Segmented Arbitrage

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Motivation

- Growing recognition that intermediaries play a central role in asset pricing
- It is common in theory and applied work to assume that all intermediaries:
  - Perfectly share risk with each other
  - Fund trades from an integrated capital market
  - Face a single constraint (e.g., balance sheet size)
- These assumptions have several implications:
  - Consistent risk pricing across securities
  - Strong comovement of risk premia and arbitrage spreads
  - Liquidity injections to any intermediary have the same aggregate effect
- How substantive are these assumptions?

Assessing Intermediary Behavior is Hard

- These assumptions are difficult to assess empirically because:
  - Quantities are not easily observable
  - Little is known about capital flows within and across institutions

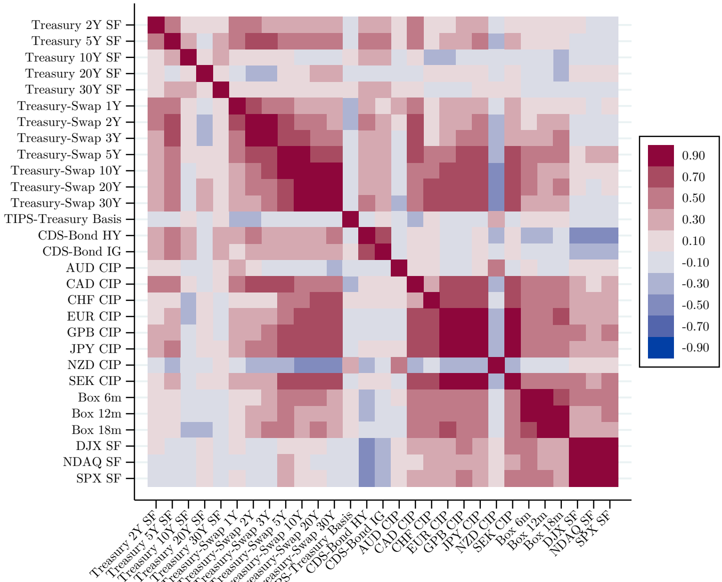
- Many studies try to circumvent data constraints by linking average realized returns to sectoral measures of intermediary health

- But these tests of integration are limited by the fact that average returns are a very noisy proxy for risk premia (Merton, 1980)

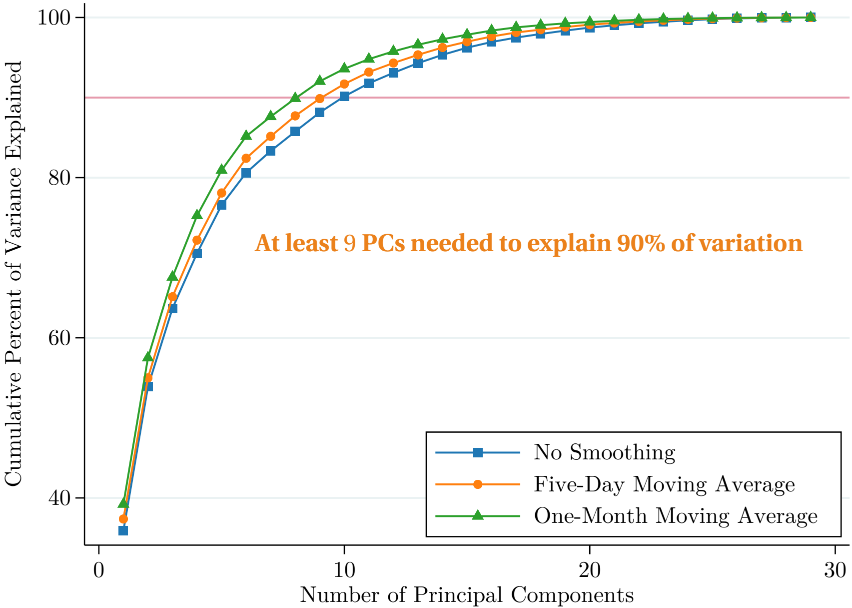
This paper

- Segmentation in the intermediary sector has a large effect on asset prices
- Argument based on the dynamics of (nearly) **riskless arbitrage**
- Several reasons why studying arbitrage is useful:
  - Intermediated (Haddad and Muir, 2021)
  - Expected returns are nearly observable, so higher powered tests
  - Agency problems should be relatively weak (riskless trades)
- 29 arbitrage trades spanning 7 broad strategies in the Dodd-Frank era:
  1. Covered Interest Parity (CIP)
  2. Equity Spot-Futures
  3. Box spread (Put-call parity)
  4. CDS-Bond Basis
  5. TIPS-Treasury Basis
  6. Treasury-Swap Spread
  7. Treasury-Futures Basis

Key Result: $\overline{\rho} = 0.21$



Key Result: High-Dimensional Factor Structure



Why is Arbitrage Segmented?

- **Funding segmentation:** some trades rely on specific funding sources
  - Ex: Treasury repo can be used for Treasury spot-futures arbitrage but not equity
  - Trades that rely on different funding sources have lower correlations
  - Higher ρ within strategies and between trades that need unsecured funding
  - Yet even within unsecured arbitrages (CIP, Box, and Equity), intermediary-specific funding relationships create segmentation

- **Balance sheet segementation:** arbitrageurs specialize, so different trades reflect different balance sheet constraints
  - JP Morgan is relatively important for equity spot-futures arbitrage
  - Deutsche Bank (was) relatively important for CDS-Bond arbitrage
  - Hedge funds are important for repo intensive trades

Data

Arbitrage Trades

1. **Foreign exchange (FX):** Covered interest parity (CIP) bases (Du et al., 2018)
    - G-10 countries minus Denmark and Norway
2. **Equity spot-futures**: S&P 500, Dow, and Nasdaq 100
3. **Equity options**: Put-call parity or “box spreads” (van Binsbergen et al., 2019)
    - 6m, 12m, and 18m S&P 500 index options.
4. **CDS-bond**: Aggregate individual bases into IG and HY indices
5. **TIPS-Treasury:** Basis vs inflation swaps (Fleckenstein et al., 2014)
6. **Treasury-swap spread**: 1, 2, 3, 5, 10, 20, and 30 year
7. **Treasury spot-futures**: first-deferred futures on the 2, 5, 10, 20, and 30 year

For each, we compute implied riskless rates (r) and arbitrage spreads (s)

Additional Data

1. **Money Market Mutual Funds (MMFs)**
   - Portfolio holdings and flows from SEC form N-MFP
   - Use to build aggregate and fund/borrower-specific flow

2. **CFTC Quantity Data**
   - Open interest in futures by trader “type”
   - Three types: dealers, asset managers, leveraged funds

3. **Hedge fund returns** from Preqin
   - Measure fund-specific returns in specific arbitrage strategies

First Key Result: Low correlations

Conceptual Framework

Academic research typically assumes intermediaries:

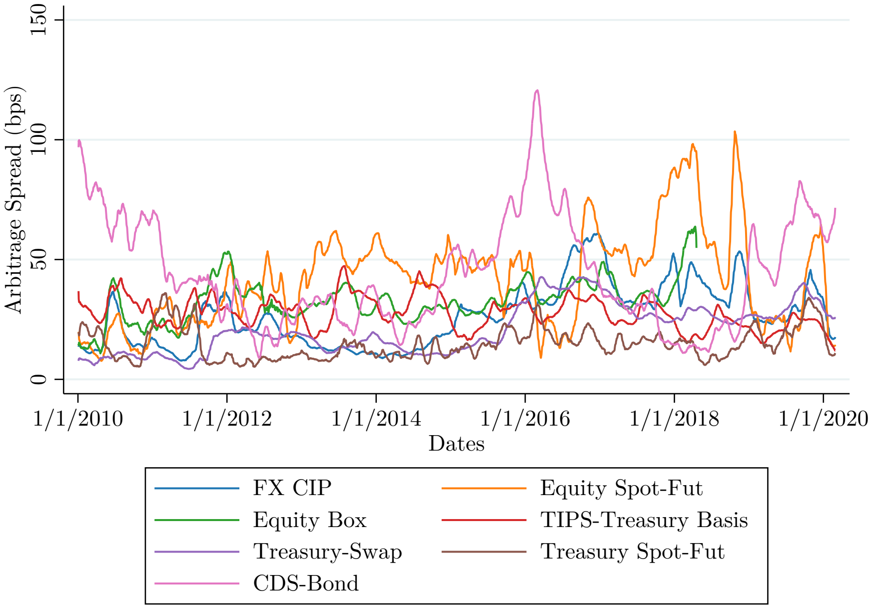
1. **Can be analyzed at the sectoral level ("representative intermediary")**
   - Sensible if the marginal cost of a trade is the same across all institutions

2. **Face a limited number of constraints**
   - E.g., a single balance sheet constraint on leverage

3. **Fund operations from an integrated funding market**
   - Means that trades with the same risk have same marginal funding cost

These assumptions imply a low-dimensional factor structure for arbitrage spreads

Evidence from Time Series



Distribution of Pairwise Correlations

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
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: $\rho_{ij} > 0.67$

- Pairwise correlations are low on average ($\overline{\rho} = 0.21$)
- 75% of pairs have a correlation of less than 0.43
- Concerns: Low daily correlations may be driven by
  1. Noise-trader or convergence risk
  2. Measurement error (e.g., execution-related)

Are Low Correlations Driven by Convergence Risk?

- Focus on trades with short tenors (CIP, Equity S-F, and Treasury S-F)
- Correlations are still low: $\overline{\rho} = 0.19$

ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
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: $\rho_{ij} > 0.67$

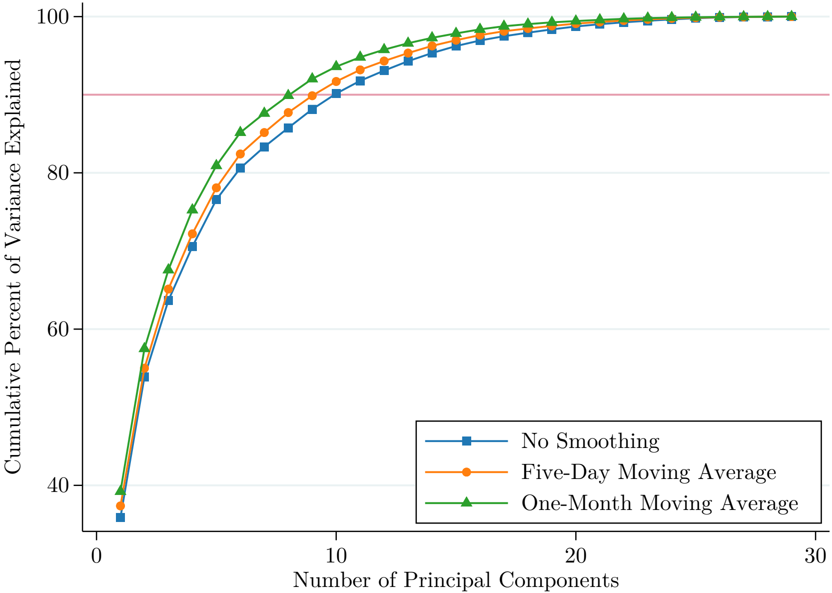
Are Low Correlations Driven by Measurement Error?

- Any measurement error or noise will bias correlations down

- We address this possibility in three ways:
  1. Smoothing the data
  2. Measuring how large noise would need to be to generate $\overline{\rho} = 0.21$
  3. Directly estimating size of noise and adjusting correlations accordingly

- Main conclusion: measurement error isn't driving low correlations

Results Robust to Smoothing



Measured vs. True Correlations

- Suppose true spreads $s^*_{i,t}$ are observed with error:

$$s_{it} = s^*_{it} + \varepsilon_{it}$$

- Let n_i be the noise-to-signal variance ratio:

$$n_i = \frac{Var[\varepsilon_{it}]}{Var[s^*_{it}]}$$

- The measured correlation ρ_{ij} and true correlation ρ^*_{ij} are linked as follows:

$$\rho_{ij} = \frac{\rho^*_{ij}}{a_i a_j}$$

where correlation "adjustment factors" $a_i = \sqrt{1 + n_i} \geq 1$

How large would measurement error need to be?

- When $n_i = n$, then the wedge between ρ_{ij} and ρ^*_{ij} simplifies to:

$$\rho_{ij} = \frac{\rho^*_{ij}}{1+n}$$

- To observe $\overline{\rho} = 0.21$ when $\rho^*_{ij} = 1$, error variance would need to be **4x** the variance of the true spread ($n \approx 4$)

- Alternative framing: for $n < 0.5$ and $\rho^*_{ij} = 1$, we should observe $\rho_{ij} > 0.67$
  - Yet 88% of pairs reject the null that $\rho_{ij} > 0.67$

- **Main point:** Lots of noise needed to generate such low observed correlation

Directly measuring correlation adjustment factors

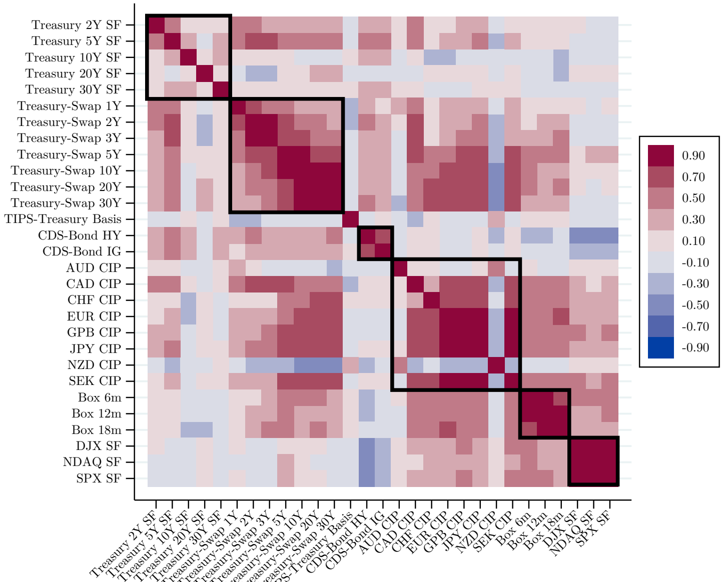
- Under certain conditions, correlation adjustment factors a_i can be inferred from instrumental variable regressions

- Our instrument logic: any execution-induced error today should be uncorrelated with errors from the previous quarter

- Concretely, consider the Treasury spot-futures arbitrage today (9/19/2022):
  - Spread computed from first-deferred contract (expires Dec 2022)
  - Instrument based on spreads on June 2022 contract

- **Main finding:** Average adjusted correlation is still low ($\overline{\rho} = 0.19$)

Correlations are High within Strategies



Funding Segmentation

Why is Arbitrage Segmented?

- High-dimensional factor structure cuts against the common assumption of a representative intermediary or arbitrageur

- Instead implies that arbitrage activity is segmented

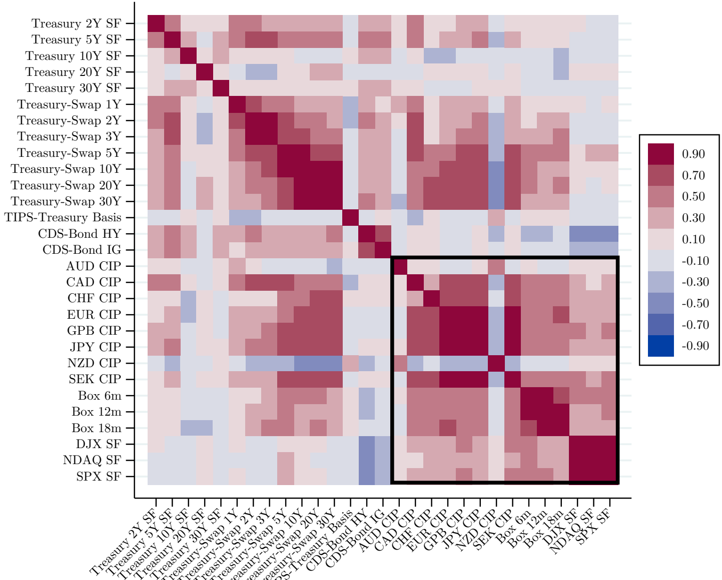
- We now document two sources of this segmentation:
  1. **Funding segmentation**
  2. Balance sheet segmentation

Funding Segmentation: Margin Requirements

		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

- CIP, equity spot-futures, and box require more **unsecured** funding
- Label as "unsecured" trades and label the rest "**secured**" trades

Correlation of Secured vs Unsecured Trades



Arbitrage-Implied Riskless Rates and Funding Conditions

- Unsecured trades should be more sensitive to unsecured funding conditions
- Test using OLS regressions:

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

	Dep Variable: Δ Implied RF	
	Unsecured	Secured
Δ Treasury	0.86**	0.93**
	(7.47)	(42.12)
Δ TED	0.48**	0.07
	(4.23)	(1.26)
R^2	0.18	0.60
N	1,625	1,773

Isolating Funding Shocks

- Are funding conditions *causing* spreads to move?

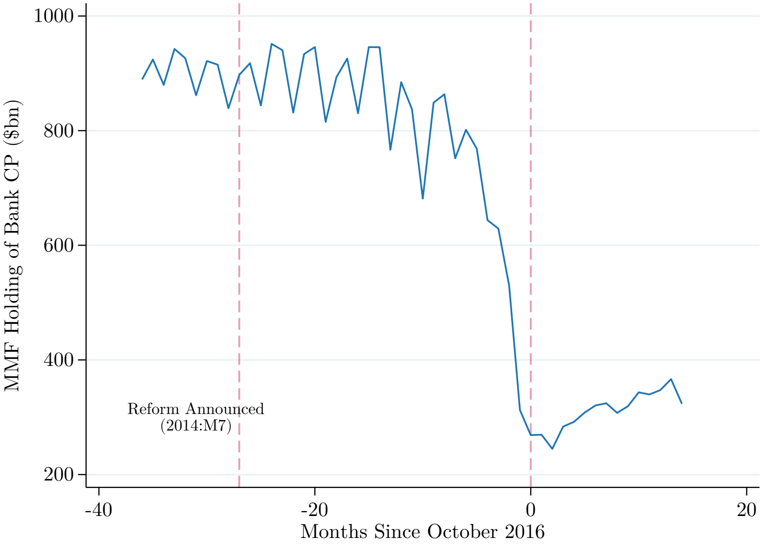
- Or are spreads and TED rising because bank balance sheets are tightening?

- Isolate funding shocks using 2016 money market fund (MMF) reform

2016 MMF Reform

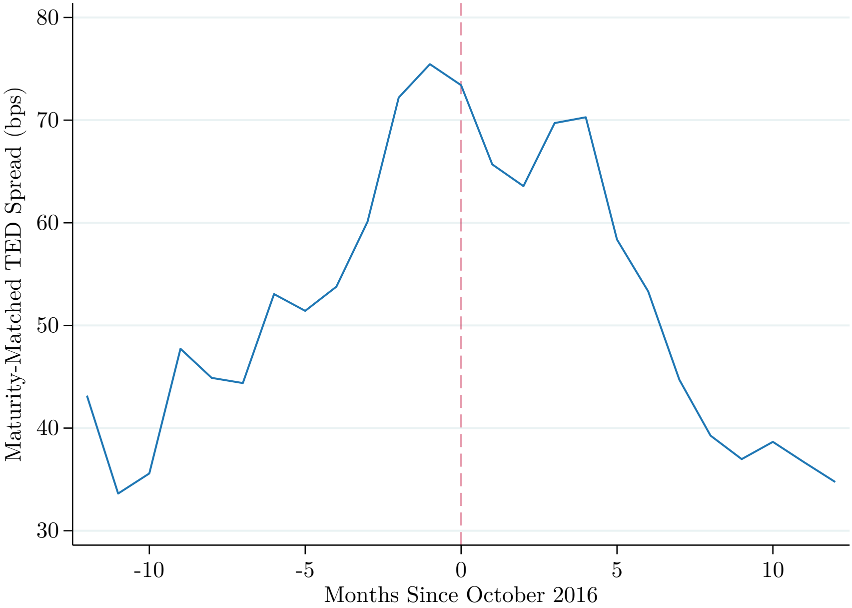
- Modified SEC Rule 2a-7 and required prime MMFs to use floating NAVs
- Government funds not affected by the reform
- To accommodate clients, many prime funds converted to gov't funds
- Prime funds were large unsecured lenders to banks, so reform plausibly represents a funding shock that is distinct from bank balance sheet shocks

MMF Holdings of Bank Commercial Paper



$550 billion drop in unsecured funding

TED Spread Rises



And Unsecured Spreads Rise

Comparison to OLS Estimates

- MMF reform implies the elasticity of unsecured arbitrage to TED is 0.58
- Close to the full-sample OLS estimates of 0.48
- Suggests most of the comovement between the TED spread and unsecured trades in our sample is driven by funding, not bank balance sheet shocks

Further Funding Segmentation

- Preceding evidence show divide between unsecured and secured funding markets helps to explain observed correlations (CIP, Box, Equity S-F)

- Is funding more segmented than the divide between secured and unsecured?

- Natural to expect, given sticky relationships between MMFs and banks (Chernenko and Sunderam, 2014; Rime et al., 2017; Li, 2021; Hu et al., 2021)

- Implies shocks to specific funding sources should move specific spreads

Illustration Using Fidelity Money Market Funds

- Fidelity MMFs are dominant in equity repo lending (Hu et al., 2021)

- Test whether Fidelity MMFs impact equity S-F arbitrage over and above TED

- To isolate funding supply shocks, instrument using "passive flows":

$$\text{MMF sector flows at } t \times \text{Fidelity's share of MMF assets at } t-6$$

- Idea: Fidelity is small relative to overall MMF sector (~16% of assets)

Equity Spot-Futures Arbitrage and Fidelity MMF Flows

	Dep Variable: Δ Implied RF		
	(1) Equity S-F	(2) CIP/Box	(3) Secured
Δ Treasury	0.73**	0.78**	0.92**
	(2.19)	(6.13)	(36.56)
Δ TED	0.88**	0.27*	0.05
	(3.85)	(1.90)	(0.73)
Fidelity Flows	-3.46**	-0.24	-0.51
	(-2.18)	(-0.43)	(-1.23)
Estimation	IV	IV	IV
R^2	0.10	0.19	0.54
N	294	1,033	1,447

Funding supply shocks to Fidelity MMFs only impact Equity-SF spreads

Balance Sheet Segmentation

Why is Arbitrage Segmented?

- Low correlation between arbitrages is partly due to funding segmentation

- Some arbitrage trades are exposed to local funding supply shocks
  - Unsecured vs Secured trades
  - Equity Spot-Futures and Fidelity

- Next: low correlations are also driven by balance sheet segmentation
  - Intermediaries specialize in certain trades
  - When their firm-specific constraints tighten, spreads rise

Evidence from Aggregate Futures Positions

	Earns Arbitrage (% of days)		
	Dealers	HFs	Asset Mgrs
2-Year Treasury Notes	46	62	33
5-Year Treasury Notes	61	65	26
10-Year Treasury Notes	58	74	31
Treasury Bonds	44	37	22
S&P 500 Index	87	98	1
Nasdaq Index	79	29	14
Dow Jones Industrial Average	93	8	8
Average Treasury	52	60	28
Average Equity	87	45	8

Dealers and hedge funds appear to focus on different trades

JP Morgan and Equity Spot-Futures Arbitrage

- Several sources suggest JPM is a big player in Equity S-F arbitrage
- Coalition Greenwich (S&P subsidiary) reports JPM has had largest share of equity derivatives market since 2015
- According to regulatory filings, JPM held the most equities in its trading books among U.S. bank holding companies
  - 37% over full sample and 56% in 2010
- Study how a balance sheet shock to JPM impact Equity S-F arbitrage

The London Whale: Background

- JPM's CIO tasked with hedging credit risk in the bank's lending portfolio

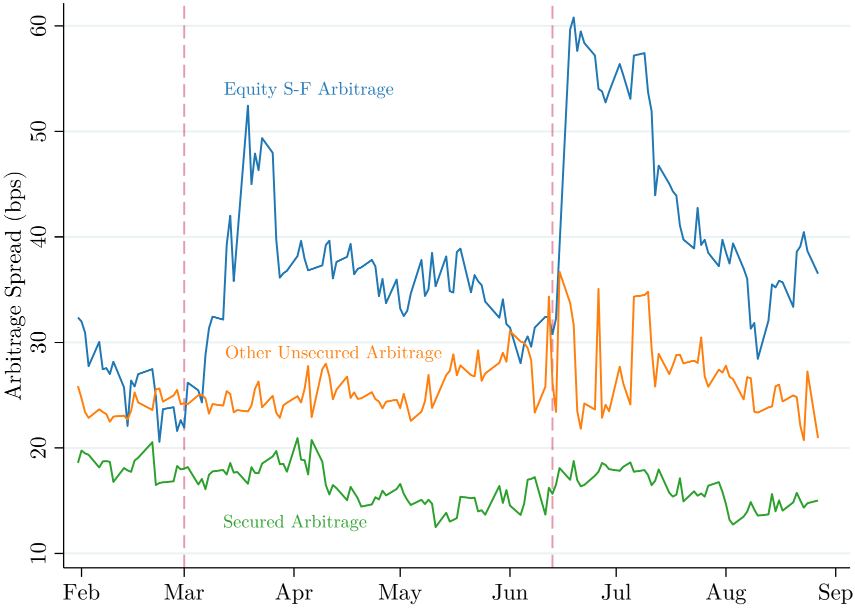
- The firm aimed to reduce hedges at onset of 2012

- Initially offset credit protection it had bought by selling credit protection
  - But rogue trader (the "whale") sold much more CDS than required
  - At peak, JPM was one of largest CDS sellers in the market

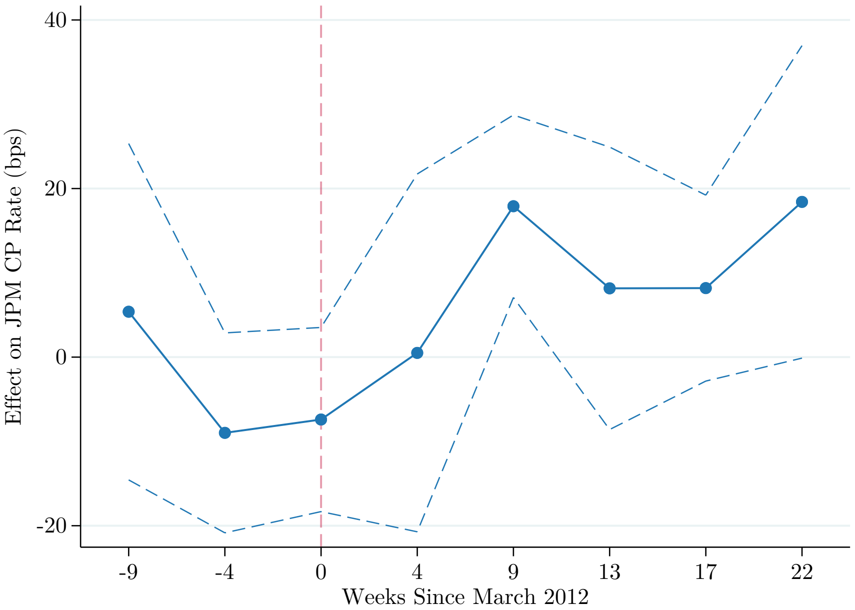
- Rising CDS spreads caused positions to lose over $6 billion

- Two key moments:
  - Mar. 2012: Risk limits are breached + losses of $550 million (75% of YTD losses)
  - June 13, 2012: CEO Jamie Dimon testified before Congress and announced that significant additional losses were to be expected

The London Whale: Large Impact on Equity Spot-Futures



The London Whale: No Impact on JPM Commerical Paper Rates



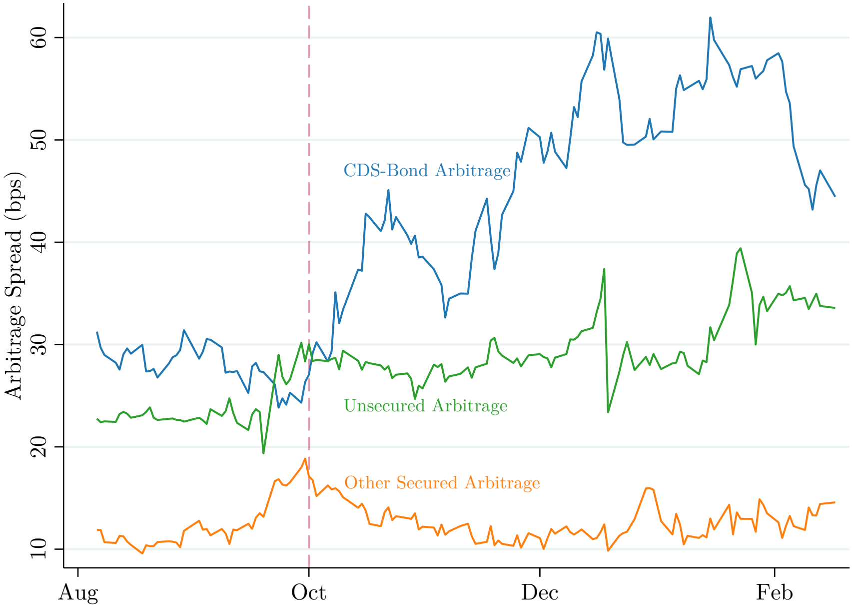
Another Example of Balance Sheet Segmentation

- In late 2014, Deutsche Bank (DB) exited the CDS market (Wang et al., 2021)

- DB had a large presence in the market
  - 2013 annual report: $2 trillion in CDS notional outstanding

- Exact timing of DB's exit is unknown, but known to be in fall of 2014
  - Sept. 2014: Sold large portion of CDS portfolio to Citi (Bloomberg)
  - Nov 17, 2014: Publicly announced exit from CDS market
  - Dec. 2014: $1.4 trillion in CDS outstanding (2014 annual report)

CDS-Bond Bases Rise with DB exit



Hedge Funds and Balance Sheet Segmentation

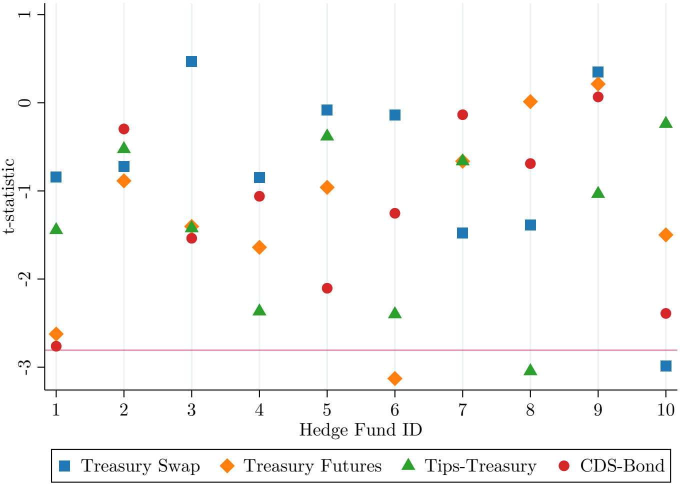
- HFs appear active in Treasury spot-futures arbitrage (Barth and Kahn, 2021)
- Check if low HF returns (tighter constraints) are followed by spread increases
- Measure HF returns using Barclay's Aggregate Fixed Income Arbitrage Index

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

	Dep Variable: Δ Arbitrage Spread	
	Unsecured	Secured
FI Arb HF Return$_{t-1}$	-0.03	-0.69**
	(-0.06)	(-2.95)
R^2	0.00	0.01
N	1,625	1,773

Evidence from 10 largest Fixed-Income Arbitrage HFs

Run predictive regressions for each of the 10 largest FI-arbitrage HFs (Preqin data)



Suggests different hedge funds matter for different secured trades

Crisis Periods

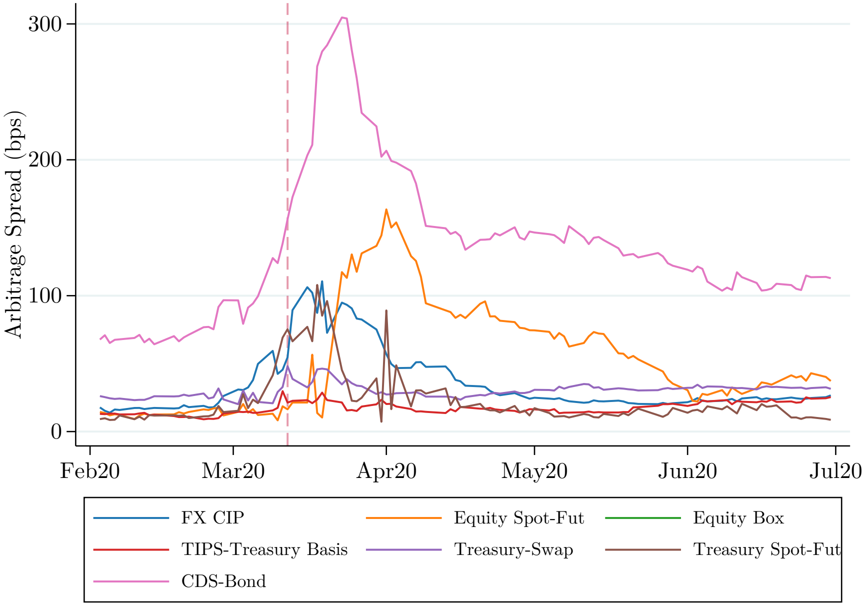
Covid Correlations (March-May 2020)

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

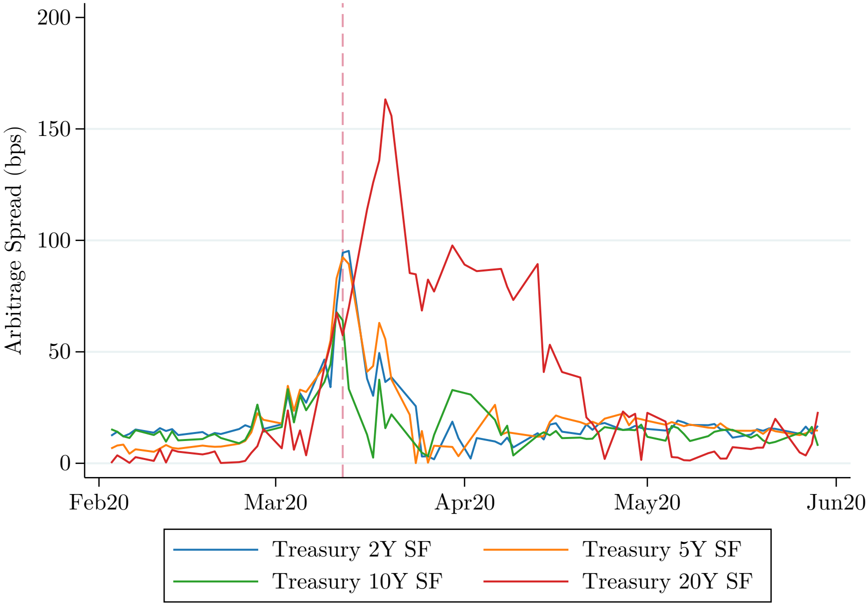
55% of pairs reject H_0: $\rho_{ij} > 0.67$

Correlations did not rise by large amount during Covid

Low Correlation of Arbitrage Spreads During Covid



Particularly Stark in Treasury-Futures Arbitrage



2008 Global Financial Crisis

Pre-crisis: Jan-2005 to June-2007

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

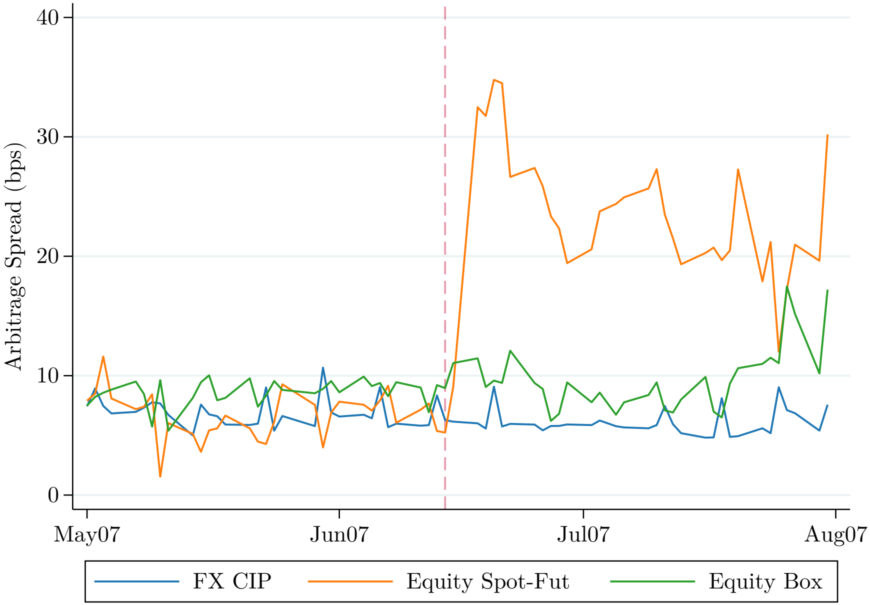
98% of pairs reject H_0: $\rho_{ij} > 0.67$

Crisis: July-2007 to June-2009

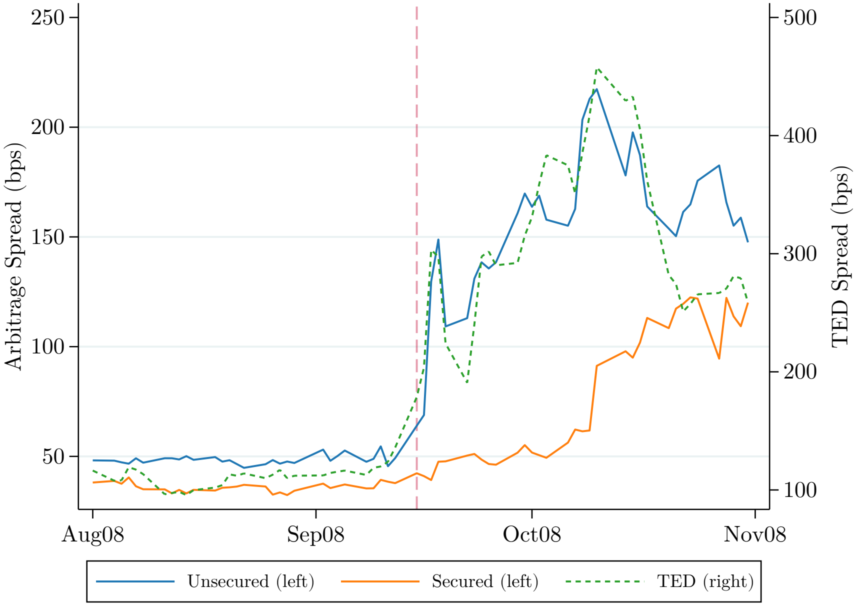
ρ_{ij}								p-value	
Mean	Sd	Min	p25	p50	p75	Max	N	$\overline{\rho} > 0.67$	$\rho_{ij} = \rho$
0.73	0.19	0.16	0.66	0.78	0.86	0.99	136	1.00	0.00

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

Balance Sheet Segmentation in July 2007



Funding Costs and Unsecured Arbitrages After Lehman



Implications and Questions

Main Point: Arbitrage appears to be quite segmented

Implications:

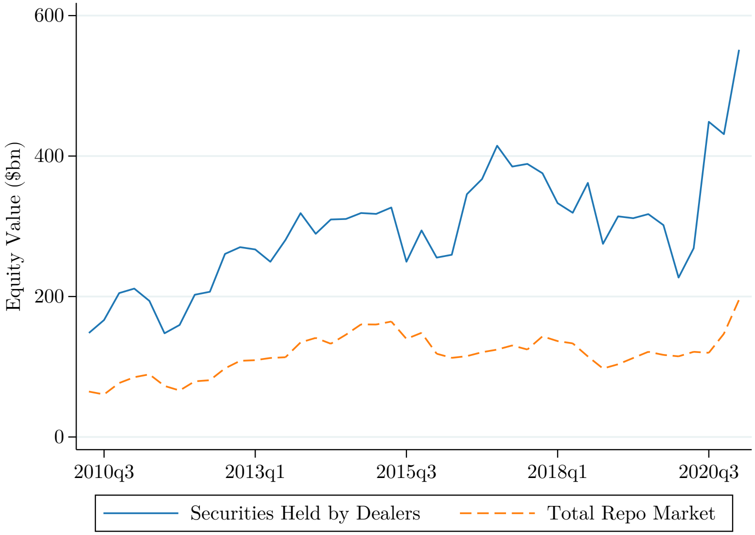
- All spreads are not equally informative about health of financial system
- Fire sales need not have economy-wide effects
- Liquidity and capital injections must be carefully tailored

Questions:

- Which spreads reflect the health of the "core"?
- Can we use spreads to understand specific market dislocations?
- How much does each type of segmentation contribute to factor structure?
- What determines which firms do what trades?

Thanks!

Equities: Dealer Holdings vs Repo Financing



Back

Appendix: Trade Details

1. **Foreign exchange (FX):** $(1+OIS_t^{foreign})F_t^{FX} = (1+OIS_t^{US}+z_t)S_t$
   - S_t is the spot rate, and F_t^{FX} is the forward rate in USD/foreign
2. **Equity spot-futures**: $F_t^{equity} = P_t^{equity}(1-\delta_t+OIS_t^{US}+z_t)$
   - P_t^{equity} is the spot price, F_t^{equity} is the futures price, and δ_t is the expected dividend yield (from Bloomberg)
3. **Equity options**: $Put_t - Call_t = -P_t^{equity}(1-\delta_t)+(1+OIS_t^{US}+z_t)K$
   - K is the strike; estimate with regression across strikes
4. **CDS-bond**: $z_t = AssetSwap_{i,t} - \mathrm{CDS}_{i,t}$
   - $AssetSwap_{i,t}$ is from Bloomberg
5. **TIPS-Treasury:** $z_t = y_{TIPS,t}+\pi_t - y_t$
   - $y_{TIPS,t}$ is the TIPS yield, y_t is the nominal yield, and π_t is the fixed rate on an inflation swap
6. **Treasury-swap spread**: $z_t = y_t - y_{\mathrm{sw},t}$
   - $y_{sw,t}$ is the fixed rate on an OIS swap
7. **Treasury spot-futures**: $F_t^{Treasury} = P_t^{Treasury}(1-c_t+OIS_t^{US}+z_t)$
   - c_t is the coupon; use first-deferred futures contract

References

Barth, D. and R. J. Kahn (2021). Hedge funds and the treasury cash-futures disconnect.

Chernenko, S. and A. Sunderam (2014). Frictions in shadow banking: Evidence from the lending behavior of money market funds. *The Review of Financial Studies 27*(6), 1717–1750.

Du, W., A. Tepper, and A. Verdelhan (2018). Deviations from covered interest rate parity. *The Journal of Finance 73*(3), 915–957.

Fleckenstein, M., F. A. Longstaff, and H. Lustig (2014). The tips-treasury bond puzzle. *the Journal of Finance 69*(5), 2151–2197.

Haddad, V. and T. Muir (2021). Do intermediaries matter for aggregate asset prices. *The Journal of Finance 76*(6), 2557–2596.

Hu, X., J. Pan, and J. Wang (2021). Triparty repo pricing. *Journal of Financial and Quantitative Analysis 56*(1), 337–371.

Li, Y. (2021). Reciprocal lending relationships in shadow banking. *Journal of Financial Economics 141*(2), 600–619.

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics 8*(4), 323–361.

Rime, D., A. Schrimpf, and O. Syrstad (2017). Segmented money markets and covered interest parity arbitrage.

van Binsbergen, J. H., W. F. Diamond, and M. Grotteria (2019). Risk-free interest rates. Technical report, National Bureau of Economic Research.

Wang, X., Y. Wu, H. Yan, and Z. Zhong (2021). Funding liquidity shocks in a quasi-experiment: Evidence from the cds big bang. *Journal of Financial Economics 139*(2), 545–560.