Segmented Arbitrage*

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November 2021

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 twenty-nine arbitrage spreads that we study is 22%. These low correlations are inconsistent with models in which an integrated intermediary sector faces a single constraint and sets all prices. We show that at least two types of segmentation drive arbitrage dynamics. First, funding is segmented—certain trades rely on specific funding sources so arbitrage spreads are sensitive to localized funding shocks. Second, balance sheets are segmented—intermediaries specialize in certain arbitrages so arbitrage spreads are sensitive to idiosyncratic balance sheet shocks. Our results suggest specialization on both the asset and liability sides of intermediary balance sheets is important for understanding their role in capital markets.

*We thank Sam Hanson, Erik Stafford, and seminar participants at Copenhagen Business School and the University of Houston for helpful comments.

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1 Introduction

There is a 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 set of constraints, fund from a homogeneous household sector, and perfectly share risk with each other. 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, foreign exchange, and fixed income markets. We take this approach for three reasons. First, arbitrage is intermediated by financial institutions such as broker-dealers and hedge funds and cannot be easily performed by households. Second, the realized returns to arbitrages are accurate measures of their 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). Third, since arbitrage spreads are observable, the agency problems inherent in financial intermediation are likely smaller in this setting than in others. Frictions constraining financial institutions in riskless arbitrage are likely to loom larger in the intermediation of risky assets.

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. These 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 risk-free assets at the risk-free rate. Intermediaries may fund from different sources with different costs, and certain trades may require them to fund from a specific source (e.g., Treasury repo). We model these frictions in reduced form to focus on their implications for arbitrage spreads.

We first study an integrated intermediary sector. In this case, the factor structure of arbitrage spreads reveals the number of constraints and funding sources facing the representative intermediary. For instance, if the representative intermediary faces a single constraint (e.g., a leverage constraint), then all arbitrage spreads are determined by the shadow cost of the constraint. Thus, spreads will be perfectly correlated and follow a single-factor structure. Similarly, if the representative intermediary funds itself from a single source, then arbitrage spreads will again be perfectly correlated since all spreads will be driven by conditions in that funding market. These kinds of single-factor structures are widely assumed in theoretical and applied work on intermediaries.[1]

We then show how segmentation can reduce correlations between arbitrage spreads. We focus on two types of segmentation. The first is what we call funding segmentation—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. This kind of segmentation means that trades that can use the same funding source will tend to move together, but their correlation with trades that use different funding sources will be lower. The second type of segmentation that we highlight is balance sheet segmentation—different trades are performed by different specialist arbitrageurs. For example, some arbitragers may specialize in equity spot-futures, while others may specialize in Treasury spot-futures arbitrage. This form of segmentation implies that trades performed by the same arbitrageurs, and thus subject to the same balance sheet shocks, will be more correlated with each other than trades performed by different arbitrageurs.

We then 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 risk-free rate implied by no-arbitrage conditions (e.g., spot-futures parity) and actual short-term money market rates.

Our first result is that the daily correlation of spreads is low on average. The average pairwise correlation is 0.22 and 75th percentile of pairwise correlations is 0.42. These low correlations could in principle be driven by measurement error. However, measurement error would have to be large to explain our results since observed correlations are far from one. We can easily reject the null that the average pairwise correlation is above 0.67. In addition, we can reject the null that the individual pairwise correlation is above 0.67 for 87% (355/406) of trade pairs.[2] Furthermore, we observe a similar factor structure if we use weekly or monthly moving averages of arbitrage spreads. For instance, after taking monthly moving averages, eight principal components are still required to explain 90% of the common variation in arbitrage spreads. The data are far from the single-factor structure predicted by models with an integrated intermediary sector facing a single constraint.

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 they require more unsecured funding, we refer to these high-margin strategies as "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 these patterns reflect the higher exposure of unsecured arbitrages to

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

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

conditions in unsecured funding markets, which we proxy for with the Treasury-Eurodollar (TED) spread. We find that unsecured arbitrage spreads are nearly five times more sensitive to movements in the TED spread than secured arbitrages.

While the higher loading of unsecured arbitrage spreads on the TED spread is consistent with funding segmentation, it could also be driven by a 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 Du et al. (2019), we take two approaches. First, using a shift-share design, we instrument for the TED spread with the lagged share of unsecured lending by money market funds (MMFs) to banks. Second, we build an event study around the 2016 MMF reform, which resulted in a sharp contraction in unsecured lending by MMFs. Both designs show that unsecured arbitrage spreads are sensitive to the supply of unsecured funding, while secured arbitrage spreads are not. In other words, segmentation in funding markets is an important driver of segmentation in arbitrage activity.

We next provide evidence that funding markets are more segmented than the simple divide between secured and unsecured trades. Even within the unsecured lending market, there are persistent relationships between individual funders and intermediaries (Chernenko and Sunderam, 2014; Li, 2021; Hu et al., 2021). Thus, shocks to individual funding sources may move specific arbitrage spreads without moving others. We illustrate this idea by studying JP Morgan's role in equity spot-futures arbitrage. We first provide suggestive evidence from regulatory filings that JP Morgan plays an important role in this market. We then show that negative shocks to the supply of JP Morgan's unsecured funding raise equity spot-futures arbitrage spreads, even relative to other unsecured strategies.[4]

Our result so far highlight the role of funding segmentation. We next provide evidence

[4]We find a similar effect when looking at supply shocks to Fidelity MMFs. Hu et al. (2021) show that Fidelity MMFs are particularly active in equity repo financing.

that balance sheet segmentation also contributes to the overall low correlation of arbitrage spreads. In other words, it is not the case that a representative intermediary facing segmented funding engages in all strategies. We first provide event study evidence that the balance sheet constraints of certain intermediaries affect some trades more than others. One clear example is 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 commercial paper rates but did result in a tightening of the firm's risk limits (Senate, 2014). Using a difference-in-difference design, we show that the episode caused spreads on equity spot-futures arbitrage to rise relative to other spreads. We find similar results studying Deutsche Bank's exit from the CDS market in 2014.[5] CDS-bond bases rise relative to other arbitrage spreads during this event. Both cases illustrate the importance of particular intermediary balance sheets for particular arbitrages.

Finally, we examine the impact of hedge fund balance sheet constraints on fixed income arbitrage spreads. We focus on hedge funds because they have become increasingly active in fixed income arbitrage in recent years (Barth and Kahn, 2021). We measure their balance sheet constraints indirectly, using monthly returns as a proxy. The idea is that hedge funds face tighter balance sheet constraints following losses. At these times, arbitrage spreads should be higher for the trades in which hedge funds are important intermediaries. Consistent with this hypothesis, we find that aggregate hedge fund returns are negatively correlated with spreads on secured trades. Moreover, we document that specific hedge funds appear to matter for specific trades. For example, the hedge funds whose balance sheet shocks are important for the CDS-Bond basis are not the same as those that matter for the Treasury swap spread.

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

[5] Wang et al. (2021) show this event impacted the liquidity of the CDS market.

(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.[6] A second strand of the literature, including 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 asset prices.[7] 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 options (van Binsbergen et al., 2019), foreign exchange (Du et al., 2018), short-term money markets (Bech and Klee, 2011; Duffie and Krishnamurthy, 2016), and Treasury markets (Fleckenstein et al., 2014; Jermann, 2020; Barth and Kahn, 2021). Our paper departs from this part of the literature by simultaneously analyzing law of one price violations across many different markets. In doing so, we are able to characterize the nature of segmentation within the intermediary sector.

Overall, our results highlight the importance of segmentation in financial intermediation. We show that segmentation emerges from both sides of the intermediary balance sheet. Segmented balance sheets and segmented funding both impact arbitrage spreads. In this respect, we build on research that documents how shocks to specialized risk-bearing capacity can disconnect risk premia across markets (Shleifer and Vishny, 1997; Froot, 2001; Mitchell et al., 2007; Gabaix et al., 2007; Duffie, 2010; Chernenko and Sunderam, 2012; Hanson, 2014; Siriwardane, 2018; Eisfeldt et al., 2018). Our focus on fundamentally riskless arbitrage trades highlights the pervasiveness of these issues. The arbitrages we study are relatively

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

[7] Adrian et al. (2014) and He et al. (2017) argue in favor of integration by failing to reject the null that the price of risk to intermediary capital differs across market. 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.

straightforward to execute and have expected returns that are essentially observable. These characteristics should mitigate the typical agency problems thought to underlie segmentation and slow moving capital, 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.

2 Motivating Model

To fix ideas, we begin with a stylized model in which intermediaries determine arbitrage spreads while potentially facing multiple frictions. Suppose there are N arbitrage trades that are riskless. Normalize the risk-free rate to zero and assume that trade n has arbitrage spread $s_{n,t}$ at time t. For simplicity, we assume arbitrageurs have net long positions, which means 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 atomistic arbitrageurs engage in these trades and face several frictions, which we model in reduced form.[8] First, there are funding frictions. Suppose that there are L funding sources with associated cost $f_{1,t}, ..., f_{L,t}$ (in excess of the risk-free rate of zero) per unit borrowed.[9] One dollar of trade n can be financed with $w_{n,l}$ dollars from funding source $l \in L$. This assumption capture 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 risk-free rate. For instance, the basket of S&P 500 equities and a 3-month futures sale is riskless, yet arbitrageurs cannot fund that basket at the risk-free rate. In practice, the purchase of equities is often funding by unsecured borrowing at a rate above the risk-free rate. The

[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.

[9] We assume for simplicity here that funding is elastic, so that arbitrageurs can raise any amount of funding from source l at cost $f_{l,t}$. In our empirics, however, we will be careful to distinguish between variation in $f_{l,t}$ driven by the supply of funding versus the demand for funding.

assumption that $w_{n,l}$ does not vary over time corresponds to the empirical notion that rates on funding fluctuate more than haircuts (Copeland et al., 2010).

Let arbitrageur demand for trade n be $q_{n,t}$. In addition to funding frictions, there are K balance sheet requirements of the form $\sum_n q_{n,t} v_{n,k} = V_{k,t}$, which are meant to capture equity capital and liquidity constraints. These requirements may be set by regulators or by arbitrageurs themselves for internal risk-management purposes. The assumption that $v_{n,k}$ does not vary over time corresponds to the idea that the way trades enter each constraint is fixed over time. Arbitrageurs can adjust their balance sheets on each dimension at cost $\frac{1}{2} c_{k,t} V_{k,t}^2$, which capture the agency costs of external finance (e.g., signaling or debt overhang costs) and other adjustment costs.[10]

The arbitrageur's problem is:

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

Since arbitrageurs are atomistic, they take $s_{n,t}$ as given.

Generic solution. The first order condition for $q_{n,t}$ is

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

In other words, the spread on trade n is driven by funding costs and the marginal costs of balance sheet adjustment. 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 $q_{n,t} = a_{n,t}$.[11]

Eq. (1) shows that with a representative intermediary, arbitrage spreads generically have an $L + K$ factor structure. Since each funding source and balance sheet constraint can move separately and arbitrage spreads load differently on these factors, there are $L + K$ possible sources of variation in arbitrage spreads.

[10]Note that these costs cannot be risk based, as we are only considering riskless arbitrages.

[11]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 $a_{n,t} - b_n s_{n,t}$).

Single balance sheet constraint. Though it is very stylized, the model allows us to nest common assumptions in the intermediary asset pricing literature. For instance, many models of intermediaries feature a single balance sheet constraint, which can be captured by setting $f_{l,t} = 0$ for all l, $c_{1,t} \neq 0$, and $c_{k,t} = 0$ for all $k > 1$. [12] In this case, Eq. (1) reduces to

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

From this expression, it is clear that spreads will be perfectly correlated. There is a single factor $c_{1,t} V_{1,t}$ that moves all trades proportionally. This single factor is driven by multiple shocks (balance sheet shocks $c_{1,t}$ and outside demand shocks $a_{n,t}$).

Single funding factor. Another simple structure used by the intermediary literature is one with a single funding factor: $f_{n,1} > 0$, $f_{n,l} = 0$ for $l > 1$ and no balance sheet factors ($c_{k,t} = 0$,$v_{n,k} = 0$). 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.[13]

Segmented Funding. We next consider the impact of segmentation on spreads. We consider two types of segmentation: funding segmentation and balance sheet segmentation. 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 1 with corresponding cost $f_{1,t}$, while trades $n = N_1 + 1, ..., N$ can be funded only using

[12] 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 the ability to fully fund trades at the risk-free rate with trades loading on a single balance sheet requirement ($k = 1$).

[13] 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 $w_{n,equity} f_{equity,t}$ is equal to the arbitrageur's credit spread.

source 2 with corresponding cost $f_{2,t}$. If there are no further frictions ($V_k = 0$), we have

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

In this case, all trades that can be funded using source 1 are perfectly correlated and all trades that can be funded using source 2 are perfectly correlated. The correlation between the two groups equals the correlation between $f_{1,t}$ and $f_{2,t}$.

Segmented Balance Sheets. We next consider balance sheet segmentation. 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 therefore 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 costs $\varepsilon_{n,i}$ associated with arbitrageur i doing trade n. Further suppose that for trades $n = 1, ..., N_1$ arbitrageurs $i \in I$ have a cost advantage $\varepsilon_{n,i} < \epsilon_{n,j}$ over all other arbitrageurs $j \notin I$. Conversely, assume that for trades $n = N_1 + 1, ..., N$ the cost advantage is reversed so that arbitrageurs $i \in I$ have higher costs $\varepsilon_{n,i} > \epsilon_{n,j}$ than arbitrageurs $j \notin I$. 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. 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 sizes of the arbitrageur groups are similar in magnitude to the outside demand for the trade groups,[14] then spreads will be given by

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

Intuitively, spreads for trades $n = 1, ..., N_1$ will reflect the shadow cost of the balance sheet constraint of arbitrageurs in group I. For trades $n = N_1 + 1, ..., N$, spreads will reflect the shadow cost of the balance sheet constraint of arbitrageurs outside group I.

[14]This condition ensures that differences in marginal balance sheet costs do not swamp cost advantages.

The model also highlights what we can learn from spreads alone and what conclusions require ancillary data. For instance, if we observe a high-dimensional factor structure for spreads, we can reject simple models where a representative intermediary is subject to a single constraint or funds from a single source. However, a high-dimensional factor structure does not distinguish a representative intermediary subject to many constraints from either funding or balance sheet segmentation. In our results below, we will therefore start with the factor structure of spreads before providing direct evidence of segmentation. For instance, we will directly show that certain spreads comove with funding costs associated with 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

We analyze 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 risk-free rate based on observed asset prices and then subtract a maturity-matched risk-free rate. For arbitrage trades that mature in less than 2-years, the risk-free rate we use is the overnight indexed swap (OIS) rate; for longer-maturity trades, we use Treasury yields. We provide a detailed description of each arbitrage and its associated data source in 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

Spot-Futures Arbitrage in Treasuries For Treasury markets, we measure arbitrage spreads from spot-futures parity violations across the term structure. We study five such arbitrage trades, associated with 3-month futures on the 2-year, 5-year, 10-year, 20-year, and

30-year Treasury. On average, the implied risk-free rate from Treasury futures is higher than the 3-month OIS rate. To earn this spread, an arbitrageur would sell Treasury futures and hedge the position by buying Treasuries (see Appendix A.1.7).

Treasury Swap Arbitrage For interest rate swap markets, we measure arbitrage spreads between the fixed rate on overnight indexed swaps and Treasury yields. We study seven such arbitrage trades, associated with the 1-year, 2-year, 3-year, 5-year, 10-year, 20-year, and 30-year Treasury. On average, these fixed rates are higher than maturity matched Treasury yields. To earn this spread, an arbitrageur would pay fixed on interest rate swaps and hedge the position with cash Treasuries (see Appendix A.1.8).

TIPS-Treasury Arbitrage We follow Fleckenstein et al. (2014) and construct the difference in yield between a synthetic nominal Treasury, constructed from TIPS and inflation swaps, and the true nominal Treasury yield. On average the synthetic nominal Treasury yield is higher than the true nominal Treasury yield. To earn this spread, an arbitrageur would sell a synthetic Treasury and hedge the position with cash Treasuries (see Appendix A.1.9).

CDS-Bond Basis For U.S. corporate bond and credit default swap (CDS) markets, we measure arbitrage spreads from the difference between cash-bond implied credit spreads and CDS spreads. 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 1683 and 307, respectively. On average, credit spreads from cash-bonds are larger than those from CDS contracts. To earn this spread, the arbitrageur would buy corporate bonds and sell maturity-matched CDS contracts and Treasuries (see Appendix A.1.3).

CIP Arbitrage For foreign exchange (FX) markets, we measure arbitrage spreads from covered interest parity (CIP) violations, following Du et al. (2018). The cross-currency interest rate spread implied by FX spot and futures prices differs from actual rate spreads. On average, for the euro-US dollar and Japanese Yen-US dollars currency pairs, foreign currency futures are too expensive relative to spot and the difference in OIS rates across currencies. To earn this spread, the arbitrageur would borrow US dollars, exchange to foreign currency in the spot market, invest in foreign currency deposits, and lock in the future exchange rate with a futures sale (see Appendix A.1.4). We study 3-month CIP violations for eight currencies, the G-10 currencies excluding Denmark and Norway, for which we do not have OIS rates.

Spot-Futures Arbitrage in Equities For U.S. equity markets, we measure arbitrage spreads from spot-futures parity violations for three major equity indices, S&P500, Dow Jones, and NASDAQ. Our measure of equity market arbitrage spreads is the difference between the implied risk-free rates on 3-month futures and OIS rates. On average, the implied risk-free rate from equity futures is higher than the 3-month OIS rate. To earn this spread, the arbitrageur sells futures and hedges by purchasing the underlying spot equities (see Appendix A.1.1).

Box Arbitrage in Equity Options We study arbitrage spreads implied by put-call parity in equity options markets following van Binsbergen et al. (2019). To earn this spread, the arbitrageur implements a box-spread trade (see Appendix A.1.2), buying and selling put and call options with the same strike to implement put-call parity. We study three such trades, based on S&P500 options with maturities of 6 months, 12 months, and 18 months.

Table 1 provides summary statistics on the trades. The data is daily and spreads are reported in annualized basis points (bps). Unless otherwise specified, 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. 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 14 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.[15]

3.1.2 Quantity Data

In addition to data on arbitrage spreads, we use data from the Commodity Futures Trading Commission (CFTC) on quantities.[16] 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 use regulatory filings by money market mutual funds to measure their holdings and total net assets (TNAs). Money market mutual funds are required to file form N-MFP with the Securities and Exchange Commission (SEC) every month. These filings include detailed breakdowns on the funds' portfolios.

3.3 Hedge Fund Returns

We also use hedge fund returns from the Prequin 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 may be involved in the arbitrages we study.

[15] This difference in average spreads rules out simple models in which there is one constraint to arbitrage and each trade has the same weight on the constraint.

[16] The data are available here: https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm.

3.4 Characterizing Arbitrage Comovement

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 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 0.22 and 75th percentile of pairwise correlations is 0.42.[17] These results are at odds with simple structures for the intermediary sector. As we showed in Section 2, in many simple models with a representative intermediary, arbitrage spreads should be perfectly correlated. In particular, if the representative intermediary has either a single balance sheet constraint or faces a funding market with a one factor structure, then spreads should be perfectly correlated. Indeed, the model shows that if a representative intermediary faces a funding market with an L factor and has K balance sheet constraints, then arbitrage spreads should have a $L + K$ dimensional factor structure. In Figure 3, we conduct a principal components analysis of spreads. The figure shows the cumulative percentage of variation in arbitrage spreads explained as the number of principal components we consider rises. Consistent with the low correlations we documented above, it takes 11 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 the representative intermediary faces a large number of funding shocks and constraints, or there is significant segmentation in arbitrage.

A natural concern here is that measurement error biases the observed correlations towards zero. However, there are three reasons why we think measurement error is unlikely to drive

[17] Note that these low correlations apply to spreads. Correlations are higher between implied risk-free rates derived from arbitrage trades because all of those risk-free rates (imperfectly) track the true riskless rate.

the low correlations we observe. First, the measurement error would have to be large. To see why, suppose that the observed spread $s_{i,t}$ equals the true spread $s^*_{i,t}$ plus white noise:

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

Further suppose that the variance of measurement error $\varepsilon_{i,t}$ is a fraction θ of the variance of the true spread, $Var[\varepsilon_{i,t}] = \theta Var[s^*_{i,t}]$. In this case, the observed correlation between two spreads would be a fraction $1/(1+\theta)$ of their true correlation.[18] Under the assumption that all spreads are perfectly correlated and the variance of white noise is less than 50% of the variance of true spreads ($\theta < 0.5$), then the observed pairwise correlation of spreads 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 can reject the null that the individual pairwise correlation is above 0.67 for 87% (355/406) of arbitrage pairs in our sample.

The second reason that measurement error is unlikely to explain our results is that they our robust to smoothing. 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 8 principal components to cumulatively explain 90% of the variation in our arbitrage spreads.

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 do still have an interesting structure. Figure 3 shows that there is important common variation in spreads as emphasized by the previous literature, including Du et al. (2018), Du et al. (2019), and van Binsbergen et al. (2019). The first three principal components of spreads

[18]Formally, suppose we have two observed spreads s_1 and s_2 that are equal to the true spread plus noise: $s_{i,t} = s^*_{i,t} + \varepsilon_{i,t}$. Further suppose $Var[\varepsilon_{i,t}] = \theta Var[s^*_{i,t}]$. Then $Corr[s_{1,t}, s_{2,t}] = \frac{1}{1+\theta} Corr[s^*_{1,t}, s^*_{2,t}]$.

cumulatively explain about 60% of variation. If spreads were completely uncorrelated, we would expect them to only explain 33%.[19] Thus, our principal components analysis suggests significant underlying economic structure to arbitrage spreads.

Figure 2 and Table 2b 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, the average pairwise correlation of our three box trades is 0.87 and the average pairwise correlation of CIP spreads is 0.37. We explore these sources of correlation further in the next sections of the paper, arguing that they reflect segmentation in funding markets and segmentation in intermediary balance sheets.

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 risk-free 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. This friction opens the door to the debt overhang problem highlighted by Andersen et al. (2019). As the cost of funding for certain arbitrage trades moves, spreads will move as well.

We proceed in three steps. We start with suggestive evidence that there are differences in funding across the 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 2b, and the relatively low degree of comovement

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

between those spreads and the others we study. Finally, we show that segmentation within funding markets also helps explain why the box, CIP, and equity-spot futures spreads are not perfectly correlated.

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.[20] For currencies, little data is available from this source because the quantity of tri-party repo backed by international collateral is typically very small (less than 0.5% of total tri-party repo). Therefore we report data from central bank lending operations by the Bank of England and the European Central Bank.[21] 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 much 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 arbitrage spreads for trades that are unsecured funding intensive. In other words, frictions in funding markets—the inability to fund a risk-free portfolio at the risk-free rate—induces

[20] https://www.newyorkfed.org/data-and-statistics/data-visualization/tri-party-repo#interactive/margins

[21] https://www.bankofengland.co.uk/-/media/boe/files/markets/eligible-collateral/summary-tables-of-haircuts-for-bank-lending-operations.pdf, https://www.ecb.europa.eu/mopo/implement/omo/pdf/EUR-USD_tender_procedure.pdf

segmentation in arbitrage.

We start with OLS evidence in Table 4a. We work with implied risk-free rates from different arbitrages, as opposed to spreads that subtract out a benchmark risk-free rate, to ensure that the comovement we study is not generated by variation in the benchmark we use. In the first two columns, we run the following monthly panel regression:

$$\Delta r_{i,j,t} = \alpha_{i,j} + \beta_1 \Delta y_{i,t} + \beta_2 \Delta TED_t + \varepsilon_{i,j,t}, \tag{2}$$

where $r_{i,j,t}$ is the implied risk-free rate from individual trade i in broad strategy j in month t, $y_{i,t}$ is the yield on a Treasury with the same maturity as the horizon of the trade—a proxy for the true risk-free rate, and TED_t is the maturity-matched Treasury-Eurodollar (TED, i.e., Treasury minus LIBOR) spread—a proxy for unsecured funding costs.[22] Standard errors are clustered by broad strategy and month.

In the first column of Table 4a, 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 is higher than the margin requirements listed in Table 3, which may reflect that these trades require more unsecured funding on the margin than on average.

The second column of Table 4a 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, only one-quarter the magnitude (0.12 vs 0.50). In a panel regression (untabulated) that pools all trades, this difference is statistically significant at the 1% level. The remaining columns of Table 4a run the regression strategy-by-strategy, showing that the coefficient on TED is higher for all unsecured strategies than it is for any of the secured strategies.

[22] When the trade has a longer horizon than our available LIBOR data, we use the longest maturity available, which is 12 months.

Previous literature, including Garleanu and Pedersen (2011), has noted that arbitrage spreads are sensitive to the TED spread, particularly during periods when the financial system is stressed like the 2008-09 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 4a are consistent with funding segmentation, they are also consistent with balance sheet segmentation. For instance, suppose dealers specialize in unsecured trades. Then a deterioration in their balance sheet health could lead to a simultaneous rise in the TED spread and unsecured arbitrage spreads. To distinguish the role of funding segmentation, it therefore helpful to isolate how shocks to the supply of unsecured funding impact unsecured arbitrages. We take two related approaches to answering this question.

First, we instrument for the change in the TED spread using flows into and out of money market mutual funds (MMFs), an important source of unsecured funding. We take a Bartik-style approach, with the instrument in month t defined as the percentage change in total MMF assets under management between $t-1$ and t, multiplied by the share of MMF assets invested in unsecured lending to banks at time $t-k$. We measure these quantities in our N-MFP data. Anderson et al. (2019) also use this instrument, studying how CIP bases move around the 2016 MMF reform. As shown in Appendix Table A1 the first stage for the instrument is strong. As discussed in Goldsmith-Pinkham et al. (2020), the exclusion restriction here is that the share of MMF assets invested in unsecured lending to banks at time $t-k$ is uncorrelated with demand for funding from arbitrageurs at time t.[23] In other words, we do not require that aggregate flows into MMFs are uncorrelated with arbitrageur demand, only that past portfolio weights are uncorrelated with current arbitrageur demand.

Table 4b shows the results. The first two columns show results measuring MMF portfolio

[23] The value-weighted mean share of MMF portfolios in unsecured lending is 21% over our sample with a standard deviation of 10%. Much of this variation occurs around the time of the 2016 MMF reform, which we study below. Appendix Table A1 shows that we obtain similar results from the IV if we exclude 2016.

shares $k = 1$ month in the past. In the first column, we see that spreads on our unsecured trades are strongly related to the instrumented TED spread. The coefficient on the TED spread is larger than it is for our OLS results in Table 4a. One reason for this would be that when the TED spread is rising, these arbitrages suffer negative demand shocks. For instance, suppose that when investor risk aversion rises, investor demand to go long equity futures falls and the TED spread rises at the same time. Such shocks could drive down the correlation between the TED spread and the equity spot-futures arbitrage spread, lowering the coefficient in Table 4a. By isolating true funding supply shocks, our IV analysis in Table 4b reveals a strong relationship between funding and arbitrage spreads.

In the second column of Table 4b, we study spreads on secured trades. The results are similar to our OLS results, showing that these trades are not sensitive to unsecured funding conditions as measured by the TED spread. Indeed, the coefficient on the TED spread is slightly lower in the IV specifications than in OLS regressions and is not statistically distinguishable from zero.[24]

The remaining columns of Table 4b show that we obtain similar results if we measure MMF portfolio shares with longer lags, setting $k = 12$ for a one-year lag or $k = t - 1$ to take shares from the first observation in the sample. The coefficients are similar across these variations, though they are measured with less statistical precision when using MMF portfolio shares from the beginning of the sample because of a weaker first stage.

To supplement our IV analysis, we follow Anderson et al. (2019) and study the 2016 MMF reform. This reform modified SEC Rule 2a-7, which governs MMFs. In particular, the reform required prime MMFs, which lend unsecured to banks, to report floating net asset values (NAVs) rather than the stable (fixed) NAVs they had previously been allowed to report. Many MMF clients strongly prefer stable NAVs and so following the reform, many prime MMFs converted themselves into government MMFs. This allowed the MMFs to continue reporting stable NAVs, as their clients preferred, but as shown in Figure 4a, it significantly restricted

[24]This suggests that some shocks jointly affect secured and unsecured trades. The instrument, however, isolates shocks to unsecured funding.

their ability to lend unsecured to banks. Unsecured MMF lending to banks fell approximately \$550 billion as a result of the reform. Our analysis is similar Anderson et al. (2019); the key difference is that we examine a cross-section of arbitrage spreads to make the point that some spreads are affected by the funding shock more than others. In contrast, Anderson et al. (2019) focus on CIP and the arbitrage banks can perform between the federal funds rate and the interest rate on excess reserves, showing that both are affected by the shock.

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 will be 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. Again, this is consistent with the idea that unsecured funding shocks induce comovement in arbitrage spreads for unsecured trades but result in low correlations between secured and unsecured trades.

While Figure 4c looks similar to a differences-in-differences analysis, it is formally closer to a placebo test. In particular, the parallel trends assumption should hold under the null of perfectly integrated arbitrages. However, under our preferred interpretation—that unsecured-funding intensive arbitrages are segmented from other 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-funding intensive and other arbitrages would have remained fixed in the absence of the 2016 MMF reform. Instead, we simply interpret Figure 4c as showing that following a shock to unsecured funding, only certain arbitrages are affected.

Table 5 provides formal regression evidence corresponding to these figures. We run the following regression specification:

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

where $s_{i,t}$ is the arbitrage spread of trade i on date t. Following the reform, spreads on unsecured-funding intensive arbitrages rise about 20 basis points relative to other arbitrage spreads.[25] Furthermore, the effect appears to be long-lived. We cannot reject the hypothesis that the difference between unsecured-funding intensive arbitrages and other arbitrages are the same for all 16 months in our sample after the reform (through December 2017).

Taken together, the analysis in Tables 4b and 5 shows that segmentation in funding market is one broader driver of segmentation in arbitrage trades. Some trades—equity spot-futures, box spreads, and CIP—require more unsecured funding than others, and therefore these trades are more exposed to broad conditions in unsecured funding markets, as measured by the TED spread. Consequently, these trades tend to comove more with each other, than they do with secured trades.

4.3 Segmentation within Unsecured Funding

We next provide evidence that funding markets are more segmented than the simple divide between secured and unsecured trades we documented above. In particular, we argue that segmentation within unsecured funding markets helps to explain why the equity spot-futures, box, and CIP trades, while more correlated than other trades, are still not very 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), (Rime et al., 2017), (Li, 2021), (Hu et al., 2021)), we argue that relationships between intermediaries and their funding sources mean that shocks to individual funding sources move specific arbitrage spreads without moving others.

Our analysis proceeds in three steps. First, we use data from bank regulatory filings to provide suggestive evidence that JP Morgan is a particularly important intermediary for equity spot-futures arbitrage. According to Coalition Greenwich, a subsidiary of S&P that provides benchmarks for the financial services industry, JP Morgan has had the largest share

[25]The 25 bps increase in the TED spread is also consistent with the sensitivity of the TED spread to MMF flows that we find in Table A1.

of the market for equity derivatives since 2015.[26] This accords with data from the Y-9C regulatory filings. We use these filings to examine the trading book securities holdings of the top 25 bank holding companies by size over our sample period. Of those 25 holding companies, JP Morgan had by far the largest holdings of equity securities in its trading book over the period, accounting for 37% of all equity holdings. JP Morgan's dominance was greater earlier in the sample; for instance, it held 53% of all equities in trading books in 2010Q1. This evidence suggests that JP Morgan could play an outsized role in equity spot-futures arbitrage.

We next show that funding shocks to JP Morgan move equity spot-futures spreads but not other arbitrage spreads. In Table 6, we show that funding shocks to JP Morgan affect equity spot-futures spreads over and above the effect of the TED spread. In columns 1-3, we augment Eq. (2) with flows of unsecured funding to JP Morgan. Similar to Table 4b, we instrument for these flows using a Bartik-style approach because raw flows mix the demand for funding from JP Morgan with the supply of funding from MMFs. The instrument, which isolates supply shocks, is defined in month t as the percentage change in total MMF assets under management between $t-1$ and t, multiplied by the share of MMF assets invested in unsecured lending to JP Morgan at time $t-k$. Similar to our analysis in Table 4b, the exclusion restriction here is that JP Morgan's share of unsecured funding at $t-k$ is uncorrelated with its demand for funding at t.

In column 1 of Table 6, the dependent variable is the spread on equity spot-futures spreads. The coefficient on flows to JP Morgan is negative and significant. When JP Morgan receives a positive funding supply shock, equity spot-futures arbitrage spreads decline. A one percentage point increase in flows to JP Morgan is associated with a one basis point decline in equity spot-futures spreads. Column 2 shows that JP Morgan funding supply shocks have no impact on other trades that are unsecured funding-intensive, suggesting that JP Morgan is not the marginal intermediary for those trades. Column 3 shows that trades that are not

[26] https://www.bloomberg.com/news/articles/2020-03-26/jpmorgan-s-equity-derivatives-haul-said-to-soar-to-1-5-billion?sref=wacugGYd

unsecured funding-intensive are also not sensitive to JP Morgan's funding supply shocks.

Finally, to sharpen the analysis, we show that similar results obtain if we focus on Fidelity's family of MMFs. During our sample period, Fidelity MMFs were the largest provider of unsecured funding to JP Morgan, accounting for 22% of the firm's total unsecured borrowing on average. Furthermore, Hu et al. (2021) find that Fidelity MMFs were the largest provider of equity-repo financing from 2010 to 2013. In columns 4-6, we redo the analysis focusing on shocks to Fidelity. We augment Eq. (2) with flows to Fidelity MMFs, instrumenting for these flows with the percentage change in total MMF assets under management between $t-1$ and t, multiplied by the share of MMF assets managed by Fidelity at time $t-k$. We again find strong evidence that shocks to Fidelity affect equity spot-futures arbitrages, but not other arbitrages.

Taken together, our results suggest that funding segmentation is an important driver of segmentation in asset prices. Unsecured-funding intensive trades are broadly segmented from other trades because unsecured funding is segmented from secured funding, with the TED spread capturing these differences. Within unsecured funding, there is additional segmentation, which appears to be driven by relationships between funding sources and intermediaries. This segmentation means that even unsecured-funding intensive trades are somewhat segmented from each other.

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.

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 only in a net position to earn the spread on 7% 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 66% of days. Dealers are in a net position to earn the arbitrage spread on 58% of days, though their share of gross and net outstanding is 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

As argued in Section 4.3, JP Morgan appears to be a particularly important intermediary for equity spot-futures arbitrages. In this section, we examine the impact of an exogenous balance sheet shock to JP Morgan—the so-called London Whale episode—on equity spot-futures arbitrage spreads.

The London Whale episode was a result of activities in JP Morgan's Chief Investment Office (CIO) designed to hedge credit risk in the bank's lending portfolio. The Senate Permanent Subcommittee on Investigations issued a detailed report on the episode, from which we draw the following background information.[27] 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

[27] The report is available here: https://www.hsgac.senate.gov/imo/media/doc/REPORT%20-%20JPMorgan%20Chase%20Whale%20Trades%20(4-12-13).pdf

incurred significant basis risk, both in terms of 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 throughout 2012, reaching over \$6 billion by the end of the year.[28] 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 arbitrages. Losses incurred in the London Whale episode disproportionately tightened JP Morgan's balance sheet constraints, 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 spreads on unsecured trades, we run the regression:

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

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.

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 during over the same sample period. There is little evidence that funding costs

[28] At the time, the firm's market capitalization was about \$125 billion.

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 arbitrages and shocks to its balance sheet constraints therefore disproportionately impact those arbitrages.

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 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.[29] 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 affect on CDS-bond arbitrage spreads, as compared to other arbitrage spreads.

Figure 6a depicts spreads around the exit event. Throughout late 2014, CDS-bond arbitrage spreads rise, but other arbitrage spreads do not. Figure 6b provides formal statistical evidence, showing that the difference between CDS-bond arbitrage spreads and other secured spreads is significant at the 5% level. 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. This tightening moved CDS-bond arbitrages but not other arbitrage spreads.

[29] Notionals do not fall to zero because a substantial fraction of derivatives activity is for portfolio risk management, not arbitrage.

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 the 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.

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.[30] We run monthly regressions of the form:

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

where $s_{i,t}$ is the spread on trade i at time t and f_{t-1} is the return on the fixed income arbitrage hedge fund index at $t-1$. Standard errors are clustered by month and trade in columns 1-3 and by month in the remaining columns. The monthly return series is standardized to have mean 0 and unit standard deviation.

Column 1 of Table 8 shows that when we pool all arbitrage trades, there is no relationship between between fixed income hedge fund returns and spreads. Columns 2 and 3 disaggregates these results to reveal an important distinction between unsecured and secured trades. While the spreads of unsecured trades do not load on fixed income hedge fund returns, the spreads of secured trades do. Following a one-standard deviation increase in hedge fund fixed income arbitrage returns, secured arbitrage spreads decrease by 0.7 bps. This is consistent with the evidence in Table 7, which suggested that hedge funds are particularly important for secured trades. The remaining columns of Table 7 examine the relationship between individual

[30] For more information, see https://portal.barclayhedge.com/cgi-bin/indices/displayHfIndex.cgi?indexCat=Barclay-Hedge-Fund-Indices&indexName=Fixed-Income-Arbitrage-Index

arbitrage strategies and hedge fund returns. While none of the unsecured trades load on hedge fund returns, both Treasury-Swap spreads and CDS-bond bases load strongly.

Since we have individual hedge fund returns, we can explore more granular balance sheet segmentation. In Figure 7, we examine the relationship between the individual returns of the 10 largest fixed income arbitrage hedge funds. We use the Bonferri adjustment to calculate critical values because we are running 10 regressions for each arbitrage strategy. Figure 7 shows that different hedge funds appear to be particularly important for different arbitrage strategies. For instance, the CDS-bond basis is negatively and significantly correlated with returns of the biggest fixed income arbitrage hedge fund, while the third largest hedge fund appears to be particularly important for the TIPS-Treasury spread, and the ninth largest appears to be particularly important for the Treasury-Swap spread. Consistent with the idea that hedge funds are not particularly important for unsecured-funding intensive trades, we find no such relationships for these trades in Appendix Figure A3. It is worth noting that these results do not imply that single hedge funds are the only intermediaries that are marginal in a particular trade. Instead, they are likely to be representative of a broader set of intermediaries all following similar strategies and hence subject to similar balance sheet constraints.

Overall, these results suggest that balance sheet segmentation is important for explaining the low correlations of arbitrage spreads. Different intermediaries appear to play particularly important roles in different arbitrage strategies. As a result, when an intermediary playing an important role in one arbitrage suffers a balance sheet shock, the spread for that arbitrage can move without other arbitrage spreads being significantly affected.

6 Implications and 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. Given that riskless arbitrage is segmented, it is natural to think all arbitrage is segmented.

While we have studied funding segmentation and balance sheet segmentation as two separate frictions, it is possible that they interact in important ways. One natural interpretation of our results is that funding segmentation in part drives balance sheet segmentation. There are good reasons to think that dealers have an advantage in raising unsecured funding relative to hedge funds and other intermediaries. Given this advantage, it is natural for dealers to specialize in unsecured trades, which in turn generates balance sheet segmentation by making dealer balance sheets particularly important for those trades. 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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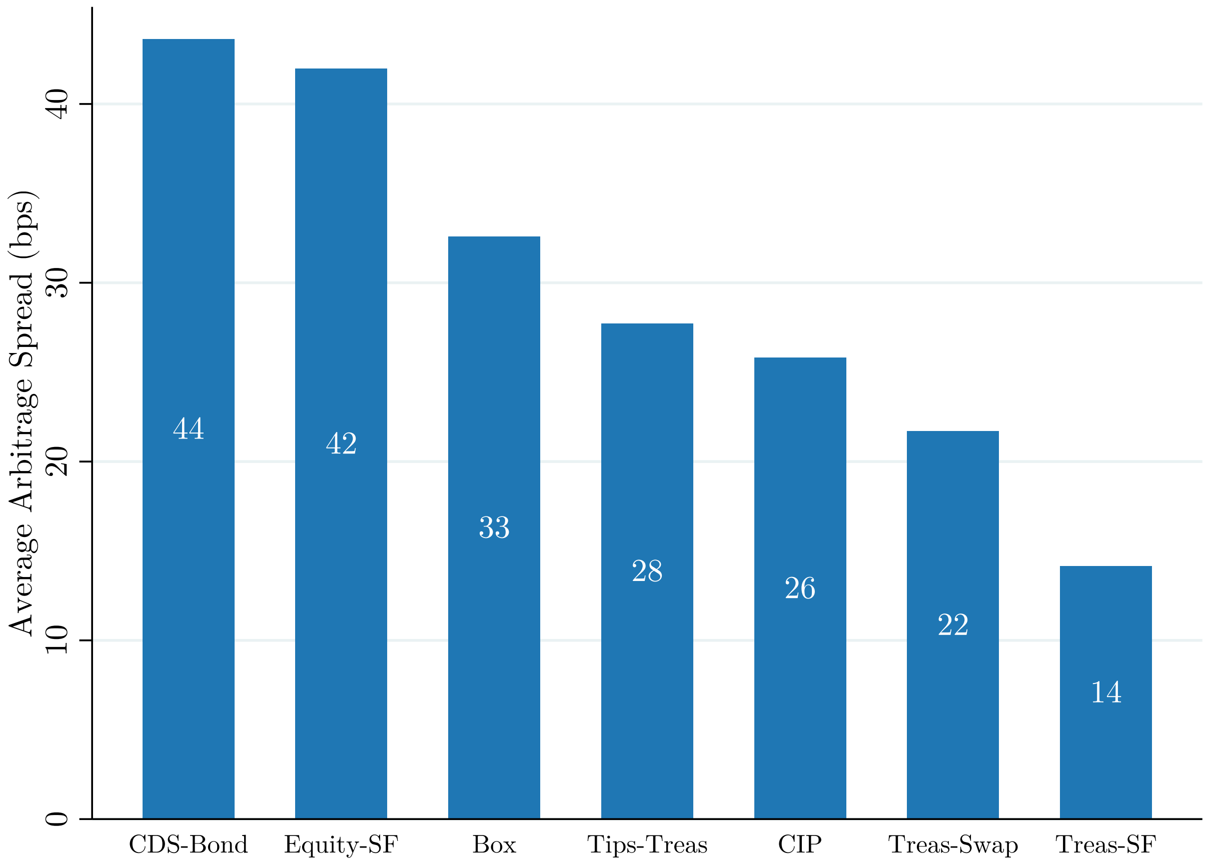
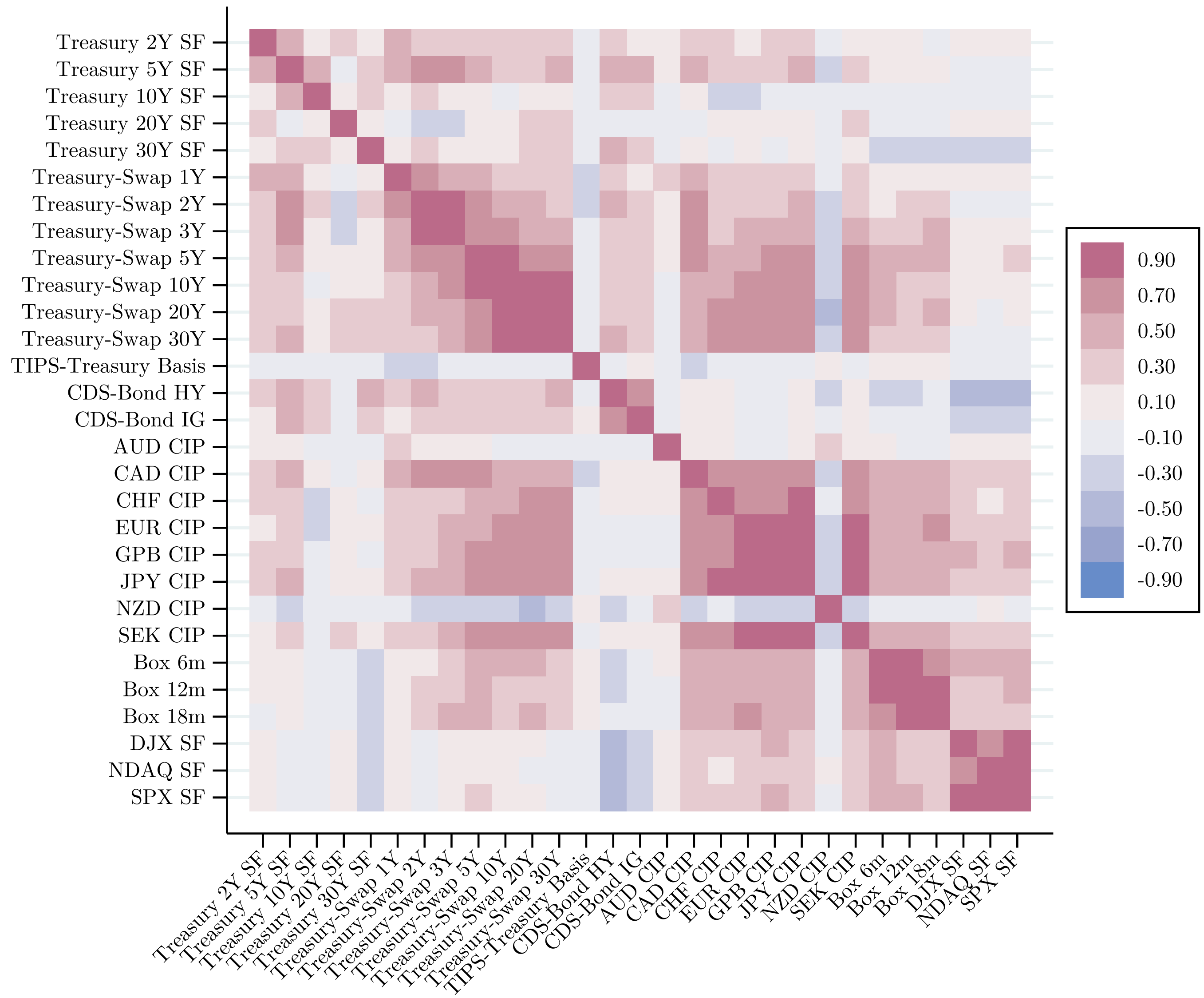
Figure 1: Arbitrage Spreads by Strategy



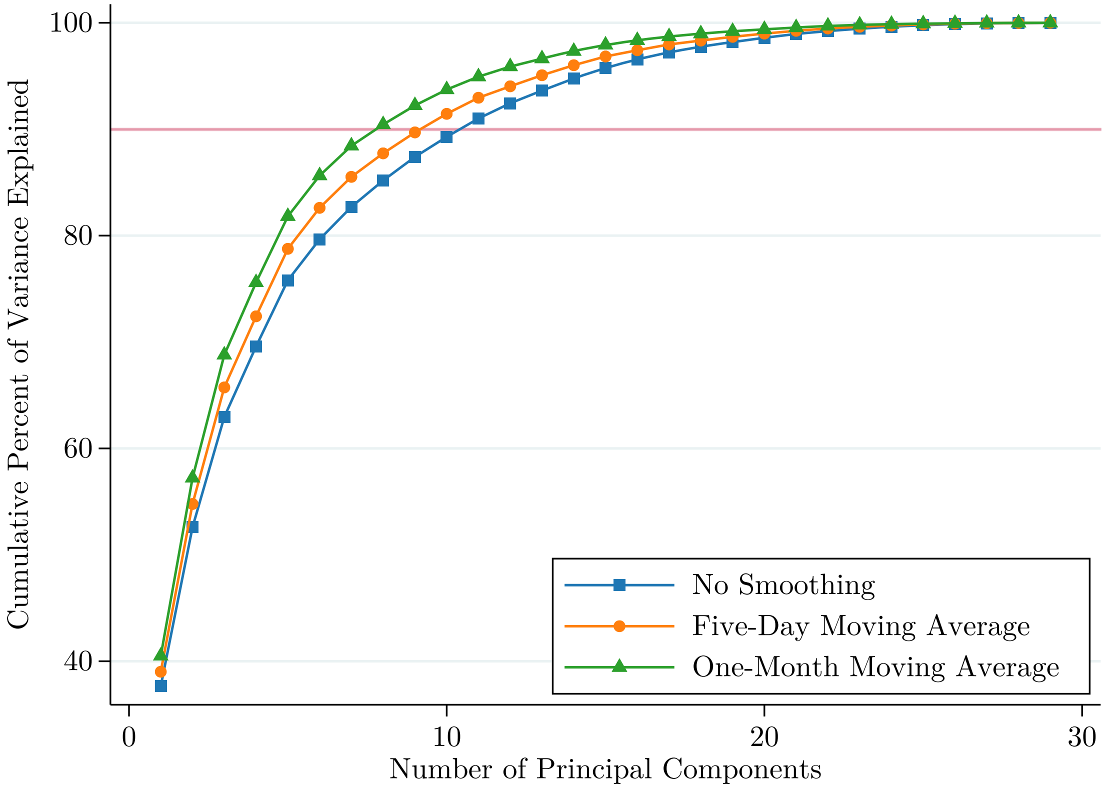
Notes: This figure shows average arbitrage spreads by strategy. Data is daily and spans January 1, 2010 to February 29, 2020

Figure 2: Correlation of Arbitrage Spreads



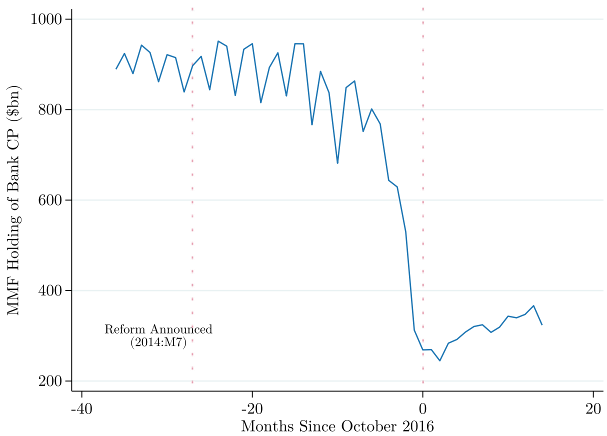
Notes: The figure shows the correlation matrix across all arbitrage trades in our sample. See section 3.1 for details on each trade. Data is daily and spans January 1, 2010 to February 29, 2020

Figure 3: The Factor Structure of Arbitrage Spreads

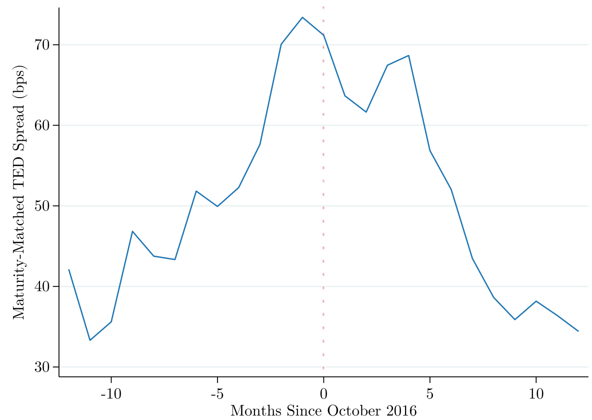


Notes: This figure summarizes principal component analysis for the arbitrage spreads in our sample. Each line shows the results of principal component analysis after we smooth each arbitrage spread over a different moving average window. The x-axis shows the number of components and the y-axis shows 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

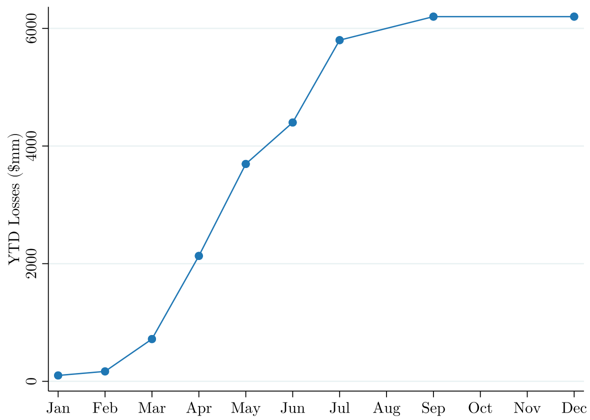


(b) Average Maturity-Matched TED Spread

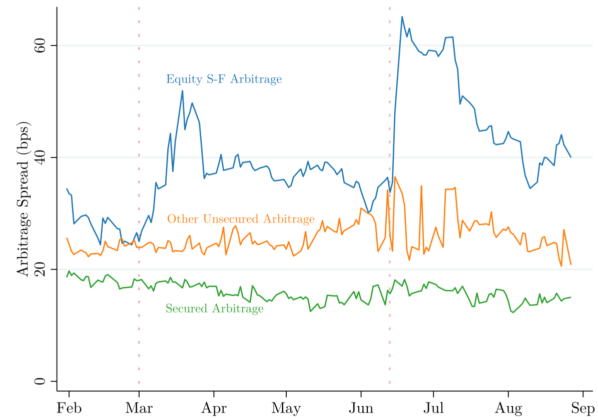
(c) Unsecured vs Secured Arbitrage Spreads

Notes: This figure summarizes money market fund (MMF) behavior, funding costs, and arbitrage spreads around the 2016 MMF reform. Compliance for 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 bought by MMFs. Panel B shows the average maturity-matched TED spread (LIBOR - Treasury) for the arbitrages in our sample. 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.

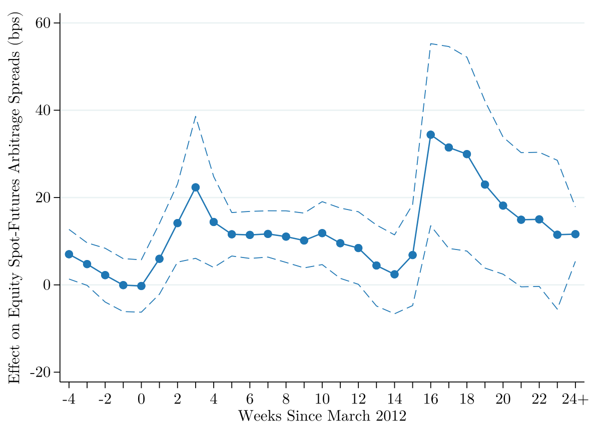
Figure 5: Event Study of the 2012 JPM London Whale



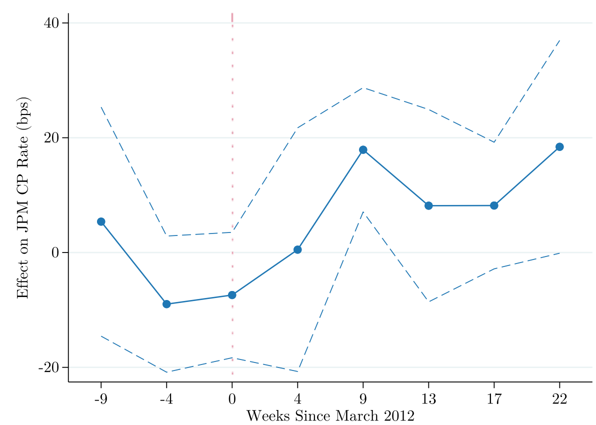
(a) 2012 YTD Losses on Credit Positions



(b) Arbitrage Spreads



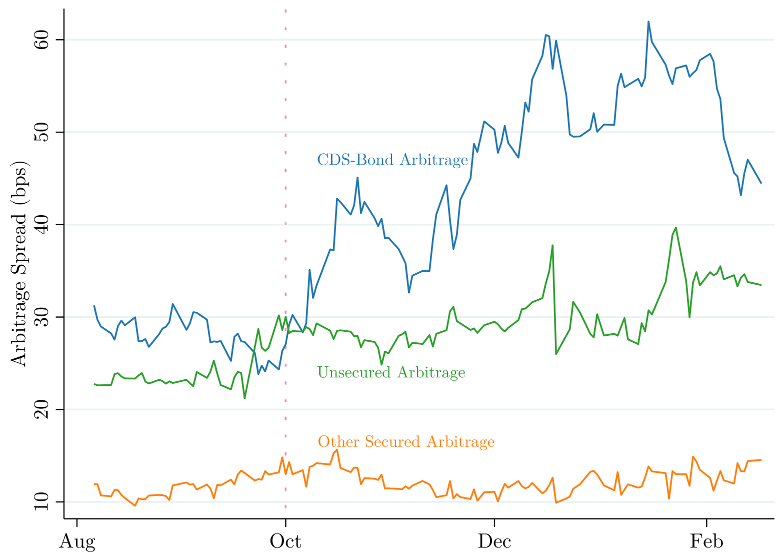
(c) Impact on Equity Spot-Futures Arbitrage



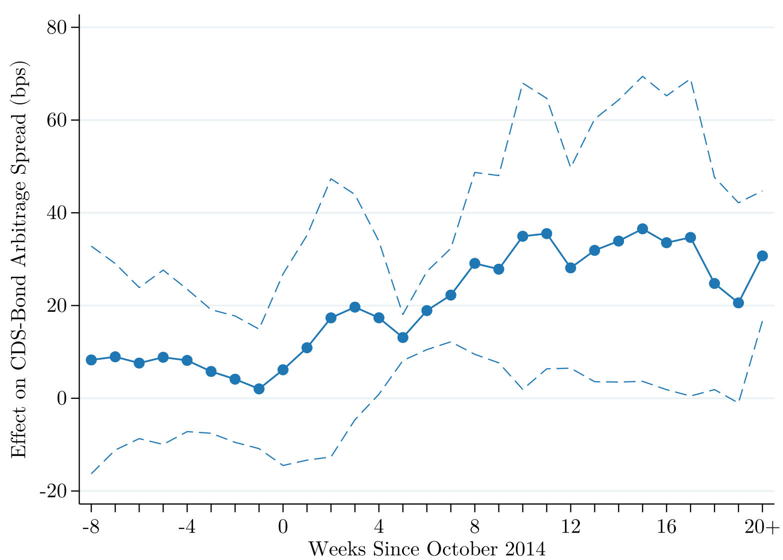
(d) Impact on JPM CP Rates

Notes: This figure summarizes J.P. Morgans's (JPM) losses, aggregate credit conditions, equity spot-futures arbitrage spreads, and JPM commerical paper (CP) borrowing rates around the 2012 JPM London Whale incident. Panel A of the figure shows the 2012 YTD 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 arbitrage (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 on which 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 interval. 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



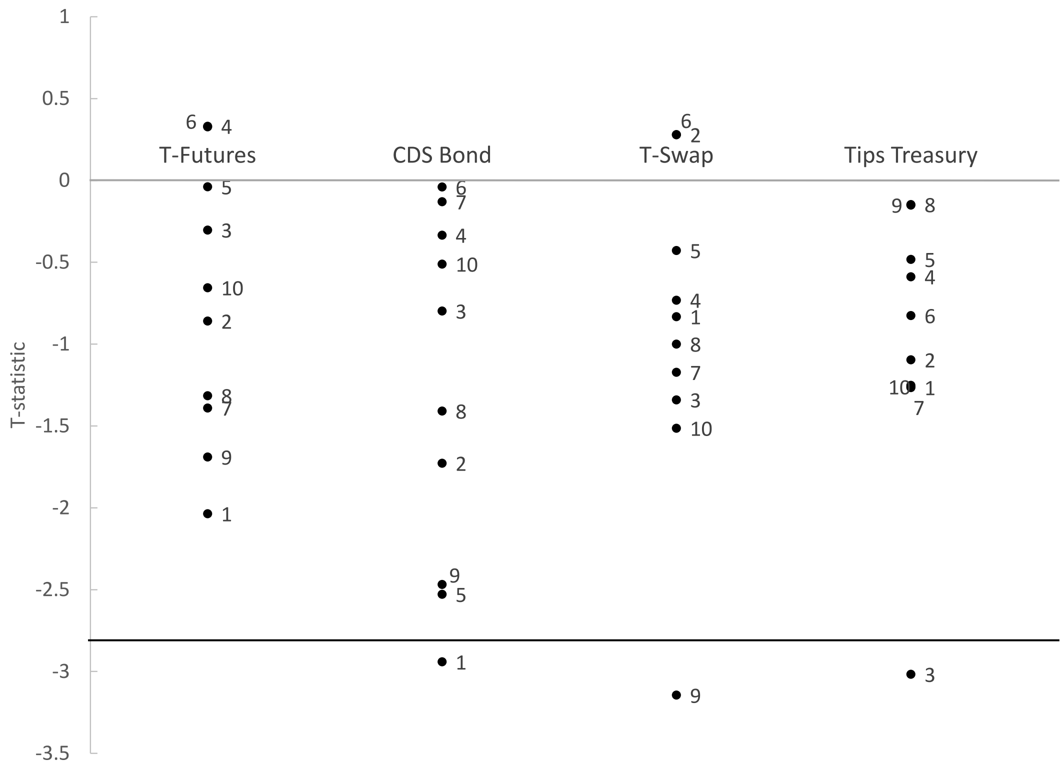
(a) Arbitrage Spreads



(b) DiD Estimates

Notes: This figure summarizes the behavior of arbitrage spreads around the 2014 exit of Deutsche Bank (DB) from the CDS market. Panel B shows the daily average arbitrage spreads of CDS-Bond arbitrage, other secured arbitrage (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 shows the estimated impact on CDS-Bond arbitrage spreads, relative to other secured arbitrages. The solid lines show the point estimates from a dynamic difference-in-difference model and the dotted lines show the associated 95% confidence interval. See Section 5.3 for more details.

Figure 7: Fixed Income Arbitrage Hedge Funds and Secured Arbitrages



Notes: This figure plots the t-statistics of regressing monthly changes in arbitrage spreads on one month lagged fixed income arbitrage hedge fund returns. We have four secured funding arbitrage strategies (Treasury Futures, CDS-Bond, Treasury-Swap, and Tips-Treasury) and returns from the 10 largest Fixed Income Arbitrage Hedge Funds from Preqin. Since we perform 10 regressions, we implement the Bonferroni adjustment to the standard 5% significance threshold, resulting in a t-statistic threshold of 2.81 (demarcated by the black reference line). We cluster standard errors by trade and month. There are three different hedge funds whose returns significantly negatively predict changes to next month CDS-Bond, Treasury-Swap and Tips-Treasury arbitrage spreads.

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	46	45	22	0	128	Jan-10	Feb-20	2,491
NDAQ SF	38	39	21	0	115	Jan-10	Feb-20	2,482
SPX SF	42	41	19	0	102	Jan-10	Feb-20	2,534
AUD CIP	12	10	10	0	59	Jan-10	Feb-20	2,541
CAD CIP	12	9	10	0	62	Jan-10	Feb-20	2,541
CHF CIP	53	51	30	11	199	Jan-10	Dec-17	2,000
EUR CIP	35	33	21	0	120	Jan-10	Feb-20	2,539
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	10	6	0	69	Jan-10	Feb-20	2,538
SEK CIP	27	21	22	0	100	Jan-10	Feb-20	2,507
Treasury 2Y SF	13	12	9	0	59	Jan-10	Feb-20	2,538
Treasury 5Y SF	12	9	10	0	54	Jan-10	Feb-20	2,538
Treasury 10Y SF	17	14	14	0	114	Jan-10	Feb-20	2,538
Treasury 20Y SF	17	13	15	0	79	Jan-10	Feb-20	2,530
Treasury 30Y SF	11	9	9	0	65	Jan-10	Feb-20	2,515
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	71	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 different arbitrage spreads, which are all converted to absolute values. All 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 (mid-contract minus near-contract) for the S&P 500, Dow Jones, and Nasdaq indices, respectively. Treasury iY SF is the Treasury-Futures arbitrage for i-year maturity Treasuries. CDS-Bond denotes the average CDS-Bond basis for all firms with available data. See Section 3.1 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	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
0.22	0.32	-0.51	-0.03	0.20	0.42	0.97	406	0.00	0.00

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

(b) Average Within and Across-Strategy Correlations

	CIP	Box	Equity-SF	Treasury-SF	Treasury-Swap	TIPS-Treasury	CDS-Bond
CIP	0.37	0.36	0.23	0.06	0.38	-0.07	0.00
Box	0.36	0.87	0.36	-0.09	0.31	0.05	-0.14
Equity-SF	0.23	0.36	0.83	-0.05	0.05	-0.10	-0.39
Treasury-SF	0.06	-0.09	-0.05	0.22	0.22	-0.07	0.29
Treasury-Swap	0.38	0.31	0.05	0.22	0.62	-0.16	0.30
TIPS-Treasury	-0.07	0.05	-0.10	-0.07	-0.16	-	0.00
CDS-Bond	0.00	-0.14	-0.39	0.29	0.30	0.00	0.70

(c) Within-Strategy Factor Structure

	Cum. Variance			
	PC1	PC2	k	N
Treasury-Futures Basis	0.39	0.61	5	2,507
Treasury-Swap Spread	0.68	0.88	7	2,105
Equity S-F	0.89	0.96	3	2,475
BOX-OIS	0.91	0.98	3	2,048
CIP	0.64	0.82	8	1,980
CDS-Bond Basis	0.85	1.00	2	2,540

Notes: Panel A summarizes the distribution of pairwise correlations for all arbitrage strategies. Panel B shows the average pairwise correlation within and across trades in each strategy. Panel C shows the cumulative percent of variation captured by the first and second principal component within each arbitrage strategy.

Table 3: Margin Requirements for Arbitrage Strategies

		Margin Requirement (%)		
Arbitrage	Collateral	p10	Median	p90
Treasury S-F	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 S-F	Equities	5	8	15
CIP	Foreign Currency	6	6-12	12

Notes: This table shows the margin requirements for trades within 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

(a) OLS Estimates

	Dep Variable: Δ_d Implied RF								
	Unsecured	Secured	CIP	Box	Equity S-F	TSwap	TFut	Tips-T	CDS-Bond
Δ Treasury	0.86**	0.93**	0.85**	0.97**	0.79**	0.99**	0.77**	1.03**	0.71**
	(7.84)	(43.29)	(5.98)	(9.30)	(2.91)	(60.78)	(5.92)	(57.10)	(9.82)
Δ TED	0.50**	0.12**	0.37**	0.55**	0.77**	0.04	0.23**	0.13	-0.25
	(4.46)	(1.98)	(2.38)	(4.37)	(3.78)	(1.04)	(2.08)	(1.49)	(-1.14)
R^2	0.18	0.71	0.22	0.37	0.11	0.95	0.16	0.95	0.53
N	1,599	1,775	942	294	363	807	605	121	242

(b) IV Estimates

	Dep Variable: Δ Implied RF					
	1-Month Lag for IV		12-Month Lag for IV		Initial Weights for IV	
	Unsecured	Secured	Unsecured	Secured	Unsecured	Secured
Δ Treasury	1.26**	0.92**	1.33**	0.91**	1.29**	0.94**
	(4.66)	(28.76)	(4.45)	(24.74)	(2.90)	(22.34)
Δ TED	1.57**	0.09	1.75**	-0.00	1.66	0.21
	(2.60)	(0.44)	(2.50)	(-0.02)	(1.58)	(0.73)
R^2	-0.05	0.71	-0.14	0.72	-0.09	0.71
N	1,277	1,470	1,123	1,305	1,277	1,470

Notes: Panel A of this table shows OLS regressions of arbitrage-implied riskless rates on maturity-matched Treasury and TED spreads. The maturity-matched TED spread for each trade is defined as $LIBOR(l) - Treasury(l)$, where l is the maturity of the nearest-maturity LIBOR rate. Panel B shows IV estimates using passive flows out of money-market mutual funds (MMFs) based on lags of aggregate portfolio weights. The columns under "Initial Weights for IV" use weights observed at the beginning of our sample to construct the instrument. See Section 4.2 for details on instrument construction. Unsecured trades include CIP, Box-Spreads, and Equity spot-futures. Secured trades are all others. Standard errors are clustered by strategy-month. Analysis based on end-of-month changes in all variables.

Table 5: Analysis of 2016 MMF Reform

	Dep Variable: Arb. Spread (bps)	
	(1)	(2)
β	10.83**	
	(2.09)	
$\beta_{j=-4}$		-5.19
		(-0.71)
$\beta_{j=-3}$		1.19
		(0.13)
$\beta_{j=-2}$		6.80
		(0.72)
$\beta_{j=-1}$		10.46
		(1.35)
$\beta_{j=0}$		16.67*
		(2.01)
$\beta_{j=1}$		17.76*
		(2.02)
$\beta_{j=2}$		21.89**
		(2.55)
$\beta_{j=3}$		14.76*
		(1.99)
$\beta_{j\geq4}$		8.08
		(1.67)
p: $\beta_j = 0, \forall j < 0$		0.00
p: $\beta_0 = \beta_1 = \beta_2...$		0.03
Adjusted R^2	0.59	0.60
N	55,822	55,822

Notes: This table showsestimates of the effect of the 2016 money market reform on arbitrage spreads. Column (1) presents estimates of the following regression: $s_{it} = \alpha_i + \alpha_t + \beta 1[i \in Unsecured] \times 1[t \geq \text{October2016}] + \varepsilon_{it}$, where s_{it} is the arbitrage spread of trade i on date t, $1[i \in Unsecured]$ 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: $s_{it} = \alpha_i + \alpha_t + \sum_{j=-4}^{3} \beta_j 1[i \in Unsecured] \times 1[t = \text{October2016} + j] + \beta_{j\geq4} 1[i \in Unsecured] \times 1[t \geq \text{February2017}] + \varepsilon_{it}.$. In column 2, we also report p-values from the null hypothesis that 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 date and trade. Data is daily and all arbitrage spreads are expressed in basis points.

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

	Dep Variable: Δ Implied RF					
	(1) Equity S-F	(2) Other Unsecured	(3) Secured	(4) Equity S-F	(5) Other Unsecured	(6) Secured
Δ Treasury	0.66	0.77**	0.93**	0.73**	0.78**	0.93**
	(1.57)	(6.29)	(42.20)	(2.26)	(6.47)	(42.63)
Δ TED	0.29	0.24	0.09	0.92**	0.28**	0.10
	(0.81)	(1.48)	(0.95)	(3.94)	(2.02)	(1.46)
Flows to JPM (IV)	-1.25**	-0.07	-0.02			
	(-2.25)	(-0.39)	(-0.15)			
Flows to Fidelity MMFs (IV)				-3.49**	-0.20	-0.05
				(-2.38)	(-0.39)	(-0.15)
R^2	-0.36	0.20	0.70	0.11	0.19	0.70
N	309	1,070	1,525	309	1,070	1,525

Notes: This table presents regression estimates of changes in arbitrage-implied riskless rates on the flow of unsecured lending to JPM or total flows out of Fidelity money market funds. In both cases, we instrument actual flows using passive flows based on the lagged amount of borrowing or lending relative to the aggregate. For example, the instrument for JPM flows is defined as $(w_{t-1} \times \Delta A_t)/J_{t-1}$, where A_t is the net assets of all money market funds at time t, J_t is the amount of unsecured lending to JPM, and $w_t = J_t/A_t$. We also include the change in maturity-matched Treasuries and the change in the maturity-matched TED spread. The maturity-matched TED spread for each trade is defined as $LIBOR(l) - Treasury(l)$, where l is the maturity of the nearest-maturity LIBOR rate. 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. Standard errors are clustered by strategy-month. Analysis based on end-of-month changes in all variables.

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	49	69	38
5-Year Treasury Notes	12	30	48	14	32	38	64	67	31
10-Year Treasury Notes	12	30	48	12	30	31	59	77	31
Treasury Bonds	12	25	56	25	14	43	62	51	38
S&P 500 Index	21	30	41	27	18	45	88	98	0
Nasdaq Index	35	31	29	41	19	29	80	29	13
Dow Jones Industrial Average	52	32	11	45	29	15	94	8	8
Average Treasury	12	31	48	16	27	36	58	66	35
Average Equity	36	31	27	38	22	30	87	45	7

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 calcuation 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

	Δ Arb Spread									
	All	Secured	Unsecured	CIP	Box	E-SF	TSwap	T-SF	Tips-T	CDS-Bond
FI Arb Ret (t-1)	-0.63	-1.31**	0.08	-0.41	-0.88	2.17	-0.71**	-0.85	-1.46*	-4.23*
	(0.50)	(0.57)	(0.99)	(0.94)	(1.17)	(2.05)	(0.31)	(0.98)	(0.79)	(2.18)
Adjusted R^2	0.00	0.01	-0.00	-0.00	0.00	0.00	0.01	0.00	0.02	0.04
N	3,374	1,775	1,599	942	294	363	807	605	121	242

Notes: We regress monthly changes in arbitrage spreads on the previous month return of the Barclay's index of fixed income arbitrage hedge funds. The monthly return series is standardized. Standard errors are clustered by month and trade for the pooled regressions (columns All, Secured, and Unsecured) and clustered by month for all other columns.