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Segmented Arbitrage
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ABSTRACT

We use arbitrage activity in equity, fixed income, and foreign exchange markets to characterize the frictions and constraints facing intermediaries. The average pairwise correlation between the 29 arbitrage spreads that we study is 21%. These low correlations are inconsistent with canonical intermediary asset pricing models. We show that at least two types of segmentation drive arbitrage dynamics. First, funding is segmented—certain trades rely on specific funding sources, making their arbitrage spreads sensitive to localized funding shocks. Second, balance sheets are segmented—intermediaries specialize in certain trades, so arbitrage spreads are sensitive to idiosyncratic balance sheet shocks.

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A data appendix is available at http://www.nber.org/data-appendix/w30561

1 Introduction

There is growing recognition that financial intermediaries play a key role in determining asset prices. Much of the research on intermediaries treats them as a monolith, assuming that all financial institutions face the same, typically limited, set of constraints, fund homogeneously from the household sector, and perfectly share risk with each other. This view of intermediaries has several implications. It suggests that all risk premia should strongly comove with aggregate intermediary balance sheet strength, and conversely that all risk premia should be equally informative about the health of the intermediary sector. In addition, if intermediaries are strongly integrated, fire sales in any market have economy-wide effects on credit creation because intermediaries will reduce lending and instead provide that market with liquidity.

In this paper, we argue that the assumption of a representative intermediary, while helpful for many applications, understates the importance of frictions within the intermediary sector and their implications for prices. We provide empirical evidence that segmentation within the intermediary sector has a first-order impact on asset prices. We focus our analysis on arbitrage spreads—riskless returns in excess of riskless rates—that arise from violations of the law of one price in equity, fixed income, and foreign exchange markets. We take this approach for two reasons. First, arbitrage is intermediated by financial institutions such as broker-dealers and hedge funds and cannot be easily performed by households (Haddad and Muir, 2021). Second, arbitrage spreads are accurate measures of expected returns, the key objects in any asset pricing theory. Thus, arbitrages offer a high-power setting for understanding the frictions faced by intermediaries. In contrast, studies analyzing risky assets must work with average realized returns, a noisy proxy for expected returns (Merton, 1980).

To fix ideas, we begin with a stylized model in which intermediaries determine arbitrage spreads. In the model, a continuum of intermediaries participates in a set of fundamentally riskless arbitrage trades. Intermediaries potentially face two types of frictions that break the Modigliani and Miller (1958) theorem. First, they may face balance sheet constraints like regulatory capital requirements, which are costly to satisfy due to external financing frictions. Second, intermediaries may face frictions that prevent them from raising financing to fund riskless assets at the riskless rate. Intermediaries may fund from different sources with different costs, and certain trades may require them to fund from a specific source. We model these frictions in reduced form to focus on their implications for arbitrage spreads.

In the model and throughout the paper, we distinguish between three assumptions typically embedded in theoretical and applied work using a representative intermediary. First, balance sheet integration means that the marginal balance sheet cost associated with a given riskless asset is equalized across intermediaries. Second, funding integration means intermediaries can fund all riskless assets from the same source. Third, the set of constraints intermediaries face is limited. These assumptions result in one- or two- factor structures for arbitrage spreads.[1] For instance, if the representative intermediary faces a single constraint (e.g., a leverage constraint) and funding is frictionless, then all arbitrage spreads are determined by the shadow cost of the constraint. Thus, spreads are perfectly correlated and follow a single-factor structure. Similarly, if the representative intermediary faces no constraints and funds itself from a single integrated, but frictional, source, then arbitrage spreads are again perfectly correlated since all spreads will be driven by conditions in that funding market.

We then use the model to illustrate how segmentation can reduce correlations between arbitrage spreads. Funding segmentation—violations of funding integration—means that trades using the same funding source will be more correlated with each other than trades using different sources. For instance, Treasury repo financing can be used for Treasury spot-futures arbitrage but cannot be used for equity spot-futures arbitrage. Thus, shocks to the Treasury repo market will affect one set of arbitrage spreads but not the other. Similarly, balance sheet segmentation—violations of balance sheet integration—implies that trades performed by the same arbitrageurs will be more correlated with each other than trades performed by different arbitrageurs.

We next turn to the data, focusing on the decade following the 2007-2009 financial crisis.

[1] See, e.g., He et al. (2017); He and Krishnamurthy (2013); Adrian et al. (2014); Ivashina et al. (2015); Gromb and Vayanos (2018); Andersen et al. (2019).

We study 29 arbitrage trades that fall into seven broad strategies: (i) equity spot-futures arbitrage, (ii) equity options arbitrage, which enforces put-call parity, (iii) currency spot-futures arbitrage, which enforces covered interest parity (CIP), (iv) CDS-bond arbitrage, (v) Treasury spot-futures arbitrage, (vi) Treasury-interest rate swaps arbitrage, and (vii) Treasury-inflation swaps arbitrage. For each arbitrage trade, we define the spread as the difference between the riskless rate implied by no-arbitrage conditions (e.g., spot-futures parity) and a relevant benchmark rate.

Our first result is that the daily correlation of spreads is low on average. The average pairwise correlation is 0.21, and the 75th percentile of pairwise correlations is 0.43. While these low correlations could be driven by measurement error, this measurement error would have to be large to explain our results since observed correlations are far from one. We easily reject the null that the average pairwise correlation is above 0.67. In addition, we reject the null that the individual pairwise correlation is above 0.67 for 88% (358/406) of trade pairs.[2] Furthermore, we observe a similar factor structure if we smooth the data. For instance, after taking monthly moving averages, 9 principal components are required to explain 90% of the variation in arbitrage spreads. Correlations are also low among the subsample of arbitrage trades with short tenors (3-6 month horizons), suggesting that convergence or noise trader risk (Delong et al., 1993) is not the source of the high-dimensional factor structure. Moreover, measurement error cannot explain the direct evidence of segmentation we describe below. The data are therefore far from the one- or two-factor structure predicted by models in which balance sheet and funding integration hold in an intermediary sector facing few constraints.

We then show that funding segmentation is one reason that correlations between arbitrage spreads are low. Our analysis starts from the observation that equity spot-futures, equity options, and CIP arbitrage face relatively higher margin requirements than other strategies. Because these high-margin strategies require more unsecured funding, we refer to them as

[2] If true arbitrage spreads are perfectly correlated and the variance of the measurement error is less than half the variance of true spreads, then the observed pairwise correlation should exceed 0.67 (see Section 3.4.3).

"unsecured" arbitrages, while we call the remaining ones "secured" arbitrages.[3] Unsecured arbitrages are more correlated with each other than they are with secured arbitrages. We provide evidence that this higher correlation reflects the higher exposure of unsecured arbitrages to conditions in unsecured funding markets, which we proxy for with the Treasury-Eurodollar (TED) spread. We find that unsecured arbitrage spreads are nearly seven times more sensitive to movements in the TED spread than are secured arbitrage spreads.

While the higher loading of unsecured arbitrage spreads on the TED spread is consistent with funding segmentation, it could also be driven by balance sheet segmentation. For example, if broker-dealers specialize in unsecured arbitrages, then a deterioration of their balance sheets could cause both the TED spread and unsecured arbitrage spreads to rise. To isolate the role of funding segmentation, it is therefore useful to trace out how shocks to the supply of unsecured funding differentially impact unsecured versus secured arbitrages. Following Anderson et al. (2019), we conduct an event study around the 2016 money market fund (MMF) reform, which resulted in a sharp contraction in unsecured lending by MMFs. During the reform, the TED spread and unsecured arbitrage spreads rise, while secured arbitrage spreads do not, demonstrating that segmentation in funding markets is an important driver of arbitrage spreads.

We then provide evidence that funding markets are more segmented than the simple divide between secured and unsecured trades because funding providers specialize (Chernenko and Sunderam, 2014; Li, 2021). Thus, shocks to individual funding sources move specific arbitrage spreads without moving others. We illustrate this idea by studying supply shocks to Fidelity MMFs, which Hu et al. (2021) show are particularly active in funding holders of equity securities. These shocks move equity spot-futures arbitrage spreads, but not others.

We next show that balance sheet segmentation also contributes to the low overall correlation of arbitrage spreads. In other words, it is not the case that intermediary balance sheets are integrated and a representative intermediary facing segmented funding is marginal in all

[3] Secured arbitrages include Treasury spot-futures, Treasury-swap, TIPS-Treasury, and CDS-bond.

strategies. We first provide event study evidence that the balance sheet constraints of certain intermediaries affect some trades more than others. We study the "London Whale" episode, in which JP Morgan lost over $6 billion through its credit derivatives hedging program in 2012. This event is useful for our purposes because it did not materially affect the firm's funding rates but did result in a tightening of the firm's risk limits (U.S. Senate, 2014). We show that the episode led equity spot-futures arbitrage spreads to rise relative to others.

We then examine the impact of hedge fund balance sheet constraints on arbitrage spreads using fund returns as a proxy for these constraints. We find that the aggregate returns of fixed income arbitrage hedge funds are negatively correlated with spreads on secured trades, but not unsecured trades, suggesting that hedge fund balance sheets are particularly important for these trades. Moreover, specific hedge funds appear to matter for specific trades. For example, the hedge funds with balance sheets important for CDS-Bond arbitrage are not the ones that are important for TIPS-Treasury arbitrage. Overall, our evidence suggests that arbitrage activity is segmented due to fragmented funding sources (e.g., unsecured vs secured) and specialization within and across financial institutions (e.g., dealers vs hedge funds).

Our paper belongs to the rapidly expanding literature on financial intermediaries and their role in capital markets. One strand of the literature, including Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Garleanu and Pedersen (2011), Adrian and Boyarchenko (2012), He and Krishnamurthy (2013), and Brunnermeier and Sannikov (2014), assumes a representative intermediary and theoretically studies how different constraints on its activity impact equilibrium asset prices or arbitrage spreads. Our results suggest that these theories most naturally describe market segments, rather than providing a uniform account of dynamics across all capital markets.[4] A second strand of the literature, including Pasquariello (2014), Adrian et al. (2014), He et al. (2017), and Du et al. (2019), aims to empirically link sector-level measures of intermediary constraints to risky

[4]A recent theoretical literature has emphasized the importance of intermediary heterogeneity for macroeconomic outcomes and optimal macroprudential policy (Begenau and Landvoigt, 2021; Jamilov, 2021).

asset prices.[5] Our results suggest that accounting for which intermediaries are active in a market and how they fund themselves is likely to improve the performance of these kinds of intermediary-based asset pricing models. A third strand of the literature studies law of one price violations in specific markets, including equity (van Binsbergen et al., 2019; Hazelkorn et al., 2021), foreign exchange (Du et al., 2018), Treasury (Fleckenstein et al., 2014; Jermann, 2020; Barth and Kahn, 2021), and corporate bond markets (Siriwardane, 2018).[6] Our paper departs from this research by simultaneously analyzing law of one price violations across many different markets, which enables us to characterize the frictions and constraints faced by the intermediary sector.[7]

2 Motivating Model

To fix ideas, we begin with a stylized model in which intermediaries face multiple frictions and determine arbitrage spreads. The model highlights how balance sheet constraints, balance sheet segmentation, and funding segmentation all impact arbitrage spreads. The key point is that the three assumptions typical of the intermediary asset pricing literature—(i) a small number of constraints, (ii) balance sheet and (iii) funding integration—result in highly correlated arbitrage spreads. Violating any of the three assumptions can result in the high-dimensional factor structure for arbitrage spreads we document below. Balance sheet and funding segmentation further predict that some spreads move with proxies for balance sheet and funding costs, but others do not.

[5] Adrian et al. (2014) and He et al. (2017) fail to reject the null of integration based on a test of whether the prices of risk for intermediary factors differ across markets. However, their tests use realized average returns to proxy for ex-ante risk premia, which lowers their power. Accordingly, Bryzgalova (2015) finds that the quarterly intermediary capital factor is weak in the sense that it has a small covariance with asset returns.

[6] There is also work documenting segmentation in short-term money markets (Bech and Klee, 2011; Duffie and Krishnamurthy, 2016). Our paper shows how that segmentation ultimately impacts risky asset prices.

[7] Boyarchenko et al. (2018) study the impact of the supplementary leverage ratio on relationships between prime brokers and their clients, and argue that the regulation made a large number of arbitrage trades less attractive for dealers.

2.1 Setup

Formally, suppose there are N arbitrage trades that are riskless. Normalize the riskless rate to zero and let $s_{n,t}$ denote the arbitrage spread on trade n at time t. For simplicity, we assume arbitrageurs are always net long, so that all spreads in the model are positive. In the empirics, we will work with the absolute value of spreads since arbitrageurs can be net long or net short each trade.

A unit measure of competitive and atomistic arbitrageurs engages in these trades, supplying $q_{n,t}$ of trade n.[8] Arbitrageurs face two main frictions, both of which are modeled in reduced form. First, there are K balance sheet requirements of the form $\sum_n q_{n,t}v_{n,k} = V_{k,t}$. These requirements capture equity capital and liquidity constraints, which may be set by regulators or by arbitrageurs themselves for internal risk-management purposes. We assume that the contribution of trade n to constraint k, $v_{n,k}$, is fixed over time. Arbitrageurs can adjust their balance sheets to meet requirement k at total cost $\frac{1}{2}c_{k,t}V_{k,t}^2$, which capture costs of external finance or other adjustment costs. The existence of balance sheet requirements does not imply balance sheet segmentation. Even with multiple balance sheet requirements, all arbitrageurs can face the same marginal balance sheet cost for a given trade, which means that we can model a single, representative intermediary for all trades. We introduce balance sheet segmentation below.

Second, there are funding frictions. There are L funding sources with associated cost $f_{1,t}, ..., f_{L,t}$ (in excess of the riskless rate of zero) per unit borrowed. One dollar of trade n can be financed with $w_{n,l}$ dollars from funding source $l \in L$. This assumption captures violations of the Modigliani and Miller (1958) theorem in funding markets. Despite the fact that all N trades are riskless, arbitrageurs may not be able to fund the basket of securities and derivatives that underlie each trade at the riskless rate. The assumption that $w_{n,l}$ does not vary over time corresponds to the empirical notion that rates on funding fluctuate more

[8]As discussed in Wallen (2019), market power among intermediaries may be important in certain markets. The results here would be qualitatively unchanged in oligopolistic market structures if the elasticity of demand from outside investors is constant over time.

than haircuts (Copeland et al., 2010). If $L = 0$, then funding is frictionless. If $L = 1$, then funding is frictional but integrated, and if $L > 1$ (and $w_{n,l}$ varies across trades and financing sources), then funding is segmented.

The arbitrageur's problem is:

$$\max \sum_{n=1}^{N} \left(q_{n,t} \left(s_{n,t} - \sum_{l} w_{n,l} f_{l,t} \right) \right) - \frac{1}{2} \sum_{k=1}^{K} c_{k,t} V_{k,t}^2. \tag{1}$$

Since arbitrageurs are atomistic, they take $s_{n,t}$ as given. To close the model, we assume that outside demand for trade n is inelastic and given by $a_{n,t} > 0$. Market clearing then requires that $q_{n,t} = a_{n,t}$.[9]

2.2 Canonical Intermediary Asset Pricing Models

Though it is stylized, the model allows us to nest common assumptions in the intermediary asset pricing literature. We discuss two typical structures here, both of which feature balance sheet and funding integration.

Balance sheet and funding integration with a single balance sheet constraint. Many models of intermediaries consider a single balance sheet constraint and frictionless funding (e.g., He and Krishnamurthy (2013)). This case can be captured by setting $f_{l,t} = 0$ for all l, $c_{1,t} \neq 0$, and $c_{k,t} = 0$ for all $k > 1$.[10] The solution to Eq. (1) is then given by

$$s_{n,t} = v_{n,1} c_{1,t} V_{1,t} = v_{n,1} c_{1,t} \left(\sum_{n} a_{n,t} v_{n,1} \right). \tag{2}$$

From this expression, it is clear that spreads will be perfectly correlated. There is a single factor—the marginal cost of the balance sheet constraint, $c_{1,t} V_{1,t}$—that moves all trades proportionally. Trades that face a higher balance sheet requirement $v_{n,1}$ load more heavily

[9] We make the assumption that outside demand is completely inelastic for simplicity. Our key results would not qualitatively change if outside demand were elastic (e.g., given by $a_{n,t} - b_n s_{n,t}$).

[10] This is equivalent to setting $w_{n,l} = 0$ for all n, l and $v_{n,k} = 0$ for all $k > 1$, which can be interpreted as the ability to fully fund trades at the riskless rate with trades loading on a single balance sheet requirement ($k = 1$).

on this factor, but all spreads move linearly with the marginal cost of the constraint. This one-factor structure in spreads holds despite the fact that there are a large number of primitive shocks in the model. In particular, the balance sheet shocks $c_{1,t}$ and the outside demand shocks $a_{n,t}$ for each trade n fluctuate independently, yet a one-factor structure still obtains. The intuition is that these independent shocks all move the marginal cost of balance sheet, but ultimately that marginal cost is all that matters for spreads.

Balance sheet and funding integration with a single funding factor. Another simple structure featuring both balance sheet and funding integration involves no constraints and a single frictional funding factor: $c_{k,t} = 0$, $v_{n,k} = 0$, $f_{n,1} > 0$, and $f_{n,l} = 0$ for $l > 1$. Then we simply have spreads driven by the funding factor: $s_{n,t} = w_{n,1} f_{1,t}$. In this case, we again have perfect correlations across spreads. Spreads may load differentially on the funding factor, but they all move linearly with it.[11]

2.3 Integration with Many Constraints

While much of the intermediary asset pricing literature features perfectly correlated arbitrage spreads, balance sheet and funding integration need not imply them. In particular, balance sheet and funding integration admit a single frictional funding source ($L = 1$) and arbitrarily many balance sheet constraints ($K > 0$). In this case, all riskless arbitrages are funded from the same source and marginal balance sheet costs are equated across arbitrageurs for each trade n. Spreads are given by:

$$s_{n,t} = w_{n,1} f_{1,t} + \sum_{k=1}^{K} v_{n,k} c_{k,t} V_{k,t} \tag{3}$$

and feature a $K + 1$ factor structure. Thus, a high-dimensional factor structure for arbitrage spreads rules out balance sheet and funding integration with a small number of constraints.

[11] Andersen et al. (2019) has this reduced form, though formally they obtain the result by microfounding the costs of external equity with a debt overhang problem. With this microfoundation, the marginal cost of external equity funding for a riskless asset, $w_{n,equity} f_{equity,t}$, is equal to the arbitrageur's credit spread.

2.4 Segmentation

We next consider the impact of segmentation on spreads. We consider two types of segmentation: funding segmentation and balance sheet segmentation.

Segmented funding. By funding segmentation, we mean that certain trades can use certain funding sources while other trades cannot. For instance, Treasury repo financing can be used for Treasury spot-futures arbitrage but cannot be used for equity spot-futures arbitrage. To see the implications of this kind of segmentation, suppose that trades $n = 1, ..., N_1 < N$ can be funded only using source $l = 1$ with corresponding cost $f_{1,t}$, while trades $n = N_1 + 1, ..., N$ can be funded only using source $l = 2$ with corresponding cost $f_{2,t}$. If there are no further frictions, we have

$$s_{n,t} = \begin{cases} w_{n,1} f_{1,t} \text{ if } n \leq N_1 \\ w_{n,2} f_{2,t} \text{ if } N_1 < n \end{cases}. \tag{4}$$

In this case, spreads have a two-factor structure. All trades that can be funded using source 1 are perfectly correlated, as are all trades that can be funded using source 2, but the correlation between the two groups is the correlation between $f_{1,t}$ and $f_{2,t}$. Extending the argument to more than two funding sources, segmented funding can create a high-dimensional factor structure for arbitrage spreads.

Segmented balance sheets. Finally, we consider balance sheet segmentation with frictionless funding. We use balance sheet segmentation to describe environments in which certain trades are done by one set of intermediaries and are therefore subject to their balance sheet constraints, while other trades are done by another set of intermediaries and are subject to their balance sheet constraints. One could microfound this segmentation with a small amount of specialization in different trades. For instance, suppose there are small marginal costs $\varepsilon_{n,i}$ associated with arbitrageur i doing trade n and there are two types of arbitrageurs. Arbitrageurs $i \in I$ have a marginal cost advantage $\varepsilon_{n,i} < \epsilon_{n,j}$ for trades $n = 1, ..., N_1$ over all other arbitrageurs $j \notin I$. Conversely, arbitrageurs $j \notin I$ have a marginal cost advantage $\varepsilon_{n,j} < \epsilon_{n,i}$ for trades $n = N_1 + 1, ..., N$. In other words, one group of arbitrageurs has a cost advantage in one set of trades, while the other has a cost advantage in a different set of trades. Since each group is a continuum, there is a representative arbitrageur for each. Finally, suppose there is a single balance sheet constraint ($f_{l,t} = 0$ for all l, $c_{1,t} \neq 0$, and $c_{k,t} = 0$). If the outside demand for each group of trades is similar,[12] then spreads are given by

$$s_{n,t} = \begin{cases} \varepsilon_{n,i} + \upsilon_{n,1} c_{1,t} V_{1,t,I} \text{ if } n \leq N_1 \\ \varepsilon_{n,j} + \upsilon_{n,1} c_{1,t} V_{1,t,\sim I} \text{ if } N_1 < n \end{cases}. \quad (5)$$

In other words, spreads have a two-factor structure. Intuitively, spreads for the first group of trades ($n = 1, ..., N_1$) reflect the shadow cost of the balance sheet constraint for arbitrageurs in group I. For the second group of trades ($n = N_1 + 1, ..., N$), spreads will reflect the shadow cost of the balance sheet constraint for arbitrageurs outside group I. Extending the argument to more than two groups of arbitrageurs, segmented balance sheets can create a high-dimensional factor structure for arbitrage spreads.

2.5 Empirical Implications

The model highlights what we can learn from spreads alone and what conclusions require ancillary data. For instance, a high-dimensional factor structure for spreads rejects simple models in which both balance sheet and funding integration obtain and the representative intermediary is subject to a single constraint. As Eq. (3) shows, however, a high-dimensional factor structure by itself does not distinguish between situations in which (i) both balance sheet and funding integration obtain, but the representative intermediary is subject to many constraints and (ii) either balance sheets or funding markets are segmented. As Eq. (4) shows, the empirical signature of funding segmentation is a covariance between certain spreads and certain funding rates. Similarly, Eq. (5) shows that the empirical signature of balance sheet segmentation is a covariance between certain spreads and individual intermediary balance sheet costs. Our empirics below follow this outline. We begin by describing the factor

[12] Formally, we need an assumption ensuring that marginal cost advantages (ε's) are not swamped by differences in adjustment costs (c's) or outside demand (through the V's).

structure of arbitrage spreads and then provide direct evidence of both types of segmentation. For instance, we will directly show that certain spreads comove with the costs of particular types of funding. And we will show that certain spreads directly respond to shocks to the balance sheets of specific intermediaries.

3 The Factor Structure of Arbitrage

3.1 Data and Arbitrage Trades

Our main analysis sample covers 29 arbitrage trades over the period from January 1, 2010 to February 29, 2020. This period spans the post-financial crisis era and predates the Covid-19 pandemic. For each arbitrage trade, we construct an implied riskless rate based on observed asset prices and then subtract a maturity-matched benchmark riskless rate. For arbitrage trades that mature in less than two years, the benchmark is based on overnight indexed swap (OIS) rates; for longer-maturity trades, it is based on Treasury yields. Our choice of benchmark rates means that our arbitrage spreads do not represent true riskless profits that are available to unconstrained intermediaries, since they are not constructed using the exact funding rate that a trader implementing the arbitrage would face. Instead, our arbitrage spreads capture funding and other frictions faced by arbitragers, which are precisely what we seek to characterize. A detailed description of each arbitrage spread and its construction is contained in Internet Appendix A.1. Here, we provide a short description of the trades, which can be grouped into 7 broad categories or "strategies".

3.1.1 Arbitrage Strategies

Foreign Exchange Arbitrage We follow Du et al. (2018) and measure arbitrage spreads in foreign exchange markets with deviations from covered interest parity (CIP). For each currency we study, we define the CIP arbitrage spread as the difference between the dollar OIS rate and a synthetic riskless rate that is implied by currency forwards, currency spot rates, and foreign OIS rates. We build CIP arbitrage spreads for all G-10 currencies except the Danish and Norwegian krones because OIS rates are not available for these two currencies. We use 3-month CIP violations to avoid any confounding effects that the quarter-end spikes documented in Du et al. (2018) may have on correlations. We obtain data on spot and forward exchange rates and OIS rates from Bloomberg. See Internet Appendix A.1.1 for more details.

Equity Options Arbitrage (Box Arbitrage) We infer riskless rates and arbitrage spreads from S&P 500 (SPX) equity options based on the put-call parity relationship. As discussed in Ronn and Ronn (1989) and van Binsbergen et al. (2019), implied riskless rates from put-call parity are often called box rates in practice. We adopt this naming convention and refer to this arbitrage as the box trade for the remainder of the paper. We take box rates for six, twelve, and eighteen month tenors directly from van Binsbergen et al. (2019), who estimate them using minute-by-minute pricing data for SPX options. Arbitrage spreads are then computed by subtracting off a maturity-matched OIS rate.

Equity Spot-Futures Arbitrage For equity futures markets, we measure arbitrage spreads based on violations of spot-futures parity. As we discuss in Internet Appendix A.1.3, the spot and futures markets for equities close at different times, which prevents us from using the spot-futures parity relationship to accurately compute implied riskless rates from closing prices alone.[13] Instead, we compute implied forward rates based on the relative pricing of futures contracts with different tenors. To illustrate, consider a futures contract on an asset that does not pay a dividend. In this case, spot-futures parity implies that the current futures price F_{T_1} for a contract with tenor T_1 and the spot price S satisfy $F_{T_1} = S(1 + r_{T_1})$, where r_{T_1} is the riskless rate between today and T_1. Next, consider another futures contract with tenor $T_2 > T_1$. Under the parity condition, the ratio of the two futures prices F_{T_2}/F_{T_1} equals the gross forward rate $1 + f_{T_1,T_2}$ between T_1 and T_2.

[13] Hazelkorn et al. (2021) avoid this issue by using high-frequency data for both futures and spot markets.

We estimate implied forward rates using Bloomberg futures data on the S&P 500, Dow Jones Industrial, and Nasdaq 100 indices. For each index, our analysis is based on the nearby and first-deferred contracts, which are the most liquid. Internet Appendix A.1.3 provides more details about our implementation, including how we account for dividends and compute arbitrage spreads from implied forward rates.

Treasury Spot-Futures Arbitrage For Treasury futures markets, we measure arbitrage spreads based on violations of spot-futures parity, following Fleckenstein and Longstaff (2020) and Barth and Kahn (2021). We study five such trades, associated with the first-deferred futures contract on the 2-year, 5-year, 10-year, 20-year, and 30-year Treasury. We measure arbitrage spreads using the first-deferred contract to avoid complications with the nearby contract in the futures delivery month (Fleckenstein and Longstaff, 2020). We obtain futures-implied riskless rates directly from Bloomberg and define arbitrage spreads by subtracting off a maturity-matched OIS rate. See Internet Appendix A.1.4 for more details.

Treasury Swap Arbitrage For interest rate swap markets, we measure arbitrage spreads using OIS swap spreads, defined as the difference between the fixed rate on overnight indexed swaps and Treasury yields. We study seven such trades, associated with 1-year, 2-year, 3-year, 5-year, 10-year, 20-year, and 30-year Treasuries. OIS swap rates are from Bloomberg. As discussed in Jermann (2020), Du et al. (2022), and Hanson et al. (2022), only negative OIS swap spreads indicate a guaranteed arbitrage. We show in Internet Appendix A.1.5 that this condition is satisfied for the large majority of observations in our analysis sample.

TIPS-Treasury Arbitrage We follow Fleckenstein et al. (2014) and construct the difference in yield between a synthetic nominal Treasury, constructed using Treasury Inflation Protected Securities (TIPS) and inflation swaps, and the true nominal Treasury yield. We obtain TIPS data from the Treasury, inflation swap data from Bloomberg, and nominal Treasury data from CRSP. In Internet Appendix A.1.6, we provide additional details and confirm that we accurately match the series from Fleckenstein et al. (2014).

CDS-Bond Arbitrage For U.S. corporate bond and credit default swap (CDS) markets, we follow Duffie (1999) and measure arbitrage spreads based on the difference between cash-bond implied credit spreads and CDS spreads. Cash bond and CDS pricing data both come from Markit. We form CDS-bond bases for both investment-grade and high-yield bonds, aggregating over bonds in each ratings category. The average number of bonds used to compute the daily investment grade and high-yield bases is 1,690 and 307, respectively. Internet Appendix A.1.7 contains the full construction methodology.

Summary Statistics Table 1 provides summary statistics. The data is daily and spreads are reported in annualized basis points (bps). Unless otherwise noted, we work with absolute values of spreads since the sign of the spread depends on whether arbitrageurs are net long or short a particular leg of the trade. The number of observations varies slightly across trades, mainly due to availability from raw data providers (e.g., Bloomberg vs Markit) and differences in trading holidays across swaps and futures markets. The box trades have fewer observations because we use data from van Binsbergen et al. (2019), who end their analysis in 2018.

Table 1 shows that there is significant variation in spreads, both across trades on average and within trades over time. For many individual trades, the daily standard deviation of spreads is around half the mean spread. Figure 1 shows average spreads by broad strategy. Average spreads vary significantly from 15 bps for the Treasury spot-futures arbitrage to 44 bps for the CDS-bond basis. While not the focus of our analysis, it is worth noting that we can easily reject the hypothesis that average spreads are equal across individual trades or broad strategies.

3.1.2 Quantity Data

In addition to data on arbitrage spreads, we use data from the Commodity Futures Trading Commission (CFTC) on quantities.[14] The CFTC publishes weekly "Traders in Financial Futures" reports, which break down open interest for futures markets in which 20 or more traders hold large positions. The position data is supplied by clearinghouses and other reporting firms. The reports break down positions into four trader types: dealers, asset managers, leveraged funds, and other reporting entities. These classifications are based on the predominant business purpose self-reported by traders on the CFTC Form 40.

3.2 Money Market Fund Holdings

We obtain data on the holdings and total net assets (TNAs) of money market mutual funds (MMFs) from Crane data. The data is compiled from form N-MFP, which MMFs are required to file with the Securities and Exchange Commission (SEC) every month.

3.3 Hedge Fund Returns

We also use hedge fund returns from the Preqin Pro Hedge Fund Database. This database includes performance data on over 24,000 hedge funds. Importantly for our purposes, the database contains descriptive information on fund strategies, which allows us to focus on funds that self-report being involved in the arbitrage trades that we study.

3.4 Characterizing Arbitrage Comovement

3.4.1 Baseline Results

We now turn to our first main result: the correlation between arbitrage spreads is low. Figure 2 presents this result graphically, depicting a heat map of pairwise correlations between the absolute value of different spreads. Darker red indicates higher positive correlations. With

[14] The data are available at this link.

the exception of the diagonal, little of the figure is dark red, indicating that correlations are generally low.

Table 2a provides formal statistical evidence on pairwise correlations. The average pairwise correlation is 0.21, and the 75th percentile of pairwise correlations is 0.43. These results are at odds with simple structures for the intermediary sector, in which there is only a single balance sheet constraint or a single funding factor. As shown in Section 2, in these cases, arbitrage spreads should be perfectly correlated. In Figure 3, we conduct a principal components analysis of spreads. Consistent with the low correlations documented above, it takes 10 principal components to cumulatively explain 90% of the variation in arbitrage spreads. Furthermore, the last column of Table 2a shows that we can reject the null of equal correlations across all arbitrage pairs. Thus, the data suggest a complex structure for the intermediary sector. Either balance sheet and funding integration hold, but the representative intermediary faces a large number of different constraints, or there is significant segmentation in arbitrage.

3.4.2 Noise-Trader Risk

We next consider two issues that might confound our interpretation of low arbitrage correlations. The first is convergence or noise trader risk (Delong et al., 1993). As noted by Du et al. (2022) and Hanson et al. (2022), dynamic considerations like convergence risk typically add at most one factor to the structure of arbitrage spreads if intermediaries face a single constraint. Intuitively, the risk that the single constraint tightens in the future moves all spreads together, just as the contemporaneous tightness of the constraint did in Section 2. Thus, it is theoretically unlikely that the low observed correlation of arbitrage spreads is driven by convergence risk in a world where a representative intermediary faces a single constraint.

A simple empirical approach to mitigating the effect of convergence risk on arbitrage correlations is to exclude trades with long tenors. Table 2b does so, reporting the distribution of pairwise correlations for the CIP, Treasury spot-futures, and equity spot-futures arbitrages. These are all trades with less than six months to maturity and their arbitrage spreads are relatively simple to measure compared to some of the longer-tenor strategies (e.g.,the CDS-Bond basis). In the subset of short-tenor trades, the average correlation is still low at 0.19, and the 75th percentile of correlations is 0.35. Thus, it does not appear that convergence risk is the main driver of the low correlations we observe.

3.4.3 Measurement error

Measurement error is another important issue to consider when interpreting low arbitrage correlations. To see why, suppose that the observed spread $s_{i,t}$ equals the true spread $s^*_{i,t}$ plus an error term that is independent across arbitrages:

$$s_{i,t} = s^*_{i,t} + \varepsilon_{i,t},$$

where the variance of the true spread is $Var[s^*_{i,t}] = \sigma_i^2$ and the variance of the measurement error $\varepsilon_{i,t}$ is $Var[\varepsilon_{i,t}] = \sigma_{i,\varepsilon}^2$. Let ρ^*_{ij} denote the correlation between the true spreads and ρ_{ij} denote the correlation between the observed spreads. In this setting, the true correlation ρ^*_{ij} and measured correlation ρ_{ij} are related as follows:

$$\begin{aligned} \rho_{ij} &= \rho^*_{ij}/(\lambda_i \lambda_j) \\ \lambda_i &= \sqrt{\frac{\sigma_i^2 + \sigma_{i,\varepsilon}^2}{\sigma_i^2}}. \end{aligned} \tag{6}$$

Because the adjustment factor λ_i is above 1 for all i, observed correlations will be biased toward zero. Thus, if arbitrage is fully integrated and the representative intermediary faces a limited number of constraints ($\rho^*_{ij} \approx 1$), measurement error may lead us to incorrectly conclude otherwise based on low measured correlations.

We address potential measurement error in a few complementary ways. To start, consider the simple case in which the variance of measurement error is a constant proportion θ of the variance of true spreads, $\sigma^2_{i,\varepsilon} = \theta\sigma^2_i$. In this case, Eq. (6) simplifies to $\rho_{ij} = \rho^*_{ij}(1+\theta)^{-1}$. If the variance of the measurement error is less than half that of true spreads ($\theta < 0.5$) and true spreads are perfectly correlated, measured pairwise correlations should be greater than 0.67. However, in Table 2a we reject the null that the average pairwise correlation of all spreads is greater than 0.67. Moreover, we reject the null that the individual pairwise correlation is above 0.67 for 88% (358/406) of pairs. One can also reverse the exercise and ask how large measurement error would need to be in order to generate the correlations that we observe. If $\sigma^2_{i,\varepsilon} = \theta\sigma^2_i$ and true spreads are perfectly correlated, $\theta \approx 4$ would be required to generate a measured correlation of 0.21.

If true spreads more persistent than measurement errors, another approach is to smooth the data. Figure 3 shows that we obtain very similar results if we compute principal components after taking a five-day or one-month moving average of spreads. Averaging should increase the ratio of variation driven by true spreads as opposed to noise, but it has little effect on the principal components analysis. Even after taking one-month moving averages of spreads, it takes 9 principal components to cumulatively explain over 90% of the variation in our arbitrage spreads.

Eq. (6) also shows that the attenuation bias induced by measurement error can be directly addressed with knowledge of the adjustment factors, λ_i. These factors reflect how much of the total observed spread variance is driven by the true spread. If arbitrage spreads follow a one-factor model, the adjustment factors can be estimated using instrumental variables (IV) regressions (Hausman, 2001). Specifically, for each spread i we first run the following OLS regression:

$$s_{jt} = \alpha_i + \beta_i^{OLS} s_{it} + \varepsilon_{it}, \tag{7}$$

where we pool all observations for which $j \neq i$. We then run an analogous IV regression with two instruments for s_{it}: (i) the observed arbitrage spread on the last day of the previous quarter, and (ii) the average observed arbitrage spread in the previous quarter. The idea behind these instruments is that any error induced by execution details of individual trades in the current quarter should be uncorrelated with errors from the previous quarter. Concretely, consider the Treasury spot-futures trade and suppose the contract we use to compute $s_{i,t}$ expires in September. Our instruments instead reflect an entirely different futures contract (i.e., the June contract).

Let β_i^{IV} denote the IV estimate from regression (7). Under the null of a one-factor model for arbitrage spreads and assuming our instruments are valid, the ratio of the IV and OLS estimates reveals the measurement error variance relative to true variance (Hausman, 2001):

$$\lambda_i = \sqrt{\frac{\beta_i^{IV}}{\beta_i^{OLS}}}.$$

We estimate the λ_is individually and use them to adjust the measured correlations up according to Eq. (6). To be maximally conservative, we focus on trades with short tenors for which convergence risk should be relatively unimportant (see Section 3.4.2). The average adjusted correlation equals 0.19, similar to the overall average measured correlation and the average for short-tenor trades. The distributions of adjusted and unadjusted correlations are also comparable: the 25th and 75th percentile of adjusted correlations are -0.07 and 0.42, respectively. These results cut against the idea that true spreads follow a one-factor structure but their measured correlation is biased toward zero by noise.

The final reason we think measurement error is unlikely to be driving our results is that the correlations are not uniformly low. While spreads are far from perfectly correlated, they still have an interesting structure. Figure 3 shows that there is important common variation in spreads as emphasized by the previous literature, including Pasquariello (2014), Du et al. (2018), Du et al. (2019), and van Binsbergen et al. (2019). When considering all trades, the first three principal components of daily spreads cumulatively explain 64% of their variation. If spreads were completely uncorrelated, we would expect them to only explain 33%.[15] Thus,

[15] If spreads were uncorrelated, then the first three principal components would simply be the three spreads with the largest variance, and the total variance of spreads would be the sum of individual spread variances.

our principal components analysis reveals a meaningful underlying economic structure to arbitrage spreads.

Figure 2 and Table 2c suggest two places to look for this structure. First, cross-strategy correlations are relatively high for the box, CIP, and equity-spot futures spreads. Second, correlations are higher within strategy than across strategy. For instance, Table 2c shows the average pairwise correlation of the three box trades is 0.87 and the average pairwise correlation of CIP spreads is 0.35. We explore these sources of correlation further in Sections 4 and 5 of the paper, arguing that they reflect funding and balance sheet segmentation.

4 Segmented Funding

In this section, we argue that funding frictions are a key reason that the correlation of arbitrage spreads is low. As discussed in Section 2, the underlying violation of the Modigliani and Miller (1958) theorem is that certain riskless portfolios cannot be funded at the riskless rate. For instance, the equity spot-futures arbitrage involves holding the underlying equities and selling equity futures. Taken together, this position is riskless, but it cannot be funded with (for instance) Treasury repo. As the cost of funding for certain arbitrage trades moves, spreads move as well.

We proceed in three steps. We start with suggestive evidence that there are differences in funding structures across the different arbitrage strategies we study. We then provide more formal empirical evidence that movements in funding costs affect arbitrage spreads. In particular, we show that they help explain the relatively high degree of comovement between the box, CIP, and equity-spot futures spreads in Table 2c, and the relatively low degree of comovement between those spreads and the others we study. Finally, we show that specialization in funding creates segmentation that goes beyond the divide between unsecured and secured funding markets.

In our data, the ratio of the sum of the largest three variances to the sum of all variances is about 33%.

4.1 Suggestive Evidence on Margins

Table 3 shows that there are meaningful differences in the availability of secured financing across arbitrage strategies. The data primarily come from the Federal Reserve Bank of New York's Tri-party Repo Infrastructure Reform Task Force.[16] The Treasury spot-futures, Treasury-swap, and TIPS-Treasury arbitrages can be largely financed with Treasury repo, requiring only a 2% margin. In other words, intermediaries need little unsecured debt or equity funding to enter into these arbitrages. Conversely, the box, CIP, and equity spot-futures arbitrages require higher margins between 8% and 12%. For these arbitrages, unsecured funding conditions are much more important. We will therefore frequently group these trades together, labeling them "unsecured", while we label the remaining trades (Treasury spot-futures, Treasury-swap, TIPS-Treasury, and CDS-bond) "secured."

4.2 Shocks to Unsecured Funding and Arbitrage Activity

In this section, we show that variation in unsecured funding conditions induces comovement in unsecured arbitrage spreads but not secured spreads. We start with OLS evidence in Table 4. We work with implied riskless rates from different arbitrages, as opposed to spreads that subtract out a benchmark riskless rate, to separate changes in secured and unsecured funding conditions. In the first two columns, we run the following monthly panel regression:

$$\Delta r_{i,j,t} = \alpha_{i,j} + \beta_1 \Delta y_{i,t} + \beta_2 \Delta TED_t + \varepsilon_{i,j,t}, \tag{8}$$

where $r_{i,j,t}$ is the implied riskless rate for individual trade i in broad strategy j in month t and $y_{i,t}$ is the yield on a Treasury with the same maturity as the horizon of the trade—a proxy for the true riskless rate. TED_t is the maturity-matched Treasury-Eurodollar spread

[16] For currencies, we report data from central bank lending operations by the Bank of England and the European Central Bank because the quantity of tri-party repo backed by international collateral is typically small (less than 0.5% of the total). Margin data from the NY Fed can be found here, Bank of England data can be found here, and ECB data can be found here.

(i.e., LIBOR minus Treasury) and proxies for unsecured funding costs.[17] Standard errors are clustered by strategy-month.

In the first column of Table 4, the sample consists of unsecured trades (equity spot-futures, CIP, and box). These trades load on the Treasury yield with a coefficient close to 1, but also have a high loading on the TED spread, consistent with the idea that these trades require a significant amount of unsecured funding. Indeed, the coefficient on the TED spread of 0.48 is higher than the margin requirements listed in Table 3, possibly because these trades require more unsecured funding on the margin than on average.[18]

The second column of Table 4 shows a stark contrast for secured trades. These trades also load on the Treasury yield with a coefficient close to 1, but their loading on the TED spread is much lower (0.07 vs 0.48) and is not statistically distinguishable from zero.[19] The remaining columns of Table 4 run the regression strategy-by-strategy. The coefficient on the TED spread is higher for all unsecured strategies than it is for any of the secured strategies. Moreover, we cannot reject the null that the TED spread loading is zero for each of the secured strategies, but we can for each of the unsecured ones.

Previous research has noted that arbitrage spreads are sensitive to the TED spread (e.g., Garleanu and Pedersen, 2011), particularly during stressed periods like the 2007-09 financial crisis. Our focus here is to highlight differences in the sensitivity of arbitrage strategies to the TED spread. We interpret these differences as showing that frictions in funding markets drive cross-sectional differences in arbitrage spreads.

While the results in Table 4 are consistent with funding segmentation, they could also reflect balance sheet segmentation. For instance, suppose broker dealers specialize in unsecured trades. Then a deterioration in their balance sheet health could lead to a simultaneous rise

[17] ICE Benchmark Association does not publish LIBOR rates beyond one year. Thus, when the tenor of the trade exceeds one year, we construct the TED spread using the one-year LIBOR and Treasury yields.

[18] In Internet Appendix A.2.1, we provide suggestive evidence in favor of this interpretation for equity spot-futures arbitrage. We show that the value of equity securities held by dealers is nearly double the size of equity triparty repo, cutting against the idea that dealers fully finance their equity positions with equity repo.

[19] Note that correlations with the Treasury yield are very high for some secured trades because these trades involve Treasuries.

in the TED spread and unsecured arbitrage spreads.

To isolate the role of funding segmentation, we follow Anderson et al. (2019) and study the 2016 MMF reform. The reform modified SEC Rule 2a-7, which governs MMFs. It required institutional prime MMFs to switch from reporting stable to floating net asset values (NAVs), while allowing government MMFs to continue reporting stable NAVs. Thus, following the reform, many prime MMFs converted to government MMFs to accommodate client preferences for stable NAVs. Prior to the reform, prime MMFs were a significant source of unsecured funding for banks, so the reform plausibly represents a funding shock that is distinct from bank balance sheet shocks. Indeed, as shown in Figure 4a, unsecured MMF lending to banks fell approximately $550 billion as a result of the reform. Anderson et al. (2019) study how global banks respond to this shock, arguing that they withdraw from CIP and central bank reserve arbitrage. In contrast, we use the shock to trace out funding segmentation in the cross section of arbitrage.

Figure 4b shows that the MMF reform shock generated a significant rise in the TED spread. As the reform was anticipated, spreads start rising before the reform is implemented. For example, five months before the reform, MMFs were more willing to lend to banks unsecured for four months than six months. Figure 4c shows that around the time of the reform, spreads on unsecured arbitrages rise relative to secured arbitrages. Thus, unsecured funding shocks induce comovement in arbitrage spreads for unsecured trades but result in low correlations between secured and unsecured trades.

Table 5 provides formal regression evidence corresponding to these figures.[20] We first

[20]While Figure 4c and Table 5 look similar to a differences-in-differences analysis, they are formally closer to a placebo test. In particular, the parallel trends assumption should hold under the null of integrated funding. However, under our preferred interpretation—that the unsecured arbitrages are segmented from the secured arbitrages—there is no reason for the parallel trends assumption to hold. That is, we do not think that the gap in spreads between unsecured and secured arbitrages would have remained fixed in the absence of the 2016 MMF reform. Instead, we simply interpret this evidence as showing that only unsecured arbitrages are affected by a shock to unsecured funding.

estimate the following OLS regression:

$$s_{i,t} = \alpha_i + \alpha_t + \beta 1[i \in Unsecured] \times 1[t \geq \text{October2016}] + \varepsilon_{i,t}, \tag{9}$$

where $s_{i,t}$ is the absolute value of the arbitrage spread for trade i on date t, α_i is a trade fixed effect, and α_t is a time fixed effect. We estimate the regression using data through October 2017 to focus on the one-year impact of the reform on arbitrage spreads. Column (1) shows that unsecured spreads rose by an average of 12 bps in the year following the reform. In column (2), we estimate a dynamic version of Eq. (9) to more carefully study the response of spreads to the reform over time. Unsecured spreads initially rise 17 bps relative to other arbitrage spreads in the October 2016 and remain elevated near that level for the subsequent three months, after which they only partially revert between February and October 2017. These findings indicate that the effect of the funding shock on arbitrage activity persisted for many months.

Furthermore, the passthrough of 0.58 implied by the 2016 MMF reform event study is similar to the OLS estimate of 0.48 in Table 4, and we cannot reject the null hypothesis that they are equal.[21] This suggests that most of the comovement between the TED spread and unsecured trades in our sample is driven by funding shocks, as opposed to bank balance sheet shocks. Taken together, the analysis in Tables 4 and 5 shows that funding segmentation is one broad driver of low correlations among arbitrage spreads. Some trades—equity spot-futures, box spreads, and CIP—require more unsecured funding than others. These trades are therefore more exposed to broad conditions in unsecured funding markets, as measured by the TED spread. As a result, unsecured trades tend to comove more with each other than they do with secured trades. In other words, funding segmentation impacts asset prices.

[21] Around the reform, the TED spread and unsecured spreads increased by 30 and 17 bps, respectively. This implies that the passthrough of changes in the TED spread to unsecured spreads equals 0.58.

4.3 Further Funding Segmentation

We next provide evidence that funding markets are more segmented than the simple divide between secured and unsecured trades. In particular, we argue that additional funding segmentation helps to explain why the equity spot-futures, box, and CIP trades, while more correlated than other trades, are still not highly correlated with each other. Building on the MMF literature (e.g., Chernenko and Sunderam, 2014; Rime et al., 2017; Li, 2021; Hu et al., 2021), we document that specialization in certain types of funding by MMFs is reflected in arbitrage spreads.

In particular, Hu et al. (2021) find that Fidelity MMFs were the largest provider of equity-repo financing in their sample, which runs from 2010 to 2013. In Table 6, we show that funding shocks to Fidelity move equity spot-futures arbitrage spreads over and above the effect of the TED spread. We augment Eq. (8) with flows into Fidelity MMFs. Columns 1-3 report OLS results. Column 1 shows that equity spot-futures arbitrages spreads fall when funds flow into Fidelity MMFs, consistent with the idea that a positive Fidelity funding supply shock reduces the cost of funding equity holdings and hence equity spot-futures spreads. Columns 2 and 3 show that flows to Fidelity have no impact on either other unsecured trades (box and CIP) or secured trades, suggesting that Fidelity funding supply shocks do not affect these trades. These results also suggest that flows into Fidelity are not proxying for aggregate unsecured funding conditions or aggregate intermediary balance sheet health.

One concern with these OLS results is that flows to Fidelity may be driven by the demand for funding rather than the supply of funding. In other words, the relationship between Fidelity flows and the cost of funding equity holdings is ambiguous, which biases the estimated OLS coefficients towards zero.[22] In columns 4-6, we try to address this concern by instrumenting for flows to Fidelity with "passive flows"—flows to the aggregate MMF sector

[22]Another concern is that the OLS results reflect balance sheet segmentation. It could be that specific intermediaries are important for equity spot-futures arbitrage and flows to Fidelity reflect the health of those intermediaries' balance sheets. In this case, however, the most natural interpretation is that both balance sheet and funding segmentation are at work. Flows to Fidelity reflect the health of particular intermediaries over and above the TED spread because Fidelity has funding relationships with those intermediaries.

in month t interacted with Fidelity's share of MMF assets measured at $t-6$. The idea is that Fidelity is small relative to the overall MMF sector (it accounts for an average of 16% of total assets) and therefore aggregate flows are not driven by demand for Fidelity funding.[23] Consistent with the idea that the OLS coefficients are biased towards zero, column 4 shows that the relationship between Fidelity flows and equity spot-futures arbitrages spreads is stronger when we instrument. However, the relationship with spreads on other unsecured trades and secured trades remains close to zero and statistically insignificant. Overall, the evidence shows within the unsecured market, funding is segmented. The cost of funding equity holdings moves independently of other funding costs.

Taken together, our results suggest that funding segmentation is an important driver of segmentation in asset prices. Unsecured trades are broadly segmented from secured trades because unsecured funding is segmented from secured funding, with the TED spread capturing these differences. Beyond the simple divide between secured and unsecured funding, there is additional segmentation, which appears to be driven by specialization among funding sources.

5 Segmented Balance Sheets

We next provide evidence of a second driver of segmentation in asset prices: balance sheet segmentation across intermediaries. As discussed in Section 2, if different intermediaries specialize in different trades, then the tightness of their individual balance sheet constraints will affect some arbitrage spreads but not others.

We provide three complementary types of analysis. First, we provide suggestive evidence from CFTC quantity data that different intermediaries are more central for different trades. We then examine two event studies: JP Morgan's London Whale episode in 2012 and Deutsche Bank's exit from the CDS market in 2014. Finally, we show that the tightness of fixed income hedge fund balance sheet constraints are important for certain secured trades.

[23] In Internet Appendix Section A.2.2, we report the first stage.

5.1 Suggestive Evidence from Quantities

Table 7 uses the CFTC data to provide suggestive evidence that different intermediaries play bigger roles in certain arbitrage trades. The CFTC summarizes positions in different futures of different types of intermediaries: dealers, hedge funds (labeled by the CFTC as "leveraged funds"), and asset managers. For each intermediary type and contract, the CFTC reports total gross positions long and short of the intermediary type in the contract, as well as total positions in the contract netted by intermediary type. The data is silent on the specific intermediaries that are active in a particular trade, and therefore does not perfectly reveal the marginal price setter for each contract. It does, however, give us a sense of which intermediaries are most active in which contract.

We compute three different measures of activity. First, we look at an intermediary type's gross share of activity in a contract—the sum of the intermediary type's long, short, and spread positions in that contract, divided by the total long, short, and spread positions in the contract. Second, we net within each intermediary type, taking the difference between gross long and gross short positions for the intermediary type. We then report the intermediary type's net position as a fraction of the total net positions across intermediaries. Finally, we report the fraction of days the intermediary type's net position is in the direction that would earn the arbitrage spread. A high fraction of days earning the spread is suggestive evidence that the intermediary type is an important arbitrageur for the contract, accommodating demand from other sectors.

All three measures tell the same story. Dealers are the biggest players in equity futures, while hedge funds and asset managers play a more important role in Treasury futures. For instance, dealers are in a net position that earns the arbitrage spread in equity futures on 87% of days, while hedge funds are in a net position to earn the spread on 45% of days, and asset managers are in a net position to earn the spread on only 8% of days. Moreover, dealers have the largest share of equity futures in terms of gross and net positions. In contrast, hedge funds appear to be the most active in Treasury futures, as their net position earns the arbitrage spread on 60% of days. Dealers are in a net position to earn the arbitrage spread on 52% of days, though their shares of gross and net outstanding are relatively small compared to hedge funds and asset managers.

While certainly not definitive, these numbers suggest that dealer balance sheet constraints are likely to be particularly important for equity futures, while hedge fund balance sheets are more important for Treasury trades. The notion that hedge funds are particularly active in Treasury spot-futures arbitrage is also consistent with Barth and Kahn (2021). We next turn to event studies for more definitive evidence.

5.2 Event Study: the London Whale

In this section, we first provide suggestive evidence that JP Morgan is a particularly important intermediary for equity spot-futures arbitrage. We then examine the impact of balance sheet shocks to JP Morgan on equity spot-futures arbitrage spreads. According to Coalition Greenwich, a subsidiary of S&P that provides benchmarks for the financial services industry, JP Morgan has had the largest share of the market for equity derivatives since 2015.[24] This accords with data from bank regulatory filings, which provide further suggestive evidence. In particular, we use the Y-9C regulatory filings to examine the trading book securities holdings of all U.S. bank holding companies. JP Morgan had by far the largest holdings of equity securities in its trading book over our sample, accounting for 37% of the total. JP Morgan's dominance was greater earlier in the sample; for instance, it held 56% of all equities in trading books in 2010. This evidence suggests that JP Morgan could play an outsized role in equity spot-futures arbitrage.

We now turn to the impact of an exogenous balance sheet shock to JP Morgan—the so-called "London Whale" episode"—on equity spot-futures arbitrages spreads. The London Whale episode was a result of activities by JP Morgan's Chief Investment Office (CIO) designed to hedge credit risk in the bank's loan portfolio. The Senate Permanent Subcommittee on

[24]The full report can be found here.

Investigations issued a detailed report on the episode, from which we draw the following background information.[25] At the beginning of 2012, JP Morgan wished to reduce the size of its hedges in the credit derivatives market. Rather than simply exiting its existing positions, the CIO instead sought to offset the credit protection it had bought by selling credit protection. In doing so, it became one of the biggest players in credit derivatives markets, with other traders nicknaming it the London Whale. In addition, it incurred significant basis risk, in terms of both the credit quality and maturity of the credit protection it had bought versus sold.

As shown in Figure 5a, this risk taking resulted in significant losses, which reached over $6 billion by the end of 2012. For context, the firm's market capitalization at the time was about $125 billion. Figure 5a shows that losses began to accelerate in March 2012, with monthly losses totaling $550 million and representing 75% of the firm's year-to-date losses. The Senate report also indicates that several internal risk limits were breached for the first time during the month. Another important event occurred on June 13, 2012, when JP Morgan CEO Jamie Dimon testified before Congress and announced that significant additional losses were to be expected at the firm's next conference call with shareholders. We therefore use March 1, 2012 and June 13, 2012 as the focal points of our event study.

Figure 5b shows that around these critical dates equity spot-futures arbitrage spreads increased relative to other spreads. These results are consistent with the idea that JP Morgan is a particularly important intermediary for equity spot-futures arbitrage. Losses incurred in the London Whale episode tightened JP Morgan's balance sheet constraints relative to other intermediaries, moving equity spot-futures spreads but not other arbitrage spreads.

Figure 5c provides formal regression evidence of the comparison between equity spot-futures arbitrage spreads and other unsecured-funding intensive trades. In a weekly panel of

[25]The report is available at the following link.

the absolute value of spreads on unsecured trades, we estimate the regression:

$$s_{i,t} = \alpha_i + \alpha_t + \sum_{j=-4}^{24} +\beta_j 1[i \in \text{Equity Spot-Futures Arbitrage}] \times 1[t = j] + \varepsilon_{i,t}. \tag{10}$$

Figure 5c plots the coefficients β_j as well as 95% confidence intervals and shows that the patterns observed in Figure 5b are statistically significant. Equity spot-futures arbitrage spreads significantly increased compared to other unsecured arbitrage spreads following the event dates (March 1, 2012 and June 13, 2012) and remained elevated for several months.

Finally, to bolster the argument that these results are due to balance sheet constraints and not funding costs, Figure 5d shows the evolution of rates on JP Morgan's commercial paper over the same period. There is little indication that short-term funding costs move substantially, which we take as evidence that the London Whale was primarily a balance sheet shock. Taken together, this evidence suggests that JP Morgan is an important intermediary for equity spot-futures arbitrage and shocks to its balance sheet constraints disproportionately impact those trades. In other words, balance sheet segmentation helps to explain the low correlation of arbitrage spreads.

5.3 Event Study: Deutsche Bank's exit from CDS

In our second event study, we examine Deutsche Bank's exit from the CDS market. As discussed in Wang et al. (2021), in late 2014 Deutsche Bank announced that it was exiting the single-name CDS market and sold a significant fraction of its CDS portfolio to Citigroup. Consistent with a substantial adjustment in Deutsche Bank's participation in the CDS market, the notional value of CDS contracts outstanding fell from 2 trillion euros in its 2013 annual report to 1.4 trillion in its 2014 annual report. The exact timing of Deutsche Bank's exit is unknown, but Bloomberg reported the sale to Citigroup in September 2014, and Deutsche Bank publicly announced the exit on November 17, 2014. Wang et al. (2021) study the effects of Deutsche Bank's exit on CDS market liquidity. In contrast, we are interested in its effect on CDS-bond arbitrage spreads, as compared to other arbitrage spreads.

Figure 6a depicts spreads around the exit event, which we center around the first week of October. Throughout late 2014, CDS-bond arbitrage spreads rise, but other arbitrage spreads do not. Figure 6b provides formal statistical evidence by running a regression analogous to (10) for the CDS-Bond basis relative to other secured trades. The plot shows that the differential impact of Deutsche Bank's exit on CDS-bond arbitrage spreads relative to other secured spreads is significant at the 5% level. Furthermore, the relative widening of the CDS-bond arbitrage spread persisted for over 5 months. These results are consistent with the idea that Deutsche Bank was a particularly important intermediary for CDS-bond arbitrages. Its decision to exit the market is akin to a tightening of its balance sheet constraints, which moved CDS-bond arbitrage spreads but not other spreads.

5.4 Hedge Fund Balance Sheet Constraints

We next turn to the impact of hedge fund balance sheet constraints. We measure hedge fund balance sheet constraints indirectly, using monthly hedge fund returns as a proxy. The idea is that following negative returns, hedge funds face tighter balance sheet constraints. At these times, arbitrage spreads should be higher for the trades in which hedge funds are important intermediaries. Using lagged returns also helps rule out simple reverse causality stories in which widening arbitrage spreads cause low returns.

In Table 8, we first use Barclay's fixed income arbitrage hedge fund index to measure returns. Barclays collects monthly return information from funds aiming to profit from price anomalies between related fixed income securities, including interest rate swap arbitrage, US and non-US government bond arbitrage, and forward yield curve arbitrage.[26] We run monthly regressions of the form:

$$\Delta s_{i,t} = \alpha + \beta f_{t-1} + \varepsilon_{i,t}, \tag{11}$$

[26] See this link for more information.

where $s_{i,t}$ is the absolute value of the spread on trade i at time t and f_{t-1} is the return on the fixed income arbitrage hedge fund index at $t-1$. The monthly return series is standardized to have mean zero and unit variance.

The first column of Table 8 shows that lagged fixed income hedge fund returns do not predict future increases in unsecured arbitrage spreads. In contrast, the second column shows a negative forecasting relationship for future changes in secured arbitrage spreads. A one-standard deviation return loss for fixed income hedge funds forecasts a 0.7 basis point increase in future secured arbitrage spreads. The remaining columns of Table 8 reveal that the relationship is driven primarily by the link between fixed income hedge fund returns and the Treasury-swap and CDS-Bond arbitrages. Overall, these results support the idea that hedge fund balance sheet constraints are more relevant for secured trades than unsecured trades.

We explore more granular balance sheet segmentation using individual hedge fund returns. We start by estimating the forecasting regression in Eq. (11) for each strategy and each of the top ten largest fixed income arbitrage hedge funds according to Preqin. This means we run ten different regressions for each strategy. We adjust our approach to hypothesis testing by computing critical values using the Bonferroni adjustment. Figure 7 displays the resulting t-statistic from these forecasting regressions. In the plot, hedge funds are indexed from one to ten along the x-axis and plot markers correspond to different strategies. The figure shows that different hedge funds are important for different arbitrage strategies. For instance, returns for hedge fund 1 negatively forecast future changes for both the CDS-bond and Treasury-futures arbitrages, with the t-statistics just at the Bonferroni threshold. Hedge fund 6 appears to be relevant for Treasury-futures arbitrage, while hedge fund 8 appears relevant for the TIPS-Treasury arbitrage, and hedge fund 10's balance sheet is important for the Treasury-swap arbitrages. It is worth noting that these results do not imply that the hedge funds we study are the only intermediaries that are marginal in a particular trade. Rather, they are likely to be representative of a broader set of intermediaries all following similar strategies and hence subject to similar balance sheet constraints.

To summarize, the results from this section suggest that balance sheet segmentation is important for explaining the low correlations of arbitrage spreads. Intermediaries appear to specialize in certain arbitrage strategies. Furthermore, when an intermediary that is important for one arbitrage suffers a balance sheet shock, the spread for that arbitrage can move without significantly affecting other arbitrage spreads. The price effects of shocks to specialized arbitrageurs imply that intermediary balance sheets are segmented.

6 Discussion and Conclusion

6.1 Persistence of Segmentation

While our empirical results have documented that both funding and balance sheet segmentation impact asset prices, it remains unclear how long this segmentation persists. Following market dislocations, capital will ultimately flow to profitable arbitrage opportunities; the question is how quickly (Duffie, 2010; Duffie and Strulovici, 2012). While our analysis does not provide precise answers to this question, it does suggest that dislocations are not corrected in a matter of days or even weeks. First, consider our results on smoothing in Figure 3. Even after taking one-month moving averages of spreads, it takes 9 principal components to cumulatively explain 90% of the variation in our arbitrage spreads. In other words, spreads on average diverge for more than one month. Second, Figure 4c shows that the impact of the 2016 MMF reform persisted for several months, indicating that funding segmentation is quite persistent. Third, Figures 5d and 6a show instances where balance sheet shocks to JP Morgan and Deutsche Bank have long-lived impacts on asset prices.

6.2 Arbitrage in Crises

A key result of this paper is that correlations between arbitrage spreads are low, which we argue reflects both balance sheet and funding segmentation in the intermediary sector.

An alternative interpretation is that balance sheet and funding integration obtain but the intermediary sector faces fixed costs and thus will only enter trades when spreads are sufficiently high. If the overall level of spreads is too low due to small imbalances between end-user supply and demand for derivatives, then intermediaries will not enter and in-sample correlations will be low.

To assess this alternative interpretation, we study the behavior of arbitrage spreads during the onset of the Covid-19 pandemic. From March through May 2020, the average level of spreads rose to 49 basis points, nearly double the average level in our main sample. Over the same period, Table 9a shows that the average pairwise correlation of spreads rose to 0.32, a modest increase from the average of 0.21 observed in our analysis sample. These low correlations are also readily apparent in Figure 8a, which plots strategy-level spreads starting in March 2020. The figure shows how different trades diverge at the onset of the pandemic, with the CDS-Bond and equity spot-futures arbitrages peaking several days after other arbitrages. This divergence is particularly stark within Treasury spot-futures arbitrage, as Figure 8b shows that arbitrage spreads based on futures for 20-year Treasuries remained elevated much longer than those based on shorter-maturity Treasuries. Overall, the fact that correlations do not rise sharply at the onset of the Covid-19 pandemic, despite the broad increase in the level of spreads, reinforces our argument that arbitrage activity is segmented.

It is also interesting to compare the comovement of arbitrage spreads during the Covid-19 pandemic to the Global Financial Crisis (GFC). Table 9b shows the average pairwise correlations of spreads for the period of June 2007 through June 2009. For this analysis, we cannot include the Treasury spot-futures and swap arbitrages due to data limitations. The average correlation during the GFC was 0.73, materially higher than during Covid-19.

One interpretation of this finding is that post-GFC regulation has raised the cost of conducting arbitrage activity (Du et al., 2018), thereby making it more difficult for integrated arbitrageurs to enter markets. However, a few additional patterns in the data suggest some caution in drawing this conclusion. For instance, Table 9c indicates that correlations were also low prior to the GFC. In addition, Figure 9 provides evidence of both balance sheet and funding segmentation prior to the passage of the Dodd-Frank Act in 2010. Consistent with the presence of balance sheet segmentation, Figure 9a shows that equity spot-futures spreads rose sharply relative to other unsecured trades after two Bear Stearns hedge funds took heavy losses due to margin calls (Khandani and Lo, 2011). Consistent with the presence of funding segmentation, Figure 9b shows that both the TED spread and unsecured arbitrage spreads rose sharply after Lehman Brothers declared bankruptcy. In contrast, secured arbitrage spreads did not rise for several weeks.

6.3 Conclusion

In this paper, we show that riskless arbitrage is segmented. The average correlation between arbitrage spreads is low. We show that this low correlation is due to both funding and balance sheet factors.

Overall, our results demonstrate the importance of both balance sheet and funding segmentation in financial intermediation. In this respect, we build on research that documents how shocks to specialized risk-bearing capacity can disconnect risk premia across markets. Our focus on fundamentally riskless arbitrage trades highlights the pervasiveness of these issues. The arbitrages we study are relatively straightforward to execute and have expected returns that are essentially observable. These characteristics should mitigate the typical agency problems thought to underlie segmentation, slow moving capital, and the limits of arbitrage, yet in practice arbitrage still appears fairly segmented. It seems natural to expect more segmentation in the intermediation of risky assets where agency problems are likely to be more severe. More broadly, our results suggest that exploring the boundaries of the firm for financial intermediaries – why certain trades are grouped together in a market segment – is a promising direction for future research.

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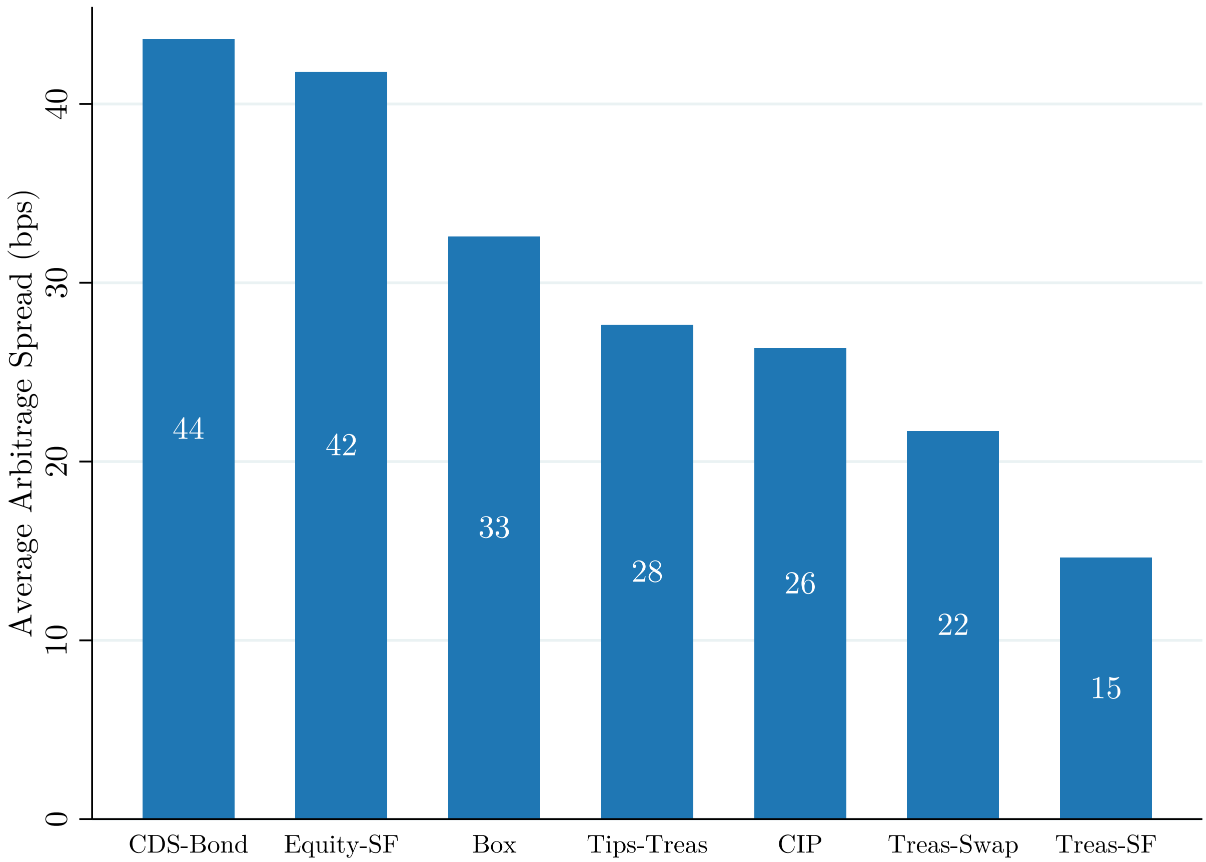
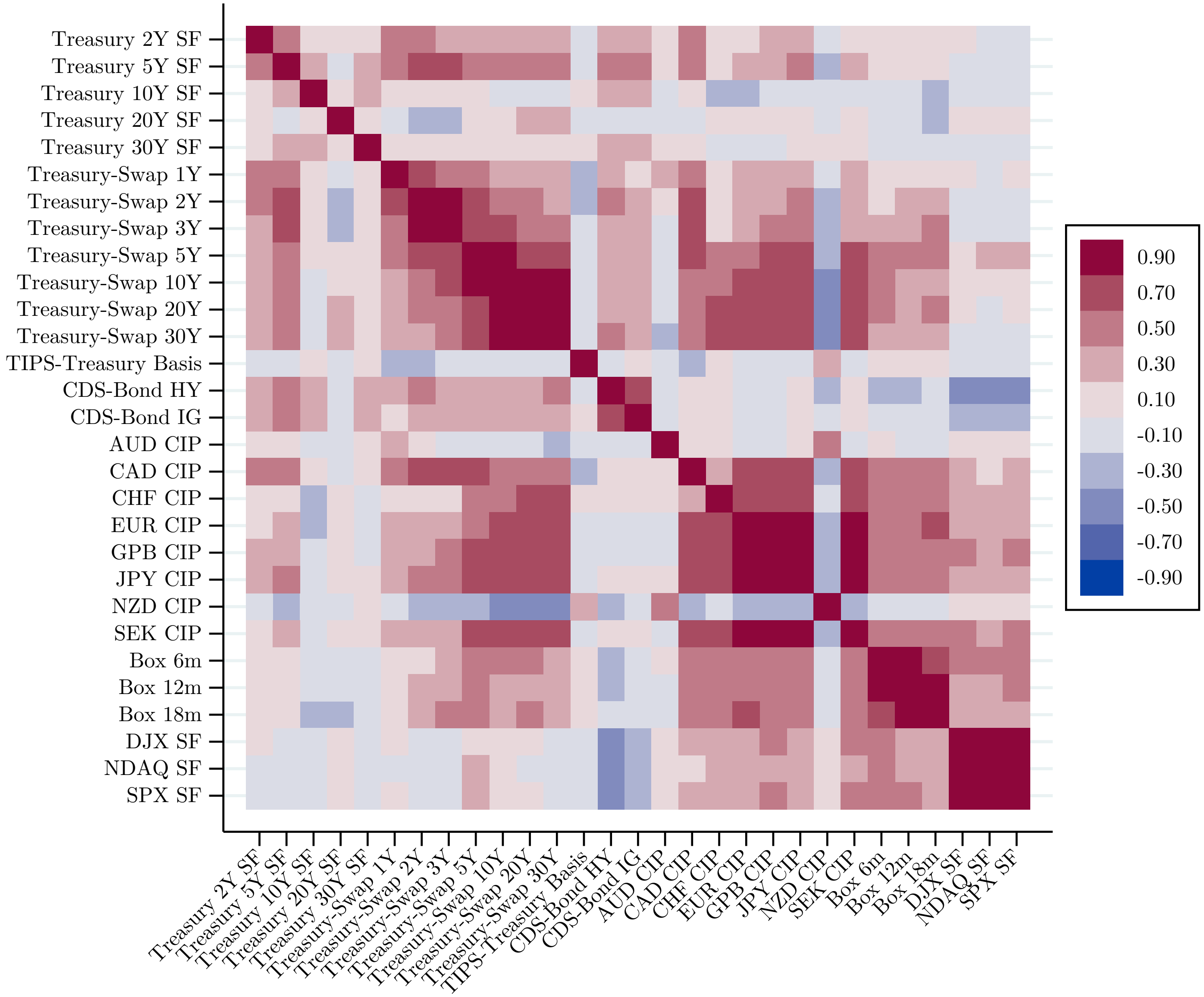
Figure 1: Arbitrage Spreads by Strategy



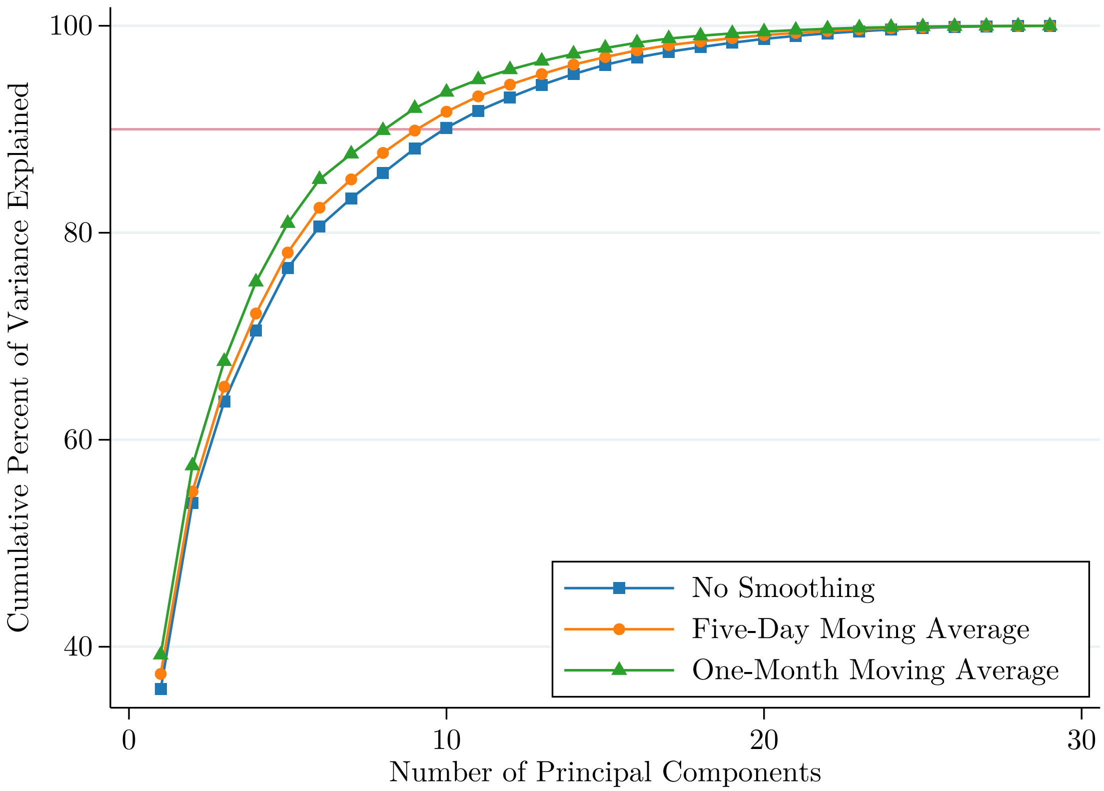
Notes: This figure shows average absolute values of arbitrage spreads by strategy. Data is daily and spans January 1, 2010 to February 29, 2020.

Figure 2: Correlation of Arbitrage Spreads



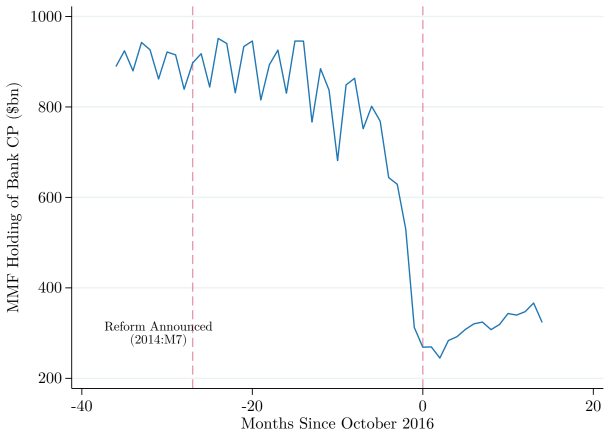
Notes: The figure shows the correlation matrix of the absolute value of arbitrage spreads across all trades in our sample. See Section 3.1 for details on each trade. Data is daily and spans January 1, 2010 to February 29, 2020.

Figure 3: The Factor Structure of Arbitrage Spreads

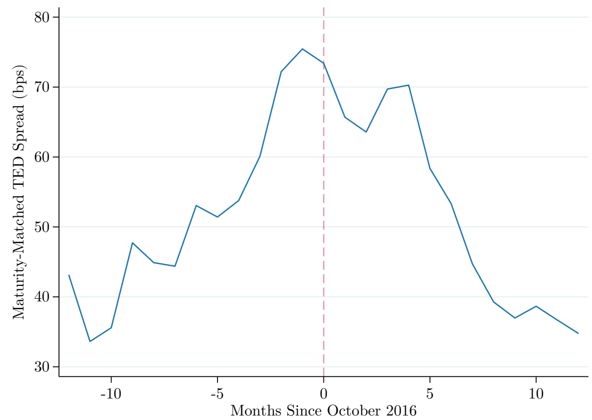


Notes: This figure summarizes principal component analysis for the absolute values of arbitrage spreads in our sample. Each line shows the results of principal component analysis after we smooth our arbitrage spreads over a different moving average window. The x-axis shows the number of components and the y-axis shows the cumulative proportion of variance captured by those components. The red horizontal line on the plot is at the 90% level. See Section 3.1 for details on each trade. Data is daily and spans January 1, 2010 to February 29, 2020.

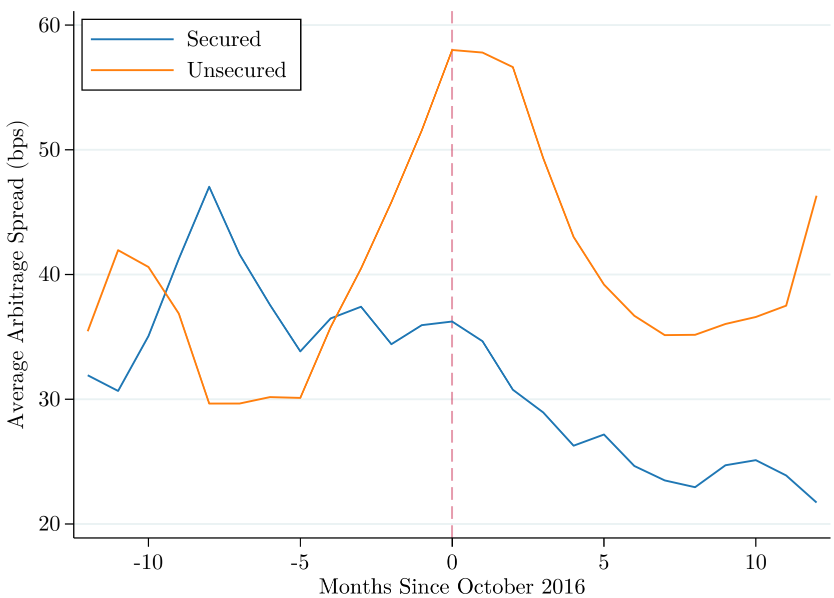
Figure 4: Event Study of the 2016 Money Market Reform



(a) MMF Holding of Bank CP



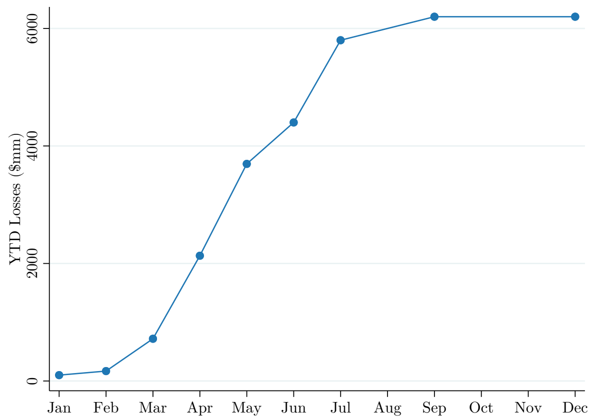
(b) Average Maturity-Matched TED Spread



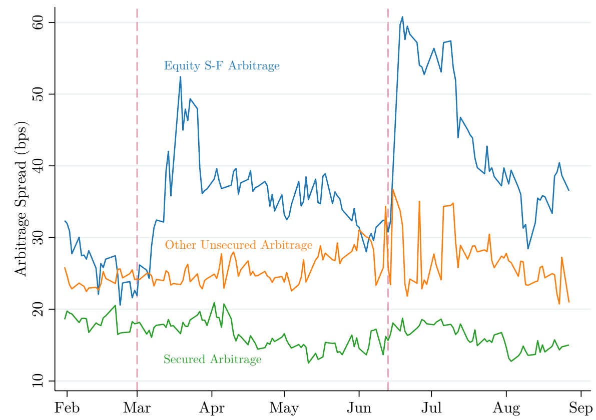
(c) Unsecured vs Secured Arbitrage Spreads

Notes: This figure summarizes money market fund (MMF) behavior, funding costs, and the absolute values of arbitrage spreads around the 2016 MMF reform. Compliance with the reform was required by October 2016 and so we define the reform event as occurring in October 2016. Panel A of the figure shows the time series of bank commercial paper held by MMFs. Panel B shows the average maturity-matched TED spread (LIBOR - Treasury) for the arbitrages in our sample. Denote l as the maturity of the nearest-maturity LIBOR for a given trade. The maturity-matched TED spread for the trade is then defined as $LIBOR(l) - Treasury(l)$. For trades with tenors longer than 1 year, we set $l = 1$ year based on the availability of LIBOR rates. Panel C shows the average arbitrage spread of trades that rely heavily on unsecured funding (CIP, Box, and Equity-Spot futures) and those that rely more on secured funding.

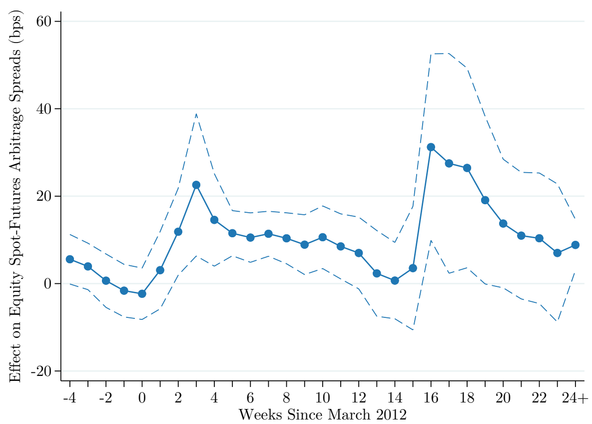
Figure 5: Event Study of the 2012 JPM London Whale



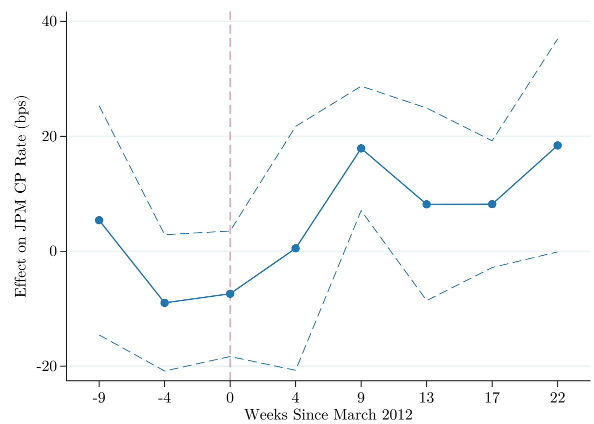
(a) 2012 YTD Losses on Credit Positions



(b) Arbitrage Spreads



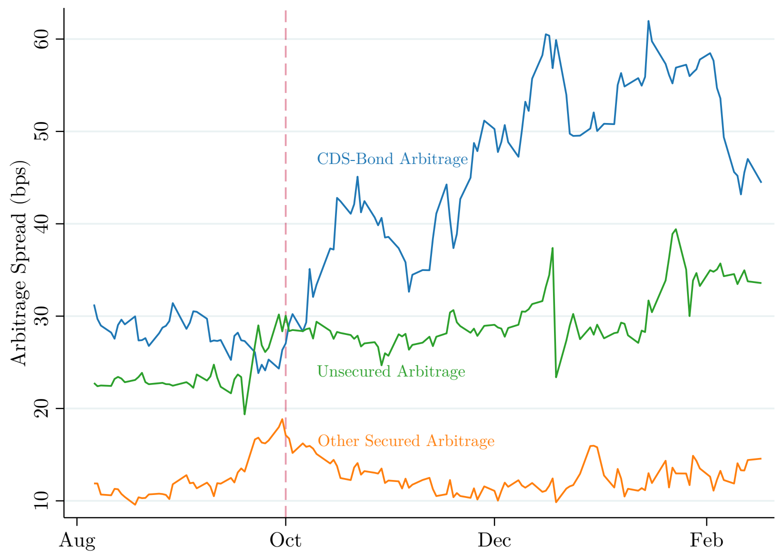
(c) Impact on Equity Spot-Futures Arbitrage



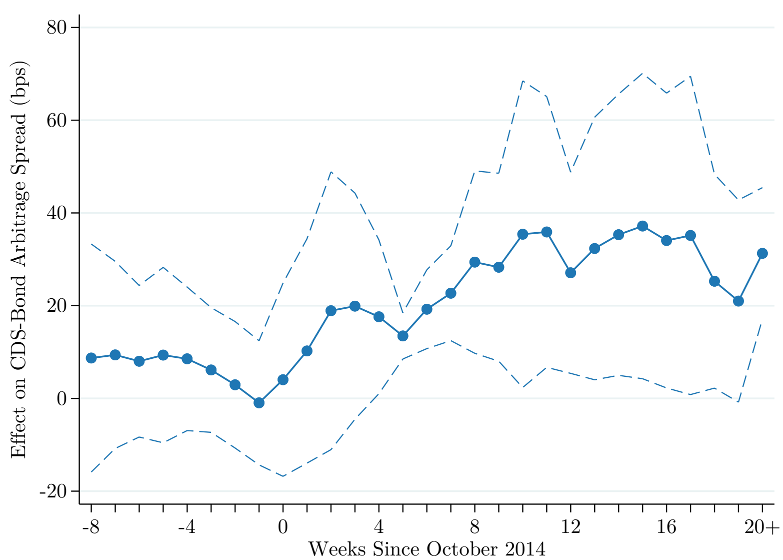
(d) Impact on JPM CP Rates

Notes: This figure summarizes JP Morgan's (JPM) losses, the absolute value of equity spot-futures arbitrage spreads, and JPM commercial paper (CP) borrowing rates around the 2012 JPM London Whale incident. Panel (a) of the figure shows the 2012 year-to-date losses on JPM's credit derivative portfolio, as reported by the U.S. Senate investigation into the incident. Panel (b) shows the daily average arbitrage spreads of equity spot-futures, other unsecured arbitrages (CIP and Box), and secured arbitrages in 2012. The first vertical line in the plot is March 1, 2012, which is when losses began to accelerate. The second dotted line is June 13, 2012, the first day that the CEO of JPM appeared before the U.S. Senate Committee on Banking, Housing, and Urban Affairs to testify about the Whale trades. Panel (c) shows the estimated impact on equity spot-futures arbitrage spreads, relative to other unsecured arbitrages (CIP and Box). The solid lines show the point estimates from a dynamic difference-in-difference model and the dotted lines show the associated 95% confidence intervals. Panel (d) shows the estimated impact on JPM's commercial paper (CP) rate, relative to the CP rates of other large global banks. See Section 5.2 for more details.

Figure 6: Event Study of the Deutsche Bank's 2014 Exit from CDS Trading



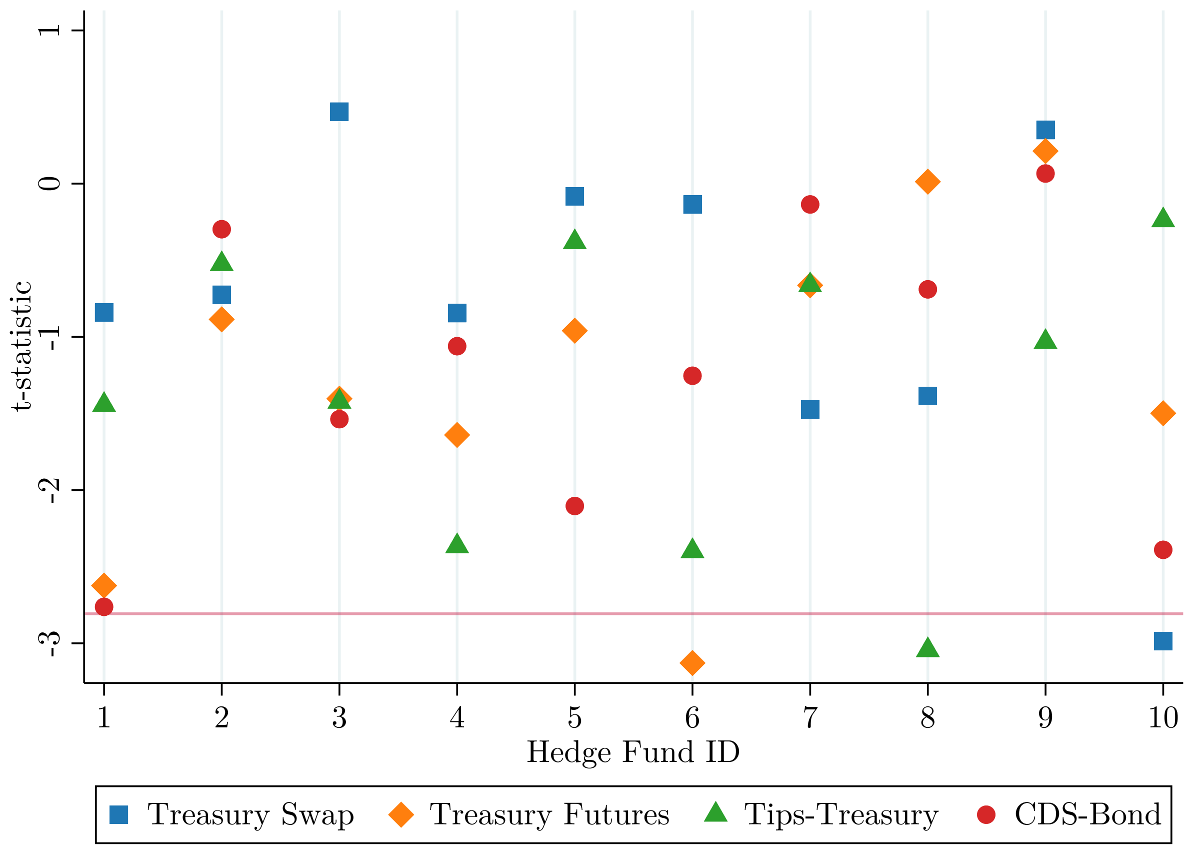
(a) Arbitrage Spreads



(b) Impact on CDS-Bond Basis

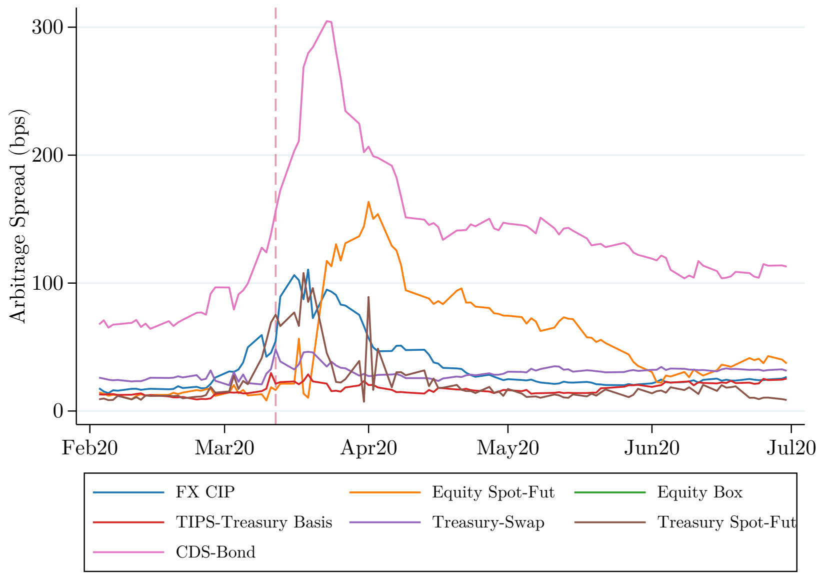
Notes: This figure summarizes the behavior of the absolute values of arbitrage spreads around the 2014 exit of Deutsche Bank (DB) from the CDS market. Panel (a) shows the daily average arbitrage spreads of CDS-Bond arbitrage, other secured arbitrages (Treasury Futures, Treasury Swap, and TIPS-Treasury), and unsecured arbitrages in the last half of 2014. The first vertical line in the plot is October 1, 2014. The exact timing of DB's exit is unknown, but there are reports that they sold a large portion of their CDS portfolio to Citibank in September 2014 and they publicly announced the exit on November 17, 2014. Panel (b) plots the point estimates from a dynamic difference-in-difference model and the associated 95% confidence intervals around the event. See Section 5.3 for more details.

Figure 7: Fixed Income Arbitrage Hedge Funds and Secured Arbitrages

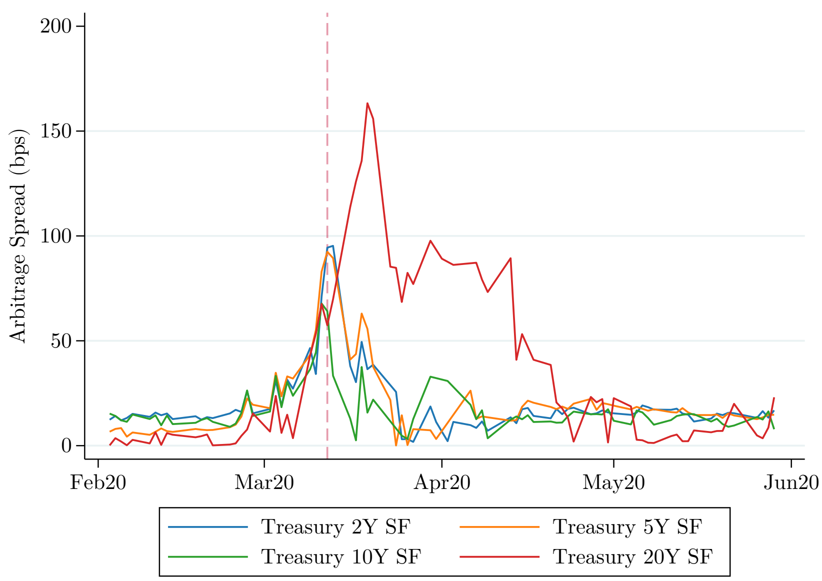


Notes: This figure plots the t-statistics from regressing monthly changes in the absolute values of arbitrage spreads on the lagged return of ten different fixed income hedge funds. Each hedge fund is indexed along the x-axis, and the y-axis shows the t-statistic from the regression. The different plot markers correspond to different strategies. We obtain returns of the ten largest Fixed Income Arbitrage Hedge Funds from Preqin. The horizontal red line corresponds to the Bonferroni-adjusted t-statistic that corresponds to a 5% significance threshold, which accounts for the fact that we run ten separate regressions for each strategy. Within each regression, we cluster standard errors by month.

Figure 8: Arbitrage Spreads at the Onset of Covid



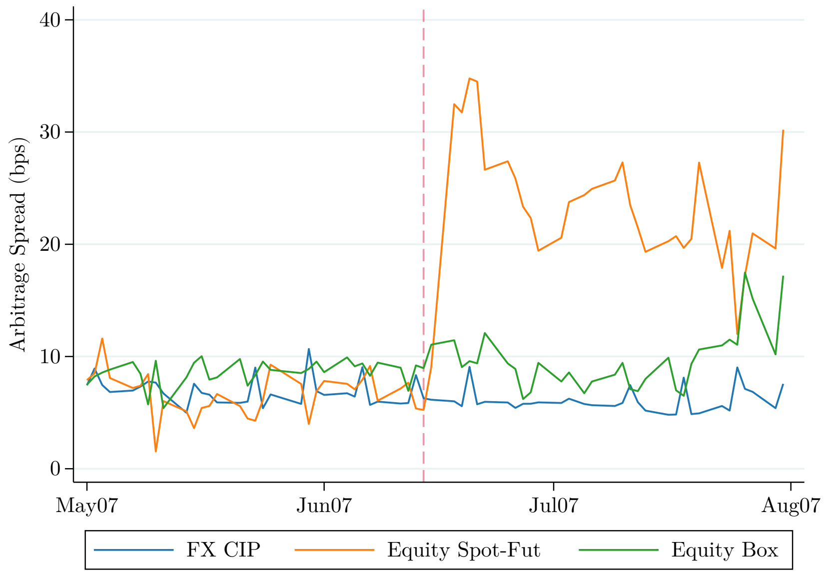
(a) Average Strategy-Level Spreads



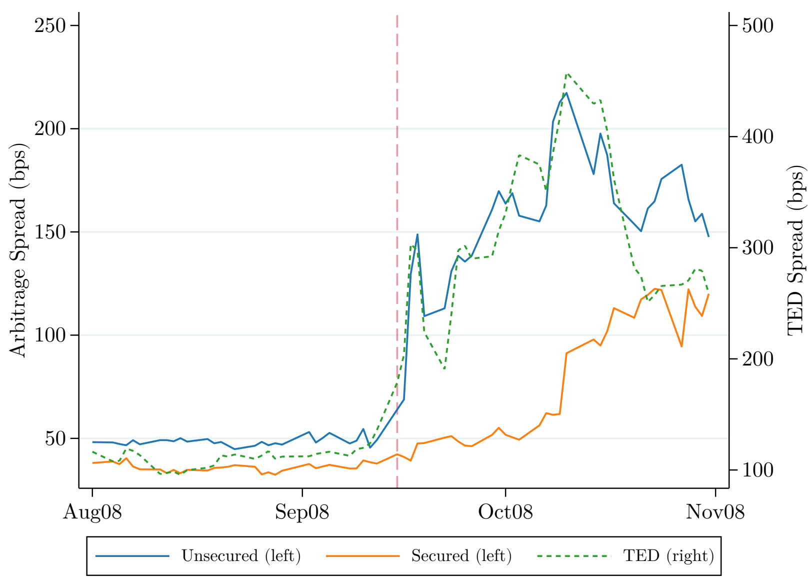
(b) Treasury Spot-Futures Arbitrage

Notes: Panel (a) of this figure shows the average level of the absolute values of arbitrage spreads by strategy at the onset of the Covid-19 pandemic. Panel (b) plots individual Treasury spot-futures arbitrage spreads over the same period.

Figure 9: Segmentation Prior to the Dodd-Frank Era



(a) Collapse of Bear Stearns Hedge Funds



(b) Lehman Bankruptcy and Run on MMFs

Notes: Panel (a) plots the average absolute values of arbitrage spreads for unsecured trades (CIP, Equity spot-futures, and Box) around the period when two of Bear Stearns's hedge funds were unwound. The red dotted line corresponds to June 14, 2007, the day that Merrill Lynch reportedly issued a margin call to the distressed hedge funds (Khandani and Lo, 2011). Panel (b) plots the average spread of secured and unsecured trades (left axis) and the 3-month TED spread (right axis) around the time of the Lehman Brother's bankruptcy and the run on the Reserve Primary Money Market Fund. The red dotted line corresponds to September 15, 2008, the day that Lehman Brothers declared bankruptcy.

Table 1: Summary Statistics for Arbitrage Spreads

	Mean	p50	Std. Dev	Min	Max	First	Last	N
Box 6m	34	34	11	0	82	Jan-10	Mar-18	2,048
Box 12m	33	32	10	0	87	Jan-10	Mar-18	2,048
Box 18m	31	31	9	2	64	Jan-10	Mar-18	2,048
Dow SF	45	45	24	0	139	Jan-10	Feb-20	2,487
NDAQ SF	38	40	22	0	123	Jan-10	Feb-20	2,474
SPX SF	42	41	20	0	116	Jan-10	Feb-20	2,481
AUD CIP	13	11	10	0	59	Jan-10	Feb-20	2,541
CAD CIP	12	9	10	0	62	Jan-10	Feb-20	2,541
CHF CIP	51	47	27	11	198	Jan-10	Feb-20	2,541
EUR CIP	35	33	21	0	118	Jan-10	Feb-20	2,541
GPB CIP	17	12	14	0	93	Jan-10	Feb-20	2,541
JPY CIP	45	41	24	10	125	Jan-10	Feb-20	2,541
NZD CIP	11	11	7	0	71	Jan-10	Feb-20	2,541
SEK CIP	27	21	22	0	99	Jan-10	Feb-20	2,541
Treasury 2Y SF	13	12	9	0	62	Jan-10	Feb-20	2,342
Treasury 5Y SF	13	9	11	0	58	Jan-10	Feb-20	2,380
Treasury 10Y SF	18	15	15	0	113	Jan-10	Feb-20	2,463
Treasury 20Y SF	17	13	14	0	79	Jan-10	Feb-20	2,469
Treasury 30Y SF	11	9	10	0	180	Jan-10	Feb-20	1,716
Treasury-Swap 1Y	6	5	5	0	32	Jan-10	Feb-20	2,541
Treasury-Swap 2Y	10	9	6	0	34	Jan-10	Feb-20	2,541
Treasury-Swap 3Y	12	10	8	0	36	Jan-10	Feb-20	2,541
Treasury-Swap 5Y	17	15	10	0	44	Jan-10	Feb-20	2,541
Treasury-Swap 10Y	26	25	12	0	59	Jan-10	Feb-20	2,541
Treasury-Swap 20Y	35	35	15	8	70	Sep-11	Feb-20	2,105
Treasury-Swap 30Y	54	51	19	23	100	Sep-11	Feb-20	2,105
TIPS-Treasury Basis	28	27	7	9	55	Jan-10	Feb-20	2,541
CDS-Bond IG	22	20	13	0	79	Jan-10	Feb-20	2,540
CDS-Bond HY	65	59	36	1	188	Jan-10	Feb-20	2,540

Notes: This table presents summary statistics on the absolute values of different arbitrage spreads. Trades are grouped by strategy (e.g., CIP). All CIP trades are for 3 month tenors. SPX, DJX, and NDAQ SF are spot-futures arbitrages for the S&P 500, Dow Jones, and Nasdaq indices, respectively. Treasury iY SF is the Treasury spot-futures arbitrage for i-year maturity Treasuries. CDS-Bond denotes the average CDS-Bond basis for investment grade (IG) and high-yield (HY) firms. See Section 3.1 and Internet Appendix A.1 for details on the construction of arbitrage trades. The columns First and Last are the month and year of the first and last observation for each series.

Table 2: Correlations Within and Across Arbitrage Strategies

(a) Distribution of All Pairwise Correlations

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\bar{\rho} > 0.67$	$\rho_{ij} = \rho$
0.21	0.32	-0.54	-0.02	0.19	0.43	0.96	406	0.00	0.00

88% of pairs reject H_0: $\rho_{ij} > 0.67$

(b) Distribution of Pairwise Correlations for Short-Tenor Trades

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\bar{\rho} > 0.67$	$\rho_{ij} = \rho$
0.19	0.32	-0.40	-0.02	0.15	0.35	0.89	120	0.00	0.00

87% of pairs reject H_0: $\rho_{ij} > 0.67$

(c) Average Within and Across-Strategy Correlations

	CIP	Box	Equity S-F	Treasury S-F	Treasury-Swap	TIPS-Treasury	CDS-Bond
CIP	0.35	0.36	0.27	0.06	0.36	-0.06	-0.00
Box	0.36	0.87	0.38	-0.05	0.34	0.05	-0.14
Equity S-F	0.27	0.38	0.86	-0.05	0.03	-0.10	-0.41
Treasury S-F	0.06	-0.05	-0.05	0.19	0.21	-0.04	0.28
Treasury-Swap	0.36	0.34	0.03	0.21	0.62	-0.16	0.30
TIPS-Treasury	-0.06	0.05	-0.10	-0.04	-0.16	-	-0.00
CDS-Bond	-0.00	-0.14	-0.41	0.28	0.30	-0.00	0.70

Notes: Panel A summarizes the distribution of pairwise correlations for all arbitrage strategies. The columns under p-value report tests of the null that the average pairwise correlation is above 0.67 and the null that all pairwise correlations are equal, respectively. Panel B mirrors Panel A and summarizes the distribution of pairwise correlations for all arbitrage strategies with tenors of less than six months. Panel C shows the average pairwise correlation within and across trades in each strategy.

Table 3: Margin Requirements for Arbitrage Strategies

		Margin Requirement (%)		
Arbitrage	Collateral	p10	Median	p90
Treasury Spot-Futures	Treasuries	2	2	2
Treasury-Swap	Treasuries	2	2	2
TIPS-Treasury	Treasuries	2	2	2
IG CDS-Bond	IG Corporate Bond	3	5	8
HY CDS-Bond	HY Corporate Bond	3	8	15
Equity Box	Equities	5	8	15
Equity Spot-Futures	Equities	5	8	15
CIP	Foreign Currency	6	6-12	12

Notes: This table shows margin requirements for each strategy. Margin data primarily come from the Federal Reserve Bank of New York's Tri-party Repo Infrastructure Reform Task Force. For currencies, we report data from central bank lending operations by the Bank of England and the European Central Bank.

Table 4: Arbitrage-Implied Riskless Rates and Funding Conditions

	Dep Variable: Δ Implied RF								
	Unsecured	Secured	CIP	Box	Equity S-F	TSwap	TFut	Tips-T	CDS-Bond
Δ Treasury	0.86**	0.93**	0.85**	0.96**	0.78**	0.99**	0.80**	1.03**	0.71**
	(7.47)	(42.12)	(5.66)	(9.19)	(2.88)	(60.79)	(8.80)	(33.75)	(9.81)
Δ TED	0.48**	0.07	0.35**	0.56**	0.77**	0.04	0.16	0.14	-0.24
	(4.23)	(1.26)	(2.24)	(4.45)	(3.81)	(0.94)	(1.38)	(1.62)	(-1.12)
R^2	0.18	0.60	0.22	0.37	0.11	0.95	0.11	0.91	0.53
N	1,625	1,773	968	294	363	807	603	121	242

Notes: This table shows monthly OLS regressions of arbitrage-implied riskless rates on maturity-matched Treasury yields and TED spreads. All variables are expressed in basis points. Define l and m, respectively, as the maturities of the nearest-maturity LIBOR and Treasury for a given trade. The maturity-matched TED spread for the trade is then defined as $LIBOR(l) - Treasury(l)$ and the maturity-matched Treasury yield is defined as $Treasury(m)$. l does not equal m for longer-tenor trades (e.g., 30-year Treasury swap) because the maximum maturity LIBOR rate we observe is one year. t-statistics are reported under point estimates and are based on standard errors clustered by strategy-month.

Table 5: Analysis of 2016 MMF Reform

	Dep Variable: Arb. Spread (bps)	
	(1)	(2)
β	11.82**	
	(2.26)	
$\beta_{j=-4}$		-5.25
		(-0.72)
$\beta_{j=-3}$		-0.33
		(-0.04)
$\beta_{j=-2}$		6.61
		(0.70)
$\beta_{j=-1}$		11.04
		(1.42)
$\beta_{j=0}$		17.40**
		(2.09)
$\beta_{j=1}$		18.28**
		(2.07)
$\beta_{j=2}$		21.43**
		(2.49)
$\beta_{j=3}$		16.35**
		(2.16)
$\beta_{j\geq 4}$		9.27*
		(1.90)
p: $\beta_j = 0, \forall j < 0$		0.00
p: $\beta_0 = \beta_1 = \beta_2 ...$		0.13
Adjusted R^2	0.60	0.60
N	54,710	54,710

Notes: This table shows estimates of the effect of the 2016 money market reform on the absolute values of arbitrage spreads. Column (1) presents estimates of the following daily regression: $s_{it} = \alpha_i + \alpha_t + \beta 1[i \in \mathit{Unsecured}] \times 1[t \geq \text{October2016}] + \varepsilon_{it}$, where s_{it} is the absolute value of the arbitrage spread for trade i on date t, $1[i \in \mathit{Unsecured}]$ is a dummy variable that equals 1 if trade i relies heavily on unsecured funding (CIP, Box, and Equity spot-futures), and $1[t \geq \text{October2016}]$ is a dummy variable that equals 1 on or after October 2016. Column (2) shows estimates of the regression: $s_{it} = \alpha_i + \alpha_t + \sum_{j=-4}^{3} \beta_j 1[i \in \mathit{Unsecured}] \times 1[t = \text{October2016} + j] + \beta_{j\geq 4} 1[i \in \mathit{Unsecured}] \times 1[t \geq \text{February2017}] + \varepsilon_{it}$. Arbitrage spreads are expressed in basis points. In column 2, we also report p-values for the null hypothesis that the coefficients prior to October 2016 (β_j for $j < 0$) are equal to zero, as well as the null hypothesis that the coefficients on or after October 2016 are equal to each other (β_j are equal for $j \geq 0$). All regressions include fixed effects for trade (α_i) and date (α_t). t-statistics are reported under point estimates and are based on standard errors clustered by trade and date. The estimation sample ends one year after the reform in October 2017.

Table 6: Arbitrage-Implied Riskless Rates and Funding Shocks to Fidelity

	Dep Variable: Δ Implied RF					
	(1) Equity S-F	(2) CIP/Box	(3) Secured	(4) Equity S-F	(5) CIP/Box	(6) Secured
Δ Treasury	0.70**	0.79**	0.92**	0.73**	0.78**	0.92**
	(2.07)	(6.31)	(39.25)	(2.19)	(6.13)	(36.56)
Δ TED	0.85**	0.28**	0.04	0.88**	0.27*	0.05
	(3.61)	(1.99)	(0.50)	(3.85)	(1.90)	(0.73)
Fidelity Flows	-2.57**	-0.38	0.43*	-3.46**	-0.24	-0.51
	(-2.83)	(-1.01)	(1.70)	(-2.18)	(-0.43)	(-1.23)
Estimation	OLS	OLS	OLS	IV	IV	IV
First-Stage F				102	154	266
R^2	0.11	0.19	0.56	0.10	0.19	0.54
N	309	1,088	1,523	294	1,033	1,447

Notes: This table presents regression estimates of monthly changes in arbitrage-implied riskless rates on flows out of Fidelity money market funds. The first three columns show OLS estimates, and the last three columns show IV estimates, where the instrument is net flows for the entire money market fund sector interacted with Fidelity's share of money market fund assets, lagged by six months. We also include the change in the maturity-matched Treasury yield and the change in the maturity-matched TED spread. Define l and m, respectively, as the maturities of the nearest-maturity LIBOR and Treasury for a given trade. The maturity-matched TED spread for the trade is then defined as $LIBOR(l) - Treasury(l)$ and the maturity-matched Treasury yield is defined as $Treasury(m)$. l does not equal m for longer-tenor trades (e.g., 30-year Treasury swap) because the maximum maturity LIBOR rate we observe is one year. See Section 4.3 for details on instrument construction. Columns (1) and (4) show estimates using only Equity spot-futures, columns (2) and (5) show estimates for other unsecured trades (CIP and Box), and columns (3) and (6) show estimates for all secured trades. All implied riskless rates are in basis points and flows are in percentage points. t-statistics are reported under point estimates and are based on standard errors clustered by strategy-month. The F-statistic from the first-stage of the IV is reported at the bottom of the table.

Table 7: Trading Behavior in U.S. Futures Markets

	Gross Share (%)			Position Size (% of Net)			Earns Arbitrage (% of days)		
	Dealers	HFs	Asset Mgrs	Dealers	HFs	Asset Mgrs	Dealers	HFs	Asset Mgrs
2-Year Treasury Notes	11	37	38	13	33	30	46	62	33
5-Year Treasury Notes	12	30	48	14	32	38	61	65	26
10-Year Treasury Notes	12	30	48	12	30	31	58	74	31
Treasury Bonds	12	25	56	25	14	43	44	37	22
S&P 500 Index	21	30	41	27	18	45	87	98	1
Nasdaq Index	35	31	29	41	19	29	79	29	14
Dow Jones Industrial Average	52	32	11	45	29	15	93	8	8
Average Treasury	12	31	48	16	27	36	52	60	28
Average Equity	36	31	27	38	22	30	87	45	8

Notes: This table summarizes the weekly positions of dealers, hedge funds, and asset managers using weekly reports on the Commitments of Traders provided by the Commodity Futures Trading Commission (CFTC). We use hedge funds (HFs) to designate traders who classified by the CFTC as "leveraged funds". Gross positions by type are computed as the sum of long, short, and spread positions. Gross share is the percent of total gross positions outstanding across all reporting agents. The columns listed under Position Size (% of Net) are computed as follows: (i) compute the net position of each type i in week t as $Net_{it} = Long_{it} - Short_{it}$; (ii) compute the total net outstanding of the market Net_{it} by summing $|Net_{it}|$ across all reporting agents; and (iii) Position Size (% of Net) is then $|Net_{it}|/Net_t$. We include the CFTC's "Other Reporting" agents in our calculation of gross and net outstanding, but do not report their share in the table. This means that shares in the table will not sum to 100. The Gross Share and Position Size are weekly averages for each contract. The columns under Earns Arbitrage shows the percent of days on which the net position of the type would earn the observed arbitrage spread.

Table 8: Fixed Income Arbitrage Hedge Fund Returns and Arbitrage Spreads

	Dep Variable: Δ Arbitrage Spread								
	Unsecured	Secured	CIP	Box	Equity S-F	TSwap	TFut	Tips-T	CDS-Bond
FI Arb HF Return$_{t-1}$	-0.03	-0.69**	-0.10	-0.67	0.67	-0.40**	-0.41	-0.55	-2.33**
	(-0.06)	(-2.95)	(-0.16)	(-1.04)	(0.68)	(-2.45)	(-0.82)	(-1.19)	(-2.72)
R^2	0.00	0.01	0.00	0.02	0.00	0.02	0.00	0.01	0.06
N	1,625	1,773	968	294	363	807	603	121	242

Notes: This table shows regressions of monthly changes in the absolute values of arbitrage spreads on the lagged aggregate return of hedge funds that specialize on fixed income arbitrage, as measured by Barclay's Aggregate Fixed Arbitrage Index. The aggregate return series is standardized to have mean zero and unit variance. The columns Unsecured and Secured pool strategies based on whether they rely on unsecured funding (CIP, Equity Spot-Futures, and Box). The remaining columns run the regression by strategy. Standard errors are clustered by strategy-month.

Table 9: Correlations in Crises

(a) During the Onset of Covid

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
0.32	0.37	-0.68	0.04	0.35	0.61	0.99	300	0.00	0.00

55% of pairs reject H_0: $\rho_{ij} > 0.67$

(b) During Global Financial Crisis

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
0.73	0.19	0.16	0.66	0.78	0.86	0.99	136	1.00	0.00

18% of pairs reject H_0: $\rho_{ij} > 0.67$

(c) Prior to Global Financial Crisis

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
0.10	0.21	-0.28	-0.05	0.06	0.21	0.90	136	0.00	0.00

98% of pairs reject H_0: $\rho_{ij} > 0.67$

Notes: This table summarizes the distribution of pairwise correlations for arbitrage strategies in different subsamples. In all cases, the columns under p-value are, respectively, based on tests of the null that average correlations are above 0.67 and the null that all pairwise correlations are zero. Panel A is based on all arbitrage strategies between March 1, 2020 through May 31, 2020. Panel B is based on the period between June 1, 2007 through June 30, 2009. Panel C is based on the period between January 2, 2004 and June 1, 2007. Treasury spot-futures and Treasury swap arbitrage are not included in Panels B and C due to data limitations.