China Walls

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Abstract

We evaluate the enforcement of information barriers—China Walls—within conglomerates. We test for information sharing between walled-off dealers and their affiliate funds using 23 million trades between 2019-2024 in the Israeli Shekel market, where the US SEC enforces the China Walls. Our difference-in-differences design compares the trade volumes and profits of funds that are affiliated with, clients of, or entirely unrelated to a dealer around the days when the dealer is especially likely to hold valuable information. The dealers never trade nor share information with their affiliate funds, despite that they consistently share information with their clients and that the funds within the same conglomerate intensely share information among themselves. From a back-of-the-envelope calculation, extending the China Walls around the funds would eliminate $23.7 billion in trades, comprising 58% of their trades on the event dates. Our findings persist during crisis and noncrisis periods, and across granular cells of fund and asset characteristics. We reveal remarkable regulatory capacity to control information flows within conglomerates.

JEL classification: G21, G28, G14, G15

Keywords: Banking conglomerates, trading networks, information barriers, information sharing, regulatory capacity

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1 Introduction

Professional service is rife with conflicts of interest. Accountancies audit and consult for the same firms, big law firms routinely represent one client while advising its competitors, and banking conglomerates manage their own investment funds and act as brokers for the funds of others. Underlying these conflicts is the incentive of affiliates to share privileged information with each other, which contributed to the last financial crisis (Griffin, 2021). In response, regulators began to tightly enforce information barriers within professional-service conglomerates—China Walls[1]—to preempt information sharing between conflicted affiliates.[2] Yet, it is unknown whether today's China Walls are effectively enforced, because information sharing is difficult to identify and compliance in one circumstance does not imply compliance elsewhere.

We document remarkably effective enforcement of today's China Walls in the foreign exchange market. In this market, dealers intermediate all trades, and each client fund is connected to a subset of the dealers. The China Walls isolate dealers from their affiliate funds to prevent the sharing of privileged information gleaned from client orders. Our empirical design compares the trading activities and profits of funds that are affiliates of, connected to, and completely unrelated to a dealer around the days when the dealer holds especially valuable private information. Heightened trading or profits by the affiliate funds around those days would pinpoint violations of China Walls by the dealer. Failure to detect violations plausibly implies compliance in other times, when the dealer has less valuable information

[1]"China Walls," or more commonly "Chinese Walls," "information barriers,'' "ethical screens," and so on, was originally a reference to the Great Wall of China (Gozzi, 2003). We adopt "China Walls," because it is concise and the closest to the original reference.

[2]Regulators enforce China Walls in many professional-service firms beyond our focus of banking conglomerates. Consultancies must maintain information barriers between teams that advise competing client firms (DOJ/FTC 2016 HR Guidance). The auditor arms of accountancies must likewise be walled off from other services arms (PCAOB Rules 3523 and 2-01). Law firms cannot take on new cases that may harm any current or former clients unless the lawyers assigned to the new cases were "screened" from matters involving the clients who could potentially be harmed (ABA Model Rules 1.0(k) and 1.10(a)(2), which are widely enforced by state courts).

to share. Unrelated funds act as controls to eliminate confounding variation, and connected funds allow us to potentially falsify our design.

We apply this design to the near universe of foreign exchange trades involving the Israeli Shekel, covering 23 million trades from 2019 to 2024. The Shekel market is large and liquid, with average daily trades worth USD 13 billion. Among them, 83% are trades in the US dollar-Shekel currency pair. The largest dealers in the Shekel market are identical to those in the broader US dollar market, and the Israeli financial regulations are mainly based on the US regulations. An exception is that Israel does not impose China Walls, leaving the US Security and Exchange Commission (whose jurisdiction reaches worldwide) as the main enforcer of China Walls in our setting. Appendix A details the legal context.

Figure 1 illustrates our difference-in-differences design. GS Dealer and GS Fund are affiliates. (GS, MS, and BoA are illustrative names.) Unrelated Fund is unaffiliated and never trades with the other firms in the figure. An event is a trade (event trade) by the GS Dealer (event dealer) that belongs in the top 0.1 percentile of the GS Dealer's trades by dollar value. We compare the daily gross dollar volumes and the daily one-week future profit-and-loss of the GS Fund (affiliate fund) and the Unrelated Fund (control fund) around the event day. We conclude that event dealers share information with their affiliate funds if the daily volumes or profits of the affiliate funds increase relative to the unrelated funds around the event day. This approach fails to detect information sharing from dealers to their affiliate funds and, reversing their roles, from funds to their affiliate dealers.

Two falsification tests support our design. First, we verify whether the design reliably detects information sharing where it exists. Since dealers are well known to share information with their client funds (Barbon, Di Maggio, Franzoni, and Landier, 2019; Boyarchenko, Lucca, and Veldkamp, 2021), a reliable design must detect information sharing between such connected dealers and funds. In Figure 1, the BoA Fund is a client of the GS Dealer. Our first falsification test compares the daily volumes and profits of the BoA Fund (connected fund) and the Unrelated Fund around the day of the GS Dealer's exceptionally large trade.

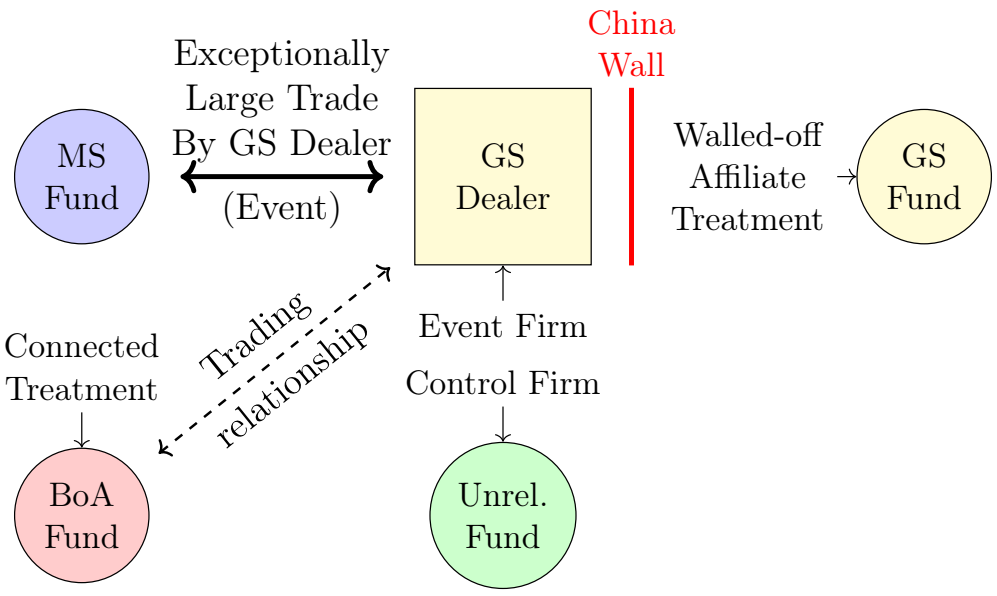


Figure 1: Identifying Information Sharing from Dealers to Affiliate Funds

We consistently detect information sharing from dealers to their connected funds. Second, we exploit funds that are affiliates but not walled off from each other to determine whether affiliates do share information with each other in the absence of China Walls. Affiliate funds intensely share information among themselves.

Section 2 explains the logic behind our design. The key identifying assumption is that especially valuable information prompts exceptionally large trades. If so, our findings also rule out information sharing between affiliate dealers and funds in other circumstances, when there would be less incentive for the dealers to violate their China Walls. The assumption is consistent with standard theory (Kyle, 1985; Easley and O'Hara, 1987) and empirically holds in other markets (Kumar, Mullally, Ray, and Tang, 2020; Pinter, Wang, and Zou, 2024). A threat is the possibility that firms would split orders to disguise their private information. Appendix B jointly tests this assumption and the claim that our design reliably detects information sharing. Consistent with these claims, exceptionally large trades predict future returns, smaller trades do not, and we detect information sharing between connected dealers and funds only around the large trades.

One novel component of our design is the use of unrelated funds as controls. Under the

plausible assumption that dealers would never leak information to a fund that is neither an affiliate nor its client, using the unrelated funds as controls preserves all variation due to information sharing. Yet, doing so removes any confounding variation from public news or macroeconomic shocks. For example, a surge in the aggregate demand for a currency would lead dealers to receive larger trade requests while raising the volumes of their affiliate funds. The unrelated funds would also see their volumes rise, partialing out this confounder. Separately, the event trade itself may have price or liquidity impacts that could confound our results. Since these impacts would affect both affiliate and unrelated funds, our choice of control again partials out such confounders.

Section 3 describes the data. The dealers virtually *never* trade with their affiliate funds, consistent with the onerous constraints of their China Walls. As a preliminary analysis, we compare the correlations in daily gross volumes within affiliate dealer-and-fund pairs to those of unrelated pairs and connected pairs. The unrelated pairs have highly correlated daily volumes over wide leads and lags, indicating the presence of spurious correlation. Foreshadowing our results, the correlations in volume within the affiliate pairs are indistinguishable from those within the unrelated pairs, whereas the contemporaneous correlation within the connected pairs is significantly higher.

Section 4 implements our design as stacked difference-in-differences specifications with never-treated controls, following Cengiz, Dube, Lindner, and Zipperer (2019). Our millions of observations and thousands of events and funds provide sufficient statistical power to detect even tiny differences between affiliate and unrelated funds. In the 11 trading days around an exceptionally large trade by an event dealer, the daily gross dollar volumes of the funds affiliated to this dealer are statistically indistinguishable from those of the unrelated funds, differing by -0.001 standard deviation on the event day (clustered std. error: 0.003 sd). In contrast, the funds connected to the event dealer increase their volumes by 2.0 sd (std. error: 0.004 sd) on the event day relative to the unrelated funds. We rule out any mechanical effects from trades between the connected dealers and funds, as we exclude (from

each event) all funds that trade with the event dealer on or after the event date. All results remain when we replace gross volumes with one-week future profits or net volumes signed in the direction of the event trade.

Section 5 applies this design to the subsample of funds. We flexibly control for overlaps in the funds' dealer connections to remove the effects of common shocks through shared dealers. On a day when an event fund makes an exceptionally large trade, the funds affiliated to the event fund increase their volumes by 1.4 sd (std. error: 0.01 sd) relative to the unrelated funds.

Section 6 scours event, asset, and fund characteristics for China Wall violations and never detects them. Across crisis and noncrisis periods, asset classes, currencies, and fund types, the dealers consistently share information with their connected funds and so do the funds affiliated to each other. Hedge funds experience the largest jumps in volumes and profits upon receiving this information, echoing the evidence that hedge funds are particularly sensitive to information (Di Maggio, Franzoni, Kermani, and Sommavilla, 2019; Kumar et al., 2020).

In sum, we detect extensive information sharing among affiliated funds and between dealers and their clients, and yet precisely estimated zero sharing between affiliate dealers and funds—exactly where China Walls are present. This trio of results consistently holds for gross volumes, future profit-and-loss, and net volumes and in every currency, asset, and fund-type cell. They are robust to granular fund-by-event, calendar-date, and event-date fixed effects. We conservatively preserve all variation due to information sharing while removing marketwide shocks, dealer overlaps, trades within dealer-fund pairs, and the market impacts of event trades. Our peculiar intersection of results precisely point to effectively enforced China Walls.

Context and previous work on China Walls. The US regulators did not enforce China Walls before 2018. Previously, banking conglomerates voluntarily adopted China Walls to protect against corporate liability from insider trading by their employees. The 2010 Dodd-Frank Act allowed US regulators to conduct "risk-based" enforcement, under which

they can prosecute firms for practices that substantially raise the risk of a crime, even without evidence that the crime has actually occurred. The US Securities and Exchange Commission (SEC) began to exercise this power to enforce China Walls in 2018: insufficiently maintaining China Walls itself, not only insider trading, is now a prosecutable offense. Appendix A provides further detail.

Existing evidence on China Walls exploit samples that predate 2018. This evidence identifies extensive breaches, as legal proceedings confirm.[3] We instead evaluate the China Walls during the recent period of their active enforcement.[4] As importantly, we contribute a novel identification strategy that uses unrelated funds as controls to isolate the effects of information sharing. We validate our strategy in conditions where one expects information sharing. Applying this design to a large and granular dataset yields precise estimates and robust evidence that today's China Walls effectively preempt information sharing.

Broader contributions. We belong to the literature on the capacity of states to regulate firms.[5] In their settings, a large extent of regulatory enforcement occurs through private litigation by parties involved in the regulated activity (e.g., employer vs employee, insider vs outside shareholder; Glaeser and Shleifer (2003), La Porta, Lopez-De-Silanes, and Shleifer (2006)). In our setting, a China Wall violation involves affiliates under common corporate control, eliminating the threat of counterparty litigation. Information sharing is difficult to measure as it can be done in plausibly deniable ways, and bankers often do so (Peluso, 2020).

[3] Lehar and Randl (2006), Irvine, Lipson, and Puckett (2007), Seyhun (2008), Massa and Rehman (2008), Chen and Martin (2011), Ivashina and Sun (2011), Li (2018), Li, Mukherjee, and Sen (2021), Kondor and Pintér (2022), and Haselmann, Leuz, and Schreiber (2023) find evidence of China Wall violations in various settings. The latest in-sample year among them is 2017.

[4] Garrett (2024) and Beck, Silva-Buston, and Wagner (2025) also document the effectiveness of recent regulations on banking conglomerates. Garrett (2024) finds that a Dodd-Frank ban on concurrent advising and bond underwriting for the same municipality lowers the financing costs of municipalities. Beck et al. (2025) find that supervisory cooperation agreements between national regulators cause banking conglomerates to shift lending to subsidiaries in countries without such agreements. We examine limits on information sharing within banking conglomerates, as opposed to limits on concurrent services or geographic coverage of regulation.

[5] Regulators have greatly reduced pollution (Keiser and Shapiro, 2019; Behrer, Glaeser, Ponzetto, and Shleifer, 2021), insider trading (Bhattacharya and Daouk, 2002), misleading financial disclosures (Greenstone, Oyer, and Vissing-Jorgensen, 2006), and discrimination in pay (Bailey, Helgerman, and Stuart, 2024) and in access to accommodation (Cook, Jones, Logan, and Rosé, 2023).

Taken together, our results reveal a remarkable regulatory capacity to control information flows beyond what is established in prior work.

We extend the empirical literature on information diffusion in financial markets. Dealers extract information from their clients' order flow (Hortaçsu and Kastl, 2012), leak information to certain clients (Barbon et al., 2019; Boyarchenko et al., 2021; Chague, Giovannetti, and Herskovic, 2023), and generally act as the conduits through which information diffuses throughout their trading networks (Di Maggio et al., 2019; Hagströmer and Menkveld, 2019; Kumar et al., 2020). We identify a stark void in this informational network driven by regulatory intervention, thereby adding China Walls as a promising source of variation in information flows that is especially relevant today, when the financial sector is highly concentrated in banking conglomerates.

Roadmap. Section 2 develops the empirical design. Section 3 describes the data and provides preliminary evidence. Sections 4 and 5 investigate whether the China Walls are effectively enforced in the Israeli Shekel market. Section 6 performs heterogeneity analyses. Section 7 concludes with complementary questions that are outside the scope of this paper.

2 Design

Section 2.1 outline the China Wall rules and the market structure in our setting. Section 2.2 describes and explains our empirical design. Section 2.3 states the regression specifications that implement this design. Section 2.4 provides a test of our central identification assumption.

2.1 China Walls in Financial Markets

China Walls refer to a collection of rules and physical barriers that aim to preempt the flow of material private information (MPI) between a walled-off subsidiary and its affiliates. MPI is any information that (a) a reasonable investor would find important for her invest-

ment decisions and (b) is not publicly disclosed.For example, proprietary analysis, inside information, or private trade requests would constitute MPI. Typical China Walls require walled-off subsidiaries to be isolated via separate entrances, opaque and soundproof barriers, and the monitoring and recording of their employees' communications.

New regulations since the 2008 financial crisis established today's China Walls around broker-dealers within banking conglomerates (and bank-owned investment advisers, which we do not examine). Today, the US SEC routinely imposes large fines for deficiencies in the dealers' China Walls. Appendix A details relevant definitions, history and legal precedents, impacts of the Dodd-Frank Act, and recent enforcement cases.

The foreign exchange market is an over-the-counter market, in which trades occur between dealers or a dealer and its client. Trades are nonanonymous, and most firms rely exclusively on one or a few relationship dealers. This market operates at high frequency, where news is rapidly incorporated into exchange rates (Menkhoff, Sarno, Schmeling, and Schrimpf, 2016). We thus expect private advantage from an MPI to dissipate in a few trading days or faster.

Our data covers the near universe of Israeli Shekel (ILS) foreign exchange trades obtained from the Bank of Israel (BOI). The ILS market structure is identical to the other foreign exchange markets. Indeed, 83% of ILS transactions are for the USD-ILS pair and the ILS and the USD markets have the same largest dealers.[6] While Israel and the US have generally similar financial regulations, Israeli rules forbid Israeli holding companies from owning both a dealer and a nondealer investment firm, as the US Glass-Steagall Act did until its 1999 repeal.[7] As such, the Israeli regulators neither mandate nor enforce the China Walls, with three implications. (a) Israeli entities cannot drive our results on information sharing between affiliate dealers and funds. (b) The banking conglomerates do not incriminate themselves when reporting data at odds with their China Walls to the BOI, and hence our data is the one in which we would most expect to observe violations of China Walls. (c) Non-Israeli

[6]This number is 85% for all foreign exchange transactions that involve the USD (Somogyi, 2022).

[7]Israel implemented these rules under 2005 "Bachar" reforms, which sought to limit conflicts of interest within banking conglomerates. See p. 191 in https://www.bis.org/publ/bppdf/bispap148_l.pdf.

regulators are the enforcers of the China Walls in our setting, especially the US SEC whose jurisdiction extends to all bank holding companies active in the US (every conglomerate in our sample).

2.2 Empirical Design

We overcome three challenges to test the hypothesis that the China Walls are effectively enforced. First, it is infeasible to evaluate enforcement in all circumstances. Second, we need a proxy that reliably isolates and detects bilateral MPI sharing. Third, the bank-owned dealers may choose not to share MPI with their affiliates even if their China Walls were absent, in which case enforcement is moot.

Defining events. In the benchmark specification, we seek events that pinpoint the days when a dealer receives especially valuable MPI, under the plausible assumption that China Wall violations are most likely to occur when gains from sharing information with affiliates are largest. Standard theory shows that an informed trader requests to trade larger quantities when she holds more valuable private information (Kyle, 1985; Easley and O'Hara, 1987). Empirically, the trades that are unusually large compared to the other trades by the same trader are particularly predictive of the traded asset's return (Kumar et al., 2020; Pinter et al., 2024). Appendix B tests this assumption. Therefore, we let an event be a dealer and a day (event day) when the event dealer makes a trade (event trade) that is exceptionally large compared to the dealer's other trades. Appendix C examines events by funds and show qualitatively identical results.

Isolating information sharing. We fix an event dealer d and one of its affiliate funds f. A proxy for MPI sharing from dealer d to fund f must isolate information that is (i) material and (ii) bilaterally shared. Receiving material information would prompt fund f to rebalance its portfolio and earn greater trading profits, increasing its trading activity and the expected returns from those trades. Fund f may also become more likely to trade in the direction of the event trade. Therefore, we measure variations in the daily gross dollar volume and the

daily one-week future returns of fund f to proxy for the sharing of MPI by the event dealer d to f. Appendix D confirms our results using net dollar volumes signed in the direction of the event trades.

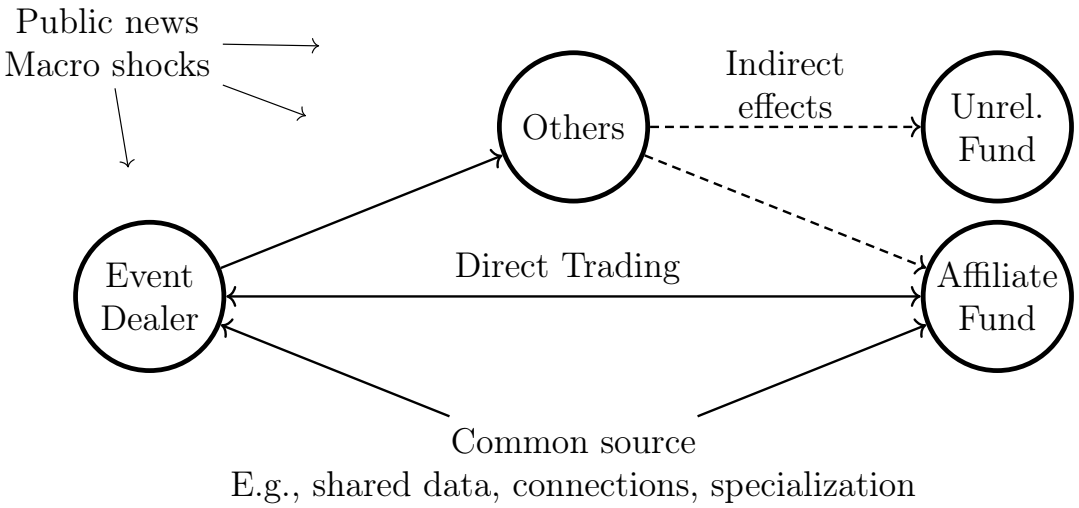


Figure 2: Potential Confounders to Measuring Bilateral Information Sharing

We remove four confounders that could simultaneously increase the incidence of exceptionally large trades by event dealer d and the large volume or returns of its affiliate fund f. Figure 2 illustrates the confounders. First, any direct trade between dealer d and fund f would cause a mechanical correlation, for example if f is the counterparty to d's event trade. We confirm that dealers virtually never trade with their affiliate funds in our sample.

Second, the arrivals of public news or macroeconomic shocks may cause trade volumes, returns, and trade sizes to covary. Third, the event trade may indirectly affect its affiliate fund f's volume through its price or liquidity impact. For example, if an event trade is between dealer d and another dealer, the second dealer offloads the newly gained inventory with fund f. The gross volume of fund f would mechanically increase.

We filter out these two confounders by comparing the affiliate fund f to the *unrelated funds*, which are neither affiliated with nor clients of the event dealer d. The unrelated funds would be as affected by the public news, macroeconomic shocks, or the indirect impacts of the event trade as the affiliate fund f. At the same time, the event dealer d would not share

MPI with an unrelated fund. This comparison isolates bilateral MPI sharing from the event dealers to their affiliate funds from the two counfounders.

Fourth, a source common to dealers and their affiliate funds, but not to the unrelated funds, may trigger the dealers' event trades while increasing the affiliate funds' volumes or returns. For example, dealer d and its affiliate fund f could be more likely than unrelated dealers and funds to share data or research sources. They could also be more likely to specialize in the same assets, or be connected to the same thirdparty dealers. Our precise null results between dealers and their affiliate funds indicate that these confounders are unimportant in practice.

Falsification test. A key remaining threat is the possibility that our design fails to reliably detect bilateral MPI sharing where it exists. We test whether our design reliably detects bilateral MPI sharing based on the stylized fact that dealers extensively share information with its client (connected) funds (Barbon et al., 2019; Kumar et al., 2020; Chague et al., 2023). A reliable design would detect the MPI sharing between the event dealers and their connected funds. We falsify our design if the daily gross volumes or one-week future returns of the connected funds do not significantly increase relative to the unrelated funds on or after the event day. We rule out any mechanical correlations due to direct trades between the event dealers and their connected funds by excluding from the falsification test any connected fund that trades with the event dealer on or after the event day.

2.3 Implementation

We adopt the stacked difference-in-differences specification with never-treated controls of Cengiz et al. (2019).[8] An event trade is a dealer trade that belongs to the top 0.1 percentile among all of the dealer's trades by dollar value. An event is a dealer and a day on which the dealer made one or more event trades. Each event creates a stack, a subsample in which an

[8]This implementation yields average treatment-on-the-treated (ATT) effect estimates that always place positive weights on all groups (Gardner, 2022), unlike those of traditional staggered two-way fixed-effects difference-in-differences specifications (Roth, Sant'Anna, Bilinski, and Poe, 2023).

observation is a treated or control fund-by-day in the 11-trading day event window around the event day. We append the stacks across all events to obtain the analytical sample.

Our main regression specification is

$$Y_{e(d)ft} = \sum_{\tau=-5}^{5} \alpha_\tau \mathbb{1}_{t=\ell_{e(d)}+\tau} Affiliate_{e(d)f} + \delta_{e(d)f} + \varphi_t + \sum_{\tau=-5}^{5} \gamma_\tau \mathbb{1}_{t=\ell_{e(d)}+\tau} + \varepsilon_{e(d)ft}. \quad (1)$$

The dependent variable $Y_{e(d)ft}$ is the gross dollar volume or the one-week future profit-and-loss (P&L) of fund f for event $e(d)$ by dealer d on calendar date t. All dependent variables are standardized at the fund level. Section 3.1 provides the precise definitions for these dependent variables. The affiliate treatment dummy $Affiliate_{e(d)f}$ equals 1 if fund f is an affiliate of the event dealer d. The dummy $Affiliate_{e(d)f} = 0$ if f is *(i)* not affiliated with and never trades with d and *(ii)* not affiliated with any event dealer of other events within the 21 trading days around the event day $\ell_{e(d)}$ ($t = \ell_{e(d)} - 10, \ldots, \ell_{e(d)} + 10$). We control for event-by-fund, calendar date, and event date fixed effects, $\delta_{e(d)f}$, φ_t, and γ_τ. These effects embed all possible event-and-fund-specific controls as well as common trends over calendar and event times. We cluster standard errors by event-and-fund and by calendar date, because our treatments are assigned event-by-fund and the incidence of events varies over time. Our clustered variances likely approximates the true variances, since we observe the near universe of trades in the Israeli Shekel, implying a high sampling probability (Abadie, Athey, Imbens, and Wooldridge, 2023).

The second specification considers the connected funds:

$$Y_{e(d)ft} = \sum_{\tau=-5}^{5} \beta_\tau \mathbb{1}_{t=\ell_{e(d)}+\tau} Connected_{e(d)f} + \delta_{e(d)f} + \varphi_t + \sum_{\tau=-5}^{5} \gamma_\tau \mathbb{1}_{t=\ell_{e(d)}+\tau} + \varepsilon_{e(d)ft}. \quad (2)$$

The connected treatment dummy $Connected_{e(d)f}$ equals 1 if fund f *(a)* trades 10 or more times with the event dealer d in our sample and *(b)* does not trade with d on or in the five days after the event day ($t = \ell_{e(d)}, \ldots, \ell_{e(d)} + 5$). Condition (a) implies that the connected and the affiliate treatments are mutually exclusive, because the dealers essentially never trade with

their affiliate funds. Condition (b) removes any mechanical effects as the connected funds trade with the event dealer. The dummy $Connected_{e(d)f} = 0$ if and only if $Affiliate_{e(d)f} = 0$, identifying the same control group consisting of the unrelated funds. All remaining aspects of equation (2) are identical to those in equation (1).

2.4 Identification Tests

We assume that a dealer makes an exceptionally large trade when the dealer learns especially valuable private information. Appendix B adjudicates the stronger assumption that dealers trade larger sizes when they have more valuable private information. Specifically, we test *(I)* this stronger assumption and *(II)* the claim that our design detects MPI sharing if and only if such sharing exists.

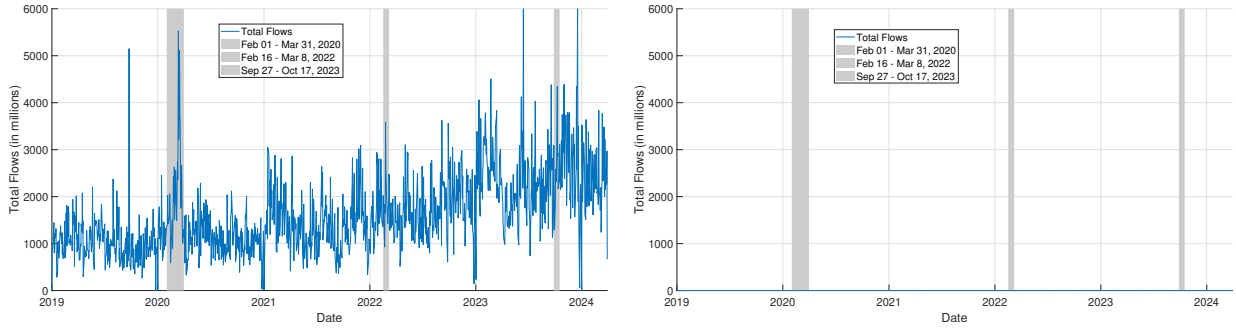
We define placebo events as a dealer and a day when the dealer makes a trade in the X to $X + 0.1$ percentile of the dealer's trades, where X is each decile, $X \in \{10, 20, \ldots, 90, 99.9\}$. Our test consists of two parts. First, we separately compute the price impacts of the exceptionally large trades (top 0.1 percentile) and the placebo event trades for each decile (down to bottom 99.9 percentile). We find that (I) the dealers' exceptionally large trades predict price movements up to four days into the future, whereas their smaller trades do not predict price movements. Second, we repeat the estimation of equation (2) ten times, each time replacing events with the placebo events of a different decile. We find that (II) our design detects MPI sharing between connected dealers and funds around the exceptionally large trades, and yields coefficients close to zero for the smaller trades.

3 Data and Descriptive Results

Section 3.1 details the raw data, sample construction, and variable definitions. Section 3.2 analyzes pairwise correlations in daily volumes between dealers and funds as preliminary evidence.

3.1 Sample Construction

Raw data. We obtain the near universe of foreign exchange trades involving the Israeli Shekel from the Bank of Israel in the sample period January 2019–March 2024, spanning 1,368 trading days.[9] Each trade specifies the currency pair (ILS and another currency), exchange rate, quantity, date and time,[10] asset class (spot, forward, swap, or option), legal names of the counterparties, their trade directions, and whether each counterparty is in Israel and whether it is a financial firm (i.e., dealers and investment funds). We mark the financial firms that can be matched to the BOI's list of foreign exchange dealers as dealers, and the other financial firms as funds. We assign each dealer or fund, partly with the aid of `ChatGPT 4.0o`: to its holding company or as unaffiliated; as a hedgefund or not; and to the country of its legal domicile if not Israel. All volume and dollar-return measures are converted to USD at the contemporaneous exchange rates retrieved from Bloomberg.



(a) Unaffiliated Dealers and Funds

(b) Affiliate Dealers and Funds

Figure 3: Daily Gross Dollar Volumes Traded Between Dealers and Funds

Figure 3a: The sum of daily gross dollar volume in USD millions across pairs of dealer and fund that are not affiliated with the same banking conglomerate. Figure 3b: The sum of daily gross dollar volume in USD millions across pairs of affiliate dealer and fund. Shaded regions mark the onsets of the Covid pandemic, the Russian Invasion of Ukraine, and the Hamas attack on Israel.

[9] All Israeli banks, including the Israeli branches of banking conglomerates, must report all their ILS foreign exchange trades to the BOI. Non-Israeli banks fall under the same reporting requirement if their foreign exchange trades (in any currency pair) in the previous year exceed $15 million per day on average, whether on their own accounts or on behalf of clients. Practically every dealer falls under the reporting requirement, covering nearly all ILS trades. We do not observe the trades between four dealers that are unaffiliated with a bank nor their trades with nondealer clients. (We observe all trades between the nonbank dealers and any of the other dealers.) Rules can be retrieved from https://www.boi.org.il/en/economic-roles/statistics/reports-to-bank-of-israel/reporting-on-activity-in-the-foreign-currency-derivative/.

[10] We do not use the time stamps, as the BOI only verifies the trade dates, not their time stamps. An improbably high 6.6% of trades report "00:00:00" in our raw sample.

Figure 3 plots the total daily gross dollar volume of trades among the dealers and funds. The dealers trade USD2.8 billion with the funds each day (Figure 3a), of which mere four trades worth USD5.51 million are between the dealers and their affiliate funds (Figure 3b). We say that the dealers "virtually never" trade with their affiliate funds. Regular sharp falloffs in volume correspond to end-of-year holidays.

Affiliation, country, and fund type. First, we determine the affiliations of most US-based dealers and funds using the quarterly organizational hierarchy data accessible via the National Information Center (https://www.ffiec.gov/npw/). We assign affiliations as of the fourth quarter in 2023, because financial firms rarely change their affiliations and typically change their legal names when they do. Second, the non-US and non-Israeli dealers and funds with obviously indicative names are assigned to the corresponding holding company (e.g., "Deutsche Bank Luxembourg S.A."). Third, the names of the remaining dealers and funds are entered into `ChatGPT 4.0o` as queries in the form, "as of `[date the legal name last appears in the sample]`, does `[legal name]` belong to a financial conglomerate or is it independent? Which holding company if any does `[legal name]` belong to?" Fourth, we verify each answer generated in step three, by searching for the legal name paired with "independent" or the `ChatGPT`-suggested holding company name. Similarly, we determine the domicile and whether each fund is a hedge fund by querying and verifying, "as of `[last date of legal name]`, which country is the legal domicile of `[legal name]`?" and "as of `[last date of a fund]`, is `[fund name]` a hedge fund?"

Table 1 shows the number of dealers and funds in our raw data. A plurality of the dealers and funds are in the US and much of the remainder are in Europe or the UK. The 46 conglomerates are each headed by a holding company that controls at least one dealer. Every dealer belongs to a conglomerate, whereas most funds do not. All dealers without an affiliate fund are in Israel, which bans holding companies from controlling a dealer alongside a fund.

Constructing the final sample. Table 2 summarizes our three-step sample construc-

Table 1: Unique Financial Firms in Raw Data

	Conglomerates	Dealers		Funds		
		All	No affiliate fund	All	No affiliate dealer	Hedge fund
US	13	94	0	4824	4307	364
Europe & UK	13	101	0	1380	968	88
Israel	11	18	18	192	192	2
Elsewhere	9	22	0	1379	1193	178
Total	46	235	18	7775	6660	632

"Conglomerates" are holding companies that each controls at least one dealer. "Dealers" include brokers and broker-dealers. All dealers without affiliate funds are domiciled in Israel, which forbids common ownership of dealers and funds.

Table 2: Each Step in Sample Construction

	Obs.	Dealers	Funds	Mean value (USD millions)		Share of trades (%)		
				Dealer obs.	Fund obs.	USD	Forward	Swap
Raw data	22,848,453	235	7,775	3.74	1.74	83.1	14.5	14.7
Drop								
options	22,667,356	235	7,775	3.74	1.73	83.1	14.6	14.8
2nd legs	20,927,534	235	7,775	2.48	1.32	83.0	15.9	7.7
Consolidate								
dealers	18,560,942	46	7,775	2.12	1.32	82.9	16.4	7.7
Aggregate to								
dealer-day	62,974	46	—	774.8	—	—	—	—
fund-day	10,643,975	—	7,775	—	0.39	—	—	—

Raw data: All foreign exchange trades reported to the Bank of Israel between January 2019 to March 2024. *Drop*: All options trades and all second legs of swap trades (see Footnote 11). *Consolidate dealers*: We combine dealers up to the conglomerate-level and drop all trades between the dealers in the same conglomerate. *Dealer-day*: Trades by each dealer aggregated at the daily level in USD terms. *Fund-day*: Trades by each fund aggregated at the daily level in USD terms. *Mean value*: Gross value in USD millions averaged across observations. *Share of trades*: Proportion of trade-level observations with the corresponding characteristic (i.e., belongs to USD-ILS currency pair or is a forward or a swap trade).

tion. First, we drop all options trades (for insufficient observations) and all second legs of swaps trades (to avoid double counting).[11] Second, we consolidate the dealers up to the conglomerate-level by dropping all trades between affiliated dealers and combining the dealers under conglomerate-level labels. Doing so treats affiliated dealers as a single economic entity, given their ability to split incoming orders and transfer assets and capital among themselves, and minimizes the noise from nonmarket trades that shift cash and inventory for tax or balance sheet purposes.[12] Third, we aggregate the daily trades of each dealer and fund to arrive at two final samples for analysis: one containing dealer-by-day observations; and the other with fund-by-day observations.

Dependent variables. Each dependent variable defined below is at the dealer or fund-by-day level. We standardize each dependent variable of fund f by dividing the variable by its standard deviation computed over the observations of f. We winsorize these variables at the top 0.5 percent for gross volume, or at both the top and the bottom 0.5 percent for the other variables, after combining observations into stacks and before estimating each regression. All results remain without winsorization.

Gross dollar volume of fund f on day t aggregates the fund's daily spot, forward, and swap trades. For each (f, t)-pair, we add together the notional amounts of the spot, forward, swap (first legs only) trades in USD terms using the exchange rate at the time of each trade.

One-week future profit-and-loss is the dollar net profit from trades by fund f on day t if the corresponding positions were held for five trading days. For each (f, t, asset class, currency pair)-quadruplet, we compute the *net* notional amount (i.e., buys less sales of the non-ILS

[11] Foreign exchange swap is a spot trade with the commitment to reverse the spot trade at a predetermined exchange rate on a future date. The first leg is the initial spot trade and the second leg is the reverse trade. For example, consider a swap trade today to buy one USD using ILS at 3.03 USD/ILS spot rate (first leg; USD/ILS means ILS per USD by convention) then promise to sell one USD for ILS at 2.86 USD/ILS in five days (second leg). This trade would yield a profit if ILS appreciates below 2.86 USD/ILS in five days. To see this, the trader can immediate sell the USD from the first leg for 3.03 ILS; then buy back one USD just before the second leg using, say, 2.78 ILS; then deliver the USD for 2.86 ILS. Overall profit is $-3.03 + 3.03 - 2.78 + 2.86 = 0.08$ ILS.

[12] Some 8% of foreign exchange spot trades are "back-to-back" trades between affiliate dealers for accounting or inventory rebalancing purposes (Bank for International Settlements, 2022). All trades by funds are market-based, since they only trade with nonaffiliate dealers.

currency for spot and forward and the opposite for the first legs of swaps; see Footnote 11) in the non-ILS currency unit (CCY). The five-trading day realized return for a given CCY is the percent change in the exchange rate, $R_t^{sf}(CCY) \coloneqq [(CCY/ILS)_{t+5}/(CCY/ILS)_t - 1]$, using the rates at 17:00 EST.[13] We multiply each net notional amount by the corresponding realized return, then convert the resulting amounts into USD using the 17:00 EST exchange rate at $t+5$ to obtain the net P&L by f in CCY on t. The daily one-week future P&L is the sum of these converted net P&L by f on t across CCY.

Table 3 summarizes the dealer-by-day and the fund-by-day analytical samples from which we combine observations into the stacks for regression analysis. All volumes, P&L, and values are in USD millions. No variables are standardized in this table. While most dealers traded more than ten times and thus are connected with several funds in our sample, the majority of funds only are only connected with one or two dealers. Some 95% of the fund-by-day observations in fact have no trades. About a quarter of dealers never trade with (are unrelated to) a fund, because they either only trade with nonfinancial firms or are one of the three nonbank dealers that need not report dealer-fund trades to the BOI. The event trades widely vary in size, corresponding to the wide variation in the sizes of the dealers and the funds. For the events that combine multiple event trades, we assign the characteristics of the largest trade among them to the whole event.

3.2 Preliminary Evidence

We look for preliminary evidence of information sharing between dealers and funds using the correlations in trading activities within dealer-fund pairs. A dealer and a fund are an *affiliate pair* if they belong to the same conglomerate, an *unrelated pair* if they are unaffiliated and never trade with each other in our sample, and a *connected pair* if they are unaffiliated

[13] Although the foreign exchange (FX) market is in theory open around the clock, 17:00 EST marks the beginning of the sole interval in a work day when all major FX markets are closed. It also avoids the various FX fixes throughout the day, around which the USD predictably appreciates then reverses (Krohn, Mueller, and Whelan, 2024).

Table 3: Summary Statistics of the Analytical Samples

	Mean	Std. Dev.	Min	25%	50%	75%	Max
Dealers ($N = 46$)							
Affiliate funds	24.35	39.81	0.00	1.00	10.50	30.00	182.00
Connected funds	162.83	297.60	0.00	0.00	6.00	152.00	1131.00
Unrelated funds	7293.87	804.25	5027.00	7153.00	7757.50	7775.00	7775.00
Funds ($N = 7775$)							
Affiliate dealers	0.14	0.35	0.00	0.00	0.00	0.00	1.00
Connected dealers	0.96	1.73	0.00	0.00	0.00	1.00	16.00
Unrelated dealers	42.57	3.11	29.00	41.00	44.00	45.00	45.00
Dealer-Day ($N = 62974$)							
Has trade	0.82	0.38	0.00	1.00	1.00	1.00	1.00
Is an event	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Gross volume	774.83	1298.78	0.00	19.51	239.01	897.63	12214.47
Net volume	36.65	213.19	-2170.21	-5.76	0.04	19.99	2093.41
1-week future return	-0.01	2.72	-119.03	-0.01	0.00	0.01	128.06
Fund-Day ($N = 10643975$)							
Has trade	0.05	0.21	0.00	0.00	0.00	0.00	1.00
Is an event	0.00	0.01	0.00	0.00	0.00	0.00	1.00
Gross volume	0.39	8.86	0.00	0.00	0.00	0.00	4210.10
Net volume	0.00	2.80	-1201.00	0.00	0.00	0.00	1046.75
1-week future return	0.00	0.07	-32.25	0.00	0.00	0.00	35.65
Dealer Events ($N = 2693$)							
Event trade value	255.56	149.72	1.53	199.96	229.16	299.67	1750.00
Has multiple event trades	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Crisis	0.06	0.24	0.00	0.00	0.00	0.00	1.00
USD	0.89	0.32	0.00	1.00	1.00	1.00	1.00
JPY	0.02	0.16	0.00	0.00	0.00	0.00	1.00
EUR	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Spot	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Forward	0.12	0.33	0.00	0.00	0.00	0.00	1.00
Swap	0.69	0.46	0.00	0.00	1.00	1.00	1.00
Fund Events ($N = 1315$)							
Event trade value	15.90	53.89	0.01	0.25	1.37	7.80	1349.84
Has multiple event trades	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Crisis	0.08	0.28	0.00	0.00	0.00	0.00	1.00
USD	0.88	0.33	0.00	1.00	1.00	1.00	1.00
JPY	0.01	0.10	0.00	0.00	0.00	0.00	1.00
EUR	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Spot	0.62	0.49	0.00	0.00	1.00	1.00	1.00
Forward	0.29	0.45	0.00	0.00	0.00	1.00	1.00
Swap	0.09	0.29	0.00	0.00	0.00	0.00	1.00

All volumes, P&L, and values are in USD millions. No variables are standardized in this table. For the events that combine multiple event trades, we assign the characteristics of the largest trade among them to the whole event.

and trade 10 or more times in our sample. We omit the dealer-fund pairs that trade one to nine times within the pair.

If the dealers do share information with their affiliate funds, the trading activities of the affiliate pairs would be more correlated than those of the unrelated pairs, whose correlation would reflect public news and other confounders that affect all dealer-fund pairs. Figure 4 presents the correlations in daily gross dollar volumes within the unrelated pairs. For each lag $l = -10 \ldots + 10$ and a pair of dealer d and fund f that are unrelated, we compute the correlation $CorrGV_{ijl}$ between the day-t gross volume of d and day-$(t + l)$ gross volume of f. We average this correlation across all unrelated pairs for each l. Figure 4a plots the results. There are strongly positive and significant correlations in the daily gross volumes between the dealers and their unrelated funds. Absent a control group, the confounders cause comovement within the unrelated pairs that may severely contaminate any proxy of bilateral information sharing.

We next estimate a simplified version of our main specifications (1)-(2). We compare the correlations $CorrGV_{ijl}$ within the affiliate and the connected pairs to the unrelated pairs. Doing so tests whether the trading activities of affiliated or connected dealers and funds are correlated once stripped of confounders. Precisely, we estimate the regression specification

$$CorrGV_{dfl} = a_l Affiliate_{df} + b_l Connected_{df} + c_d + d_f + \varepsilon_{dfl}. \tag{3}$$

The dummy variable $Affiliate_{df}$ equals 1 if dealer d and fund f are an affiliate pair and 0 if they are an unrelated pair. The dummy $Connected_{df}$ equals 1 if d and f are an connected pair and 0 if they are an unrelated pair. We exclude the trades between connected d and f when computing $CorrGV_{dfl}$ to avoid mechanical correlations due to within-pair trades. The dealer and the fund effects c_d and d_f control for time-invariant factors specific to each dealer and each fund.

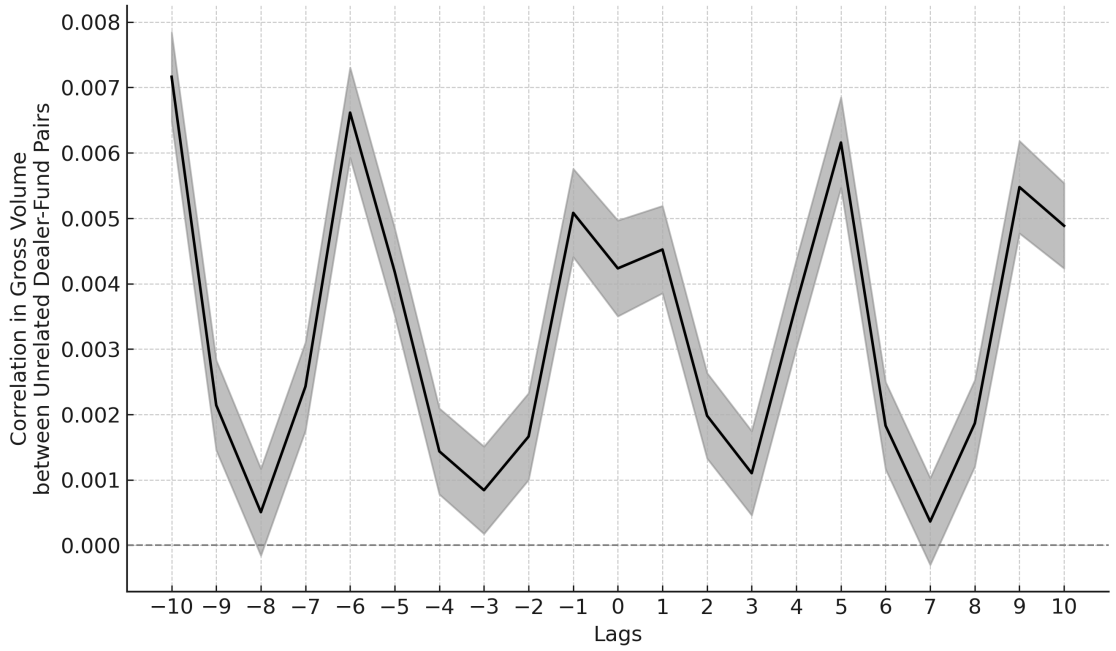
Figure 4b plots the coefficients a_l and b_l across $l = -10 \ldots 10$. The daily gross volumes of

the affiliate dealer-fund pairs are no more correlated than those of the unrelated pairs across all leads and lags l. In contrast, the connected dealer-fund pairs are contemporaneously far more correlated than the unrelated pairs. These results provide suggestive evidence that the China Walls are effectively enforced in our setting, and that our design reliably detects information sharing between dealers and their clients.

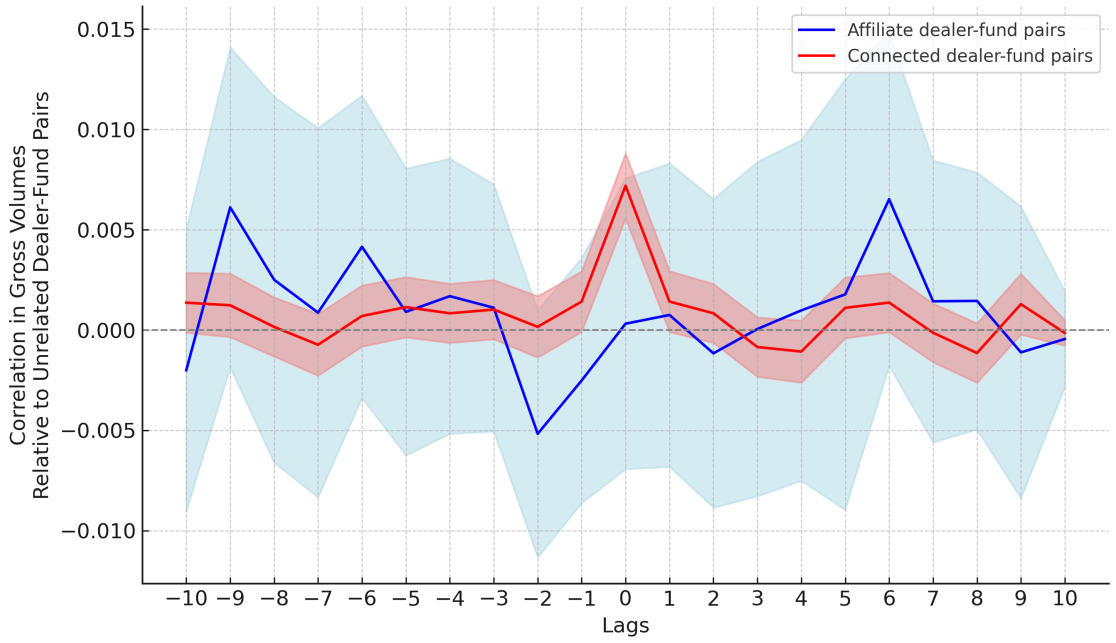
4 Are the China Walls Effectively Enforced?

We first estimate equations (1) and (2) selecting the dealers as the event firms and the funds as the treated and the control firms. Figure 5a plots in blue the differences α_τ in standardized gross volume between affiliate and unrelated funds around the days of exceptionally large trades by dealers, and in red the differences β_τ between the connected and the unrelated funds. The affiliate funds exhibit neither pretrends nor posttrends. The connected funds show no pretrends and a positive estimate on the event day. The event-day estimates are far apart: the affiliate funds increase their gross volumes on the event day by -0.001 standard deviation (std. error: 0.003 sd), whereas the connected funds increase theirs by 2.0 sd (std. error: 0.004 sd).

Figure 5b plots the coefficient estimates of equations (1) and (2) where the dependent variable is the standardized daily one-week future P&L of the funds around the days when a dealer makes an exceptionally large trade. In blue are the differences α_τ in the P&L between the affiliate and the unrelated funds around the event days. In red are the differences β_τ between the connected and the unrelated funds. Neither the affiliate nor the connected funds exhibit pretrends. The affiliate funds do not show posttrends, and the estimated increase in their one-week P&L is precisely nil. The trades of the connected funds on the event day earn an additional 0.6 sd (std. error: 0.02 sd) weekly dollar P&L. We conclude that the China Walls effectively prevent dealers from sharing private information with their affiliate

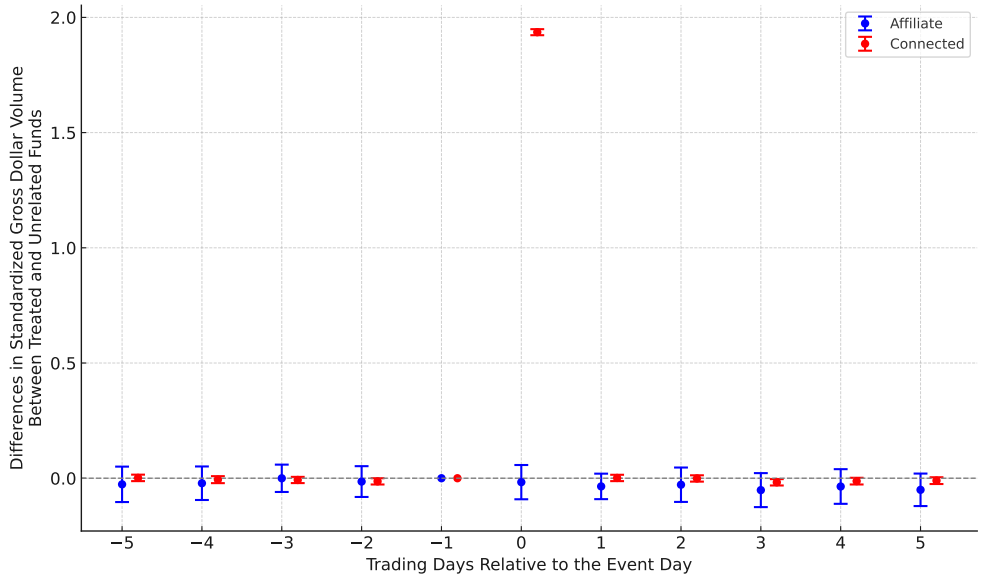


(a) Unrelated Pairs

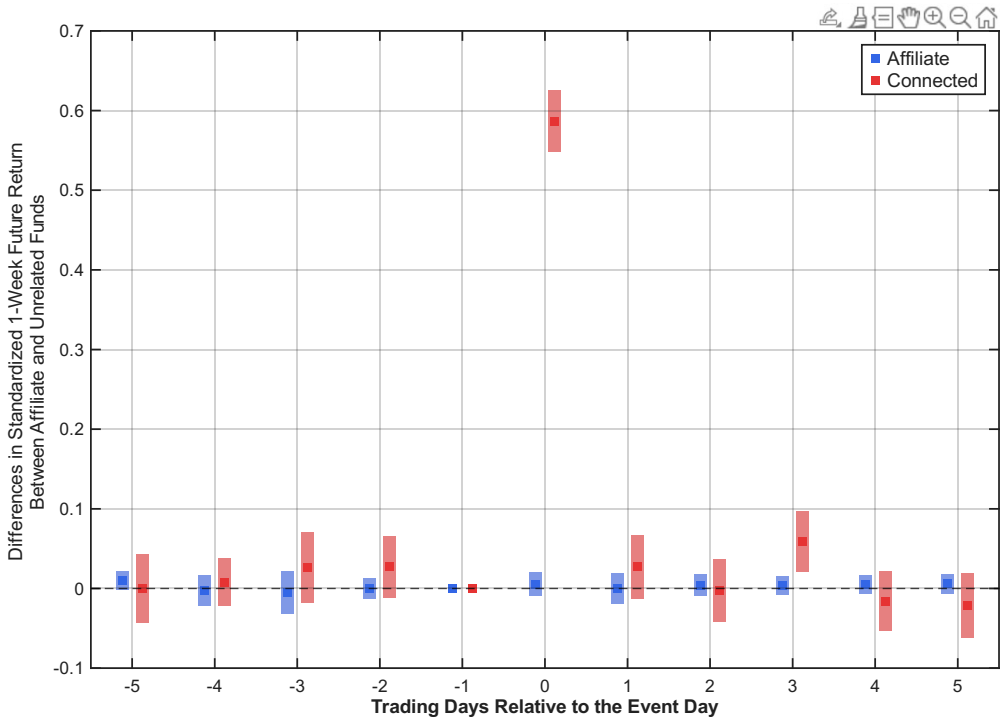


(b) Affiliate and Connected Pairs using Unrelated Pairs as Controls

Figure 4: Correlations in Daily Gross Volumes within Dealer-Fund Pairs



(a) Daily Gross Dollar Volume



(b) Daily 1-Week Future P&L

Figure 5: Coefficient Estimates from (1) and (2): Fund Responses to Dealer Events

funds. Appendix C flips the roles of the dealers and the funds to confirm that the funds do not share information with their affiliate dealers either.

Table 4 details the pooled regression counterpart to Figure 5. It crystallizes our power to detect even very small effects. Each stacked sample includes many million observations corresponding to hundreds of events and numerous affiliate, connected, and unrelated funds per event. The affiliate-treatment regressions contain fewer events than the connected regressions, because there are no affiliate funds for the Israeli and the nonbank dealers, whose events are thus dropped from the affiliate regressions. The connected regressions have fewer observations than the affiliate ones, because dealers have far more connected funds than affiliate funds (Table 3), and so many more unrelated funds are dropped to keep the control group never-treated. Last two columns of Table 4 are discussed in Section 5.2.

5 Do Affiliates Without China Walls Share Information?

We exploit the conglomerates that own multiple funds to infer whether the dealers would share private information with their affiliate funds if the China Walls were absent. The affiliate funds in the same conglomerate are not walled off from each other. If the affiliate funds share information among themselves, we infer that dealers and their affiliate funds would also share information absent the China Walls.

5.1 Design and Implementation

Figure 6 depicts the design. Dotted arrows indicate trading relationships. GS Hedge Fund's sole dealer connection is BoA Dealer. GS Mutual Fund and the GS Hedge Fund are affiliate funds whose dealer connections do not overlap. We compare the daily gross dollar volume and one-week future P&L of the GS Hedge Fund (the affiliate fund) to the Unrelated Fund around an exceptionally large trade by the GS Mutual Fund (the fund event). We control for whether the event fund and an affiliate or unrelated fund are connected to a

Table 4: Responses by Funds on and after Event Days

	Affiliate Volume	Affiliate Return	Connected Volume	Connected Return	F2F Volume	F2F Return
$Post \times Affiliate$	-0.00	0.00			0.20***	0.11***
	[0.002]	[0.008]			[0.003]	[0.010]
$Post \times Connected$			0.33***	0.25***		
			[0.008]	[0.013]		
$Post \times DealerOverlap$					0.02***	0.03***
					[0.003]	[0.003]
$Post \times Affiliate$					0.17***	0.11***
$\times DealerOverlap$					[0.018]	[0.037]
Event×Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Days-since-Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.211	0.023	0.082	0.048	0.065	0.025
Within R-squared	0.0000	0.0000	0.0071	0.0016	0.0001	0.0000
Events	1,240	1,239	2,597	2,597	608	608
Observations	204,392,853	203,897,886	103,348,695	101,851,448	81,187,547	81,061,973

Coefficient estimates from the pooled counterparts to equations (1), (2) and (4). *Volume*: Dependent variable is the standardized daily gross US dollar volume of a fund winsorized at the top 0.5 percentile. *P&L*: Dependent variable is the standardized daily one-week future P&L of a fund winsorized at the top and bottom 0.5 percentiles. An event is a dealer and a day when the dealer made a trade in the 0.1 percentile among its trades. Each event window is the 11 trading days around the event day. *Affiliate*: Fund belongs to the same conglomerate as the event dealer. *Connected*: Fund trades at least 10 times with the event dealer in our sample, and does not trade with the event dealer on or after the event day. Control funds are unaffiliated and never trades with the event dealer in our sample, and are not treated in another event during the event window. *F2F*: Estimates of (4) using the fund-by-day analytical sample, where events, treatments, and controls are defined for event funds, rather than event dealers. We include event-by-firm, calendar date, and days-since-event fixed effects. *DealerOverlap*: Treated or control fund whose set of connected dealers overlaps with that of the event fund. Standard errors in square brackets are clustered at the event-by-firm and date levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

common dealer, removing the confounding variation from overlapping dealer connections in our estimates of interest. We conclude that the enforcement of China Walls are necessary if the volumes and the P&L of the affiliate funds increase relative to the unrelated funds on or after the fund event day.

A threat to the validity of this inference is that two funds tend to be closer together in size and trading strategies than a dealer and a fund. Appendix E partitions the funds into cells of similar and differing sizes and trading strategies to evaluate this threat.

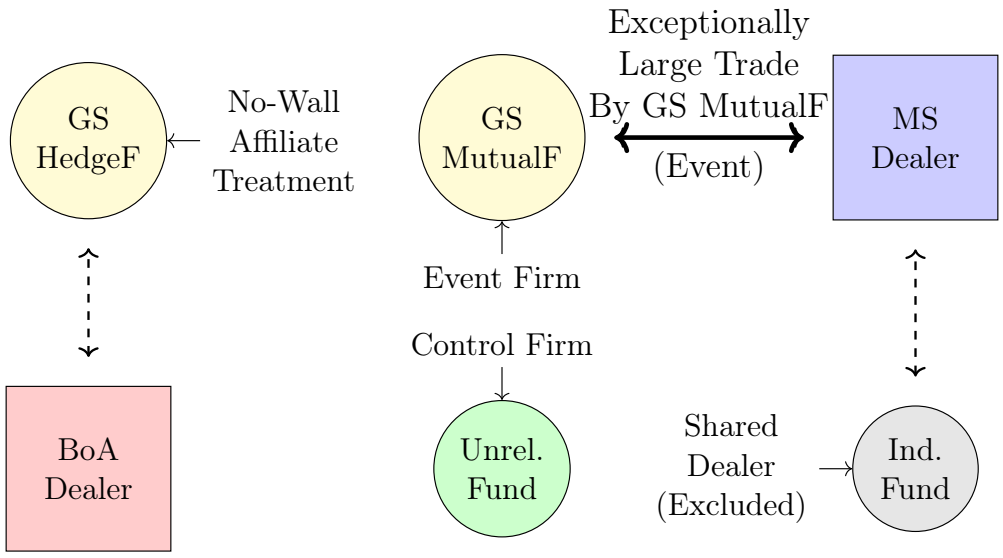


Figure 6: Identification: Information Sharing Between Affiliate Funds

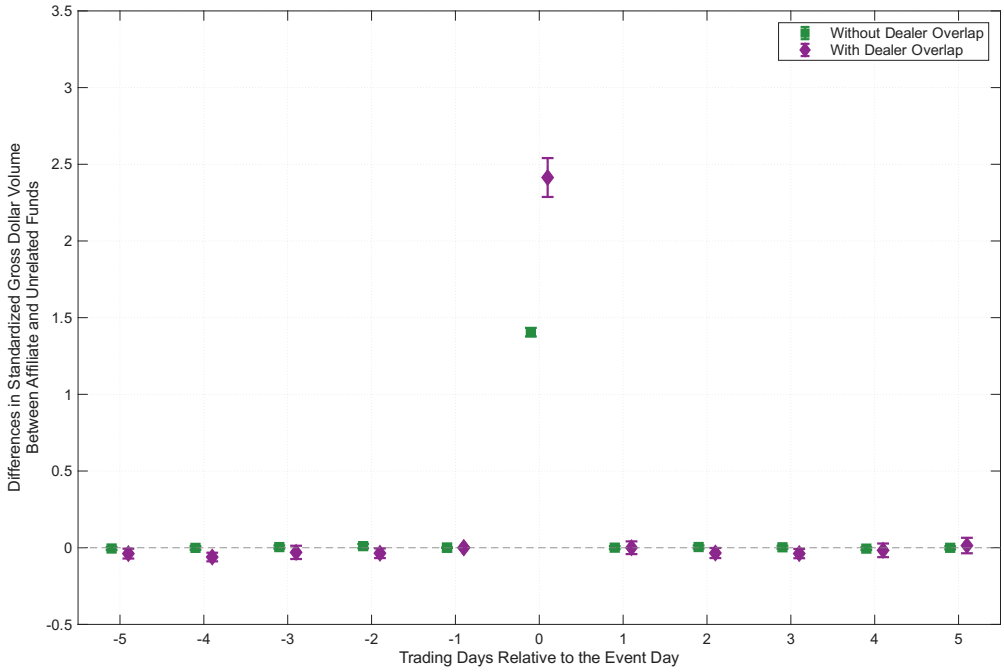
We apply the following specification to the subsample of funds:

$$
\begin{aligned}
Y_{e(i)jt} = &\sum_{\tau=-5}^{5} \nu_\tau \mathbb{1}_{t=\ell_{e(i)}+\tau} Affiliate_{e(i)j} + \delta_{e(i)j} + \varphi_t + \sum_{\tau=-5}^{5} \gamma_\tau \mathbb{1}_{t=\ell_{e(i)}+\tau} \\
&+ \sum_{\tau=-5}^{5} \kappa_\tau \mathbb{1}_{t=\ell_{e(i)}+\tau} Affiliate_{e(i)j} DealerOverlap_{e(i)j} \\
&+ \sum_{\tau=-5}^{5} \eta_\tau \mathbb{1}_{t=\ell_{e(i)}+\tau} DealerOverlap_{e(i)j} + \varepsilon_{e(i)jt}.
\end{aligned} \tag{4}
$$

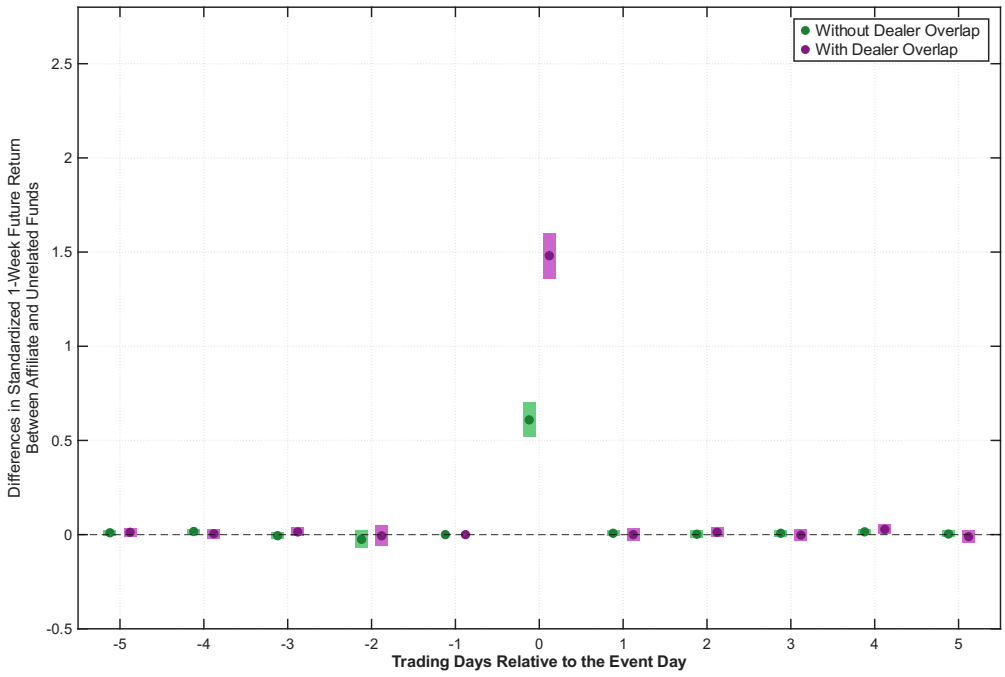
The control dummy $DealerOverlap_{e(i)j}$ equals 1 if fund j's set of connected dealers overlaps with event fund i's set of connected dealers, and equals 0 otherwise. We focus on the coefficients ν_τ, which measure the MPI sharing from the event funds to their affiliate funds without an overlapping dealer. Separate event-date effects, γ_τ and η_τ, flexibly control for any trend over event time specific to the funds with or without an overlapping dealer.

5.2 Results

Figure 7 presents the results from equation (4) estimated on the subsample of funds. In green are the differences ν_τ in standardized gross volume or one-week P&L between the



(a) Standardized Daily Gross Dollar Volume



(b) Standardized Daily 1-Week Future P&L

Figure 7: Coefficient Estimates from (4): Fund Responses to Fund Events and 95% Confidence Intervals

affiliate funds and the unrelated funds whose dealer connections do not overlap with the event fund around an exceptionally large trade by the event fund. Despite removing the common shocks through any overlapping dealers, the affiliate funds increase their gross volumes by 1.4 standard deviations (std. error: 0.01 sd; Figure 7a) and their one-week P&L by 0.6 sd (std. error: 0.05 sd; Figure 7b) on the event date. The large size of this response is consistent with affiliated funds being eager to share information among themselves. In magenta are the differences $\nu_\tau + \kappa_\tau + \eta_\tau$ between the affiliate funds whose dealer connections do overlap with the event fund and the unrelated nonoverlapping funds. As one might expect, incorporating overlapping dealer effects dramatically raises the event-date responses further.

Rightmost columns in Table 4 presents the pooled counterpart to Figure 7. They present the large sample sizes and hundreds of events that lead to our tight standard errors. There are much fewer fund events than dealer events, because most funds are independent, and so have no affiliates, and do not trade frequently, and so cannot have more than one event. Among the remaining fund events, many have zero never-treated affiliate funds within the event window, explaining the lower number in Table 4 compared to Table 3.

A back-of-the-envelope calculation shows that extending the China Walls around funds would eliminate $23.7 billion in trades, comprising 58% of their trades on the event dates ($40.8 billion). The dollar value of the eliminated trades is the product of: *(a)* the coefficient (1.4 sd) for the difference in gross volumes between the affiliate and the unrelated funds on the event day; *(b)* the average dollar value ($0.25 million) of the standard deviations in daily gross volumes among affiliate funds in the stacked sample for estimating (4); and *(c)* the total number (67,838) of the affiliate funds (counting appearance in each stack separately).

6 Heterogeneity

We test whether the China Walls are consistently effective and compare the heterogeneity in our results against intuition and prior findings. We repeat the analyses of Section 4 across

cells of fund types, currency pair, and asset class (i.e., spot, forward, or swap), and for events during crisis and noncrisis periods. To maximize the power to detect breaches of China Walls, we estimate the pooled counterparts to equations (1), (2) and (4) with interaction terms on the full analytical samples. Figure 8 presents the resulting estimates where daily gross dollar volume is the dependent variable.

Fund characteristics. The dummy $Small_f = 1$ if and only if the total gross dollar volume of the treated or control fund f is smaller than the median across all funds. A fund is "Large" if $Small_f = 0$. Other fund-specific dummies indicate whether a fund is a hedge fund or whether the share of its trades in a currency pair or asset class is greater than the median across funds.

Event-trade characteristics. The dummy $SmallEventTrade_e = 1$ if and only if the dollar value of the event trade is smaller than the median across all event trades. The event is "Large" if $SmallEventTrade_e = 0$. The dummy $Crisis_e = 1$ if and only if the event trade occurred during the initial Covid panic (February 1 to March 31, 2020), the 2022 Russian invasion of Ukraine (February 16 to March 8, 2022), or the 2023 Hamas attack (September 27 to October 17, 2023). Other event-specific dummies indicate whether the event trade was in a given currency pair or asset class. For the events corresponding to multiple event trades, we take the characteristics of the largest trade (in USD terms) among them.

Estimation. We illustrate the estimation procedure of each entry in Figure 8 using the Affiliate estimate for the "USD × USD" entry. First, we define the dummy $USDFund_f = 1$ if and only if the share of the fund's trades in the USD-ILS pair exceeds the median across all funds, and the dummy $USDEvent_e = 1$ if and only if the event trade was for USD-ILS. Analogous dummies are created for all other currency pairs. Second, we add these currency dummies and all possible interactions among them and the affiliate treatment dummy into the pooled counterpart to equation (1). Third, the point estimate in Figure 8 is the sum over the estimated coefficients for $Affiliate_{ef}$, $Affiliate_{ef} \times USDFund_f$, $Affiliate_{ef} \times USDEvent_e$,

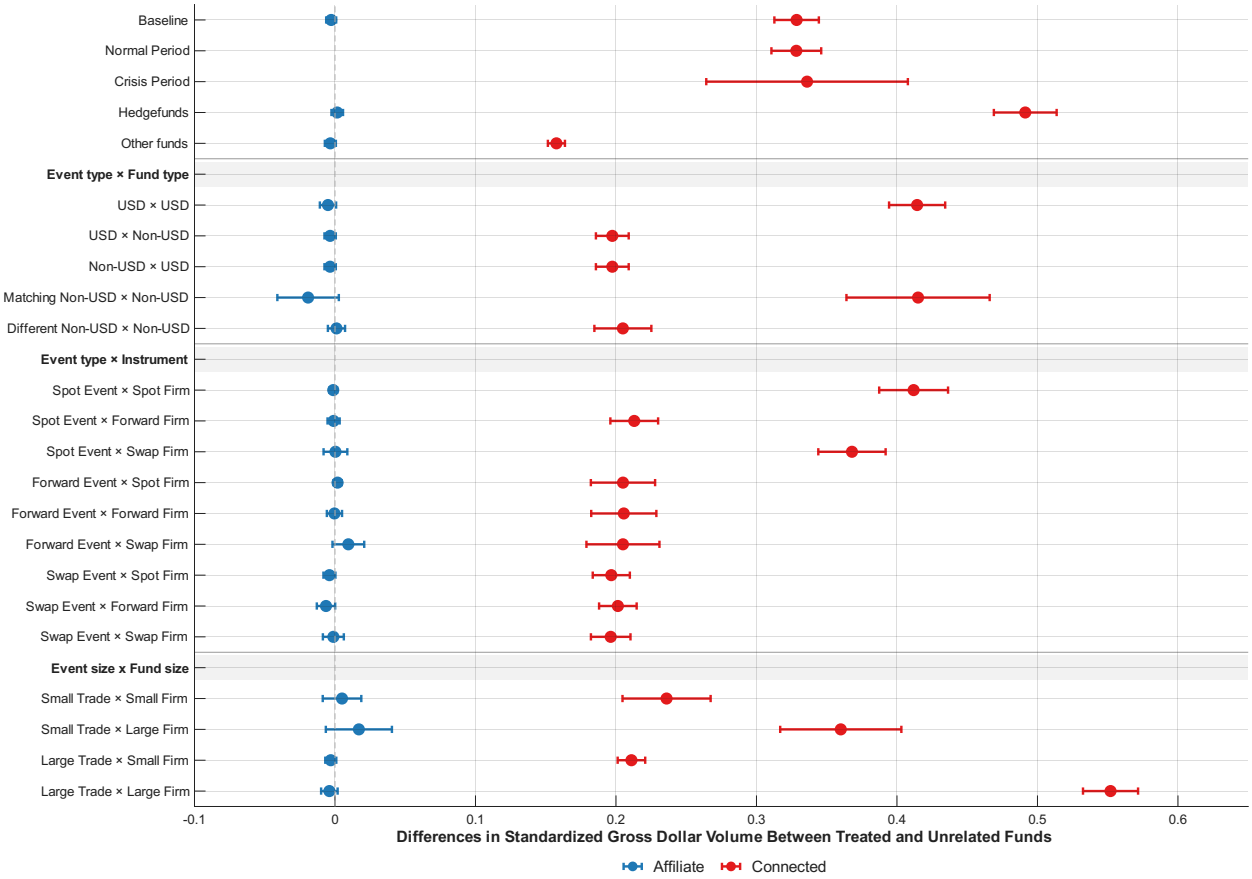


Figure 8: Responses of Funds to Dealer Events by Fund, Asset, and Event Characteristics: Standardized Daily Gross Dollar Volume and 95% Confidence Intervals

and $Affiliate_{ef} \times USDFund_f \times USDEvent_e$ terms. The standard error of this point estimate is computed using the delta method.

Discussion of Results. Figure 8 shows that we never detect information sharing from dealers to their affiliate funds across swathes of event, fund, and asset characteristics. In stark contrast, we find that the dealers share information with their connected funds in every specification. Other patterns strengthen the claim that our design reliably detects information sharing. First, the connected hedge funds respond far more strongly around exceptionally large trades by their dealers, in line with prior evidence that hedge funds are more sensitive to valuable information than other types of funds (Di Maggio et al., 2019; Kumar et al., 2020). Second, a connected fund most strongly responds to the event trades in the currency of its specialization, indicative of the connected funds responding to the same

information as the event trades. Third, the spot event trades induce the largest responses, consistent with the fact that spot volume is more predictive of currency returns than forward or swap volumes (Cespa, Gargano, Riddiough, and Sarno, 2022, Table 9).

7 Conclusion

We document that today's China Walls effectively preempt information sharing between dealers and their affiliate funds in the foreign exchange market. As information sharing can be plausibly deniable and affiliates would not litigate against each other, our results reveal remarkable regulatory capacity to control information flows within conglomerates.

What explains the effective enforcement of the China Walls? Appendix A details the "risk-based" enforcement policies that are likely responsible. These policies punish practices that elevate the risk of illegal activity even if such activity does not realize. A recent example is the US Securities and Exchange Commission case against Virtu Financial, whose key database was accessible to both their investment fund and their broker-dealer employees (US Securities and Exchange Commission, 2024). That this database allowed for the misuse of privileged information was sufficient to prosecute Virtu, despite lacking any evidence that a misuse actually occurred. More broadly, the SEC has imposed $2 billion in penalties for insufficient monitoring of broker-dealer employees since 2021, including a $125 million judgment against Morgan Stanley (US Securities and Exchange Commission, 2021).

We leave for future research the question of whether the effectively enforced China Walls are socially beneficial. Two salient alternatives to enforcing the China Walls are banning financial conglomerates or removing the China Wall restrictions. Data that spans the 1999 repeal of the Glass-Steagall Act may be able to compare the effects of banning (pre-1999) and allowing (post-1999) financial conglomerates. Data spanning 2018 may be able to compare the effects of weakly (pre-2018) and strongly (post-2018) enforcing the China Walls.

Appendix

A Detailed Context

This section provides detailed institutional context with a focus on the US.

A.1 Definitions

A *banking conglomerate* is a group of firms controlled by the same holding company and that includes a depository institution (i.e., a bank). Figure 9 summarizes the components of a banking conglomerate. A conglomerate partitions their services into insurers, commercial banks (deposits, loans), investment banks (underwriting, corporate advising), investment funds (asset management), broker-dealers (brokering, dealing, analysis, proprietary trading), and investment advisers.

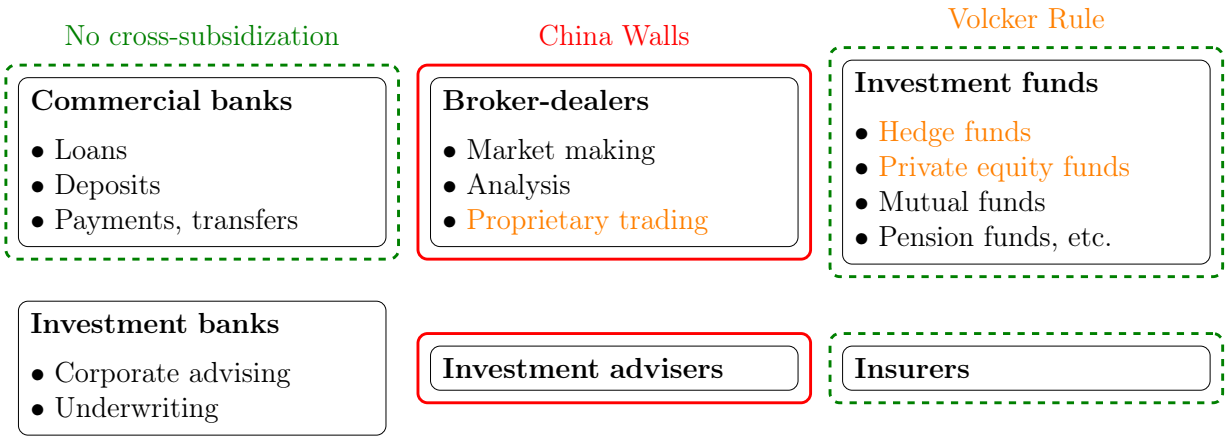


Figure 9: Stylized Banking Conglomerate and Relevant Legal Restrictions

Green dotted lines indicate restrictions on transactions and transfers: Banking laws, fiduciary duty to investors, and state-level insurance laws bar commercial banks, investment funds, and insurers from transferring capital to affiliates or trading with them at unfavorable terms. Red solid lines indicate the China Walls that aim to block the flow of information around subsidiaries in which conflicts of interest concentrate: Broker-dealers and investment advisers are required to prevent their employees interacting with the employees of affiliates. Orange fonts highlight the Volcker Rule restrictions on proprietary trading and ownership of hedge funds and private equity funds by banking conglomerates.

All regulations against the misuse or leakage of financial information target *material non-public information* (MNPI). Information is MNPI if its public disclosure would appreciably

affect market prices. In practice, common-law courts treat as MNPI any non-publicly disclosed information that reasonable investors in the relevant securities would find important for their investment decisions. For example, insider earnings information or outstanding order flows of clients are MNPI.[14] Possessing, sharing, or acting on MNPI is not generically illegal. However, financial intermediaries owe legal duties over MNPIs, as we soon elaborate.

The *China Walls* are blunt internal barriers set around subsidiaries with especially high risk of MNPI misuse. The Walls include both physical barriers and rules, typically:

- Separate offices, elevators, and entry ways for walled-off affiliates, with opaque and soundproof physical barriers when located on the same floor.
- Cool-down periods for employees transferring between walled-off affiliates.
- Watch lists that prohibit employees from trading or advising on the listed securities.
- Records of every instance where an "over-the-wall" executive (who oversees multiple affiliates walled off from each other) receives MNPI from any subsidiary, and requirement that the executive recuse themselves from any business related to the MNPI.
- Monitor and retain all business-related emails and messages sent by employees, and review those containing MNPI.
- Contingency plans when MNPI leaks through the China Walls, and the appointment of officers responsible for enforcing the Walls and handling the contingencies.

These restrictions on employee interactions effectively ban transactions between walled-off affiliates.

A.2 Key Regulations on Banking Conglomerates

The markings in Figure 9 indicate each key regulation on the banking conglomerates. Two concerns underlie the regulations. First, the conglomerates may divert publicly insured

[14] Analyses of MNPI are MNPI, whereas analyses of publicly available information are not.

deposits or insurance premiums towards risky trades or to cross-subsidize affiliates, thereby shifting risk onto the state or the insureds. Second, the conflicts of interest inherent in combining intermediation, advisory, and trading functions could disadvantage retail investors and undermine trust in financial markets.

Three constraints on banking conglomerates address these concerns. First, a bank or an insurer cannot cross-subsidize affiliates. The US Regulation W (and similar rules elsewhere) limit the outstanding value of bank-to-affiliate transactions to 20 percent of the bank's capital and 10 percent with any single affiliate.[15] These trades must occur at prevailing market prices and under punitive collateral requirements. Moreover, banks cannot trade securities issued by its affiliates, accept them as collateral, nor guarantee a trade, loan, or securities issuance that involves an affiliate. Analogous rules on insurers, which are harmonized across the US yet enforced by state authorities, prevent their capital being used to subsidize affiliates (Hamilton, 2011).

Second, the Volcker Rule restricts banking conglomerates from proprietary trading and owning risky investment funds. Specifically, a banking conglomerate cannot use its own capital to make short-term profit-seeking trades. The Rule also limits its ownership stake and exposure to hedge funds and private equity funds. Broad exemptions apply. The Rule exempts the trades linked to market making by broker-dealers and any trade held for more than 60 days. Further, hedge funds and private equity funds active entirely outside the US are exempt and, within the US, a conglomerate may sponsor and control such funds if it holds less than 3 percent of the funds' assets. Therefore, most banking conglomerates contain hedge funds and considerable scope remains for bank-affiliated broker-dealers to trade on private information using own capital.

Third, as we elaborate next, the China Walls around broker-dealers and around investment advisers seek to minimize information leakage surrounding these firms. Statutes

[15]Outstanding transaction value include loans, face value of guaranteed assets or liabilities, and gross purchases from affiliates. For example, purchasing $1 million of an asset from an affiliate would raise the outstanding value by $1 million until the bank sells $1 million of the same asset back to that affiliate. (Sales to other affiliates or of other assets do not affect the outstanding value generated by this purchase.)

single out investment advisers for their large potential impact on investment decisions. The broker-dealers are singled out, because their role as intermediaries provide constant stream of privileged information gleaned from their clients' orders. Under the argument that broker-dealers leaking this information to affiliate funds or receiving inside information from affiliates would place the investing public at a sharp disadvantage, preventing such information flows is necessary to maintain trust and participation in financial markets.

A.3 China Wall Enforcement Over Time

Origins. Under common-law tradition, insider trading on behalf of clients was encouraged. Brokers and dealers were expected to use all information that came into their possession, and further solicit inside information, to fulfill their fiduciary duty. This expectation was upended in 1961, when a landmark judgement held each conglomerate liable for damages incurred by the investing public due to trades based on its MNPI. The ruling demands that the intermediaries holding MNPI either publicly disclose or take no action whatsoever related to the MNPI. Subsequent court rulings placed the full burden of avoiding incompatible duties onto the conglomerates.[16]

Financial conglomerates were in an impossible legal jeopardy. Beyond fiduciary duty and the new duty to the investing public, the agency principle requires the firms acting as agents to safeguard the private information of their principal (Tuch, 2014). Suppose a conglomerate owns a dealer and a mutual fund, and the dealer receives a large trade request from a client hedge fund—an MNPI. By fiduciary duty, the dealer ought to share this MNPI with the mutual fund for the benefit of the fund's investors. Yet, doing so would expose the conglomerate to liability if the mutual fund trading on the MNPI cause losses to some traders.

[16] A typical case is *Black and Shearson v. Hammill Co.* (Black and Shearson, Hammill Co., 1968) which rules, "conflict in duties is the classic problem encountered by one who serves two masters. It should not be resolved by weighing the conflicting duties; it should be avoided in advance [..] or terminated when it appears." The judgement upheld awards of $25 thousand (1968 dollars) each to two customers of a dealer, which sold debentures of a failing firm whose board included a partner at the dealer's parent company. The conflicting duties were the dealer's fiduciary duty to its customers and the partner's duty to keep the inside information of the failing firm confidential.

This liability can be avoided only by publicly disclosing the hedge fund's trade request, in violation of the agency principle. These incompatible duties left financial conglomerates in near-permanent state of legal liability.

The China Walls provided a way out. In 1968, the US Securities and Exchange Commission began offering safe harbor from liability for the conglomerates that implement sufficiently strict China Walls, as determined by the SEC.[17] The logic is that walled-off subsidiaries can be considered separate entities for the purpose of determining whether a legal duty has been breached. Continuing the example, the dealer would not owe fiduciary duty to the investors of the affiliate mutual fund if this fund were walled off from the dealer. The US financial conglomerates widely adopted the China Walls, which became broadly standardized according to SEC guidelines. Financial conglomerates in other jurisdictions followed, whether through their US operations or regulatory standardization (in Australia, Canada, France, Germany, Japan, Switzerland, and the UK).

Pre-2008 crisis legal status. A 1980 US Supreme Court case (*Chiarella v. United States*) replaced the constellation of duties with one overarching duty to "disclose or abstain." A person has the duty to disclose or abstain from acting on an MNPI when: (a) she owes fiduciary duty to the source of the MNPI; and (b) the action would give her a personal benefit.

The 1980s also saw the deregulation of financial conglomeration in the US and the UK. The arguments were that full-service financial conglomerates would generate economies of scope and be more competitive versus less regulated foreign competitors. Because the duty to disclose or abstain might render full-service conglomerates nonviable, new statutes explicitly incorporated the China Walls as safe harbor and broadened their legal protections (Brooke,

[17] Alternative means to avoid incompatible-duty liabilities, such as obtaining client consent to waive fiduciary duties, are likely ineffective under most circumstances (Tuch, 2014).

Burrows, Faber, Harpum, and Silber, 1995, p. 98).[18] Suppose a fund consistently earns large profits whenever an affiliate dealer receives large order flows. Under the new statutes, presence of a China Wall between the dealer and the fund would protect the conglomerate against liabilities to the dealer's clients and to the fund's counterparties.[19]

Pre-2008 crisis regulatory regime. The China Walls were initially an legal benefit available to the banking conglomerates—not a regulatory requirement. As such, the China Walls enforcement was purely reactive, occuring in the course of assigning liability upon the discovery of fraud or breach of duty. Indeed, no US regulator proactively evaluated the China Walls between 1990 and 2012, the years when the SEC reviewed the Walls within broker-dealers as a research exercise (Office of Compliance Inspections and Examinations and US Securities and Exchange Commission, 2012).[20] The prosecutions over the LIBOR scandal highlights the nonobligatory status of China Walls precrisis: While each settlement with an implicated banking conglomerate often delves into its China Walls, the sole purpose of doing so were to determine the degree of the conglomerate's legal liability for fraud and insider trading. Lacking sufficient China Walls was not an offence in itself.

Further, financial regulators had more limited enforcement powers. Imposition of large penalties or punishment of individuals required court judgement, with 5-year statute of limitations. A firm that aided a violator could only be prosecuted if the firm knowingly assisted in the violation, a high legal bar. Most importantly, regulatory action required the evidence of actual fraud or breach of duty. Engaging in transactions with a high risk of fraud

[18]The UK removed most restrictions on financial conglomeration in 1986. The US gradually weakened the Glass-Steagall Act provisions throughout the 1980s and 90s, until largely repealing the Act in 1999. The UK Financial Services Act 1986 (FSA) and the US Insider Trading and Securities Fraud Enforcement Act 1988 (ITSFEA) explicitly provide safe harbor from a wide range of liabilities to the financial conglomerates that adopt China Walls.

[19]The China Walls grant similar protection elsewhere. For instance, in a landmark Australian case, *ASIC v. Citigroup (2007)*, Citigroup's trading arm purchased one million shares of a target firm one day before its acquisition announcement, in a deal where Citigroup's investment bank was advising the acquirer. The judge dismissed the case, on the basis that the China Wall between Citigroup's trading and investment bank arms was sufficient to preclude conflict of interest (Hanrahan, 2007).

[20]The 1990 review was in response to the 1998 ITSFEA Act that explicitly gave safe harbor to walled-off broker-dealers. The 2012 review was in response to the Dodd-Frank Act.

or duty breach, or failing to maintain China Walls that could greatly suppress the misuse of MNPI were not themselves actionable by regulators.

Current Regulatory Regime. The US Dodd-Frank Act 2010, and partly coordinated laws elsewhere, dramatically reshaped the enforcement of China Walls. The key change is the "risk-based" enforcement powers granted to financial regulators. Rather than requiring actual illegality before the regulators can act, Dodd-Frank gave them the ability to prosecute behavior that raises the risk of fraud or duty breaches. Moreover, a regulator can now prescribe corporate organization and internal rules that the regulator believes necessary to cap the risk of illegality to a reasonable level.

Today's China Walls form a heavily enforced risk-based regulatory prescription. The landmark case is the SEC's 2018 settlement with Mizuho Securities in which Mizuho paid $1.25 million partly for failing to maintain information barriers between its broker-dealer and hedge fund trading desks (US Securities and Exchange Commission, 2018). This case began a series of prosecutions by the SEC where the key issue was the effectiveness of the China Walls itself (Barrack, Moskowitz-Hesse, Richards, and Cox, 2020). As an ongoing example, in 2021, the SEC began a proactive sweep of monitoring and retension of business-related communication among employees across all broker-dealers and investment advisors. The first consequent settlement included a $125 million fine on Morgan Stanley for their failure to retain all business-related messages sent by its broker-dealer employees *on their private devices* (US Securities and Exchange Commission, 2021). As of early 2024, over $2 billion in fines have been meted out to dozens of broker-dealers and investment advisors over similar failures. Similarly, the SEC charged Virtu Financial in 2024 merely for having a database accessible to both broker-dealer and nonbroker-dealer employees—despite producing no evidence that any MNPI was leaked (US Securities and Exchange Commission, 2024). Therefore, following Dodd-Frank, the regulatory regime over China Walls morphed from reactive to proactive.

B Identification Tests

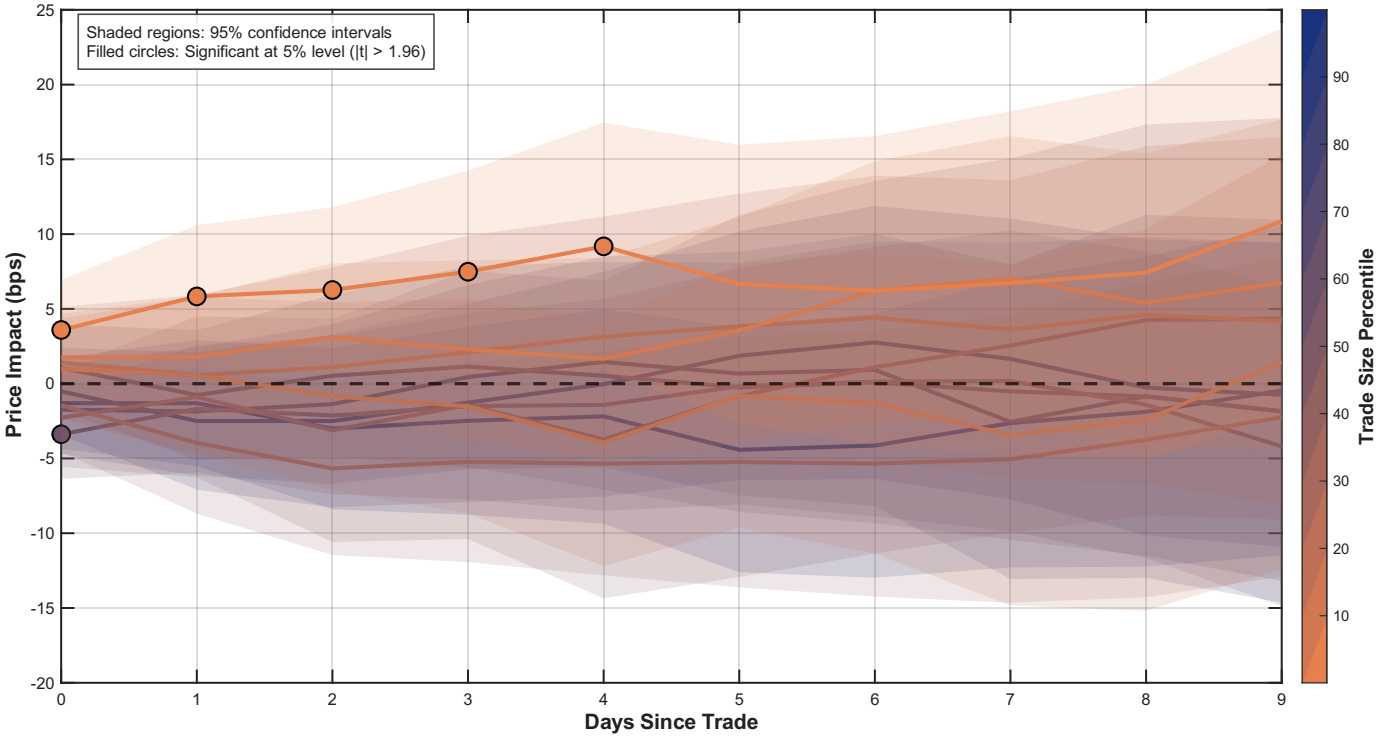
Two exercises jointly test our two assumptions that: (I) Dealers and funds trade large sizes when they have the more valuable private information; and (II) our design detects MPI sharing if and only if such sharing exists.

The first exercise is to compute the price impacts of exceptionally large, various decile (10 to 10.1st percentile and so on), and exceptionally small (99.9 to 100th percentile) trades. We call the trades in the given percentile "event trades" in this section. Under the intuition that net volumes determine prices (Kyle, 1985), we net all event trades in each day separately for funds and dealers. We do not observe the trade initiator who initiated each trade. To sign each trade, we assume that the fund was the initiator for each dealer-fund trade, and that the event dealer was the initiator for each interdealer trade. We limit to trades in the USD-ILS pair to avoid aggregating across currency pairs. For the fund trades, we exclude the funds with fewer than 1000 trades in our sample to keep meaningful variation between different percentiles.

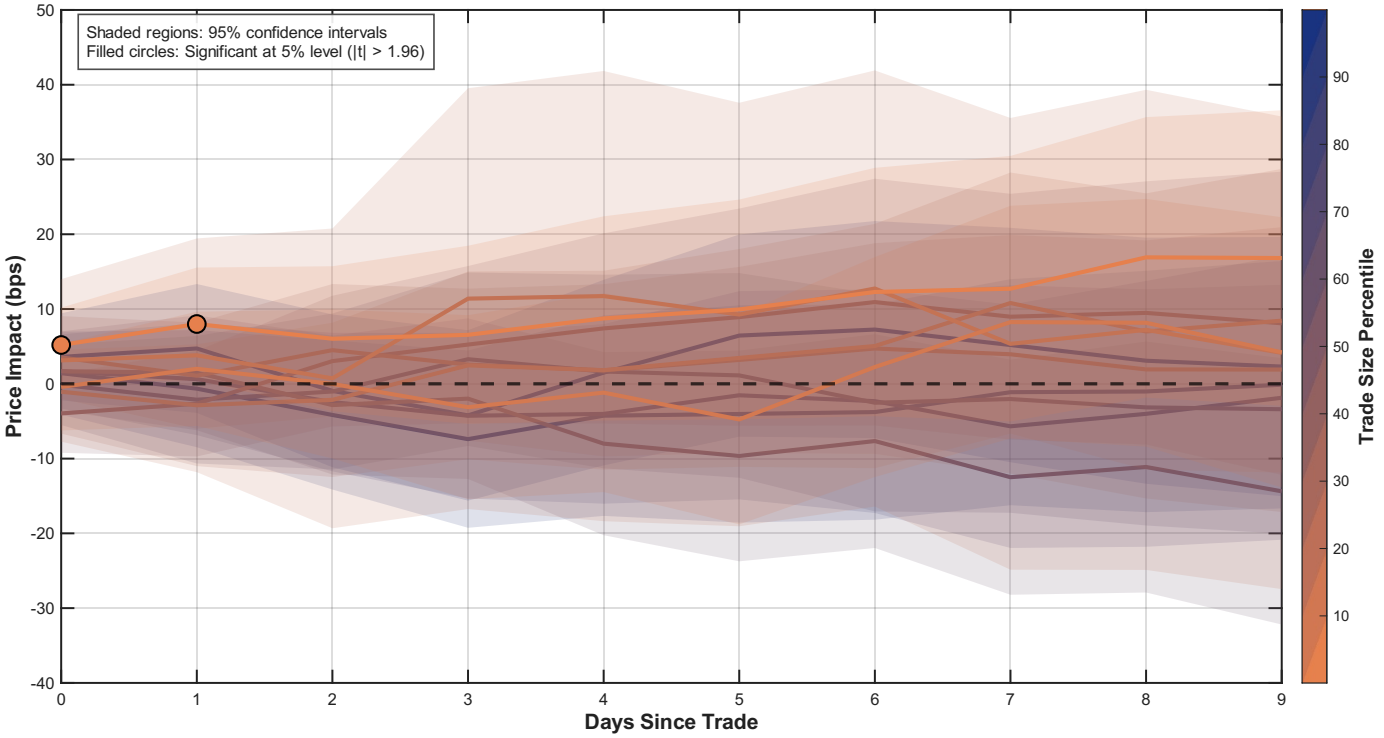
A three-step procedure obtains the price impact of firm type k, firm's trade-size percentile p, and cumulative return horizon ℓ. First, we convert the net dollar volumes on day t into trade-direction dummies $d_{t,k,p} \in \{-1, 0, 1\}$, for $k \in \{\text{fund}, \text{dealer}\}$ and percentile $p \in \{[0, 0.1], [10, 10.1], \ldots, [90, 90.1], [99.9, 100]\}$. The dummy $d_{t,k,p} = -1$ if the day's net volume is negative, $d_{t,k,p} = 1$ if its positive, and zero otherwise. Second, we calculate the cumulative returns $R_{t,t+\ell}$ between t and $t + \ell$, $\ell \in \{0, \ldots, 9\}$, using Bloomberg USD/ILS exchange rate at 17:00 EST. Third, the price impact is the coefficient $\rho_{k,p,\ell}$ in the time-series regression (5):

$$R_{t,t+\ell} = \rho_{k,p,\ell} \cdot d_{t,k,p} + \alpha_{k,p,\ell} + \sum_{g=1}^{\ell} \phi_{k,p,\ell,g} \cdot R_{t-g,t+\ell-g} + \varepsilon_{t,k,p,\ell}. \tag{5}$$

We estimate this regression for each triple (k, p, ℓ) using OLS with Newey-West standard errors. The autoregressive term accounts for serial correlation in returns. Figure 10 plots



(a) Trades by Dealers



(b) Trades by Funds

Figure 10: Price Impact Estimates for Event Trades and 95% Confidence Intervals

the price impact estimates. The net volumes from exceptionally large trades predict future returns, whereas all smaller trades do not, consistent with assumption (I).

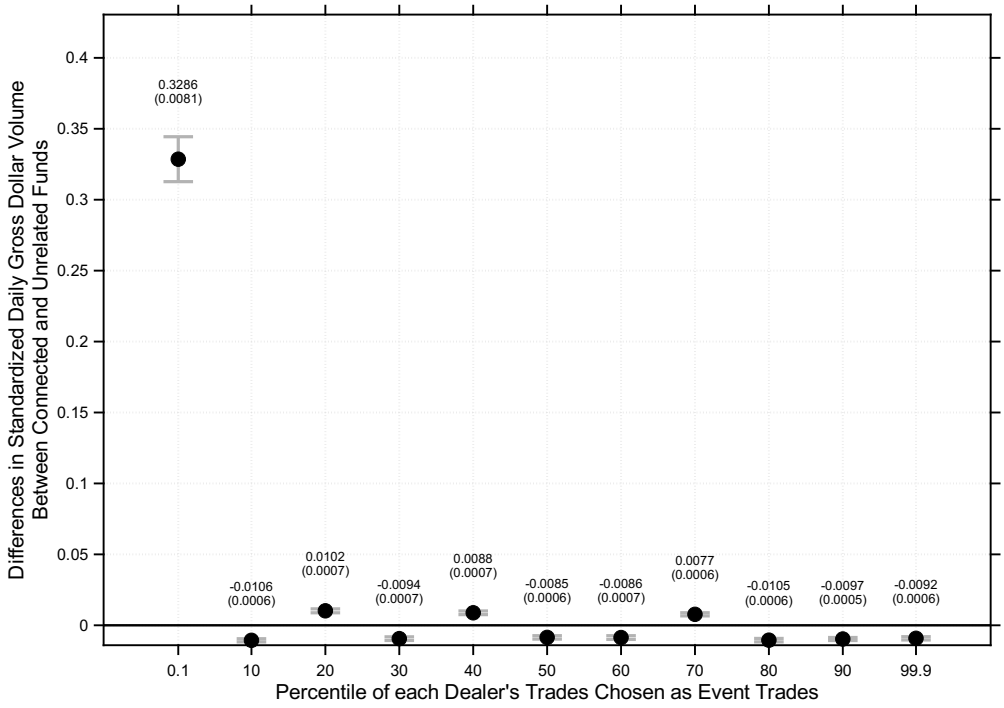
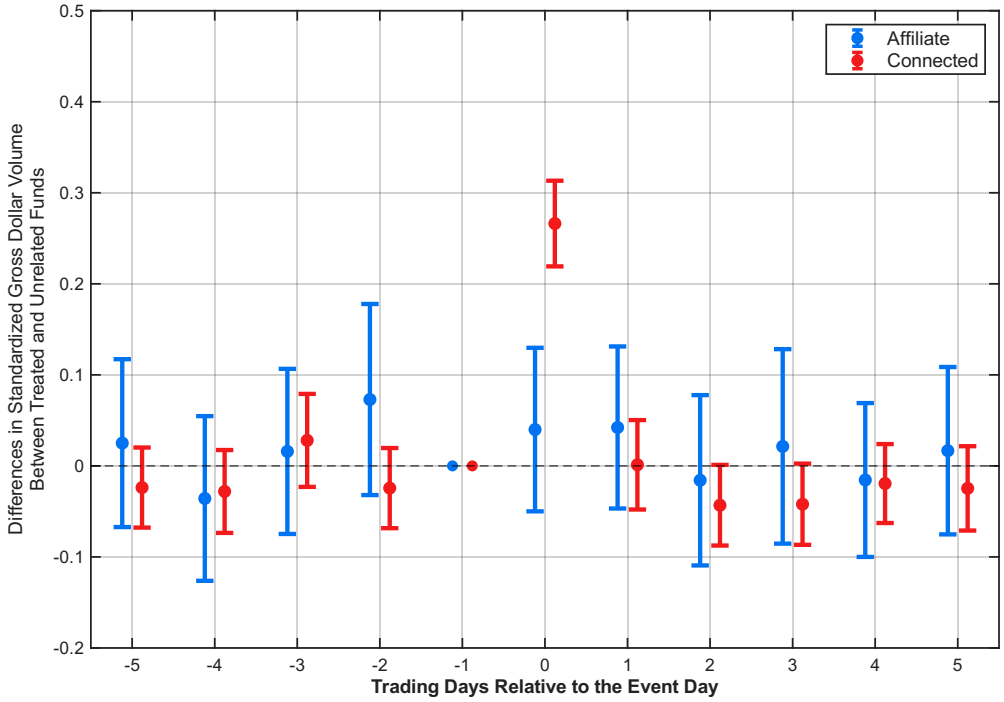


Figure 11: Placebo Estimates and 95% Confidence Intervals

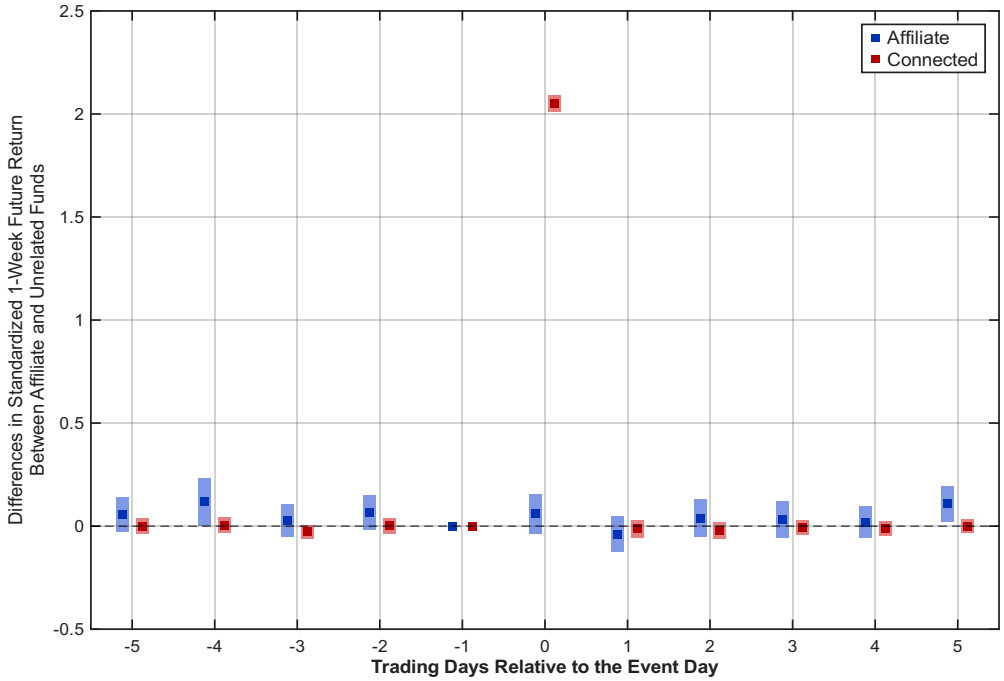
The second exercise replicates Figure 5a, except redefining event trades to be those in the various percentiles p. Figure 11 depicts the corresponding coefficient estimates for the connected funds. The estimate is close to zero for all trades smaller than the exceptionally large trade baseline of Figure 5a. Combined with Figure 10, the daily gross volumes of the connected funds only increase relative to the unrelated funds around the event trades that are predictive of returns, consistent with assumption (II).

C Information Sharing from Funds to Dealers

Figure 12 plots the responses in the daily gross dollar volumes and 1-week future returns of affiliate dealers relative to unrelated dealers around exceptionally large trades by event funds. Neither the affiliate dealers' volumes nor returns vary relative to the unrelated dealers around the event day. Both the connected dealers' volumes and returns sharply increase on



(a) Standardized Daily Gross Dollar Volume



(b) Standardized Daily 1-Week Future Return

Figure 12: Dealer Responses to Fund Events and 95% Confidence Intervals

the event day relative to the unrelated dealers. We conclude that the China Walls effectively block funds from sharing MPI with their affiliate dealers even as they do so with their connected dealers.

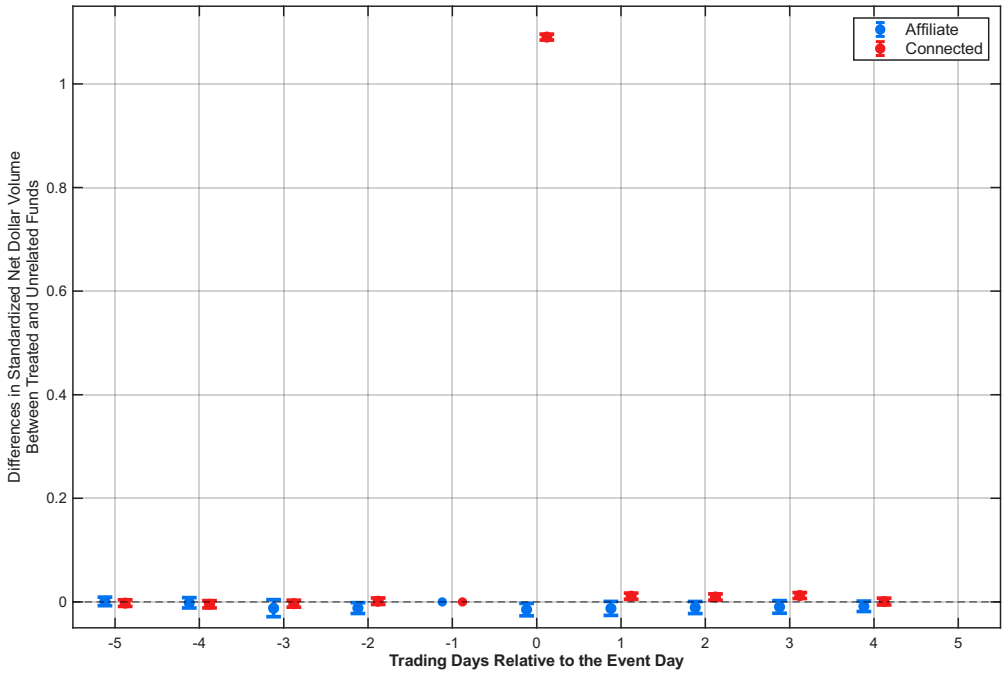
D Net Dollar Volumes

We compute *net dollar volume* following the same steps as the 1-week future returns (Section 3.1), except that we do not multiply the net notional amount by their realized returns. Figure 13a plots the responses in the daily net dollar volumes of the affiliate funds relative to the unrelated funds around exceptionally large trades by the event dealers. Figure 13b is an analogous plot for the responses of the affiliate dealers to the unrelated dealers around the fund events. Figure 14 is the corresponding plot for the subsample of funds.

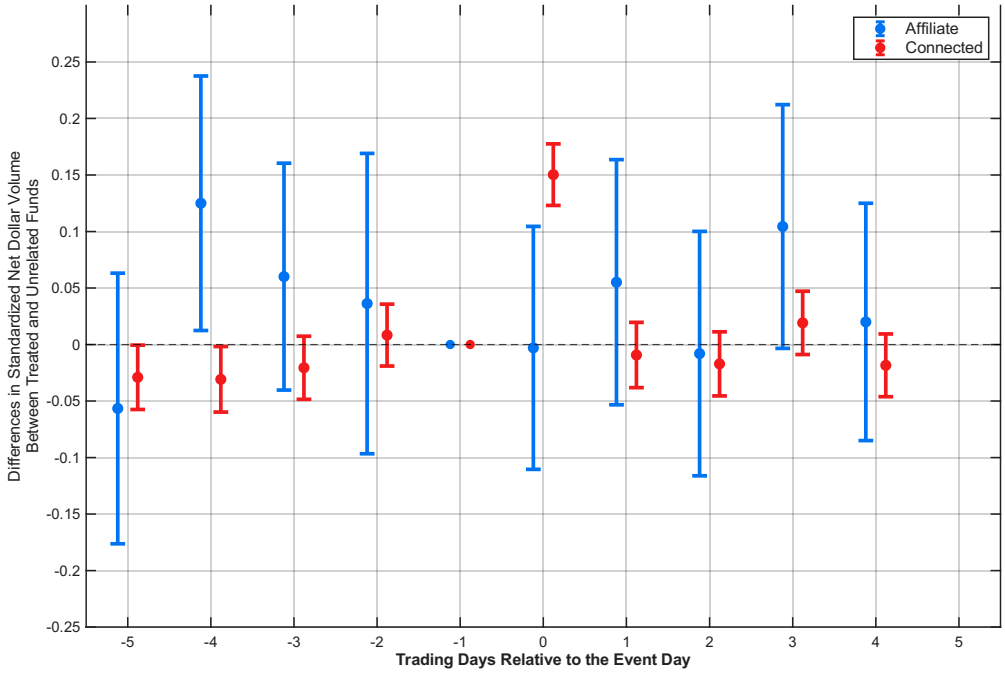
E Heterogeneity in Fund Responses to Fund Events

We test the possibility that affiliate funds only respond to an event if the event fund is similar in size and other characteristics. If so, we would be limited in our ability to infer about the dealers' willingness to share information with their affiliate funds absent the China Walls.

We estimate the pooled counterpart to (4) whose treatment variables are interacted with the rich set of dummies described in Section 6. The dependent variable is the standardized daily gross dollar volume. Figure 15 plots the results. Its estimates and their standard errors are computed as we do for Figure 8, except that we only use the coefficients that are not interacted with the $DealerOverlap_{ej}$ dummy. The estimates are consistently positive and significant, and generally large, across asset, event, and fund characteristics.



(a) Fund Responses to Dealer Events



(b) Dealer Responses to Fund Events

Figure 13: Fund and Dealer Responses in Daily Net Dollar Volume and 95% Confidence Intervals

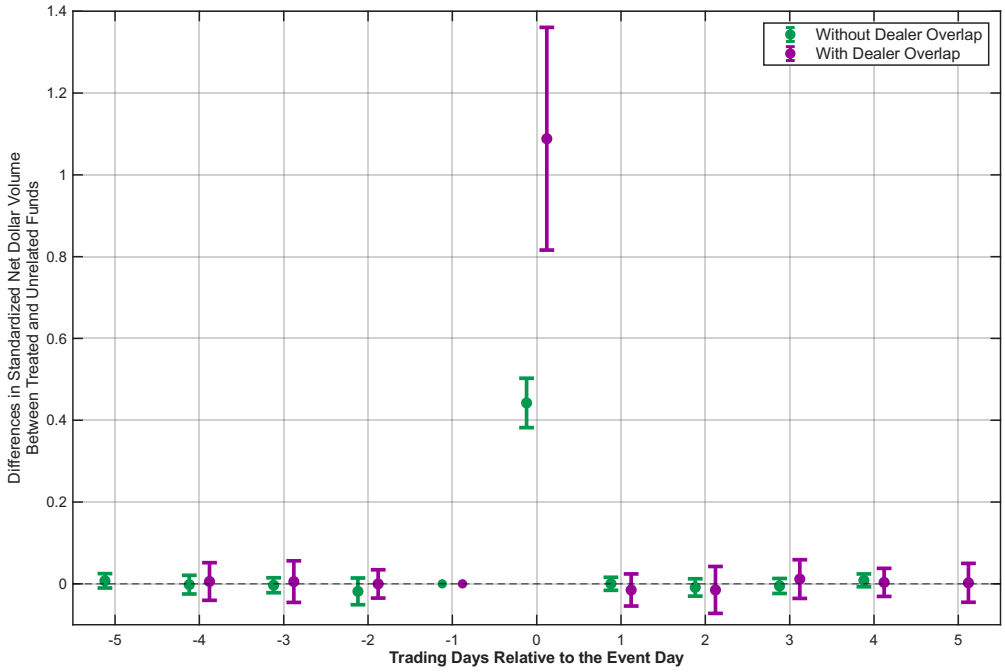


Figure 14: Fund Responses to Fund Events: Standardized Daily Net Dollar Volume and 95% Confidence Intervals

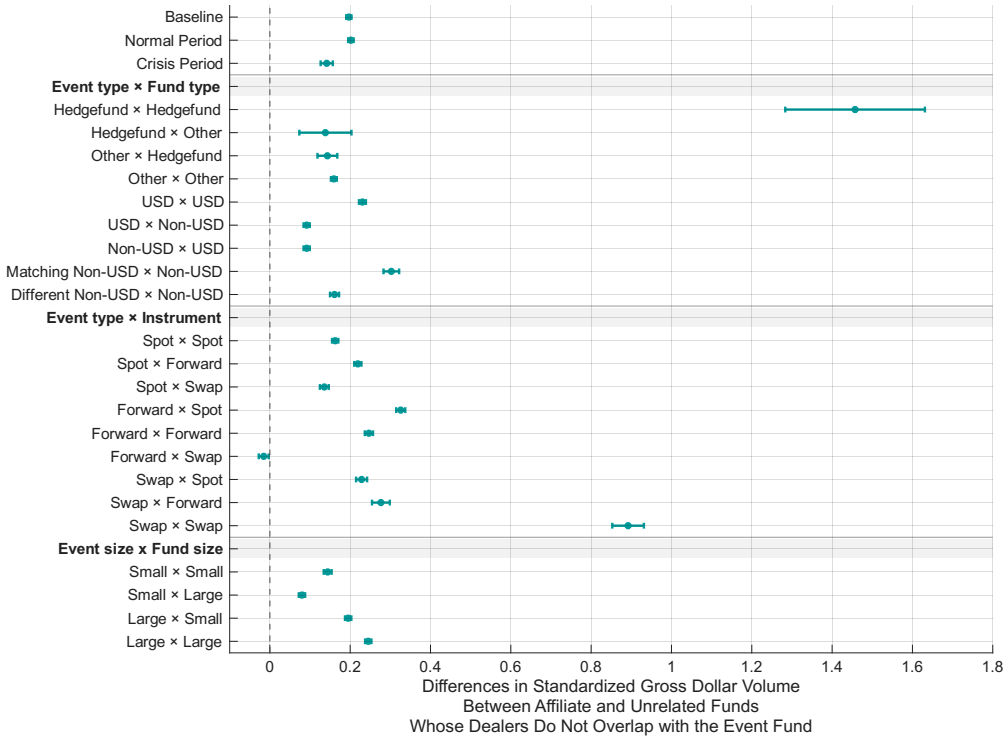


Figure 15: Fund Responses to Fund Events: Standardized Daily Gross Dollar Volume and 95% Confidence Intervals

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