross-trades by fund families with bad governance display higher effective spreads than open market trades. Column (3) runs the analysis excluding stocks for which the price is below \$5 to make sure that our results are not driven by highly illiquid stocks. Results remain similar. Column (4) adds client fixed effects to our main specification. In particular, we include a dummy variable for each (anonymous) client who sends her trades to ANcerno. This does not affect our estimates. Finally, Column (5) replaces the $month \times stock \times family$ fixed effects with $day \times stock \times family$ fixed effects. Using this specification, we estimate the beta coefficients only on the cross-trades for which we have at least one open market trade executed by the same fund family, in the same stock, *traded during the same day*. We find that the estimated coefficient remains economically and statistically significant. Alternatively, we replicate our estimations using a nearest-neighbor matching algorithm. With this approach, we compare each cross-trade only with the most similar open market trade according to a number of metrics (e.g., trade size) and we relax the assumption of linearity of the relation between the covariates and the effective spread. Results are reported in Table A4 in the Online Appendix and remain qualitatively similar. Overall, the finding that cross-trades are strategically priced on average is robust across

[19]Open market trades pay higher commissions compared to cross-trades. However, even when we perform the analyses in Table 2 taking into account commissions, the difference in effective spreads is still 32 basis points. These results are presented in Online Appendix D.

specifications. Furthermore, in Online Appendix E, we consider a placebo test, i.e., the case in which fund siblings are mostly homogeneous in terms of FPS and fees. In this case, there is less of an incentive to use cross-trades to tunnel performance. We find no evidence of mispricing of cross-trades in this sample.

### *5.2. An alternative approach: are cross-trades backdated?*

Table 3 shows that, in all specifications, cross-trades are significantly more likely than open market trades to be executed at extreme prices. Focusing on specification (5), the estimated coefficient indicates that cross-trades are 0.66 percentage points more likely than twin open market trades to be executed *exactly* at the highest or lowest price of the day. This represents an almost three times higher probability relative to an unconditional probability of 0.23 percentage points for the average trade in our sample. In the Online Appendix, we provide evidence that this result is driven by bad-governance fund families and holds in different sub-samples (see Tables A8). Overall, our results indicate that several cross-trades are likely backdated.

This empirical approach presents three advantages with respect to the analysis on the effective spread that we have conducted in the previous section. First, it does not require us to define a benchmark for the trades. Second, the results are not affected by potential misreporting of the execution time in ANcerno (see Section 2.2).[20] Third, this set of results is potentially less vulnerable to endogeneity concerns, as there is no clear rationale why cross-trades should be more likely to be priced at the highest or the lowest price of the day if no strategic pricing behavior takes place (unless cross-trading fund managers possess exceptional timing skills).[21]

This approach presents however some drawbacks with respect to our main empirical design. While the effective spread measure follows directly from the theoretical framework (see Section 3 and Online Appendix A), the rationale for looking at the highest/lowest price of the day is more ad hoc. Furthermore, relying on this empirical approach does not allow us to identify all backdated cross-trades, as, in all likelihood, several backdated cross-trades are not executed at exactly the highest or the lowest price of the day but at other opportunistically chosen prices. In the remainder, we report results based on the

[20]This is because we compare the execution price of each transaction with the highest and lowest price of the day for the stock, regardless of the time at which the transaction took place.

[21]It is however certainly possible that traders choose to cross-trade when prices in the market are extreme. In other words, reverse causation might be an issue. Therefore, we reinforce our identification using the 2004 regulatory change as an exogenous shock to the incentive to cross-trade, similar to the specification that we adopt to assess the effect of monitoring in Section 5.3. We find that the probability of a cross-trade being executed exactly at the highest or lowest price of the day decreases significantly with monitoring, consistent with a causal interpretation of our findings (see Table A7 in the Online Appendix).

effective spread in the main paper, and results on backdating as robustness in the Online Appendix.

### *5.3. Does monitoring influence the pricing of cross-trades?*

In this section, we explore the effect of regulatory induced monitoring by compliance officers on the pricing of cross-trades. In the aftermath of the late trading scandal, new rules increasing monitoring intensity on mutual fund trading activity were adopted by the SEC (details are in Section 4.2). Our goal in this section is twofold. First, we seek to validate restriction H2-b which states that cross-trades should be less strategically priced when carefully monitored. Second, we exploit the introduction of new regulation to reinforce our causality claim.

Figure 3 compares the average effective spread of cross-trades (the solid line) with open market trades (the dashed line) over time. The two lines display a parallel trend before the new rules are implemented. However, the effective spread of cross-trades decreases significantly after monitoring intensifies, while the effective spread of open market trades remains largely unaltered. In particular, the effective spread of cross-trades is *higher* than that of open market trades before the introduction of the new set of rules (see vertical line) and becomes *lower* shortly afterwards.

Table 4 reports the estimated effect of stronger monitoring on the effective spread of cross-trades in a multivariate framework. The specifications we use in Columns (1) to (5) are identical to those used in Table 2, with the exception of the additional right-hand side interaction term: *CT* $\times$ *Post Regulation*, which captures the marginal effect of the new compliance policies on the effective spread of cross-trades. The dummy variable *Post Regulation* is not included by itself in Columns (2)-(5), as it is absorbed by the time dummies.

Consistent with H2-b, we find that tighter compliance regulation has a large effect on the pricing of cross-trades. The coefficients reported in Column (5) indicate that the effective spread of cross-trades drops by 54 basis points after the introduction of improved monitoring, falling below that of open market trades (the result is significant at the 1% level). This indicates that the average difference between the effective spread of cross-trades and that of twin open market trades is -3 basis points (51-54 bps, see Column 5) *when more effective monitoring is present*, thereby making cross-trades relatively cheaper than comparable open market trades. Hence, before the regulatory change, we find evidence in line with the strategic pricing hypothesis ($H_2$), and after the regulatory change we find evidence in line with the cost reduction and fire sale absorption hypotheses ($H_0$ and $H_1$). Importantly, there can still be performance reallocation via strategic pricing as long as the effective spread is not exactly equal to zero.

Overall, this set of results indicates the presence of two types of cross-trades: "bad" and "good." Bad cross-trading inflates the performance of one fund at the expense of the other via discretionary pricing and is more frequent when monitoring is lacking. Good cross-trades, by contrast, have low effective spreads, which makes them advantageous for both trading parties with respect to similar open market trades. Good cross-trades appear to be more frequent when stronger monitoring is in place.[22]

The result in Table 4 further reinforces our causality claim. A threat to our identification stems from the possibility that the correlation between effective spreads and cross-trades arises endogenously. For instance, because a high effective spread leads the fund manager to cross the trade internally (i.e., there is an issue of reverse causality) or because an unaccounted factor drives both the effective spread and the decision to cross-trade (i.e., there is an omitted variable bias). The fact that an exogenous increase in regulatory scrutiny affects cross-trade pricing—while leaving open market trades unaffected—supports a causal interpretation of the results. For example, if high expected effective spreads are the only reason why trades are crossed and there is no performance reallocation via strategic pricing, the new regulatory environment should not matter for cross-trade pricing. Similarly, if the change in regulation proxies for an increase in market liquidity, the effect on cross-trades and open market trades should be similar (or if anything we should expect a stronger effect on open market trades). We believe that the triple fixed effect approach adopted in the previous section already mitigates these endogeneity concerns. Nonetheless, results in this section offer additional evidence in support of our causality claim.

### *5.4. Do market states influence the pricing of cross-trades?*

This section tests whether market states affect the pricing of cross-trades (restriction H2-c). Table 5 presents the results. In particular, Columns (1) to (3) illustrate the influence of market conditions on effective spreads for the period before the regulatory change, and Columns (4) to (6) for the period after. We present the results separately for these two time intervals, as we have shown that cross-trades are on average strategically (fairly) priced when weakly (strongly) monitored. The effect of market states on the pricing of cross-trades is therefore likely to depend on the intensity of monitoring.

We find that before the regulatory change the difference between the effective spread of cross-trades and that of twin open market trades is significantly *higher* in bad market conditions than in good market conditions (see Columns 1 to 3). Specifically, it is 11

[22]Furthermore, results in Table A2 in the Online Appendix exploit an additional cross-sectional dimension by using information on the corporate governance of fund families. We show that the introduction of stronger monitoring rules in 2004 has decreased the average effective spread of cross-trades by bad-governance families four times more than that of cross-trades by good-governance families.

basis points higher in market downturns, 1 basis point higher for each additional point of VIX, and 50 basis points higher when uncertainty is one standard deviation above average. These results indicate that mutual funds face a greater incentive to shift performance in bad market conditions, consistent with testable implication H2-c and the strategic pricing hypothesis ($H_2$).

The result reverses when monitoring intensifies (see Columns 4 to 6). The difference between the effective spread of monitored cross-trades and that of twin open market trades becomes *smaller* in bad market conditions, in line with the cost reduction and fire sale absorption hypotheses ($H_0$ and $H_1$). This finding may appear surprising at first sight. However, it is in line with what we should expect if monitored cross-trades are fairly priced on average. In fact, the effective spread of monitored cross-trades should be close to zero (or zero) both in good and bad market states. By contrast, the effective spread of open market trades is relatively lower in good market states than in bad market states. As a result, when we compute the *difference* between the effective spread of fairly priced cross-trades and that of open market trades, we find this difference to be lower in bad times, driven by the increase in the effective spread of open market trades. Overall, this last set of results speak to the importance of cross-trades for reducing fire-sale and illiquidity costs in bad market states.

### *5.5. Cross-trades, fund characteristics, and discussion of the results*

In the previous sections, we have provided evidence indicating that cross-trades are strategically priced on average. In this section, we test restriction H2-d by exploring which funds cross-trade at advantageous/disadvantageous prices.

Results in Table 6 indicate that some categories of funds are systematically benefited or penalized by cross-trading. This analysis is on cross-trades only. Specifically, funds that charge high fees, young funds, and funds suffering temporary liquidity shortfalls are net beneficiaries of performance reallocation. By contrast, funds that suffer persistent outflows are net subsidizers. In particular, high-fee funds buy (sell) at a 41 bps discount (premium) over the fundamental price, and young funds buy (sell) at a 61 bps discount (premium). By contrast, persistently distressed funds sell (buy) at a 39 bps discount (premium) on average.[23] This finding holds for both buys and sells, thereby ruling out the possible concern that the discount paid by distressed funds may be driven by fire sales (this result is unreported).

Our results are consistent with restriction H2-d presented in Section 3. In that section, we outline the rationale for fund families to favor high-value funds at the expense of funds of lesser value. In sum, subsidizing high-FPS funds and expensive funds helps in attracting

[23]The coefficient of $Trade\ Size$ is insignificant, likely because cross-trades are executed off market.

additional flows and increases the profits of the fund family as a whole. By contrast, penalizing even further the performance of funds already experiencing persistent outflows has moderate negative implications for the fund itself (Sirri and Tufano, 1998) and no negative externalities on the rest of the fund family (Nanda et al., 2004).

Our results are consistent with previous findings in the literature indicating that the funds that are the most likely to be favored by the fund family are young funds (Evans, 2010), high-fee funds (Gaspar et al., 2006), and funds in need of temporary liquidity injections (Bhattacharya et al., 2013; Goncalves-Pinto and Schmidt, 2013). By contrast, fund families have no strategic incentive to help funds that are persistently distressed (Bhattacharya et al., 2013). Adding to those papers, we provide for the first time trade-level evidence of tunneling through the pricing of cross-trades.

Overall, our findings also have implications for the literature on skill and performance. The finding that cross-trades are used to inflate the performance of young funds may help to explain why these funds outperform on average (see, e.g., Evans, 2010). Furthermore, the finding that the pricing of cross-trades deviates more significantly from benchmark prices during downturns may in part contribute to explain why mutual funds beat their benchmarks mostly in bad times (Sun et al., 2009; Glode, 2011; Kosowski, 2011; and Kacperczyk et al., 2016). Finally, the effect of cross-trading on returns provides one potential rationale for why changes in quarterly portfolio snapshots account for only a limited fraction of mutual fund performance (Kacperczyk et al., 2008; Puckett and Yan, 2011; and Anand et al., 2012).

## 6. Alternative benchmarks

Results in the paper are obtained using the mid price as benchmark to compute the effective spreads. In this section, we show that our results are robust to using alternative benchmarks.

**Last sale price.** In line with the requirement of Rule 17a-7, we replicate our analysis using as benchmark the last sale price at the time of execution reported by ANcerno. The results are in line with those from our main analysis (see Column 1 of Table 7).

**Price including (estimated) market impact.** We adjust the benchmark using the predicted market impact of a transaction (Column 2 of Table 7). To that end, we use the same specification employed in Keim and Madhavan (1997) and we proceed as follows. First, we estimate the expected price impact on the basis of the exchange where the stock is traded, the size of the trade, the market capitalization of the stock, and a proxy of stock illiquidity (the variables are constructed as in Keim and Madhavan, 1997). We run these estimations on open market trades only, at the daily level, and separately for buy-initiated and sell-initiated trades. Second, we adjust the last sale price for each transaction by the expected price impact of the trade.[24] For instance, if the last sale price for the stock is \$100 and the estimated price impact for the transaction is 0.01, we use \$101 (100*1.01) as benchmark price. Finally, we recompute the effective spread using this alternative benchmark. Again, the results remain qualitatively similar.

**VWAP from open to close.** As a third alternative, we replicate our baseline trade-level analysis using the volume-weighted average price of the day (VWAP). This is one of the most widely used benchmarks for calculating trading costs and it is made available by ANcerno for all stocks in our sample. The estimated coefficient remains qualitatively similar (see Column 3 of Table 7). The negative sign of the coefficient of $Trade\ Size$ in this specification derives from the fact that larger trades have a larger influence on the benchmark. Therefore, large trades are going to be closer to the benchmark price by construction (thereby exhibiting lower effective spreads), as they have a greater weight in its computation.

**VWAP from placement to execution.** Additionally, we replicate our baseline analysis using the volume-weighted average price from when the order is placed to when the trade is executed. The results are also robust to using this alternative benchmark (Column 4 of Table 7).

**Closing Price.** Finally, we use the same day closing price to calculate the effective spread (see Hasbrouck, 2007; page 148). Results are reported in Column (5) of Table 7. All in all, cross-trades appear to be strategically priced on average regardless of the benchmark used.

## 7. Conclusion

In this paper, we are the first to use mutual fund trade-level data provided by ANcerno to precisely identify cross-trades. Having transaction-level information, we are able to explore how cross-trades are priced. Our analysis finds that cross-trades are strategically priced on average and often backdated. Fund families follow a coordinated subsidization strategy to benefit from an internal market in which expensive and high-FPS funds cross-trade at advantageous prices, whereas cheap and low-FPS funds subsidize them. We find that the monitoring intensity is the pivotal element in determining how the average cross-trade is priced. In particular, we find that an exogenous increase of monitoring intensity,

[24]Formally, we run the following specification on open market trades only: $Y = \beta' X + \epsilon$, where $X$ is a vector of price impact predictors (the same as in Keim and Madhavan, 1997) and $Y$ is the realized price impact computed as the percentage deviation from the last sale price. We use the estimated $\hat{\beta}$ to calculate an estimated price impact, $y$, for all trades as $y = \hat{\beta}' X$ and compute the new effective spreads as $ES_{Pimpact} = \frac{|P-B(1+y)|}{B(1+y)}$ where $B$ is the last sale price.

arising from compliance officers becoming more independent and personally liable in the case of trading violations, was highly effective in decreasing strategic pricing.

We believe our results have important implications for both policy and research. First, an increasing number of equity trades are executed in unmonitored trading venues, such as dark pools and internalizers. This, in turn, has spurred a debate on the optimal degree of regulation for alternative trading venues. While there is broad heterogeneity in the features and rules of private markets, they all share some degree of opacity. Our evidence suggests that this opacity may create an agency problem when the incentives of the owner of the market are not aligned with those of all market participants. We argue that careful pricing rules are insufficient to resolve this problem if adequate monitoring policies are not in place. Second, our results indicate that, when adequately supervised, cross-trades effectively decrease transaction costs, especially during times of market stress. This result speaks to the importance of crossing trades off-market for reducing the costs of trading illiquid securities and limiting fire-sale costs. In this respect, the increasing consolidation of the mutual fund industry, and the consequent greater scope for cross-trading, may have important positive effects. Finally, our findings have implications for the literature that studies the determinants of mutual fund performance. Our results identify the presence of a structural break in the role played by cross-trading. Studies that overlook the contribution of cross-trading to performance before 2004 may erroneously overstate the importance of skill in explaining risk-adjusted returns, in particular during downturns. By contrast, we find that cross-trade pricing is unlikely to be a major source of performance reallocation after 2004.

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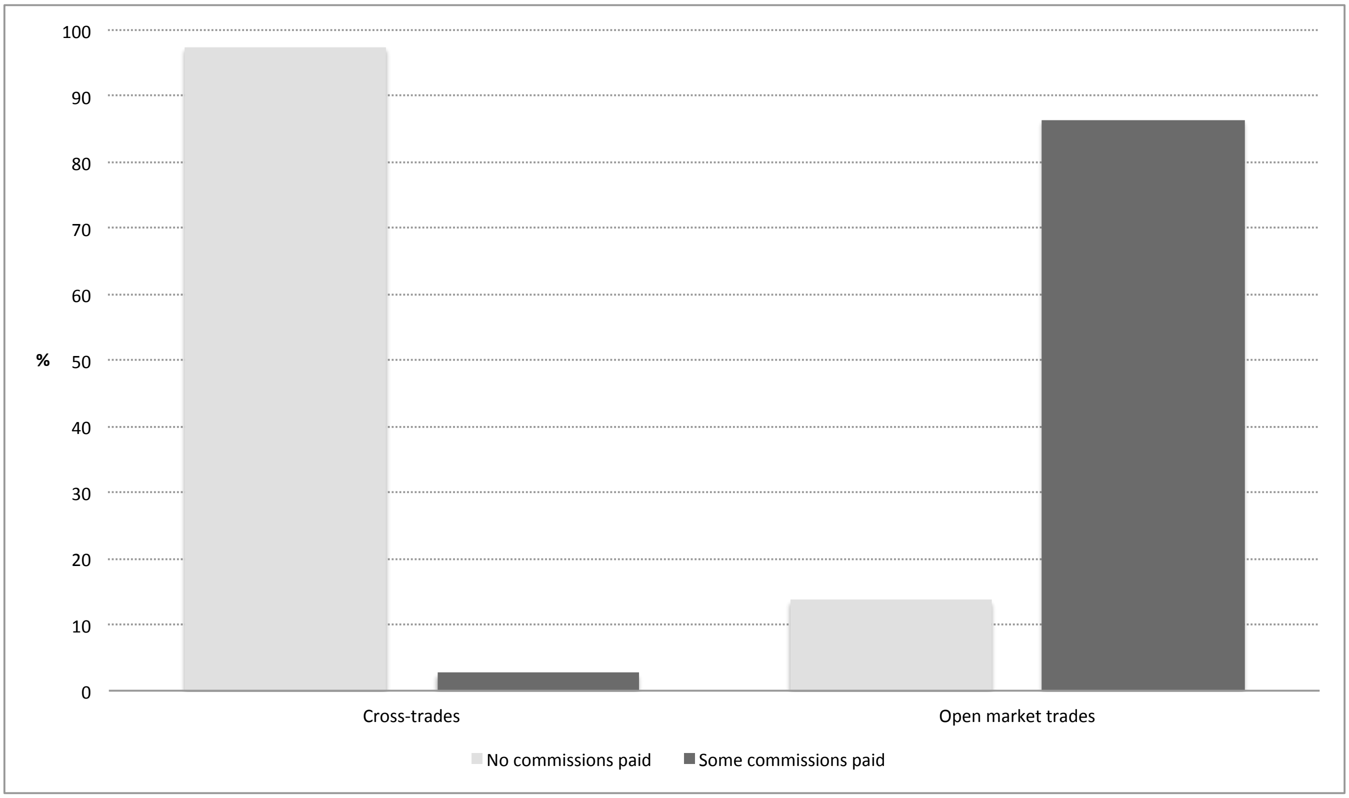


**Fig. 1.** Commissions. This figure reports the percentage of cross-trades/open market trades for which no commissions are paid. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) in the same minute of the same day, v) at the same price, but vi) traded in opposite directions. We consider all other trades as open market trades. The final sample is obtained by extracting a 10% random sample of trades without replacement from ANcerno *after* cross-trades have been identified on the full database.

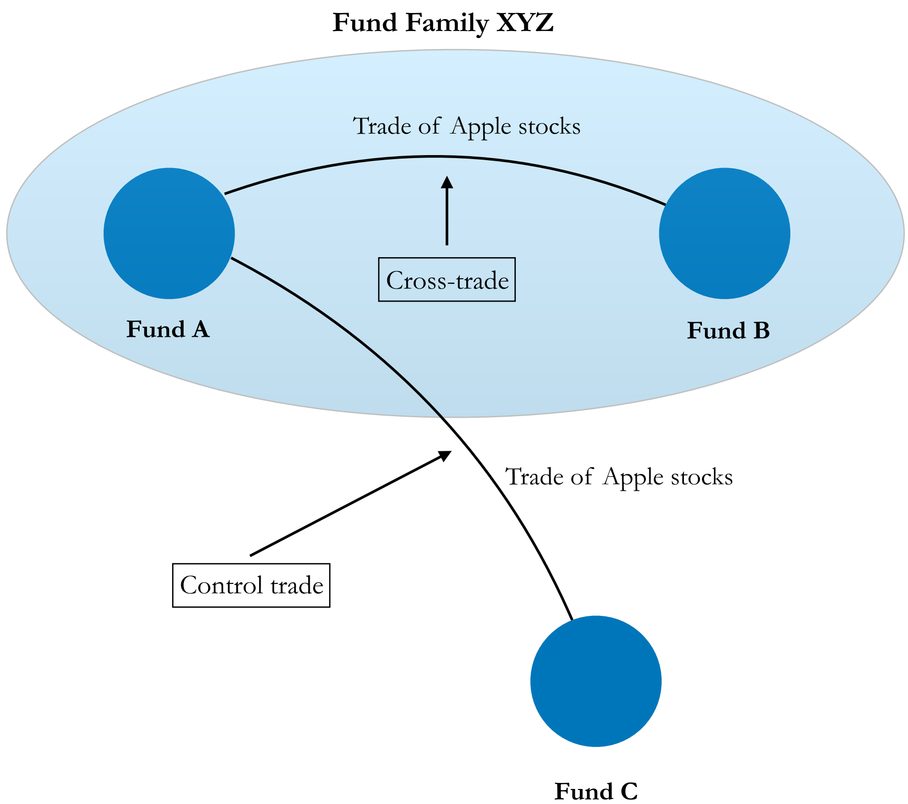


**Fig. 2.** Identification Strategy. This figure illustrates our identification strategy: Using stock×family×time fixed effects, we compare the effective spreads of cross-trades with those of open market trades executed by the same fund family, in the same stock, in the same time interval (defined as the same month or same day depending on the specification).

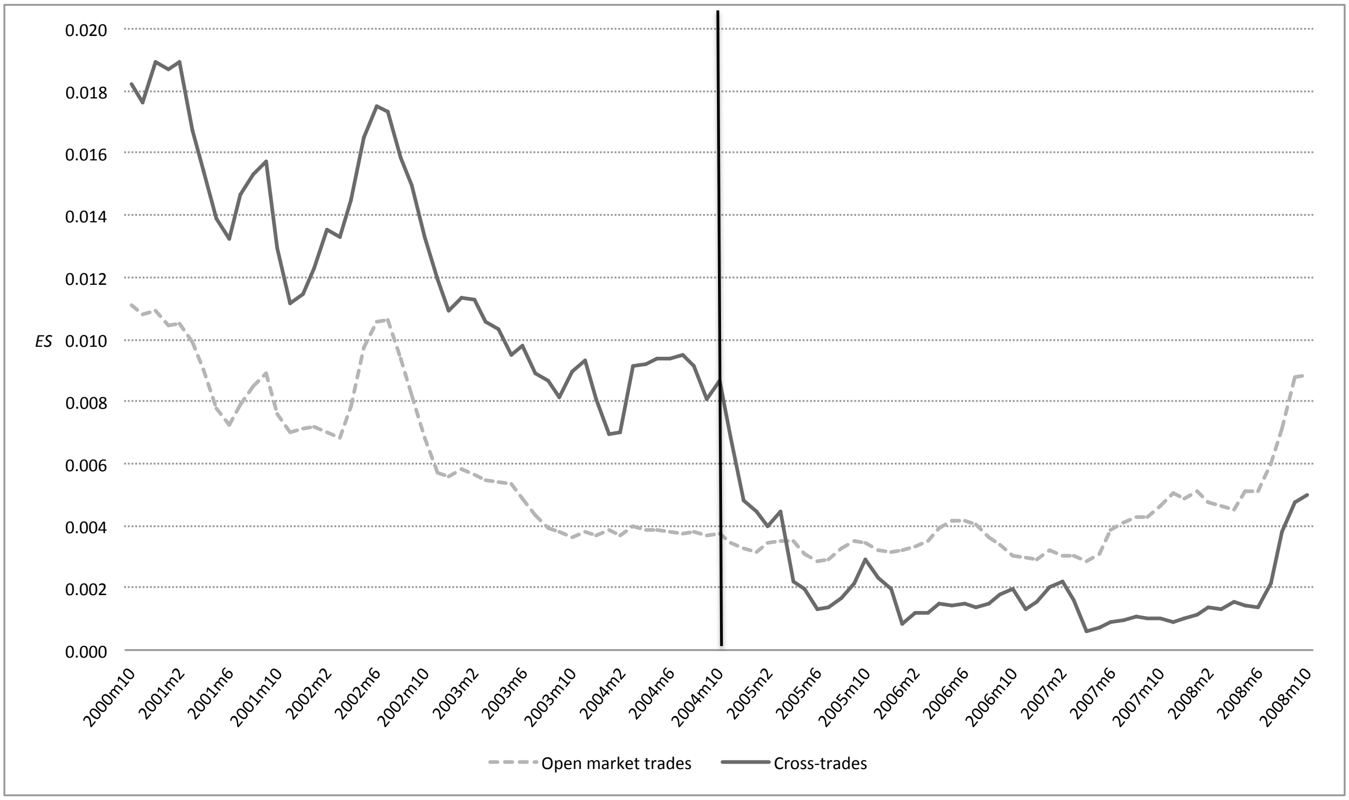


**Fig. 3.** The Average Effective Spread of Open Market Trades and Cross-Trades Around the 2004 Reform. This figure shows the three-month moving average of the effective spread of cross-trades and open market trades for the period around October 2004. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) in the same minute of the same day, v) at the same price, but vi) traded in opposite directions. We consider all other trades as open market trades. The final sample is obtained by extracting a 10% random sample of trades without replacement from ANcerno *after* cross-trades have been identified on the full database. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at the execution time obtained from TAQ. The vertical line marks the date when rules 38a-1 and 206(4)-7 and the amendments to rule 204-2 were implemented (October 2004). The new rules have the following main implications: i) compliance officers (COs), who were previously reporting only to the fund management, have to report exclusively to the board of directors (which has to include a majority of independent members), ii) fund families have to appoint a chief CO, who can be held personally liable for trading violations by the monitored fund, and iii) the SEC has increased the requirements and its control over reporting and monitoring procedures. See Hoffman et al. (2008) for an analysis of the efficacy of the new rules.

**Table 1**
Trade characteristics by venue.

This table presents mean characteristics for cross-trades and open market trades calculated over the main sample. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as, $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution from TAQ. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) in the same minute of the same day, v) at the same price, but vi) traded in opposite directions. *HighLow* is a dummy variable that equals one if a trade is executed either at the highest or the lowest price of the day. *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. *Trade Size In Shares* is the number of traded shares, *Trade Size In Dollars* is the size of the trade in dollars, *Commission (per share)* is the commission paid for each share traded, and *Commission (per dollar)* is the commission paid for each dollar traded. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Column (1) reports mean values for cross-trades, Column (2) reports mean values for open market trades, and Column (3) reports the difference between cross-trades and open market trades. *** indicates that the difference between the value for cross-trades and open market trades is significant at the 1% level.

| | Cross-Trades<br>(1) | Open Market Trades<br>(2) | Cross-Trades – Open Market Trades<br>(3) |
|---|---|---|---|
| *Effective Spread (ES)* | 0.0123 | 0.0050 | 0.0073<br>*** |
| *HighLow* | 0.0101 | 0.0022 | 0.0079<br>*** |
| *Stock Illiquidity* | 0.0010 | 0.0021 | -0.0011<br>*** |
| *Stock Market Cap. (in millions)* | 41,433 | 34,169 | 7,263<br>*** |
| *Stock Volatility* | 0.0349 | 0.0260 | 0.0089<br>*** |
| *Trade Size In Shares* | 26,360 | 6,456 | 19,904<br>*** |
| *Trade Size In Dollars* | 955,590 | 205,523 | 750,067<br>*** |
| *Commission (per share)* | 0.0007 | 0.0272 | -0.0266<br>*** |
| *Commission (per dollar)* | 0.0000 | 0.0011 | -0.0011<br>*** |
| Observations | 36,276 | 3,983,878 | 4,020,154 |

**Table 2**
The pricing of cross-trades (test of restriction H2-a).

This table reports estimates for the effective spread of cross-trades and open market trades (control group). Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. In Panel A, Column (1) reports the OLS estimate without controls or fixed effects; Column (2) includes time, stock, and family fixed effects; Column (3) includes time, stock, and family fixed effects, and time-varying stock-level controls; Column (4) includes time, stock, and family fixed effects, time-varying stock-level controls, and squared time-varying stock-level controls; Column (5) includes stock×family×time fixed effects and *Trade Size*. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. Panel B reports additional results and robustness tests. Column (1) includes only fund families that have been investigated by the SEC for violations of trading rules; Column (2) includes only fund families that have not been investigated by the SEC; Column (3) excludes stocks whose price is below $5; Column (4) includes client fixed effects; Column (5) includes day×family×stock fixed effects. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | Panel A: Main Results<br>*Effective Spread (ES)* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | 0.0073*** | 0.0044*** | 0.0043*** | 0.0042*** | 0.0042*** |
| | (14.97) | (16.61) | (17.11) | (16.98) | (17.14) |
| *Trade Size* | | | 0.0072*** | 0.0292*** | 0.0117*** |
| | | | (9.24) | (12.98) | (16.39) |
| *Stock Illiquidity* | | | 0.0465*** | 0.0251** | |
| | | | (11.41) | (2.31) | |
| *Stock Market Cap.* | | | -0.0004*** | -0.0027*** | |
| | | | (-6.18) | (-9.80) | |
| *Stock Volatility* | | | 0.0921*** | 0.1106*** | |
| | | | (19.13) | (25.95) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Family Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Family × Time Effects | No | No | No | No | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.008 | 0.178 | 0.206 | 0.209 | 0.411 |

Table 2 *(continued)*

| Dependent Variable: | Panel B: Robustness *Effective Spread (ES)* | | | | |
|---|---|---|---|---|---|
| | (1) Bad Governance | (2) Good Governance | (3) No Penny Stocks | (4) Client FEs | (5) Family×Stock× ×Day FEs |
| *CT* | 0.0046*** | -0.0018*** | 0.0042*** | 0.0042*** | 0.0039*** |
| | (19.99) | (-6.37) | (17.22) | (17.15) | (14.10) |
| *Trade Size* | 0.0126*** | 0.0100*** | 0.0115*** | 0.0118*** | 0.0056*** |
| | (13.17) | (13.23) | (16.88) | (16.40) | (11.83) |
| Stock × Family × Time Effects | Yes | Yes | Yes | Yes | Subsumed |
| Client FE | No | No | No | Yes | No |
| Stock × Family × Day Effects | No | No | No | No | Yes |
| Observations | 2,460,455 | 1,559,697 | 3,948,093 | 4,020,150 | 3,216,082 |
| $R^2$ | 0.382 | 0.456 | 0.401 | 0.411 | 0.780 |

**Table 3**
Are cross-trades backdated? (alternative test of restriction H2-a).

This table reports linear probability estimates obtained by regressing *HighLow* on *CT*. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. *HighLow* is a dummy variable that equals one if a trade is executed either at the highest or the lowest price of the day for the stock. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *HighLow* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | 0.0079*** | 0.0059*** | 0.0064*** | 0.0064*** | 0.0066*** |
| | (7.19) | (6.16) | (6.52) | (6.57) | (6.46) |
| *Trade Size* | | | -0.0299*** | -0.0905*** | -0.0566*** |
| | | | (-6.72) | (-8.25) | (-10.08) |
| *Stock Illiquidity* | | | 0.3391*** | 0.4099*** | |
| | | | (7.23) | (3.78) | |
| *Stock Market Cap.* | | | -0.0015*** | 0.0021** | |
| | | | (-7.61) | (2.04) | |
| *Stock Volatility* | | | -0.0387*** | -0.0461*** | |
| | | | (-6.45) | (-6.79) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Family Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Family × Time Effects | No | No | No | No | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.000 | 0.035 | 0.036 | 0.036 | 0.221 |

**Table 4**
The influence of monitoring on cross-trade pricing (test of restriction H2-b).

This table reports difference-in-difference estimates for the effective spread of cross-trades and open market trades (control group) before and after the introduction of rules 38a-1 and 206(4)-7 in October 2004. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *Post Regulation* equals one for trades executed from October 1st 2004 onward and equals zero for trades executed before. *Post Regulation* is absorbed by the fixed effects in Specifications (2)-(5). *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. Column (1) reports the OLS estimate without including controls or fixed effects; Column (2) includes time, stock, and family fixed effects; Column (3) includes time, stock, and family fixed effects, and time-varying stock-level controls; Column (4) includes time, stock, and family fixed effects, time-varying stock-level controls, and squared time-varying stock-level controls; Column (5) includes stock×family×time fixed effects and *Trade Size*. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective Spread (ES)* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | 0.0074*** | 0.0054*** | 0.0053*** | 0.0052*** | 0.0051*** |
| | (24.53) | (27.74) | (29.15) | (29.04) | (28.90) |
| *CT* × *Post Regulation* | -0.0082*** | -0.0063*** | -0.0060*** | -0.0059*** | -0.0054*** |
| | (-10.86) | (-9.08) | (-8.96) | (-8.94) | (-8.82) |
| *Post Regulation* | -0.0021*** | | | | |
| | (-5.14) | | | | |
| *Trade Size* | | | 0.0071*** | 0.0285*** | 0.0116*** |
| | | | (9.08) | (12.96) | (16.37) |
| *Stock Illiquidity* | | | 0.0467*** | 0.0261** | |
| | | | (11.46) | (2.41) | |
| *Stock Market Cap.* | | | -0.0004*** | -0.0027*** | |
| | | | (-6.24) | (-9.80) | |
| *Stock Volatility* | | | 0.0920*** | 0.1104*** | |
| | | | (19.12) | (25.92) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Family Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Family × Time Effects | No | No | No | No | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.023 | 0.179 | 0.207 | 0.210 | 0.411 |

**Table 5**
The influence of market states on cross-trade pricing (test of restriction H2-c).

This table reports estimates for the effective spread of cross-trades and open market trades (control group) in different market conditions. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. *Market Downturn* equals one if the cumulative market return in the past three months is below -5%. *VIX* is the CBOE monthly Volatility Index, and *Financial Uncertainty* is the financial uncertainty index from Jurado et al. (2015). Columns (1) to (3) report coefficients estimated on the pre-regulation sample (before October 1st 2004), and Columns (4) to (6) report coefficients estimated on the post-regulation sample (after October 1st 2004). We include $time \times stock \times family$ fixed effects and *Trade Size* in all specifications. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective Spread (ES)* | | | | | |
|---|---|---|---|---|---|---|
| | Pre-Regulation | | | Post-Regulation | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *CT × Market Downturn* | 0.0011*** | | | -0.0023*** | | |
| | (3.18) | | | (-3.13) | | |
| *CT × VIX* | | 0.0001*** | | | -0.0001** | |
| | | (3.91) | | | (-2.41) | |
| *CT × Financial Uncertainty* | | | 0.0050*** | | | -0.0031** |
| | | | (4.86) | | | (-2.21) |
| *CT* | 0.0047*** | 0.0028*** | -0.0019 | 0.0004 | 0.0016 | 0.0027 |
| | (25.27) | (4.81) | (-0.18) | (0.66) | (1.39) | (1.53) |
| *Trade Size* | 0.0095*** | 0.0095*** | 0.0094*** | 0.0139*** | 0.0139*** | 0.0139*** |
| | (10.44) | (10.40) | (10.36) | (13.42) | (13.43) | (13.42) |
| Stock × Family × Time Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,031,814 | 1,031,814 | 1,031,814 | 2,988,338 | 2,988,338 | 2,988,338 |
| $R^2$ | 0.373 | 0.373 | 0.373 | 0.418 | 0.418 | 0.418 |

**Table 6**

Which funds win/lose from cross-trading? (test of restriction H2-d).

This table reports estimates obtained by regressing *Signed Effective Spread (SES)* on fund characteristics. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. *Only cross-trades are included.* We define the signed effective spread of a trade as $SES = \frac{P-M}{M} \times -Side$, where $P$ is the execution price of the cross-trade from ANcerno, $M$ is the mid price of the stock at execution time obtained from TAQ, and $Side$ is equal to $+1$ for buys and $-1$ for sells. The sample is obtained by matching ANcerno cross-trades with CRSP fund characteristics based on the similarity of the aggregated quarterly fund trading behavior across databases (we describe the matching procedure in Online Appendix C). *Persistent Liquidity Shortfall* is equal to one for funds that have experienced net outflows in the previous 12 months, *Temporary Liquidity Shortfall* is equal to one for funds that have experienced net outflows in the current month, *Young Fund* is equal to one for funds of age lower than 24 months since inception, *High-Fee Fund* is equal to one for funds charging fees in the top quintile. *Trade Size* is the number of shares traded scaled by the average trading volume of the stock in the previous five days. Style is a set of dummies for the investment style of the fund based on the Thomson Reuters Investment Objective Codes (IOCs). The constant is included in all specifications but the coefficient is not reported. Errors are clustered at the monthly level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Signed Effective Spread (SES)* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Fund type: | | | | | |
| *Persistent Liquidity Shortfall* | -0.0039*** | | | -0.0035** | -0.0039** |
| | (-3.10) | | | (-2.31) | (-2.49) |
| *Temporary Liquidity Shortfall* | 0.0023** | | | 0.0019 | 0.0019 |
| | (2.15) | | | (1.59) | (1.61) |
| *Young Fund* | | 0.0046* | | 0.0057* | 0.0061** |
| | | (1.80) | | (1.96) | (2.06) |
| *High-Fee Fund* | | | 0.0052*** | 0.0041** | 0.0041** |
| | | | (3.14) | (2.25) | (2.28) |
| Controls: | | | | | |
| *Trade Size* | -0.0025 | -0.0025 | -0.0024 | -0.0024 | -0.0023 |
| | (-1.20) | (-1.21) | (-1.16) | (-1.14) | (-1.09) |
| Family Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Style Fixed Effects | Yes | Yes | Yes | Yes | No |
| Fund Fixed Effects | No | No | No | No | Yes |
| Observations | 18,008 | 18,008 | 18,008 | 18,008 | 18,008 |
| $R^2$ | 0.167 | 0.166 | 0.167 | 0.168 | 0.168 |

**Table 7**
Alternative benchmarks.

This table reports estimates for alternative definitions of the effective spread of cross-trades and open market trades (control group). Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the alternative effective spread of a trade as $Alternative\ Spread = \frac{|P-B|}{B}$, where $P$ is the execution price of the trade from ANcerno, and $B$ is, respectively, the last sale price at the time of execution (Column 1), the last sale price of the stock adjusted for the estimated price impact (Column 2), the volume-weighted average price (VWAP) of the stock during the trading day (Column 3), the VWAP from placement to execution (Column 4), and the closing price of the day (Column 5). In specification (2), we estimate the expected price impact on the basis of the exchange where the stock is traded, the size of the trade, the market capitalization of the stock, and a proxy of stock illiquidity (the variables are constructed as in Keim and Madhavan (1997)). We run these estimations on open market trades only, at the daily level, and separately for buy-initiated and sell-initiated trades. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. All columns include stock×family×time fixed effects and *Trade Size*. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Alternative Spreads* | | | | |
|---|---|---|---|---|---|
| Benchmark (B): | Last sale price (1) | Price including market impact (2) | VWAP from open to close (3) | VWAP from pl. to exec. (4) | Closing price (5) |
| *CT* | 0.0041*** | 0.0033*** | 0.0023*** | 0.0051*** | 0.0019*** |
| | (16.55) | (16.90) | (17.46) | (23.91) | (12.16) |
| *Trade Size* | 0.0123*** | 0.0138*** | -0.0189*** | -0.0082*** | -0.0095*** |
| | (16.92) | (25.92) | (-24.27) | (-17.88) | (-12.59) |
| Stock × Family × Time Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,020,154 | 4,019,491 | 4,020,154 | 3,971,916 | 4,020,154 |
| $R^2$ | 0.410 | 0.368 | 0.432 | 0.405 | 0.462 |

# Online Appendix

### Appendix A. Economic mechanism

In the following, we present a stylized framework from which we derive formally the empirical restrictions discussed in Section 3. The setup of this framework builds on theoretical models of transfer pricing within multi-division organizations and multi-firm groups (e.g., Hirshleifer, 1956; Alles and Datar, 1998). We apply the same economic intuition to exchanges of assets across fund siblings.

Consider a fund family composed of two sibling funds, A and B, that want to exchange a quantity $q > 0$ of asset $i$ among them. We assume that the fund family decides the price, $P$, of this internal transaction that maximizes its profit as a whole, which is given by the sum of the dollar fees charged by the two funds. Percentage fees, $f_A$ and $f_B$, are exogenously given.

For simplicity, we assume that the two funds have an abnormal return of 0 on top of what they lose/gain from the cross-trade and that market prices fully reflect the fundamental value of the asset. Hence, any price that differs from the market price reallocates performance between the two funds in a zero-sum game. The reallocated performance is immediately reflected into the value of the funds, as funds mark to market their positions. We denote the effective spread, $ES$, as the percentage deviation from the fundamental price. Specifically, $ES = |P - M|/M$ where $M$ is the fundamental value of the asset and $P$ is the transfer price chosen by the fund family. An effective spread equal to zero, $ES = 0$, indicates that fund siblings cross-trade at the fundamental value of the asset, i.e., no performance is reallocated across funds as $P = M$. By contrast, a positive effective spread, $ES > 0$, implies that $P \neq M$ and some performance is reallocated across funds. The initial size of the two funds is $V_A^0$ and $V_B^0$, respectively. We define as $D$ the *direction* of the performance reallocation, which is also chosen by the fund family. If $ES > 0$ and $D = 1$ fund A gains and fund B loses from the cross-trade, while if $D = -1$ fund A loses and fund B gains. This implies that the abnormal return of fund A from cross-trading will be $r_A(ES) = D \cdot ES \cdot \frac{q}{V_A^0}$ and the abnormal return of fund B will be $r_B(ES) = -D \cdot ES \cdot \frac{q}{V_B^0}$.

Strategic cross-trade pricing has potential reputational and legal costs. As a consequence, fund families face a trade-off between the benefits of using cross-trades to shift performance and the potential costs arising if the discretion in pricing cross-trades is excessive. We model the cost of transfer pricing as an expected penalty function that depends on both the magnitude of the mispricing, $ES$, and the probability that the mispricing is spotted and sanctioned. In particular, we assume that the expected penalty is convex in the effective spread: $\mathbb{E}(Penalty) = K \cdot ES^2 \cdot q$, where $K$ is a positive scalar measuring the monitoring intensity ($K > 0$).[25]

We assume that external investors reallocate resources on the basis of fund performance, as they do not (cannot) distinguish between skill and artificially reallocated performance. Investor dollar flows are allocated on the basis of realized performance, which, in our framework, depends entirely on the transfer price of the cross-trade. For simplicity, we do not model the profit maximization problem of the investors, but simply assume that investor flows are linearly increasing in the performance of the fund: $Flow_a = V_A^0 \cdot \beta_A \cdot r_A(ES)$, and $Flow_b = V_B^0 \cdot \beta_B \cdot r_B(ES)$, where $\beta_A(\beta_B)$ is the flow-performance sensitivity—FPS—of fund A (fund B). The assumption of linearity of FPS follows from Spiegel and Zhang (2013) and is analogous to the assumption in Franzoni and Schmalz (2017).[26]

Formally, the fund family maximizes its total profit $\pi$ by determining $ES^*$ and $D^*$:

$$\pi = \max_{ES} \; \underbrace{f_A\Big( \overbrace{V_A^0}^{i} + \overbrace{V_A^0 \cdot r_A(ES)}^{ii} + \overbrace{\beta_A \cdot V_A^0 \cdot r_A(ES)}^{iii} \Big)}_{\text{Dollar fees from fund A}} +$$

$$\underbrace{f_B\Big( \overbrace{V_B^0}^{i} + \overbrace{V_B^0 \cdot r_B(ES)}^{ii} + \overbrace{\beta_B \cdot V_B^0 \cdot r_B(ES)}^{iii} \Big)}_{\text{Dollar fees from fund B}} - \underbrace{\mathbb{E}(Penalty)}_{\text{Expected penalty}} \tag{A.1}$$

subject to

$$ES \geq 0. \tag{A.2}$$

We decompose the dollar profit deriving from each fund in three parts (i, ii, and iii). The different parts are the proceeds from the percentage fee charged respectively on i) the initial assets under management, ii) the value reallocated by the cross-trade, and iii) the assets allocated/withdrawn by investors in response to realized performance. The optimal effective spread from a fund family's perspective is therefore:

$$ES^* = D \cdot \frac{f_A \cdot (\beta_A + 1) - f_B \cdot (\beta_B + 1)}{2K}. \tag{A.3}$$

The optimal direction of the performance relocation, $D^*$, follows automatically as Condition (A.2) needs to be satisfied.

[25] The expected penalty function can be thought of as consisting of a probability times a penalty, where the probability of facing a penalty is a linear function of the effective spread and the size of the penalty is a linear function of the effective spread and the trade size.

[26] Empirical evidence that investors chase returns even though past returns do not predict future returns can be found in Frazzini and Lamont (2008).

The four testable restrictions described in Section 3 follow:

- *H2-a: The execution price of the cross-traded asset differs from its market price ($ES^* > 0$).*

Proof:
Condition (A.2) needs to be satisfied, which implies that $ES^* > 0$ if $f_A \cdot (\beta_A + 1) \neq f_B \cdot (\beta_B + 1)$. In words, unless fund siblings are homogeneous in terms of both flow-performance sensitivity and fees, some performance shifting is optimal.[27]

- *H2-b: In the presence of stronger monitoring the cross-traded asset is transferred at a price closer to its market price.*

Proof:
From Equation A.3 we have that $\frac{\partial ES^*}{\partial K} = -\frac{ES^*}{K} \leq 0$, as $ES^* \geq 0$ and $K \geq 0$.

We assume that flow-performance sensitivities are higher in bad market conditions. This assumption follows from investors having higher marginal utility of consumption in bad market conditions, which makes funds that outperform in bad market times more valuable *ceteris paribus*. This is in line with theoretical work positing that downturns are more revealing about the skill of asset managers (Kacperczyk et al., 2016 and Schmalz and Zhuk, 2018), which should induce higher flow-performance sensitivity in downturns.[28] Specifically, we assume that $\beta_A = b_a \cdot \xi$ and $\beta_B = b_b \cdot \xi$, where $\xi \geq 1$ is increasing in market stress and $b_a > 0$ and $b_b > 0$ are the baseline flow-performance sensitivities in good market conditions. Under this set of assumptions the next testable restriction follows:

- *H2-c: If strategically priced, the price of a cross-traded asset should deviate more from its market price in downturns.*

Proof:

$$\frac{\partial ES^*}{\partial \xi} = D \cdot \frac{f_A \cdot b_a - f_B \cdot b_b}{2K}, \tag{A.4}$$

which is positive if $ES^* > 0$.

[27] Performance shifting can be optimal even if the funds within the family are similar in terms of fees and flow-performance sensitivity, *if the flow-performance relation is convex*. If that is the case, an increase in performance of one fund generates an increase in dollar flows that is greater than the reduction in dollar flows for a similar decrease in performance experienced by another fund (i.e., the dollar gain of the winning fund more than compensates for the dollar loss of the losing fund), thereby making it optimal to create a wedge in performance between funds (Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998).

[28] Two recent papers test empirically the relation between market conditions and FPS. The results depend on the risk adjustment and the proxy of market stress (see Franzoni and Schmalz, 2017 and Starks and Sun, 2016).

• *H2-d: High-FPS funds and high-fee funds cross-trade at advantageous prices. Low-FPS funds and low-fee funds cross-trade at disadvantageous prices.*
Proof:
Remember that $D$ is equal to 1 if fund A gains and fund B loses from the cross-trade, and $D$ is equal to -1 if fund A loses and fund B gains. Rewrite (A.3) as follows:

$$D = \frac{2K \cdot ES^*}{f_A \cdot (\beta_A + 1) - f_B \cdot (\beta_B + 1)}. \tag{A.5}$$

Condition (A.2) implies that $D = 1$ if $f_A \cdot (\beta_A + 1) > f_B \cdot (\beta_B + 1)$. Hence, performance is reallocated from fund B to fund A if fund A displays higher flow-performance sensitivity and/or charges higher fees, and from fund A to fund B if fund B has higher flow-performance sensitivity and/or fees.

## Appendix B. ANcerno data

This section of the appendix provides a detailed description of the ANcerno database and how we link it to other data sources. The sample consists of institutional transaction-level data submitted by ANcerno's clients. The data are provided in batches that include all transactions submitted by a client during the interval of time covered by the batch. The exact length covered by each batch is not predefined and can range from a few trading days to several months.

A variety of clients rely on ANcerno's monitoring services. The data set includes transactions by several of the main mutual fund families domiciled in the United States, a small number of hedge funds, and several pension plan sponsors. For comparability reasons, we limit our analysis to mutual fund families (i.e., institutions that are included in Thomson Financial S12).

A client from ANcerno's perspective is any entity that submits trades, which generally are executed by an individual mutual fund, a group of funds, or a fund manager. ANcerno assigns unique codes to the clients (variable *clientcode*) and the corresponding institution as reported by the client (variable *clientmgrcode*). The exact identity of the client is anonymized.

For a limited period of time, ANcerno provided a file ("MasterManagerXref") including the list of the overarching institutions to which the trading funds are affiliated (i.e., the fund families in the case of mutual funds). This additional file includes the name of the institution (variable *manager*), e.g., PIMCO, and a number identifying the trading entity (variable *managercode*), e.g., 10. We match this file to another file ("ManagerXref") that includes both the numbers identifying the institutions (variable *managercode*) and the client codes (variable *clientcode*). In this way, we are able to match the main institution's name with the original ANcerno trade data via client codes (as the variables *clientcode* and *clientmgrcode* are included both in the "ManagerXref" file and in the main ANcerno file)—see Figure A1. The main variables that we use from the ANcerno database are reported in Table A1. Stock characteristics are obtained from CRSP and are matched to ANcerno via CUSIP. We also match trades from ANcerno to the best bid and ask prices available at the moment of execution from TAQ.

We use the S12type5 table provided by WRDS to map fund families (SEC S12 filings) to mutual funds. See Figure A2 for the detailed mapping scheme. The described procedure ensures that we retain only mutual fund families in our sample.

### Appendix C. Matching ANcerno clients to fund characteristics in CRSP

We match client codes in ANcerno to funds in Thomson Reuters/CRSP based on the similarity of their trading behavior. To conduct our matching, we proceed in the following way. First, we match fund family names in ANcerno with fund family names in Thomson Financial. Second, we aggregate all trades in ANcerno at a quarter level for each client. Third, we match the net quarterly change in stock holdings of funds in Thomson Reuters (S12) with the net quarterly change in stock holdings by ANcerno clients *affiliated with the same fund family*. If we are able to match at least 80% of all net quarterly trading observations in terms of direction (buy or sell), stock identifier (CUSIP), and exact quantity of the net quarterly change, we link the fund across the two databases. This allows us to identify the trading funds for 18,008 cross-trades. This procedure uses the most restrictive matching algorithm ("MATCH3") proposed by Puckett and Yan (2011).

There are however a number of limitations to this approach. First, clients usually do not submit to ANcerno trades for all days in a quarter. Hence, when we aggregate ANcerno trades at the quarterly level quite often we do not have a complete picture of the total trading activity of the funds, which makes it difficult to exactly match the quarterly change in holdings from Thomson Financial (S12). Second, we can only match an asset manager in ANcerno when the variable *clientmgrcode* uniquely identifies a fund. However, this is not always the case, as the identifier *clientmgrcode* in ANcerno may identify funds, fund managers, or separately managed accounts (see Hu et al., 2018). Third, some of the trades that we observe in ANcerno are unreported in Thomson Financial.[29] Overall, this limits

[29]Thomson Financial (S12) holdings do not necessarily cover the entire equity holdings of a fund. Potential exclusions include: small holdings (typically under 10,000 shares or $200,000), cases with potential confidentiality issues, reported holdings that could not be matched to a master security file, and cases where two or more managers share control (since the SEC requires only one manager in such a case to include the holdings information in their report).

the number of funds that we are able to identify in ANcerno. We prefer to restrict the number of matched funds not to descrease the quality of the matching.

**Appendix D. Cross-trades and commissions**

In the paper, we find that cross-trade prices deviate more from the benchmark than open market trades do (we estimate that cross-trades have a 42 bps larger effective spread on average) and likely reallocate performance among trading counterparties. Yet, we also show that on only 2% of cross-trades commissions are paid (see Figure 1 in the main paper). A potential concern is whether the difference in effective spreads is negligible after taking commissions into account. To answer this question we replicate our analysis adding percentage commissions to the effective spread of cross-trades and open market trades. Importantly though, from a regulatory standpoint the size of the commissions should not matter for determining the fair price of cross-trades. In any case, results reported in Table A3 indicate that cross-trades still exhibit a 32 bps higher effective spread than open market trades *after* commissions are taken into account.

**Appendix E. Passive funds**

Institutions that offer only or mostly passive funds constitute a natural placebo sample for our analysis. While passive funds commonly use cross-trades to reduce transaction costs, they have a lower incentive to strategically price cross-trades to reallocate performance. This is because passive funds are arguably more homogeneous in terms of fees and sensitivity of flows to returns. If all passive funds have a similar value to the group as whole, there is less of a reason to price cross-trades such that performance is reallocated across funds (this follows from restriction H2-d in Section 3). To run this placebo test, we replicate our analysis on all the trades of the only U.S. institution in our sample selling (almost) exclusively passive investment vehicles.

Table A6 reports results for the relation between *CT* and *Effective Spread* in this sample. Different from what we find in the original sample, there is a negative correlation between the two variables. Specifically, cross-trades are on average 12 basis points *cheaper* than open market trades, consistent with cross-trades being mainly used to reduce transaction costs rather than to shift performance. In short, we find no evidence of strategic pricing of cross-trades for an institution in which most fund siblings are passive. This result supports empirical restriction H2-d that the higher effective spreads of cross-trades in our main sample are driven by the incentive to strategically reallocate performance among funds of *different value* from a family's perspective.

## Appendix F. Further robustness tests

**Orders.** A potential concern arises because our analysis is conducted at the transaction level. While some orders are executed in a single transaction, many orders are broken down in multiple transactions that are executed at different times throughout the day and, sometimes, even over different days (see Anand et al., 2013 for a discussion of the issue). To consider a trade that is part of a larger order as a standalone execution may underestimate the total transaction costs paid to execute the entire position (as, for instance, the execution of the first portion of the order may bid up the execution cost of the second). Furthermore, the cross-trade and the twin open market trade can affect each other if they are part of the same order. We make certain that this aspect does not bias our results by replicating our analysis only on orders that are executed in a single trade (either internally or on the open market) for which, as a consequence, the effective spread of the order and that of the trade coincide. Results remain similar and are shown in Column 1 of Table A10.

**Buy- versus sell (-initiated) trades.** We test for the presence of asymmetries in our results. For instance, it is possible that a higher effective spread could arise from comparing *sell*-initiated cross-trades with (twin) *buy*-initiated open market trades. Because cross-trades are more advantageous during market downturns (in which selling is generally more expensive) this could, in principle, affect our findings. To rule out this possibility, we replicate the main analysis including respectively only buy-initiated trades (see Column 2) and only sell-initiated trades (see Column 3). We define trades as buy-initiated if the last sale price is below the execution price of the trade, and as sell-initiated if the last sale price is above the execution price. Furthermore, we separate buys (Column 4) and sells (Column 5). The results are analogous in all sub-samples.

**Proxies of Trade Size.** In our trade-level analysis, we control for the size of the trade computed as the number of shares in the transaction over the average number of shares traded in the previous five days. However, the relation between effective spread and trade size may be better described by a different specification. To mitigate the concern that our results are driven by heterogeneity in the size of the trades, we also include the number of shares in the transaction over the number of shares traded during the same day, and the number of shares in the transaction over the total number of shares outstanding. Our results are robust to including these additional proxies (see Column 6 of Table A10).

**Only S&P 500 Stocks.** We replicate our analysis leaving in the sample only S&P 500 stocks. Also in this case the result stays qualitatively similar (see Column 7 of Table A10).

## Appendix G. The liquidity of cross-traded stocks

Fund families act strategically to maximize total assets under management (see, e.g., Massa, 1998). Several papers posit that cross-trades are one of the tools used by fund families to influence fund performance, with the objective of attracting more assets to manage. Hitherto, it remains an open question *through which channel* cross-trades influence fund performance. For example, Chuprinin et al. (2015) argue that there are at least two possible channels through which cross-trades may affect performance. First, cross transactions may be executed at favorable prices. Second, cross-trading may affect performance if used to absorb fire sales by funds in distress that lack liquidity. In this latter scenario, the impact of cross transactions on performance is not the result of opportunistic pricing practices, but it is rather an effect of a better coordination of individual funds' liquidity needs by the fund family.

In this section, we provide further evidence that the channel through which cross-trades affect performance might have been altered by the regulatory change. To that end, we explore the characteristics of the stocks that are crossed internally. If cross-trading affects performance mostly by reducing fire-sale costs, we should find that the assets that are cross-traded are those that are more vulnerable to fire-sale discounts: i.e., small and illiquid stocks for which the need for optimizing trade execution is the highest. By contrast, if cross-trading affects performance mostly via the strategic pricing of internal transactions, we should find that most cross-traded assets are large and liquid. Even though it may be easier to strategically price them, illiquid assets constitute a relatively small fraction of the portfolio of equity funds. Hence, fund managers would need to cross-trade illiquid stocks in much larger volumes to be able to reallocate performance in any meaningful way. In the following, we explore which type of stocks are more likely to be cross traded before and after the increase in the independence of compliance officers in October 2004.

We find that, before the regulatory change, funds were on average cross-trading large and liquid stocks. However, after the regulatory change, relatively more illiquid stocks are cross-traded (see Table A9). This is consistent with the main channel through which cross-trades affect fund returns being strategic pricing ($H_2$) before 2004, and fire sale absorption ($H_1$) after 2004. Results in this section are mostly suggestive. However, they are in line with other findings in the paper and provide evidence on the prevalent channel through which cross-trades affect fund returns.

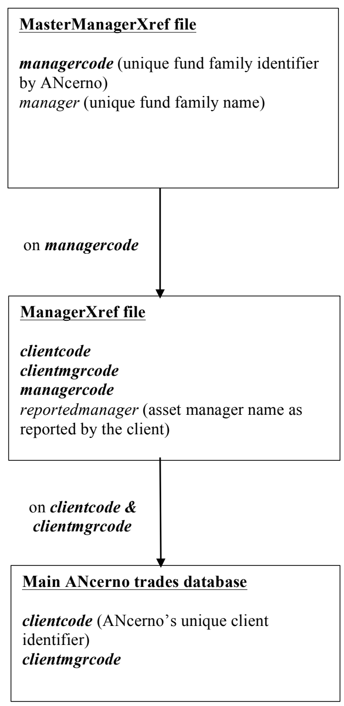


**Fig. A1.** Procedure to map fund families to ANcerno trades.

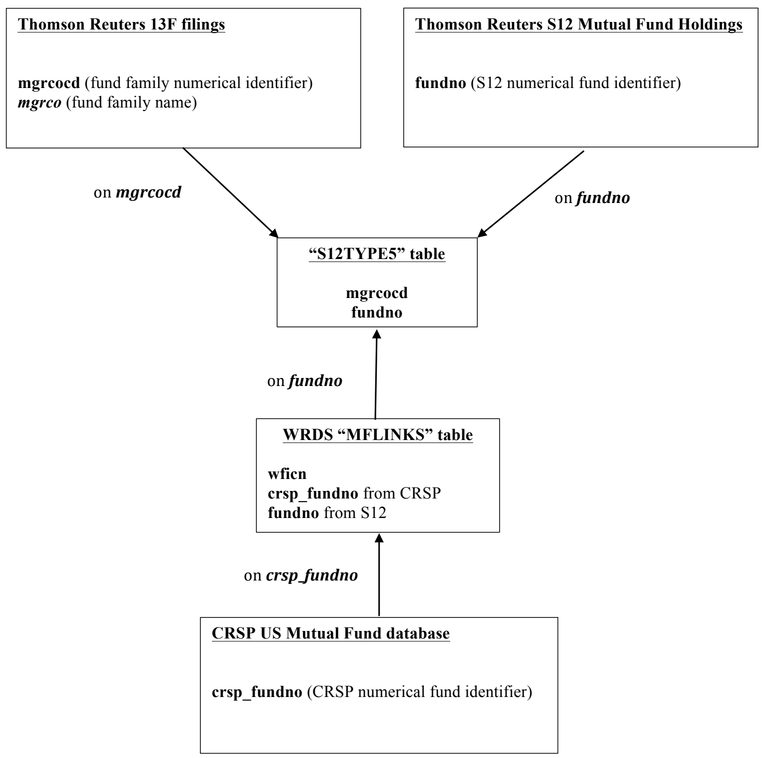


**Fig. A2.** Procedure to map fund families to individual mutual funds in CRSP.

**Table A1**
ANcerno variables.
This table describes the ANcerno variables we use in the paper.

| Ancerno Variable | Description | Source File |
|---|---|---|
| | *Fund and fund family identifiers* | |
| *clientcode* | Ancerno defined Client identifier | Main trades dataset |
| *clientmgrcode* | Ancerno defined Client Manager identifier (fund, fund manager, or separate account) | Main trades dataset |
| *managercode* | Financial institution (e.g., fund family) | ManagerXref file |
| *manager* | Financial institution's name | MasterManagerXref file |
| | *Trade variables* | |
| *tradedate* | Date of the trade | Main trades dataset |
| *xdtX* | Execution time (at minute precision) | Main trades dataset |
| *cusip* | Stock cusip | Main trades dataset |
| *Side* | Buy or sell (1 = Buy; -1 = Sell) | Main trades dataset |
| *Price* | Execution price per share | Main trades dataset |
| *Volume* | Number of traded shares | Main trades dataset |
| *CommissionUSD* | Per trade commission in USD | Main trades dataset |
| | *Benchmark variables* | |
| *xpX* | Market price at execution (at minute precision) | Main trades dataset |
| *dpC* | Closing price of the day | Main trades dataset |
| *ov* | Total shares of the block | Main trades dataset |
| *dpH* | High of the day | Main trades dataset |
| *dpL* | Low of the day | Main trades dataset |
| *dpOC* | VWAP from open to close | Main trades dataset |

**Table A2**
Heterogeneity in the impact of the 2004 reform.

This table reports difference-in-difference estimates for the effective spread of cross-trades and open market trades (control group) by bad- and good-governance fund families. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade as reported by ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *Bad Governance* is a dummy variable that takes a value of one if a fund family has been investigated by the SEC for illegal trading practices. *Post Regulation* equals one for trades executed from October 1st 2004 onwards and equals zero for trades executed before. *Post Regulation* is absorbed by the fixed effects in Specifications (2)-(5). *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective Spread (ES)* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *CT × Post Regulation × Bad Governance* | -0.0050*** | -0.0028** | -0.0029** | -0.0039*** |
| | (-4.09) | (-2.32) | (-2.50) | (-3.33) |
| *Post Regulation × Bad Governance* | -0.0029*** | -0.0020*** | -0.0012*** | -0.0010*** |
| | (-7.93) | (-7.15) | (-5.24) | (-6.12) |
| *CT × Bad Governance* | 0.0102*** | 0.0091*** | 0.0078*** | 0.0067*** |
| | (13.55) | (27.01) | (20.10) | (12.93) |
| *CT × Post Regulation* | -0.0008 | -0.0017*** | -0.0015*** | -0.0012** |
| | (-1.09) | (-3.31) | (-3.02) | (-2.09) |
| *Post Regulation* | 0.0001 | | | |
| | (0.12) | | | |
| *Bad Governance* | 0.0016*** | 0.0003 | 0.0002 | |
| | (4.53) | (1.29) | (1.28) | |
| *CT* | -0.0032*** | -0.0032*** | -0.0021*** | -0.0013** |
| | (-4.88) | (-12.37) | (-6.19) | (-2.59) |
| *Trade Size* | 0.0308*** | 0.0293*** | 0.0104*** | 0.0075*** |
| | (15.81) | (13.94) | (10.16) | (8.52) |
| Stock Fixed Effects | No | No | Yes | Yes |
| Family Fixed Effects | No | No | No | Yes |
| Time Fixed Effects | No | Yes | Yes | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.034 | 0.095 | 0.160 | 0.180 |

**Table A3**
Including commissions.

This table reports estimates for the effective spread of cross-trades and open market trades (control group) including any commission paid to the broker. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade including commissions as $ES_c = \frac{|P-M|}{M} + c$, where $P$ is the execution price of the trade as reported by ANcerno, $M$ is the mid price of the stock at execution, and $c$ is the per dollar commission paid on the trade. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective spread (ES) + Commissions* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | 0.0064*** | 0.0033*** | 0.0033*** | 0.0032*** | 0.0032*** |
| | (12.54) | (11.66) | (12.14) | (12.03) | (12.37) |
| *Trade Size* | | | 0.0101*** | 0.0382*** | 0.0148*** |
| | | | (12.79) | (15.43) | (20.19) |
| *Stock Illiquidity* | | | 0.0867*** | 0.0488*** | |
| | | | (19.01) | (4.22) | |
| *Stock Market Cap.* | | | -0.0013*** | -0.0051*** | |
| | | | (-17.40) | (-17.96) | |
| *Stock Volatility* | | | 0.0988*** | 0.1190*** | |
| | | | (19.32) | (26.90) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Family Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Family × Time Effects | No | No | No | No | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.005 | 0.210 | 0.248 | 0.252 | 0.448 |

**Table A4**
Alternative empirical methodology: nearest-neighbor matching.

This table reports estimates using a Nearest-Neighbor Matching algorithm (NNM). Observations are at the trade level; if an order is executed in multiple trades, we report an observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. Column (1) matches each cross-trade to the open market trade in the same stock, family, and day that is the closest in term of trade size. Column (2) matches each cross-trade to the open market trade in the same stock, family, day, and side (buy or sell) that is the closest in term of trade size. Column (3) matches each cross-trade to the open market trade in the same stock, family, day, side (buy or sell), and order execution (the order is filled in one execution vis-à-vis multiple executions) that is the closest in term of trade size. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP. We report the average treatment effect (ATE). Similarity between treatment (cross-trades) and control group (open market trades) is estimated using the Mahalanobis distance. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. *** indicate statistical significance at the 1% level.

| Dependent Variable: | *Effective Spread (ES)* | | |
|---|---|---|---|
| | Estimation Method: Nearest-neighbor matching | | |
| | (1) | (2) | (3) |
| | *Matched on:* | *Matched on:* | *Matched on:* |
| | Stock<br>Date<br>Family<br>Trade size | Stock<br>Date<br>Family<br>Trade size<br>Side (buy or sell) | Stock<br>Date<br>Family<br>Trade size<br>Side (buy or sell)<br>Order execution |
| ATE (*CT*) | 0.0037*** | 0.0036*** | 0.0033*** |
| | (26.03) | (20.47) | (14.79) |
| Observations | 64,764 | 42,611 | 33,014 |

**Table A5**
Including unreliable time-stamps.

This table reports estimates for the effective spread of cross-trades and open market trades (control group). Also trades that report as execution times 16:00, 16:10, and 16:20 are included. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. Column (1) reports the OLS estimate without including controls or fixed effects; Column (2) includes time, stock, and family fixed effects; Column (3) includes time, stock, and family fixed effects, and time-varying stock-level controls; Column (4) includes time, stock, and family fixed effects, time-varying stock-level controls, and squared time-varying stock-level controls; Column (5) includes stock×family×time fixed effects and *Trade Size*. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective Spread (ES)* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | 0.0028*** | 0.0024*** | 0.0023*** | 0.0022*** | 0.0023*** |
| | (5.50) | (7.46) | (7.46) | (7.39) | (7.68) |
| *Trade Size* | | | 0.0109*** | 0.0334*** | 0.0114*** |
| | | | (10.97) | (9.51) | (12.19) |
| *Stock Illiquidity* | | | 0.0254*** | 0.0052 | |
| | | | (6.83) | (0.61) | |
| *Stock Market Cap.* | | | -0.0002*** | -0.0022*** | |
| | | | (-2.81) | (-10.64) | |
| *Stock Volatility* | | | 0.1199*** | 0.1435*** | |
| | | | (25.38) | (33.44) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Family Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Family × Time Effects | No | No | No | No | Yes |
| Observations | 7,518,456 | 7,518,456 | 7,518,456 | 7,518,456 | 7,518,456 |
| $R^2$ | 0.001 | 0.202 | 0.233 | 0.236 | 0.442 |

**Table A6**
Placebo sample.

This table reports estimates for the effective spread of cross-trades and open market trades (control group) for a sample including only trades from an institution selling mostly passive investment products. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. *CT* is a dummy variable that equals one if the trade is crossed internally and zero if it is executed on the open market. Column (1) reports the OLS estimate without controls or fixed effects; Column (2) includes time and stock fixed effects; Column (3) includes time, and stock fixed effects, and time-varying stock-level controls; Column (4) includes time and stock fixed effects, time-varying stock-level controls, and squared time-varying stock-level controls; Column (5) includes stock×time fixed effects and *Trade Size*. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* computed as the log market capitalization of the stock (in millions), and *Stock Volatility* computed as the standard deviation of daily stock returns during the month. Errors are clustered at the monthly level. All observations are included and no 10% random sample is drawn. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective Spread (ES)* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | -0.0026*** | -0.0013*** | -0.0013*** | -0.0013*** | -0.0012*** |
| | (-12.51) | (-8.80) | (-8.66) | (-8.78) | (-9.04) |
| *Trade Size* | | | 0.0000* | 0.0002*** | 0.0000 |
| | | | (1.96) | (2.94) | (1.64) |
| *Stock Illiquidity* | | | 0.0138*** | 0.0433*** | |
| | | | (2.87) | (6.50) | |
| *Stock Market Cap.* | | | -0.0001 | -0.0010** | |
| | | | (-1.11) | (-2.43) | |
| *Stock Volatility* | | | 0.0541*** | 0.0699*** | |
| | | | (9.63) | (10.69) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Time Effects | No | No | No | No | Yes |
| Observations | 14,336,460 | 14,336,460 | 14,336,460 | 14,336,460 | 14,336,460 |
| $R^2$ | 0.002 | 0.173 | 0.184 | 0.185 | 0.316 |

**Table A7**

The influence of monitoring on backdating (alternative test of restriction H2-b).

This table reports linear probability estimates obtained by regressing *HighLow* on *CT*. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. *HighLow* is a dummy variable that equals one if a trade is executed either at the highest or the lowest price of the day for the stock. *Post Regulation* equals one for trades executed from October 1st 2004 onward and equals zero for trades executed before. *Post Regulation* is included in all specifications but the coefficient is not reported. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. Column (1) reports the OLS estimate without including controls or fixed effects; Column (2) includes time, stock, and family fixed effects; Column (3) includes time, stock, and family fixed effects, and time-varying stock-level controls; Column (4) includes time, stock, and family fixed effects, time-varying stock-level controls, and squared time-varying stock-level controls; Column (5) includes stock×family×time fixed effects and *Trade Size*. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP, *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Stock Volatility* is the standard deviation of daily stock returns during the month. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *HighLow* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *CT* | 0.0070*** | 0.0065*** | 0.0070*** | 0.0071*** | 0.0074*** |
| | (5.96) | (5.87) | (6.26) | (6.32) | (6.26) |
| *CT* × *Post Regulation* | -0.0053*** | -0.0036** | -0.0041*** | -0.0042*** | -0.0048*** |
| | (-3.45) | (-2.51) | (-2.81) | (-2.89) | (-3.10) |
| *Trade Size* | | | -0.0300*** | -0.0910*** | -0.0567*** |
| | | | (-6.74) | (-8.28) | (-10.09) |
| *Stock Illiquidity* | | | 0.3393*** | 0.4106*** | |
| | | | (7.23) | (3.79) | |
| *Stock Market Cap.* | | | -0.0015*** | 0.0021** | |
| | | | (-7.62) | (2.04) | |
| *Stock Volatility* | | | -0.0388*** | -0.0462*** | |
| | | | (-6.46) | (-6.80) | |
| Controls squared | No | No | No | Yes | Subsumed |
| Stock Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Family Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Time Fixed Effects | No | Yes | Yes | Yes | Subsumed |
| Stock × Family × Time Effects | No | No | No | No | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.001 | 0.035 | 0.036 | 0.036 | 0.221 |

**Table A8**
Robustness backdating.

This table reports linear probability estimates obtained by regressing *HighLow* on *CT*. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. *HighLow* is a dummy variable that equals one if a trade is executed either at the highest or the lowest price of the day for the stock. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Column (1) includes only fund families that have been investigated by the SEC for violations of trading rules; Column (2) includes only fund families that have not been investigated; Column (3) excludes stocks whose price is below $5; Column (4) includes ANcerno client fixed effects; Column (5) adds day×family×stock fixed effects. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *HighLow* | | | | |
|---|---|---|---|---|---|
| | (1) Bad Governance | (2) Good Governance | (3) No Penny Stocks | (4) Client FEs | (5) Family×Stock× ×Day FEs |
| *CT* | 0.0071*** | -0.0002* | 0.0065*** | 0.0066*** | 0.0062*** |
| | (6.54) | (-1.85) | (6.44) | (6.46) | (7.01) |
| *Trade Size* | -0.0642*** | -0.0427*** | -0.0541*** | -0.0566*** | -0.0137*** |
| | (-8.16) | (-8.04) | (-9.78) | (-10.08) | (-3.92) |
| Stock × Family × Time Effects | Yes | Yes | Yes | Yes | Subsumed |
| Client FE | No | No | No | Yes | No |
| Stock × Family × Day Effects | No | No | No | No | Yes |
| Observations | 2,460,455 | 1,559,697 | 3,948,093 | 4,020,150 | 3,216,082 |
| $R^2$ | 0.192 | 0.269 | 0.215 | 0.221 | 0.791 |

**Table A9**

Which stocks are cross traded?

This table reports estimates obtained by regressing, respectively, *Stock Illiquidity*, *Bid-Ask Spread*, and *Stock Market Cap.* on *CT* and *CT* × *Post Regulation*. *Post Regulation* is included in all specifications but the coefficient is not reported. Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. *Post Regulation* equals one for trades executed from October 1st 2004 onward. *CT* is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. *Stock Illiquidity* is the monthly average of the daily absolute stock return scaled by its daily trading volume, *Stock Market Cap.* is the log market capitalization of the stock (in millions), and *Bid-Ask Spread* is the bid-ask spread of the stock. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | Stock Illiquidity<br>(1) | Bid-Ask Spread<br>(2) | Stock Market Cap.<br>(3) |
|---|---|---|---|
| *CT* | -0.0006*** | -0.0005*** | 0.1002*** |
| | (-11.93) | (-6.21) | (8.12) |
| *CT* × *Post Regulation* | 0.0004*** | 0.0004*** | -0.0537*** |
| | (5.43) | (4.46) | (-3.85) |
| Stock Fixed Effects | Yes | Yes | Yes |
| Family Fixed Effects | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes |
| Observations | 4,020,154 | 4,020,154 | 4,020,154 |
| $R^2$ | 0.723 | 0.635 | 0.960 |

**Table A10**

Further robustness tests

This table reports estimates for the effective spread of cross-trades and open market trades (control group). Observations are at the trade level; if an order is executed in multiple trades, we include one observation for each single execution. We define the effective spread of a trade as $ES = \frac{|P-M|}{M}$, where $P$ is the execution price of the trade from ANcerno, and $M$ is the mid price of the stock at execution time obtained from TAQ. $CT$ is a dummy variable that equals one if a trade is a cross-trade and zero if a trade is executed on the open market. Cross-trades are defined as transactions occurring i) within the same fund family, ii) in the same stock, iii) in the same quantity, iv) at the same time of the same day, v) at the same price, but vi) traded in opposite directions. Column (1) includes only orders that are executed in a single transaction; Column (2) includes only trades for which the execution price is above the last sale price; Column (3) includes only trades for which the execution price is below the last sale price; Column (4) includes only buys; Column (5) includes only sells; Column (6) includes as additional proxies of trade size the number of traded shares over the shares traded during the day in the same stock ($2nd\ Proxy\ of\ Trade\ Size$) and the number of traded shares over the number of shares outstanding ($3rd\ Proxy\ of\ Trade\ Size$); and Column (7) includes only S&P 500 stocks. *Trade Size* is defined as the number of traded shares scaled by the average trading volume for the stock in the previous five days obtained from CRSP. Observations are 10% of trades randomly drawn from ANcerno without replacement, after having identified cross-trades on the whole database. Errors are clustered at the monthly level. The constant is included in all specifications but the coefficient is not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent Variable: | *Effective Spread (ES)* | | | | | | |
|---|---|---|---|---|---|---|---|
| | Trade=Order (1) | Buy Initiated (2) | Sell Initiated (3) | Buys (4) | Sells (5) | Trade Size Proxies (6) | S&P 500 Stocks (7) |
| *CT* | 0.0053*** | 0.0047*** | 0.0047*** | 0.0045*** | 0.0041*** | 0.0042*** | 0.0039*** |
| | (13.45) | (16.71) | (17.10) | (17.63) | (16.35) | (17.15) | (17.12) |
| *Trade Size* | 0.0298*** | 0.0092*** | 0.0111*** | 0.0110*** | 0.0090*** | 0.0559*** | 0.0177*** |
| | (12.87) | (12.84) | (13.81) | (13.77) | (11.17) | (34.33) | (16.81) |
| *2nd Proxy of Trade Size* | | | | | | -0.0870*** | |
| | | | | | | (-46.14) | |
| *3rd Proxy of Trade Size* | | | | | | 0.0037*** | |
| | | | | | | (17.25) | |
| Stock × Family × Time Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,133,823 | 1,904,451 | 1,978,544 | 1,972,150 | 1,994,911 | 4,020,087 | 2,489,873 |
| $R^2$ | 0.414 | 0.508 | 0.500 | 0.431 | 0.457 | 0.413 | 0.380 |