The Impact of Central Clearing on the Interest Rate Swaps Market

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# Introduction

The 2006-2008 financial crisis, the most severe economic downturn since the Great Depression, led to the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA). A key provision of the DFA required certain financial contracts to be cleared through a central counterparty (CCP). This study investigates the causal impact of this clearing mandate on prices, volatility, and liquidity in the interest rate (IR) swaps market, a major derivatives market used for hedging or speculating on interest rate risk. Despite extensive theoretical literature on central clearing, empirical studies are limited. Earlier research focused on the credit default swaps (CDS) market using event studies. Event studies cannot isolate causal impacts due to potential confounding factors. This dissertation addresses the gap in the literature by (1) examining the IR swaps market, which is larger and more widely used than the CDS market and (2) using a difference-in-differences approach to identify causal effects of the clearing mandate. Leveraging the fact that initial central clearing rules targeted IR swaps in the four largest currencies traded in the US, but did not apply to contracts denominated in other currencies, this dissertation plausibly identifies the causal impact of the regulation on pricing, liquidity, and price volatility in the IR swaps market using a difference-in-differences approach.

The dissertation is organized as follows: section 1 provides background on the IR swaps market, the financial crisis, and the clearing mandate's role in post-crisis market reforms; section 2 develops the theory of pricing, price volatility and liquidity for IR swaps under a clearing mandate; section 3 discusses the identification strategy; section 4 details my data; section 5 discusses the results and section 6 concludes.

# Background

## Interest Rate Swaps

IR swaps are financial derivatives used to hedge or speculate on interest rate movements. The three most common types of IR swaps include “vanilla” fixed-for-floating swaps, basis swaps, and cross-currency basis swaps. Vanilla fixed-for-floating swaps are the most prevalent. In this type of swap, one party exchanges fixed-rate coupon payments for floating-rate payments on a notional principal. Firms can use these instruments to convert floating-rate risk to fixed-rate risk, and vice versa. As a concrete example, imagine firm A can borrow at the London Interbank Offer Rate (LIBOR, a common variable interest rate used by banks when lending money to each other) or a fixed rate of 2.0%, while firm B can borrow at LIBOR + 0.25% or a fixed rate of 1.75%. Suppose firm A prefers borrowing at a fixed-rate and firm B prefers borrowing at a floating-rate (this could be because firm A owns fixed-income securities while firm B owns assets that pay a variable rate, and the firms would like to match their assets with their liabilities). Despite their preferences, firm A has a comparative advantage in borrowing at a floating-rate, and firm B in borrowing at a fixed-rate. To achieve their preferred arrangements, the firms can enter into an IR swap agreement with a $1M notional principal, where firm A receives a floating rate of LIBOR from firm B and pays a fixed rate of 1.75% to firm B[[1]](#footnote-2). This transforms firm A's floating-rate liability into a fixed-rate one and vice versa for firm B. The IR swaps market allows firms to borrow in the market they have a comparative advantage in and trade for their preferred interest rate arrangement.

IR swaps can be bespoke contracts, customizable to individual economic needs. As the largest over-the-counter (OTC) swaps market, it accounted for $465 trillion of the $601 trillion global OTC swaps market in 2010 (von Kleist and Mallo 2011) (the IR swaps market had increased to $715 trillion by June 2023 according to an updated version of the same report). For many currencies, there are “standardized” contracts, which have common features and are the most heavily traded. During the period studied in this dissertation, the standard US Dollar (USD)-denominated IR swaps contract had semiannual payments for one leg and quarterly payments for the other leg (that is either trading quarterly fixed-rate payments for semiannual floating rate payments, or vice-versa), with the 3-month USD-LIBOR curve used both as the floating-rate reference and for discounting future cash flows (see section 2.1 for further explanation). The standard Canadian Dollar (CAD)-denominated contract used 3-month Canadian Dollar Offer Rate (CDOR) as the reference floating rate. In addition to the currency, reference rates and payment frequency, there are many other contract details (such as day-count conventions, settlement and termination rules) that need to be specified, and these are listed in more detail in Appendix A. The CAD- and USD-denominated standard contracts use the ISDA master agreement, which detail these contract specifications. Although contract specifications can be customized to meet the requirements of the counterparties, such non-standard contracts are likely to be less liquid than the standard contracts. Standard contracts denominated in other currencies (e.g. Euro [EUR], British Pound [GBP], and Japanese Yen [JPY]) have their own conventions as well (and these conventions are documented in Appendix A).

The IR swaps market is dealer-dominated, with dealer-customer and dealer-dealer trades accounting for 80% of notional value (Bolandnazar 2020). Bolandnazar finds that 50% of trades (by notional value) are executed by the largest seven dealers, indicating market concentration among a few dealers. This concentration can impact pricing and market stability in several ways. Larger dealers might be able to reduce search costs by easily finding a counterparty from their large client base. They could also reduce costs by economizing over administrative and warehousing costs of contracts. However, because of their market position, they might have market power and be able to charge a premium over the price that would prevail in competitive markets. The failure of a large dealer (or a dealer’s major counterparty) could also drastically reduce liquidity in the system and increase transactions costs.

## Central Clearing

When a swap is cleared, the initial contract between the two parties is replaced (novated) by two contracts between each party and a central clearinghouse/derivative clearing organization (CCP, DCO or clearinghouse). The clearinghouse becomes the counterparty for each leg (that is, receiving the fixed-rate payments from one party and paying the floating-rate payments to that party, while also receiving the floating-rate payments from the other party and paying it the fixed-rate payments). Under ordinary circumstances, the clearinghouse is a sort of “pass-through” organization that transmits payments from one counterparty to the other. However, if one party fails to meet their contractual obligation, the clearinghouse can still make sure the other party gets paid. For this purpose, CCPs practice risk-control measures and have additional resources to make a counterparty whole in case of default[[2]](#footnote-3). When counterparties clear their trade through a clearinghouse, they must put up collateral (initial margin) and contribute to a default fund. In case the risk position of the counterparty changes, it can be required to put up additional collateral (variation margin). The CCP also has default fund contributions of other members, its own equity (CCP capital), and access to other lines of credit (such as the Federal Reserve discount window). The combination of these resources makes it unlikely that the failure of one counterparty would drastically affect the whole market. Since clearing members can lose their contribution to the default fund in case of the failure of a counterparty, clearing mutualizes counterparty risk among the members of the CCP.

In addition to financial resources, CCPs exercise prudent risk control measures such as monitoring members trading positions and liquidating distressed assets in an orderly fashion. Since the CCP can observe all trades that it is clearing, it has a better picture of overall riskiness (compared to a bilateral market, where one party is generally unaware of other trades its partner is entering, and thus does not have a thorough understanding of its partner’s riskiness).

Clearing can reduce demand for collateral through a practice called netting. There are two types of netting practices common in the industry: cross-product netting and multilateral netting. For a CCP that clears multiple types of contracts (e.g. interest rate swaps, forward rate agreements, overnight-index swaps, credit default swaps, etc.) cross-product netting involves netting across different derivatives products. For example, if firm A owes the CCP $10 million in collateral for IR swaps, but the CCP owes firm A $8 million for CD swaps, then firm A can just pay the CCP $2 million in net collateral.

Multilateral netting involves netting payments across multiple firms. Consider the following example involving 3 firms. The set of obligations between the firms are as follows: firm A owes firm B $100 million and firm C $200 million; firm B owes firm A $50 million and firm C $150 million; firm C owes firm A $100 million and firm B $100 million. These obligations will usually arise because firms will demand collateral from each other to protect against default, as they enter swaps contracts with each other. This initial set of obligations is visualized in Figure 1a, where the arrows indicate the direction of the obligation (which firm owes who). Without multilateral netting, the firms can still engage in bilateral netting, as shown in Figure 1b. In a bilateral netting regime, the firms “subtract” or “net out” their payment to each counterparty. Thus, the following payments would be made: firm A would pay firm B ($100 - $50) = $50 million and firm C ($200 - $100) = $100 million; firm B would pay firm C ($150 - $100) = $50 million. The total collateral demand would be $200 million. As shown in the figure, under this arrangement, firm B acts like a pass-through entity that collects a payment from firm A and transmits it to firm C. However, if firm B is unable to make the collateral payment, firm C loses some of the collateral it is due. Multilateral netting can eliminate this payment from firm B to firm C (with the CCP, which should be much better capitalized, now acting as the pass-through entity). Under multilateral netting Firm A would pay the CCP $150 million and the CCP would pay firm C $150 million (while firm B would not make any payments at all). The total collateral demand would be $150 million. Figure 1c graphically depicts this multilateral netting scenario.

Figure 1 Example of obligations between three firms (a) without any netting (b) with bilateral netting (c) with multilateral netting. Arrows indicate the direction of obligations (for example in (a) firm C owes firm B $100 million and firm C owes firm B $150 million). Under bilateral netting, firms “net out” the obligations with each counterparty on a bilateral basis. Thus, the set of two obligations between firm B and C is replaced by one obligation of $50 million from firm B to C, as shown in (b). Under central clearing, the payment from firm A to firm B can be eliminated and the clearinghiouse can simply collect $150 million in collateral from firm A and pass it directly to firm C, as shown in (c).

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| (a) |  |
| (b) |  |
| (c) |  |

Originally created for members of futures and equities exchanges, clearinghouses became more significant with regulations like the DFA (2010) and European Market Infrastructure Regulation (EMIR, 2012) mandating central clearing of derivatives. Mandated clearing can have macro and micro effects on the swaps market. At the macro level, clearing could reduce volatility but also strain the market through collateral demand during volatile or illiquid periods. Large enough losses could threaten clearinghouse solvency, transmitting effects to all members. At the micro level, central clearing may change the types of trades firms enter, potentially leading to riskier trades due to mutualized default risk (adverse selection) and riskier post-trade activities (moral hazard). Clearing is subject to economies of scale and scope, which could lead to natural monopolies. However, regulators are likely to prevent this through antitrust regulations and “local clearinghouse” requirements (that is, even though a single clearinghouse for both the US and Europe might have lower costs, US and EU regulators might require separate clearinghouses in each jurisdiction). While clearinghouses can reduce default risk and collateral demand, they also require resources for risk management activities, which may increase trading costs.

## Regulatory Background

### US Context

Following the financial crisis, Congress passed the DFA to enhance the US financial system's reliability. Since OTC derivatives markets played a role in the crisis, DFA aimed to significantly reform this market. Key objectives included improving trade data availability for regulators and market participants, requiring real-time reporting of certain trade characteristics, and mandating confidential trade data reporting to swaps data repositories and regulators. To reduce default risk for large swaps dealers, DFA requires dealers to register with the Commodities Futures Trading Commission (CFTC) or the Securities and Exchange Commission (SEC), adhere to internal business conduct standards and maintain adequate capital. To enhance liquidity, price discovery and transparency, it encourages trading to take place in centralized Swaps Execution Facilities (SEFs, usually electronic trading venues) or Designated Contract Markets (DCMs). To make trade data more readily available, it requires near real-time reporting and dissemination of price information to swaps data repositories (SDRs) and submitting additional data (called primary economic terms) to SDRs and regulators in a timely fashion. Furthermore, the DFA mandates most contracts be centrally cleared (and for uncleared contracts, requires parties to post regulatory margin/collateral to mitigate the effects of default). Table 1 summarizes the CFTC key rulemaking in these areas.

The whole set of DFA regulations (not only the central clearing mandate) are likely to affect swaps trading. To identify the causal impact of the central clearing mandate, I need to examine a period when other regulations are not varying. The CFTC implemented the DFA regulations piecemeal during the 2012-2014 period, thus leaving only small windows where the impact of the clearing mandate can be studied (this is discussed further in the Identification Strategy section). I discuss how some of the regulations in Table 1 could impact trading. One of the earliest provisions of the DFA that the CFTC implemented was the data-reporting/record-keeping requirement. This required that certain characteristics of swaps trades (such as the agreed upon rates and prices) to be reported in near real-time through SDRs. The OTC interest rate swaps market was previously relatively opaque (where quotes were usually obtained on a bilateral basis). The greater price transparency available to market participants after the implementation of the data-reporting regulation is likely to affect pricing and volatility.

The CFTC also encouraged standardization of swaps contracts (by requiring parties to put up additional collateral for non-standard contracts) and for standardized contracts to be traded on (electronic) swaps execution facilities (SEF)/exchanges. SEFs are likely to increase competition (as request for quotes are transmitted to multiple dealers simultaneously) increase pricing transparency (giving market participants access to price history, market depth and other market statistics) and increase liquidity (by allowing more participants, both dealers and end-users to participate in the market).

CFTC rulemaking also targeted the business conduct of swaps dealers and major swaps participants. This included requiring such entities to register with the CFTC, develop and maintain internal business conduct standards, set-aside capital or require margining for trades they enter, segregate customer funds and have plans for unwinding trades in case of bankruptcy. These regulations are likely to reduce the risk/impact of a dealer default (counterparty risk) and is likely to affect pricing and volatility.

Table Major Rule-Making Areas of the Dodd-Frank Act. The CFTC interpreted the DFA to contain six major rule-making areas (as well as a seventh, “other” area for miscalenous rules). Specific rules within each rule-making area are listed on the right.

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| Rulemaking Area | Major Rules |
| Swaps Dealers and Major Swaps Participants | * Registration * Internal Business Conduct Standards * Capital and Margin for non-banks * Segregation and Bankruptcy |
| Data Requirements | * Establishment of Swap Data Repositories (SDR) * Data recordkeeping and reporting requirements * Real Time Reporting * Large Swaps Trader Reporting |
| Clearing Requirements | * Establishment of Derivatives Clearing Organizations (DCO/CCP) * Clearing requirement for most common swaps * Margining requirements for uncleared swaps |
| Trading Requirements | * Establishment of Swaps Execution Facilities (SEF) * Made Available for Trade (MAT) designation/requirement |
| Position Limits | * Position Limits and Aggregation of Positions |
| Enforcement | * Anti-Manipulation * Disruptive Trading Practices * Whistleblowers |
| Other | * Investment Adviser Reporting * Volcker Rule * Reliance on Credit Ratings * Fair Credit Reporting Act * Cross-Border Applications |

### International Context

Considering the global nature of the financial system, regulators collaborated internationally to harmonize regulatory requirements. In Europe, the EU passed EMIR in 2012, which shared similar objectives as the DFA, while the Bank of England (BoE) issued regulations mandating clearing for most trades involving UK-based entities. In Asia, the Japanese Financial Services Authority (JFSA) required yen-denominated IR swaps and certain CD swaps to be cleared by the end of 2012; the Monetary Authority of Singapore (MAS) and the Securities and Futures Commission (SFC) of Hong Kong released consultation papers expressing their intentions to clear swaps denominated in certain Asian currencies. Table 2 summarizes clearing requirements internationally. Note that the table focuses only on the central clearing mandate in a global context, although other regulations (like those described in Table 1 for the US) were also enacted internationally as well.

The US and EU acted nearly simultaneously in enacting the central clearing requirement. As then part of the EU, these regulations also affected trading in the UK (where London is a major financial center of swaps trading). In Japan and Australia, authorities enacted mandatory central clearing slightly before the US and EU, for contracts designated in their respective local currency. Other financial centers, such as Hong Kong, Singapore and Switzerland enacted central clearing requirements around the 2016-2017 period. Importantly, Canada implemented a central clearing requirement in May 2017, creating a period where interest rate swaps contracts denominated in Canadian dollars did not need to be cleared either in the US or in Canada.

Table Summary of Central Clearing Requirements in Major Financial Centers. Japan and Australia required mandatory clearing of JPY-denominated and AUD-denomianted contracts traded in their jurisdictions starting at end of 2012. The US and EU required mandatory clearing (for contracts in various currencies) starting in the first half of 2013. Other countries enacted similar requirements between 2013 and 2017.

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| Jurisdiction | Relevant Laws and Regulations |
| North America | * DFA (2010) and CFTC and SEC rulemaking requires mandatory clearing of IR swaps contracts denominated in USD LIBOR, GBP LIBOR, EURIBOR and JPY LIBOR by September 2013. * Additional currencies and classes of contracts are added to the clearing requirement in 2016 to harmonize regulations across jurisdictions. * Canada requires certain CAD-denominated swaps to be cleared starting in May 2017. |
| Europe | * EMIR passes in 2012 and requires clearing of certain IR swaps contracts. Regulations come into effect in March 2013. * Bank of England releases financial market regulatory guidance in April 2013, reiterating the applicability of EMIR to UK-based traders. * Additional currencies and classes of swaps are added to the EU clearing requirements in 2016. * Switzerland established a clearing mandate for Switzerland based swaps in 2017. |
| Asia | * Japan Financial Stability Authority (JFSA) requires JPY denominated IR swaps referencing JPY LIBOR to be cleared by end of 2012. * Hong Kong requires HKD denominated swaps to be cleared starting July 2017. * MAS requires SGD contracts to be cleared by December 2017. |
| Australia | * Australian Council of Financial Regulators (CFR) pass legislation requiring mandatory clearing of Australian dollar (AUD) denominated IR swaps by end of 2012. |

## Review of Literature

### Interest Rate Swaps

Formal swap agreements were first seen in financial markets in 1981/1982. Bicksler and Chen (1986) find three uses of interest rate swaps in the market: (1) to manage mismatches in assets and liabilities (for example, depository institutions hold long-term fixed rate assets such as mortgages and short-term liabilities such as demand deposits; on the other hand, insurance companies often invest in short term assets that pay a variable rate, such as money market funds, and have long-term fixed-rate liabilities); to lower fixed-rate borrowing costs (borrowers with poor credit can often borrow at a lower cost in the floating rate market) and to manage their debt mix. The primary economic rationale for the existence of interest rate swaps is differences between firms’ costs to borrow at fixed vs. variable rates arising due to market imperfections (differences in regulations or credit market imperfections can give firms comparative advantage in borrowing in one market over another).

Smith, et. al. (1988) present two models of pricing swaps. One model replicates the payoff of a swap through a portfolio of forward or futures contracts. The other model replicates the payoff through a portfolio of floating rate and fixed rate corporate bonds. They note that for a portfolio of bonds, there is an exchange of the principal at the end of the bond term, while for an interest rate swap the principal is usually not exchanged (that is, it is a “notional” principal). Thus, the impact of a default is greater for a corporate bond than for an interest rate swap. Futures contracts on the other-hand are exchange-traded, cleared, and settled daily, so the risk of loss due to counterparty default is close to zero. For forwards, the contract value is realized only at the end of the contract period and has greater potential for counterparty default than for futures. An interest rate swap is somewhere in-between: it is periodically settled (on the payment dates).

Minton (1997) examines these valuation models. He finds that the fixed rate of the interest rate swap is discounted by ~4 bps compared to a replicating portfolio of Eurodollar futures (Eurostrips) and that movements in swap rates and Eurodollar futures rates are highly correlated. When evaluating the portfolio of bonds model, he finds that actual swap rates fall between the rate derived from a portfolio of corporate bonds and the rate derived from Eurodollar futures. Proxies for counterparty credit quality also have a significant explanatory power, suggesting counterparty risk is a factor in observed swaps pricing.

### Liquidity

Biais (1993) proposes a model for a dealer intermediated market and derives the optimal bid-ask spreads quoted by dealers with constant absolute risk aversion (CARA) (note that this is a model of general asset pricing in dealer-intermediated markets, and not specific to the IR swap market). A basic version of Biais' model motivates the liquidity model in section 2.4. Several papers empirically examine liquidity in the interest rate swap market: Sun, et. al. (1993) examine the effect of dealer credit rating on bid-ask spreads using data from Merrill Lynch and AIG Financial Products. They find that dealers with AAA credit ratings charge a spread of around ~10 bps while lower rated dealers only charge a spread of ~4 bps. Boudiaf, et. al (2024) examine the impact of monetary policy tightening on liquidity of EUR denominated swaps using a variety of liquidity measures. They find that their liquidity measures are impacted by monetary policy (specifically volatility in key policy rates reduces liquidity in the swaps market). Liu, et al (2006) decompose the “spread” between interest rate swaps and corresponding treasury bills into a credit spread and liquidity spread (arising from the lower liquidity of swaps over US government bonds). They find that the credit component of the spread is ~31 bps while the liquidity component is ~7 bps. Benos, et. al (2020) examine the impact of another Dodd-Frank mandate (trading on SEFs) on liquidity. They find a 12%-19% improvement in liquidity in the post-regulation market, driven by competition among dealers. Loon and Zhong (2014) examine liquidity in the credit default swap (CDS) market following the passage of the Dodd-Frank Act. They find that central clearing in the CDS market is associated with more liquidity.

### Price Volatility

Compared to studies of pricing and liquidity, studies of price volatility in the interest rate swap market are rare. Azad, et. al (2012) decompose volatility in the US and UK market into high-frequency and low-frequency components using asymmetric spline GARCH (AS-GARCH). They then regress the low frequency component of the volatility against several macroeconomic variables (volatility of consumer price index, volatility of industrial production, volatility of short-term interest rates, volatility of foreign exchange rates, slope of the term-structure, unemployment rate and money supply). They find that volatility of short-term interest rates affects IR swap price volatility. In addition, for GBP based contracts, the money supply is negatively associated with IR swap volatility. For USD based contracts, the volatility of industrial production and the slope of the yield curve also affects IR swap volatility.

### Systemic Risk and Contagion

Jackson and Pernoud (2021) outline two main avenues of contagion (that is financial distress at one institution spreading throughout the financial system): firstly, through defaults and firesales of assets that diminish the value of interconnected financial institutions (the network channel) and secondly, through feedback effects such as bank runs and credit freezes. For the first avenue, consider the case when a large financial institution fails. The values of other institutions that do business with the failing institution are also diminished and can cause a cascading series of failures. Each failure leads to additional bankruptcy costs and the final cost to the system at the end of the process can vastly exceed the size of initial shock. Such models are explored by Rochet & Tirole (1996) and Allen & Gale (2007; 2000).

Another way that financial institutions are interconnected are through the assets they trade. That is, even though two financial institutions might not directly do business with each other, they might own assets that are highly correlated. When a bank becomes insolvent, it often must sell assets at distressed prices. Such sales can also depress prices of related assets and drive institutions that hold those types of assets into insolvency. A prominent real-world example of this scenario is the 1998 crisis at Long Term Capital Management (LTCM). LTCM was a hedge fund that used a highly leveraged portfolio of interest rate swaps and foreign bonds (especially Russian bonds) to earn high market returns. When Russia defaulted on its debt in 1998 and devalued the Ruble, LTCM’s portfolio took a large loss. In addition, market participants became more risk-averse and stopped lending to any institutions that employed a similar trading strategy to, or held similar assets as, LTCM. This created a system-wide credit crunch. The Federal Reserve eventually organized a bailout of the fund to prevent further damage to the financial system. Other prominent examples of this type of contagion are the Asian and Eurozone financial crises, where the potential default of one country led to distressed financial conditions in neighboring countries, as market participants became more risk averse. This type of model are explored by Kiyotaki & Moore (1997) , Cifuentes et al. (2005), Gai & Kapadia (2010), Capponi & Larsson (2015) and Greenwood et al. (2015).

Besides the network avenue, contagion can also occur through feedback loops and multiple equilibria. The classic Diamond and Dybvig (1983) model illustrates how multiple equilibria can lead to panic and bank runs. Banks lend out money long term and take in deposits for short terms. If enough depositors demand to withdraw their funds at once, the bank cannot repay all of them. In fact, if depositors believe a bank is insolvent (or they believe that other depositors believe that the bank is insolvent), they have an incentive to be the first in line to pull their funds out. Thus, a change in belief about the solvency of a bank can lead to a self-fulfilling insolvency, without any decrease in the value of the bank’s actual portfolio of loans. Similarly, banks’ beliefs about the creditworthiness of their counterparties can lead them to pull back their lending, leading to the very adverse credit condition and defaults that they were anticipating. This chain of defaults can cast doubts about the solvency of other banks, eventually leading to a systemwide freeze where banks stop lending to each other. This type of models are explored by Bebchuk & Goldstein (2011), Brunnermeier (2009) and Diamond and Rajan (2011).

### Central Clearing

The policy and market implications of a central clearing mandate are discussed extensively by Pirrong (2011). Per Pirrong, CCPs should clear liquid, standardized products, as illiquid products can pose substantial risks to the CCP. CCP’s can reduce the disruptive effect of defaults by drawing on additional sources of capital and facilitating orderly liquidation of positions. However, they can also increase systemic risk by requiring additional margin during periods of financial stress. In addition, by mutualizing the risk of default, they can induce market participants to take more risk (moral hazard and adverse selection issues). CCPs are also subject to economies of scale and scope (that is, the market will converge to one or few large CCPs that can economize over costs of warehousing and multiproduct netting). Since a CCP is likely to become a systemically important financial institution, regulators must monitor it closely and have prudent measures (such as a resolution plan if the CCP collapses).

Duffie and Zhu (2011) show that theoretically concentrating clearing to one CCP can economize on collateral. Benos et al. (2019) explore the issue of economies of scale/scope among CCPs. Regulators in Europe and United States have required “local CCPs” to clear contracts that originate in their jurisdiction. They find that the same contracts trade at different prices when cleared through two different clearinghouses (LCH in the UK/Europe and CME Clearing in the US) and suggest that this difference arises due to increased collateral costs when clearing is fragmented.

Bernstein, et al. (2019) look at the impact of central clearing on equities pricing by examining the prices of the same stocks traded on New York Stock Exchange (NYSE) and Consolidated Stock Exchange (CSE). The NYSE established a clearinghouse in 1892 while the CSE did not. They find that the same stocks on the NYSE traded for 90-173 premium over the CSE price.

# Theory

## Pricing Without Credit Risks

An interest rate swap can be thought of as an exchange of a series of fixed payments by one party for a series of variable (floating) payments by the other party involved in the swap. For the fixed leg, the present value of the payments is given by (Skarr and Szakaly-Moore 2007):

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where: CF is the (fixed) cash flow, is the risk-free rate for period , is the time at which CF will be received and is the tenor (total length of the swap contract)

The present value of the floating leg is:

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where: is the floating leg payment at period , and all the other variables are as defined previously.

The present value of the contract for the party paying the fixed leg and receiving the floating leg is:

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(The counterparty's value is given by a similar formula, but with the signs reversed on the right-hand side.)

Floating rate payments are unknown in advance but are usually forecasted by a relevant yield curve. For instance, if the floating leg payment is based on USD LIBOR, a USD LIBOR curve, constructed by interpolating short-term deposit rates, medium-term Eurodollar futures, and long-term instruments like forward rate agreements and existing swaps, is used. At the outset of the contract, its value () is zero. This is achieved by determining the present value of the floating leg using the forecasted payments (using the LIBOR yield curve), and then setting the fixed rate payment in (3) such that the present values of both legs equal. The payments are discounted using the same LIBOR yield curve.

## Pricing with Counterparty Risk (Credit/Debit Valuation Adjustment)

The interest rate swap market is dominated by a handful of substantial swap dealers (SDs) and Major Swap Participants (MSPs) rather than many atomistic market participants (Bolandnazar 2020). These SDs and MSPs offer buy and sell quotes for swaps, potentially finding other participants to balance their swap exposures. Figure 2 depicts a hypothetical network model of such a market.

Figure 2 A dealer-intermediated market witouth central clearing. Three dealers (labeled D1 through D3) trade with many customers (labeled C). Dealers can engage in interdealer trades (shown with thicker arrows), and customers can trade with multiple dealers (such a customer is highlighted in red) or with other customers directly (such a customer is highlighted in green).



In the figure, three dealers (D) each engage with their set of clients (C). Note that dealers might engage in interdealer trading (indicated by thicker arrows between dealers) and bulk futures markets trading (not shown) for cash flow or risk management purposes. Customers can trade with multiple dealers (indicated by arrows going from C to multiple Ds) or occasionally engage in bilateral trades (indicated by arrows going from C to C) amongst themselves. However, bilateral trades typically have low volume. It is believed that the dealer-centric network structure lowers search costs compared to a direct customer-to-customer market.

In practice, customers and dealers must account for the risk associated with counterparties defaulting. The "risk-free" present value pricing above needs to be adjusted for this risk. If *Si*​ represents the survival probability of the counterparty at period , the expected present value of the fixed leg is:

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The fixed rate payment needs to account for the modified PV of the floating leg.

(Note that a swap's valuation with counterparty risk requires two adjustments. Only the credit valuation adjustment [CVA] is shown above. However, if one’s counterparty defaults, one no longer has to make their obligated payments to the other party either, which would increase the value of the contract. This adjustment is called the Debit Value Adjustment [DBA] and not shown above).

## Pricing Under Central Clearing

The structure of a dealer-dominated market means that a dealer's failure (possibly due to inadequate risk management or correlated customer defaults) could affect other dealers and potentially the entire market. To counter this, regulators introduced central counterparties (clearinghouses). These clearinghouses void (novate) the initial swap contract and establish two new contracts, mirroring the original, with each counterparty. Now participants only need to be concerned about the clearinghouse's potential default, rather than their counterparties. Owing to their robust capitalization, regulation, and sound risk management, clearinghouses are perceived to decrease default and contagion risks. Figure 3 visualizes a hypothetical market structure with mandated central clearing. In this picture, the bilateral obligations between dealers (D) and customers (C) have been replaced by contracts between the dealer, customer and the CCP.

Figure 3 Dealer-based Market with Central Clearing. The obligations between customers and dealers, customers and customers, and between dealers, is replaced by obligations between the CCP and the counterparty (dealer/customer).



If clearinghouses can reduce or eliminate counterparty risk, swaps values should be closer to the risk-free case rather than the case with counterparty risk. However, even if clearinghouses are successful at eliminating counterparty risk, additional cost of compliance (such as clearing fees and margin requirements) could keep swaps prices from reaching the risk-free valuation.

## Model of Liquidity (Bid-Ask Spreads)

### Liquidity with no Counterparty Risk

I adapt the model from Biais (1993) for centralized trading. I preserve the essential relationships between risk-aversion, volatility, dealers’ inventory levels and the observed bid-ask spread, but simplify the model to ease exposition. In the original model, traders (both liquidity traders and dealers) face trading costs. In addition, each market participant faces a fixed cost if they choose to become a dealer (these costs could be due to efforts dealers need to expend to monitor the market, maintain a presence on the trading floor, engage in risk-control and backoffice activities). At the start of the sequential game outlined by Biais, of the market participants choose to become dealers based on their costs and expected profits from market-making activities. However, this aspect Biais’ model is not consequential to the fundamental relationship between the bid and ask prices quoted by dealers and the volatility of underlying prices. To simplify exposition, I modify the sequential game to involve exactly 2 dealers and one liquidity trader (that is, players no longer choose their type but are predetermined to be either be dealers or a liquidity trader). In addition, I drop the fixed trading costs for dealers, as this only adds a constant level to dealers’ “reservation” quotes.

The model is a sequential game where all market participants (players) can observe the quotes (bids and asks) and (market) orders of market participants. In the first stage, two competing dealers (liquidity providers) receive a random inventory position in the risky asset between [-R, R]. In stage 2, dealers set their bid and ask prices. In the next stage there is a liquidity shock with probability . If there is a liquidity shock, a liquidity trader (liquidity demander) receives an inventory of quantity with probability (or a short position of size with the same probability). They then decide the size of the optimal market order, which is executed at the best bid or ask price posted by the dealers. If there is no liquidity shock, no trade takes place. In the final stage, the price of the risky asset is realized, and players receive their utility.

I assume that the two dealers are identical except for their inventory positions. All market participants have constant absolute risk aversion (CARA) utility , where is the trader’s wealth and is a risk-aversion parameter. If there is a liquidity shock, the liquidity trader observes the market prices and selects the quantity (size) of the market order. The final price of the risky asset is , where .

I analyze the case where the liquidity trader receives a liquidity shock (the case where they receive a shock will be analogous). At the end of the game, once the asset price is realized, the trader receives wealth:

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|  |  | (5) |

where is the net position of the trader in the risky asset at the end of the game and is the cash from selling units of the risky asset at the best (highest) bid price . The liquidity trader will maximize expected utility . The optimal quantity is:

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| --- | --- | --- |
|  |  | (6) |

where I have used the fact that

If dealer 1 has the best price, they receive the order flow and have wealth:

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where: is the bid price set by dealer 1, is the size of the market order and is their random inventory position (a number between ). If dealer 1 does not have the best price, they receive:

Dealer 1 is indifferent between trading and not trading when the expected utility from both actions is the same. This happens when:

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where the price is subscripted with to emphasize it is the reservation price. A similar analysis holds for the ask price (when dealers are competing over market sell orders in response to a negative liquidity shock):

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and in general, for dealer , the reservation prices are:

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I analyze the case of the optimal bid quote for dealer 1, assuming the competing dealer does not observe the other’s inventory level, but both assume that the other’s inventory is drawn uniformly from . A dealer can increase their probability of winning the order flow by improving their bid price but must balance this against the fact that they pay more for each unit acquired. The dealer would not like to increase the quote beyond their reservation price. The optimal bid quote for dealer 1 is:

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Similarly, the optimal ask quote is:

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and in general, the optimal bid and ask quotes for dealer are:

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The observed bid ask spread is:

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Note: Under competition with many dealers, the second term on the RHS of (14) becomes and approaches as . The bid-ask quotes collapse to the reservation quotes.

#### Sensitivity to Specification of Utility Function

In the above, I derived expressions for bid-ask spread using a Constant Absolute Risk Aversion (CARA) utility function for all market participants. In this section, I show that when the utility function is switched to Constant Relative Risk Aversion (CRRA) utility, the optimal bid-ask spreads are qualitatively similar.

Consider the same game-theoretic setup described previously. However, now players have utility functions:

The final wealth of the liquidity trader is given by:

Let be the expected final wealth. If we expect the size of the liquidity shock and order size to be relatively small, we can approximate the utility function around by a second-order Taylor series approximation:

Then

Where I have used

Since . We have:

where I write to emphasize that the trader’s expected wealth is a function of their order quantity. To find the optimal order quantity, we can set the derivative of the expected utility to zero:

We can solve this to obtain Q\*:

This is like the optimal order quantity we derived under CARA

With an additional term in the numerator, showing the order quantity is sensitive to the expected level of wealth of the trader.

We can similarly derive the reservation prices for the dealers. For simplicity, I work through the reservation bid price for dealer 1.

If dealer 1 receives a random inventory position , . If they posts the best bid price, their wealth at the end of the period is:

If they do not trade, their wealth will be:

At some price the dealer will be indifferent between trading and not trading. This will occur when .

Let be the expected wealth

The second order Taylor-series expansion about is:

Taking expectations:

Using the fact that we obtain:

We can similarly take the Taylor Series approximation of the utility function at the no-trade level of wealth:

We can substitute and into the expressions above and set . We obtain the reservation price:

We cannot solve for explicitly, but note it has a similar form to the CARA reservation price.

In competitive markets, the dealer’s markup will tend to zero and prices will tend to the reservation prices.

Thus, we find that using CRRA utility function (or with an utility function which is at least as concave as a CRRA utility function), the optimal order quantity and bid-ask spreads are qualitatively similar to the CARA utility case, except quantities and spreads are sensitive to the level of expected wealth of the players.

### Liquidity with Counterparty Risk

Under the scenario where there is counterparty risk, if the counterparty defaults the value of the asset is impaired (the holder of the non-defaulting leg no longer receives expected cash flows). However, for the defaulter, the value of the asset is enhanced (as they no longer need to make payments). I model this as an additional shock to the realized value of the asset: . The analysis remains essentially the same, but the optimal market order size, reservation quotes, and optimal quotes now become:

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The optimal order size is reduced from to , the reservation quotes are increased from to and the mark-up from the reservation prices are similarly affected. With counterparty risk, the market order size is smaller, and the bid-ask spread is larger than under no counterparty risk.

## Model of Price Volatility

### Volatility without Counterparty Risk

I develop an original model of price volatility. There are two sets of agents: market-makers who post bid and ask prices, and liquidity traders who post market orders. Assume that order-flow (net market-buy or market-sell orders) is i.i.d Normal with variance :

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Market-makers adjust their next period price based on the current period’s observed order-flow:

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where: is a parameter for the market-makers sensitivity to order-flow.

The expression for the volatility in this case is:

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### Price Volatility in Markets with Counterparty Risk

I modify the above model to include additional order-flow dynamics related to counterparty risk. Assume that when the current period’s order-flow is negative, there is additional sell-off of the risky asset in the next period due to (perceived) additional counterparty risk, and when the current period’s order flow is positive, there is additional buying of the risky asset in the next period due to (perceived) reduction in counterparty risk. The order-flow dynamics are now given by:

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Where:

The expression for the price change becomes:

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where I have used the fact on the 3rd line and that .

# Identification Strategy

This dissertation aims to analyze the impact of a policy intervention (specifically, a change in central clearing rules) on various aspects (such as prices, bid-ask spreads, and realized volatility) of certain observational units (e.g., contracts, trading days). Let denote the outcome for unit when treated, and denote the outcome when untreated. The causal effect on unit is represented by . Since both outcomes cannot be observed simultaneously, I focus on estimating the Average Treatment Effect (ATE), , by identifying an appropriate control group to estimate the counterfactual .

Modern causal inference offers several methods to estimate this average treatment effect, including randomized control trials, natural experiments, regression discontinuity designs, instrumental variables, matching, and difference-in-differences. I discuss the challenges of applying some of these methods to the research question.

In a **Regression Discontinuity Design (RDD)**, units above a threshold value of a covariate receive treatment, while those below do not (e.g., scholarships granted to students above a specific test score). If units cannot precisely control their position relative to the threshold, assignment is “as good as random” close the threshold, allowing for causal inference. However, in the context of the clearing mandate, the CFTC requirements (e.g., currency, notional value, floating rate index, tenor) can be precisely controlled by market participants. Thus, the assumptions necessary for RDD are not met.

The **Instrumental Variable (IV) approach** relies on an instrument that affects the likelihood of treatment assignment. When the treatment variable is endogenous, a straightforward comparison between treated and untreated units could yield biased results. For a valid IV approach, the instrument must be relevant (associated with treatment assignment), independent (free from unobserved confounding variables), and satisfy the exclusion restriction (influencing the outcome solely through treatment). This approach is also unsuitable here, as CFTC-defined criteria determine clearing, and no external instrument influences clearing likelihood.

The approach adopted in this dissertation is the **Difference-in-Differences (DiD) method**. In this method, an appropriate control group (e.g., Canadian Dollar-denominated contracts) is selected, though it may differ from the treatment group. Initially, a pre-treatment difference between the control and treatment groups is calculated. This difference is then compared to the difference after treatment to estimate the causal effect. A key assumption in DiD is that of parallel trends—that, in the absence of treatment, both groups would have followed similar trends. Generally, this is not true for Canadian and U.S. swaps markets, given Canada’s export-oriented economy, distinct market participants, and unique monetary and fiscal policies, all of which influence pricing, volatility, and liquidity.

However, I argue that for short periods (e.g., the 20 trading-day windows studied in this dissertation), the U.S. and Canadian swaps markets are highly coupled. This is supported by evidence of parallel pre-treatment trends (verified visually and through statistical methods) in pricing, volatility, and liquidity over short periods, as well as formal parallel trends tests.

## Pricing

I investigate the causal impact of the central clearing mandate on the interest rate swap prices by comparing the premium above the fair rate (that is, the difference between the “riskless fixed rate” described in section 2.1 and the observed fixed rate on an actual contract) on USD denominated swaps versus the premium on CAD denominated swaps before and after the mandate. I employ a difference-in-differences (DiD) identification strategy, with the CAD denominated swaps acting as the control group, which allows me to plausibly isolate the causal effect of the mandate on the swap premiums by exploiting the variation in the timing of the policy implementation.

I begin by selecting a sample of interest rate swaps denominated in both USD and CAD from the ten trading days before and after the central clearing mandate was implemented. I create two groups based on the currency of denomination: (1) the treatment group, consisting of USD denominated swaps that were affected by the central clearing mandate, and (2) the control group, consisting of CAD denominated swaps that were not subject to the mandate during the same period. By comparing the swap premiums between these two groups before and after the mandate, I can plausibly identify the causal effect of the policy on swap premiums if both groups would have followed parallel trends in the absence of the clearing mandate.

To estimate the causal effect of the central clearing mandate on swap premiums, I employ a DiD regression model, which takes the following form:

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where is the swap premium for swap at time , is an indicator variable equal to 1 if the swap is denominated in USD (treatment group) and 0 otherwise (control group), is an indicator variable equal to 1 for the period after the mandate was implemented, and is a vector of control variables. The coefficient of interest is δ, which captures the causal effect of the central clearing mandate on swap premiums.

The control variables included in are the day of the week in which the contract is traded, the time (categorized as morning, mid-day, afternoon or off-hours) at which the contract is traded, the logarithm of the notional amount, whether the variable rate is capped, and the tenor of the contract (measured in months). The trading day variable is included because there is some discussion in the asset pricing literature of pricing differences on certain days (e.g. the “Monday effect” for equities). Trading time is also similarly included to account for differences in pricing behavior during certain trading sessions during the day. For example, trading is often concentrated to the morning and afternoon sessions, with less trading activity happening mid-day and off-hours sessions. The lack of liquidity during those sessions can affect pricing. The logarithm of the notional value is included, as there is some discussion in the literature that market participants prefer larger contracts (perhaps to economize over fixed costs) and due to the higher liquidity of these larger contracts, they may be priced differently than smaller contracts. If the variable rate is “capped”, the payer of the variable leg faces less (no) risk of the variable rate increasing beyond a specified threshold (the variable rate receiver now bears this risk). This is likely to influence the pricing of the swap. Finally, the tenor (length of the contract) is included as some tenors (e.g. 10 year contracts) have more liquidity than others.

To ensure the validity of the identification strategy, I test the parallel trends assumption by both visually inspecting and statistically verifying the pre-treatment trends of swap premiums for both treatment and control groups and conducting placebo tests. I begin by formally testing the parallel trends assumption by regressing the fixed rate against the treatment indicator (i.e. the currency of the contract), time (trade date) and interaction effect, for the two-week period prior to the period of study for phase 1 (that is, from Jan 28, 2013 to Feb 22, 2012). I also include some controls for contract characteristic (a subset of the control variables discussed earlier). I run the regression

where: is an indicator variable of whether the contract is in the control group (currency is CAD) or treatment group (currency is USD) and is now a *continuous* variable (the trade date). This regression is run separately for each tenor of contract (since pricing for different tenors are different). Table 3 shows the results of such a regression for the two-year, five-year and ten-year contracts. The interaction term is not significant, suggesting the two groups were following parallel trends prior to the implementation of the mandatory clearing policy.

Table Parallel Trends Pre-Trend tests. The period of data is from contracts traded between Jan 28 – Feb 22, 2013 (i.e. ten trading days prior to the study period of phase 1). If parallel trends hold, we expect the interaction term to be not statistically significant.

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| --- | --- | --- | --- |
| **Pre-trend Analysis** | | | |
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|  | *Dependent variable:* | | |
|  |  | | |
|  | Fixed Rate | | |
|  | 2-year contracts | 5-year contracts | 10-year contracts |
|  | | | |
| Currency (USD) | -28.79 | -50.311 | -13.741 |
|  | -41.081 | -28.185 | -23.332 |
|  |  |  |  |
| Trade Date | -0.003 | -0.002 | 0.001 |
|  | -0.001 | -0.001 | -0.001 |
|  |  |  |  |
| Log Notional | 0.01 | 0.007 | 0.024 |
|  | -0.009 | -0.02 | -0.007 |
|  |  |  |  |
| Cleared | -0.063 | -0.147 | -0.077 |
|  | -0.062 | -0.035 | -0.023 |
|  |  |  |  |
| Capped | 0.103 | 0.045 | 0.033 |
|  | -0.066 | -0.034 | -0.017 |
|  |  |  |  |
| Currency (USD) \* Trade Date | 0.002 | 0.003 | 0.001 |
|  | -0.003 | -0.002 | -0.001 |
|  |  |  |  |
| Constant | 41.431 | 26.625 | -9.856 |
|  | -16.254 | -19.798 | -15.845 |
|  |  |  |  |
|  | | | |
|  | | | |

I also examine whether the parallel trends assumption holds by visually inspecting the swap rate (fixed rate of the interest rate swaps contract) prior to each phase of the implementation of the clearing mandate. I examine the three most common tenors of USD and CAD interest rate swaps (2-year, 5-year and 10-year swaps). The data is reported by Bloomberg and is usually the average of 11 or more contracts traded around 11:00 AM Eastern Time of the trading day that meet contract specifications (described earlier). Figure 4 shows a sample of these trends for the tenors specified above, showing the pre-trend for phase 1 for 10-year contracts and the pre-trend for phase 2 for 2-year contracts. Other periods and phases show similar parallel trends but are not included here for brevity. The swaps rates show a parallel pre-trend prior to the implementation of the clearing mandate, with the Canadian swaps rate always higher than the US rate. This is likely due to differences in key policy rates between the US (lower Fed Funds target rate 0%) and Canada (key policy rate target 1%). There was no change to these policy rates in 2013.

Figure 4 Pre-trends for swap pricing for 2-year swaps during phase 2 and 10-year swaps during phase 1 of the clearing mandate implementation. Red, dashed veritcalline indicates when the clearing mandate went into effect. Highlighted area is the period of study and the pre-trend is to the left of highlighted area.

A graph showing the price of a currency

Description automatically generated

A graph with a line graph and numbers

Description automatically generated with medium confidence

## Liquidity

Liquidity is a broad concept defined as how easily one can convert financial assets to cash with minimal impact to prices of those financial assets. Several measures try to capture this notion: *bid-ask spreads* measure the cost of trading (small quantities) of an asset at the best quoted sell and buy prices; *market depth* measures how much of an asset is available to trade at given price points; *price impact* measures how much prices react to buying and selling. As in the case of pricing (premium), I employ a difference-in-differences strategy to identify the impact of the central clearing mandate on liquidity, with CAD denominated contracts serving as the control group and USD denominated contracts serving as the treatment group. I use several measures of liquidity to capture the different notions discussed above.

As discussed in section 2.4 risk-averse dealers adjust their bid-ask spreads in the face of market orders from liquidity traders. To be able to compare spreads for contracts with different prices, I calculate a relative bid-ask spread based on the mid-quote:

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where the numerator is the “raw” spread and the denominator is the mid-quote. I collect end-of day bid and ask data from the Bloomberg terminal for US-dollar and Canadian-dollar denominated 2-year, 5-year and 10-year contracts for the ten-day trading period before and after the implementation of phase 1, phase 2 and phase 3 of the of the clearing regulation.

The bid-ask spread measure is “low frequency” (collected at the end of day) and does not necessarily reflect the costs traders may face throughout the trading session. To estimate the intraday liquidity that traders may experience, I use two proxies common in the literature: the Roll measure and the Amihud Illiquidity (price impact) measure.

The first measure, proposed by Roll (1984) estimates the effective spread using the time series of observed prices under assumptions of market efficiency:

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where is the first-order serial covariance of price changes. I group the contracts by tenor and calculate the Roll measure for each trade date. I focus the analysis on 2-year, 5-year and 10-year contracts (the most actively traded contacts). For some trading days and tenors, the quantity under the radical is negative. These observations are excluded from the dataset. I also exclude any days where the number of contracts traded is less than five.

In general, market liquidity is a measure of “how easily” traders can exit or enter the market. The bid-ask spread (and the Roll measure) is a common metric for how easily traders can enter or exit *small positions*. However, when trading larger positions, this liquidity may not be available (only a limited number of contracts may be available to trade at the best bid and ask prices, and dealers can change their quoted prices in the face of large market orders). A common measure of the “price impact” of a trade is the Amihud liquidity measure:

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where is the return on an asset at time and is the total volume of contracts traded (calculated as the sum of the gross notional contract value in period ). The Amihud liquidity measure, which normalizes inter-period price changes by the market size (volume) is a measure of how much prices move, scaled by the trade size. I calculate the daily Amihud liquidity measure for US and Canadian 2-year, 5-year, and 10-year contracts for each trading date (calculating average daily returns using price changes from trade to trade within a day. I use the total notional amount on a given day as the volume measure in the denominator).

For each liquidity measure discussed above, I run a difference-in-differences model:

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where is the liquidity measure of interest, is an indicator variable for whether the observation is in the treatment (US-dollar denominated market) or control (Canadian-dollar denominated market) group, is an indicator variable for whether the observation is in the post- or pre implementation period. is the parameter of interest.

For the identification strategy to be valid, the underlying variables must follow parallel trends if there was no intervention. I visually test this by plotting the time-series of the relative spread, Amihud measure, and the Roll measure for the twenty trading days before the period of the study. Figure 5 shows the path of the relative spread measure for 5-year contracts for the USD and CAD denominated markets (other contract tenors show a similar trend). As in the case for the price premium, the relative bid-ask spread measure in the US and Canadian contracts generally follow a parallel trend before the implementation of the clearing mandate. The Canadian market has higher relative spreads, likely due to the smaller size of the market. Figure 6 shows the Roll measure for the 5-year USD and CAD interest rate swaps contracts (other tenors show similar trends). Note that due to the limitation discussed above, the Roll measure is not observable on all trading days. It is difficult to make a conclusion about parallel trends due to the lack of data availability. Figure 7 shows the Amihud illiquidity measure for 5-year USD and CAD interest rate swaps contracts. As expected, the Amihud measure is larger (indicating less liquidity) for the Canadian market, due to its smaller size. As is the case with the Roll measure, there is not enough data to conclude whether the parallel trend assumptions hold for the Amihud illiquidity measure.

Figure 5 Relative Bid-Ask Spread for five year contracts (Pre-Trend of ten trading days before study period)

Figure 6 Pre-trends for Roll’s Measure for 2-year swaps during phase 2 and 10-year swaps during phase 1 of the clearing mandate implementation. Red, dashed veritcal line indicates when the clearing mandate went into effect. Highlighted area is the period of study and the pre-trend is to the left of highlighted area.

A graph with a line graph

Description automatically generated with medium confidence

A graph of different colors and lines

Description automatically generated with medium confidence

Figure 7 Pre-trends for Amihud Illiquidty Measure for 2-year swaps during phase 2 and 10-year swaps during phase 1 of the clearing mandate implementation. Red, dashed veritcal line indicates when the clearing mandate went into effect. Highlighted area is the period of study and the pre-trend is to the left of highlighted area.

A graph of a trade

Description automatically generated with medium confidence

A graph showing different types of stocks

Description automatically generated with medium confidence

## Volatility

As is common practice in literature, I use the realized volatility as my measure of volatility. If the return on an asset in the period is defined as:

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The (annualized) realized volatility of the return is then:

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where: is the number of trading days in the sample period and 252 is the approximate number of trading days in a year.

For each trading day, I select contracts with “whole number tenor years” between 1 and 10 years, as well as 15-years and 30-years (I exclude contracts that are “partial years” such as 18-, 21- and 30-month contracts). For the Canadian market, these are the most actively traded contracts. Calculating volatility requires several observations of each tenor for each trading day. I group contracts by currency, tenor, and trading day (I exclude the Memorial Day and Labor Day holidays as too few contracts are traded on those days to calculate realized volatility). The filtered dataset captures 90% of Canadian contracts traded during the period studied in the dissertation, and I can calculate volatility of several tenors for each trading day[[3]](#footnote-4). However, for some tenors (such as 4-year, 6-year, 8-year and 9-year contracts), no trades or only one or two trades occur in the Canadian market on certain dates, and I cannot calculate the volatility measure for that tenor for the Canadian-dollar denominated contract on that trading date. Ideally, I would have 24 observations for each of the 58 trading days (1,392 observations in total, one for each currency-tenor combination for each day). However, since sometimes no Canadian contract of a particular tenor is traded on certain dates, I end up with 914 observations in my data set.

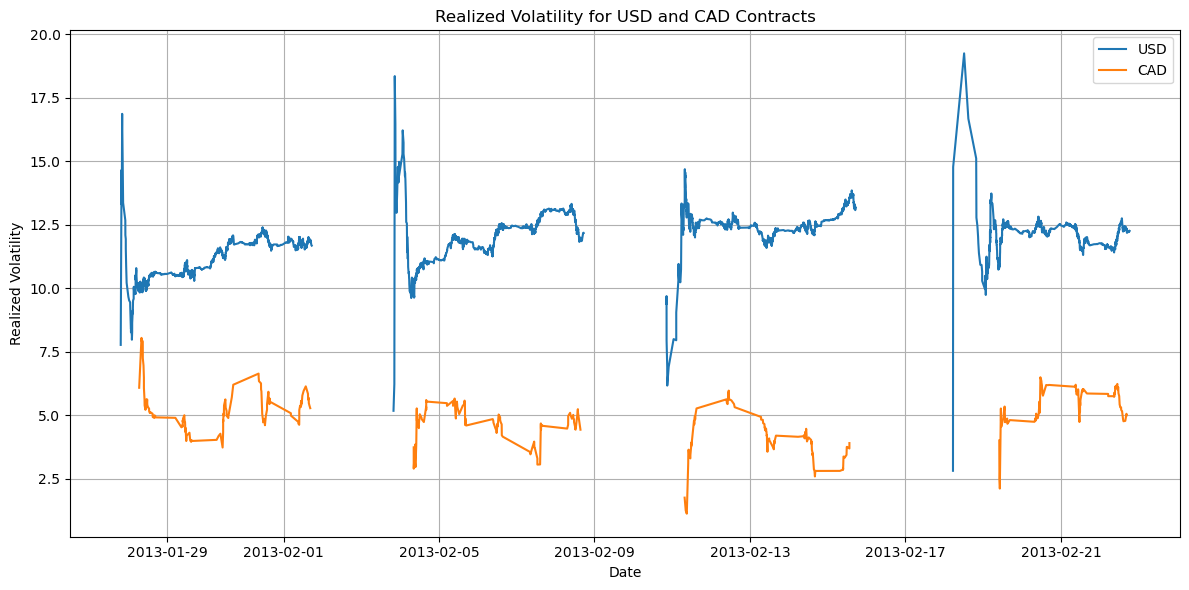
Like liquidity and pricing calculations, I classify each observation as either in the control group (if currency is CAD) or treatment group (if currency is USD), and whether it is in the pre-treatment or post-treatment period. I then perform a difference-in-difference regression:

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where is the realized volatility for contract specification in period and the rest of the variables are as described in the liquidity section. (the interaction between group and pre/post-treatment period) is the parameter of interest.

As with the other difference-in-differences specification, for the identification strategy to be valid, the two groups need to follow parallel trends in the absence of an intervention. I plot the time series (Figure 8) of the realized volatility measure for the 2-year, 5-year and 10-year contracts for the twenty trading days before the implementation of the clearing mandate. In general, the volatility measure follows a parallel trend for the US-dollar denominated and Canadian-dollar denominated markets.

Figure 8 Realized Volatility Pre-Trend



# Data

The Commodity Futures Trading Commission's (CFTC) clearing mandate on IR swaps became effective on March 11, 2013. The regulation was implemented in three phases. Phase 1, which started on March 11, mandated clearing for certain IR swaps involving swap dealers (SD), major swap participants (MSP), or active funds. Phase 2, which started on June 10, extended the mandate to additional entities, including commodity pool operators, banks and other financial institutions, while Phase 3, which started on September 9, covered all remaining entities (unless exempted, for example if the swap user is a non-financial entity that uses swaps to hedge commercial risk). I compare prices, price volatility, and liquidity before and after each of the three phases, comparing USD and CAD denominated swaps – the largest regulated and unregulated markets, respectively. To minimize the impact of interest rate policy and other macroeconomic variables, I analyze a small ten-day trading window before (Feb 25 – Mar 8, May 27 – Jun 7 and Aug 26 – Sep 6) and after (Mar 11 – Mar 22, Jun 10 – Jun 21 and Sep 9 – Sep 20) the regulation's effective date in each phase.

The CFTC defined contract specifications for swaps that must be cleared. These specifications included the currency (USD, GBP, EUR, JPY), the contract tenor (28 days to 50 years for USD, GBP and EUR based contracts, 28 days to 30 years for JPY bases contracts), and the floating leg reference (LIBOR or EURIBOR). It also specified “negative” characteristics (that is, swaps having these characteristics do not need to be cleared) including no dual currencies, no conditional notional amount and no optionality. The IR swaps covered by the mandate were the largest categories by volume.

The data are reported by the Depository Trust and Clearing Corporation Swaps Data Repository (DTCC SDR) and obtained using the SDR screen of the Bloomberg terminal. For the main part of the dissertation, I restrict my dataset to observations where the premium is within ±50 bps of the Bloomberg reported price of a swap with similar characteristics. Swaps that have a much higher premia are likely to have unseen characteristics (such as early termination clauses, conditional notional amounts, etc.) that are not observable in the dataset. In an appendix, I show that my results are robust to including these outliers.]

Note that before the regulation is passed, (voluntary) clearing in USD-denominated swaps is a little less than 61%. After phase 1 implementation, clearing increases to around 78%. After phase 2 implementation, clearing jumps to 89% and remains at that level after phase 3. The CAD-denominated market is much smaller (both in number of trades, and notional value). Clearing in Canadian IR swaps hovers around 48% prior to Phase 1. It reaches a high of around 56% in phase 2 and diminishes back to 48% after phase 3. Clearing for CAD denominated swaps is voluntary.

To calculate the theoretical counterparty-riskless price of IR swaps, I forecast future floating rate payments and discount the payments using the appropriate yield curve. I use a single curve method, the prevalent pricing method during the study period (subsequently, the market switched to a dual-curve method of pricing swaps, where one curve was used to calculate future floating-rate payments, and another curve to discount those payments to their present value). For USD swaps, I obtain the USD semiannual fixed-floating rate curve (curve S23) for each trading day from Bloomberg. I similarly obtain the Canadian yield curve (curve S11) from the Bloomberg Terminal for pricing Canadian swaps.

I use the QuantLib-python library to construct the forward curve. For the USD swaps curve, the short-end (3M or less) of the curve is anchored by LIBOR rates; the medium-end (6M – 18M) of the curve is anchored by Eurodollar futures; and the long-end (24M onward) of the curve is anchored by US swap rates.

Table 3 shows sample data for CAD and USD yield curves on September 11, 2013. Note that futures rates need to have a convexity adjustment applied since futures payoffs differ from payoffs for other instruments. The values reported in the table have this convexity adjustment applied. Values between the “pillars” (data points) of the yield curve need to be interpolated. I use piecewise linear interpolation. I verify the curve by pricing contracts using my constructed curve and comparing against calculations by Bloomberg SWPM function. I can match the output of SWPM up to 4 decimal places.

The contract characteristics reported in the DTCC SDR include swap currency, trade date and time, effective date, maturity date, fixed rate, payment frequencies, clearing status, notional value, and capped notional indicator. For USD swaps, USD LIBOR is the floating rate index for 98% of swaps, while for CAD swaps, CDOR is the index for 99% of swaps. I exclude certain swaps that make a single payment at maturity (i.e., payment frequency is 1T), which should actually be classified as an FRA. Table 4 shows the notional value and number of trades captured in my data, by clearing status and reference floating leg rate.

Table 5 shows summary statistics of the control variables used in the regression. Only contracts using LIBOR as the floating reference leg are included. Additionally, contracts that were “voluntarily cleared” prior to the mandate or “exempt from clearing” after the mandate are excluded. The leftmost column (unfiltered dataset) shows the statistics from this dataset. For the main part of the dissertation, I further filter this data to swaps whose fixed rate is within 50 bps of the Bloomberg calculated fixed rate. The rightmost column shows the statistics for this filtered dataset. Note that this filtering does not substantially alter the characteristics of the control variables. Wednesday was the most active trading day and Monday and Friday were the least active trading days. The dataset includes two trading holidays (Monday May 27, 2013 was Memorial Day and Monday, September 2, 2013 was Labor Day). I split the trading day into 4 sessions (corresponding roughly to the trading times on the NYSE) based on the reported trade time: 8:00 AM – 10:59 AM (Morning), 11:00 – 1:59 PM (Mid-Day), 2:00 PM – 4:59 PM (Afternoon) and 5:00 PM – 7:59 AM (After Hours). The mid-day trading session was most active. About 16% of contracts were traded during the off-hour trading session. The median notional value of the contract was $50M (with a range between $1,000 and $260M). The median tenor was about 7 years (with a range between 2 months and 43 years).

There are several limitations to the DTCC SDR dataset. Firstly, the dataset does not identify the counterparties. The identity of the counterparty (and more importantly, its creditworthiness) could have a significant impact on the swap price. In addition, the dataset does not mark which counterparty is the dealer (that is, whether the dealer is receiving the fixed rate or paying the fair rate). When receiving the fixed rate (and paying the floating leg), the dealer is likely to require a premium over the fair price. When paying the fixed rate, the dealer is likely to pay a discount below the fair price. I am also unable to observe non-standard contract characteristics such early termination previsions, collateral arrangements and day-count and settlement conventions. The standard-version of the interest rate swaps contract uses the International Swaps and Derivatives Association (ISDA) Master Agreement for specifying these contract terms. Deviations from the ISDA master agreement could affect the liquidity of the contract.

Table Sample data for USD and CAD yield curves

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Period | Bloomberg CUSIP | Yield | Data Source | Date Last Updated |
| 3M | EDU13 Comdty | 0.2575 | BGN | 09/11/13 |
| 6M | EDZ13 Comdty | 0.294 | BGN | 09/11/13 |
| 9M | EDH14 Comdty | 0.3574 | BGN | 09/11/13 |
| 12M | EDM14 Comdty | 0.4402 | BGN | 09/11/13 |
| 15M | EDU14 Comdty | 0.5675 | BGN | 09/11/13 |
| 18M | EDZ14 Comdty | 0.7341 | BGN | 09/11/13 |
| 2Y | USSWAP2 BGN Curncy | 0.5957 | BGN | 09/11/13 |
| 3Y | USSWAP3 BGN Curncy | 1.0014 | BGN | 09/11/13 |
| 4Y | USSWAP4 BGN Curncy | 1.45 | BGN | 09/11/13 |
| 5Y | USSWAP5 BGN Curncy | 1.865 | BGN | 09/11/13 |
| 6Y | USSW6 BGN Curncy | 2.2145 | BGN | 09/11/13 |
| 7Y | USSWAP7 BGN Curncy | 2.501 | BGN | 09/11/13 |
| 8Y | USSW8 BGN Curncy | 2.7305 | BGN | 09/11/13 |
| 9Y | USSW9 BGN Curncy | 2.919 | BGN | 09/11/13 |
| 10Y | USSWAP10 BGN Curncy | 3.0765 | BGN | 09/11/13 |
| 11Y | USSWAP11 BGN Curncy | 3.2103 | BGN | 09/11/13 |
| 12Y | USSWAP12 BGN Curncy | 3.322 | BGN | 09/11/13 |
| 15Y | USSWAP15 BGN Curncy | 3.551 | BGN | 09/11/13 |
| 20Y | USSWAP20 BGN Curncy | 3.7315 | BGN | 09/11/13 |
| 25Y | USSWAP25 BGN Curncy | 3.815 | BGN | 09/11/13 |
| 30Y | USSWAP30 BGN Curncy | 3.8565 | BGN | 09/11/13 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Tenor | CUSIP | Yield | Source | Date Last Updated |
| 1D | CCLR Index | 1.00 | CMPN | 09/11/13 |
| 1M | CDOR01 Index | 1.22 | CMPN | 09/11/13 |
| 2M | CDOR02 Index | 1.2475 | CMPN | 09/11/13 |
| 3M | BAU13 Comdty | 1.275 | BGN | 09/11/13 |
| 6M | BAZ13 Comdty | 1.2997 | BGN | 09/11/13 |
| 9M | BAH14 Comdty | 1.3491 | BGN | 09/11/13 |
| 12M | BAM14 Comdty | 1.4584 | BGN | 09/11/13 |
| 15M | BAU14 Comdty | 1.6275 | BGN | 09/11/13 |
| 18M | BAZ14 Comdty | 1.8164 | BGN | 09/11/13 |
| 2Y | CDSW2 BGN Curncy | 1.6195 | BGN | 09/11/13 |
| 3Y | CDSW3 BGN Curncy | 1.9372 | BGN | 09/11/13 |
| 4Y | CDSW4 BGN Curncy | 2.235 | BGN | 09/11/13 |
| 5Y | CDSW5 BGN Curncy | 2.4855 | BGN | 09/11/13 |
| 6Y | CDSW6 BGN Curncy | 2.6885 | BGN | 09/11/13 |
| 7Y | CDSW7 BGN Curncy | 2.8595 | BGN | 09/11/13 |
| 8Y | CDSW8 BGN Curncy | 3.003 | BGN | 09/11/13 |
| 9Y | CDSW9 BGN Curncy | 3.1335 | BGN | 09/11/13 |
| 10Y | CDSW10 BGN Curncy | 3.254 | BGN | 09/11/13 |
| 12Y | CDSW12 BGN Curncy | 3.457 | BGN | 09/11/13 |
| 15Y | CDSW15 BGN Curncy | 3.6713 | BGN | 09/11/13 |
| 20Y | CDSW20 BGN Curncy | 3.7915 | BGN | 09/11/13 |
| 25Y | CDSW25 BGN Curncy | 3.7555 | BGN | 09/11/13 |
| 30Y | CDSW30 BGN Curncy | 3.693 | BGN | 09/11/13 |

Table Number of contracts and notional values by Clearing Status and reference rate for USD and CAD IR swaps contracts

Pre Phase 1

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Currency** | **Floating Leg** | **Cleared (Count)** | **Cleared (Notional Value)** | **Uncleared (Count)** | **Uncleared (Notional Value)** | **Percent Cleared** |
| **USD** | **LIBOR** | 3,518 | 203,345.90 | 3,071 | 131,242.01 | 61% |
|  | USD-Federal Funds-H.15 | 0 | 0.0 | 16 | 2,183.00 | 0% |
|  | USD-PRIME-H.15 | 0 | 0.0 | 2 | 6.00 | 0% |
|  | USD-PRIME-H15 | 0 | 0.0 | 2 | 4.00 | 0% |
|  | USD SPRDL MANUAL | 0 | 0.0 | 1 | 100.00 | 0% |
|  | USD-AAA\_MUNI- | 0 | 0.0 | 4 | 31.00 | 0% |
|  | USD-OIS-3 | 0 | 0.0 | 1 | 6.00 | 0% |
|  | IBR | 0 | 0.0 | 2 | 200.00 | 0% |
|  | CLICP | 0 | 0.0 | 1 | 100.00 | 0% |
|  | TIS | 0 | 0.0 | 1 | 1.00 | 0% |
|  | USD-USPSA-BLOOMBERG | 0 | 0.0 | 1 | 4.00 | 0% |
| **CAD** | **CAD-BA-CDOR** | 225 | 18,811.40 | 308 | 20,363.10 | 48% |
|  | CAD-REPO-CORRA | 0 | 0.00 | 3 | 410.00 | 0% |

Post Phase 1

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Currency** | **Floating Leg** | **Cleared (Count)** | **Cleared (Notional Value)** | **Uncleared (Count)** | **Uncleared (Notional Value)** | **Percent Cleared** |
| **USD** | **LIBOR** | 4,342 | 262,257.70 | 2,125 | 76,649.65 | 77% |
|  | USD-Federal Funds-H.15 | 0 | 0.00 | 24 | 3,353.00 | 0% |
|  | IBR | 0 | 0.00 | 6 | 1,050.00 | 0% |
|  | USD-SIFMA Municipal Swap Index | 0 | 0.00 | 6 | 60.00 | 0% |
|  | USD-PRIME-H.15 | 0 | 0.00 | 2 | 6.00 | 0% |
|  | USD-PRIME-H15 | 0 | 0.00 | 2 | 3.00 | 0% |
|  | USD-Prime-H.15 | 0 | 0.00 | 1 | 2.00 | 0% |
|  | USD-USPSA-BLOOMBERG | 0 | 0.00 | 2 | 20.00 | 0% |
|  | CLICP | 0 | 0.00 | 3 | 450.00 | 0% |
|  | USD-AAA\_MUNI- | 0 | 0.00 | 2 | 25.00 | 0% |
|  | USD-BMA Municipal Swap Index | 0 | 0.00 | 2 | 6.52 | 0% |
| **CAD** | **CAD-BA-CDOR** | 126 | 9,578.00 | 140 | 11,137.31 | 46% |
|  | CAD-REPO-CORRA | 0 | 0.00 | 3 | 780.00 | 0% |
|  | CDOR | 0 | 0.00 | 5 | 105.60 | 0% |

Pre Phase 2

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Currency** | **Floating Leg** | **Cleared (Count)** | **Cleared (Notional Value)** | **Uncleared (Count)** | **Uncleared (Notional Value)** | **Percent Cleared** |
| **USD** | **LIBOR** | 6,870 | 426,753.26 | 2,954 | 118,388.28 | 78% |
|  | USD-Federal Funds-H.15 | 0 | 0.00 | 29 | 4,463.00 | 0% |
|  | COOVIBR | 0 | 0.00 | 9 | 1,800.00 | 0% |
|  | CLP-TNA | 0 | 0.00 | 6 | 1,200.00 | 0% |
|  | USD FORM 3750 | 0 | 0.00 | 1 | 100.00 | 0% |
|  | USD-AAA\_MUNI- | 0 | 0.00 | 2 | 13.00 | 0% |
|  | USD-BMA Municipal Swap Index | 0 | 0.00 | 1 | 7.00 | 0% |
|  | USD-PRIME-H.15 | 0 | 0.00 | 12 | 62.90 | 0% |
| **CAD** | **CAD-BA-CDOR** | 180 | 14,726.00 | 169 | 14,290.70 | 51% |

Post Phase 2

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Currency** | **Floating Leg** | **Cleared (Count)** | **Cleared (Notional Value)** | **Uncleared (Count)** | **Uncleared (Notional Value)** | **Percent Cleared** |
| USD | **LIBOR** | 7,975.00 | 461,124.51 | 1,449.00 | 53,548.33 | 90% |
|  | USD-Federal Funds-H.15 | 0.00 | 0.00 | 33.00 | 5,068.00 | 0% |
|  | USD-PRIME-H.15 | 0.00 | 0.00 | 5.00 | 26.00 | 0% |
|  | USD-PRIME-H15 | 0.00 | 0.00 | 1.00 | 9.00 | 0% |
|  | USD-Prime-H.15 | 0.00 | 0.00 | 1.00 | 2.00 | 0% |
|  | COOVIBR | 0.00 | 0.00 | 21.00 | 3,750.00 | 0% |
|  | CLP-TNA | 0.00 | 0.00 | 7.00 | 700.00 | 0% |
|  | USD BMA MANUAL | 0.00 | 0.00 | 1.00 | 45.00 | 0% |
|  | USD-AAA\_MUNI- | 0.00 | 0.00 | 3.00 | 20.00 | 0% |
|  | USD-BMA Municipal Swap Index | 0.00 | 0.00 | 2.00 | 10.00 | 0% |
| CAD | **CAD-BA-CDOR** | 176.00 | 11,322.08 | 174.00 | 7,969.50 | 59% |

Pre Phase 3

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Currency** | **Floating Leg** | **Cleared (Count)** | **Cleared (Notional value)** | **Uncleared (Count)** | **Uncleared (Notional Value)** | **Percent Cleared** |
| **USD** | **LIBOR** | 6,112.00 | 396,744.28 | 1,398.00 | 47,355.82 | 89% |
|  | USD-Federal Funds-H.15 | 0.00 | 0.00 | 36.00 | 4,539.00 | 0% |
|  | USD-PRIME-WEIGHTED-AVERAGE | 0.00 | 0.00 | 2.00 | 200.00 | 0% |
|  | USD-PRIME-H.15 | 0.00 | 0.00 | 5.00 | 7.00 | 0% |
|  | USD-PRIME-H15 | 0.00 | 0.00 | 8.00 | 35.56 | 0% |
|  | USD-AAA\_MUNI- | 0.00 | 0.00 | 1.00 | 10.00 | 0% |
|  | USD-SIFMA Municipal Swap Index | 0.00 | 0.00 | 1.00 | 5.00 | 0% |
| **CAD** | **CAD-BA-CDOR** | 128.00 | 9,697.20 | 134.00 | 7,487.11 | 56% |
|  | CAD-REPO-CORRA | 0.00 | 0.00 | 1.00 | 35.00 | 0% |

Post Phase 3

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Currency** | **Floating Leg** | **Cleared (Count)** | **Cleared (Notional Value)** | **Uncleared (Count)** | **Uncleared (Notional Value)** | **Percent Cleared** |
| **USD** | **LIBOR** | 7,481 | 485,507.61 | 1,461 | 58,912.20 | 89% |
|  | USD-Federal Funds-H.15 | 0 | 0.00 | 19 | 3,606.00 | 0% |
|  | TREASURY\_DTCC\_GCF\_REPO\_INDEX | 0 | 0.00 | 4 | 850.00 | 0% |
|  | USD FORM 3750 | 0 | 0.00 | 1 | 30.00 | 0% |
|  | USD-AAA\_MUNI- | 0 | 0.00 | 9 | 56.00 | 0% |
|  | USD-BMA Municipal Swap Index | 0 | 0.00 | 3 | 13.00 | 0% |
|  | USD-BMA-BMA | 0 | 0.00 | 1 | 22.00 | 0% |
|  | USD-BMA-REFB | 0 | 0.00 | 2 | 12.75 | 0% |
|  | USD-PRIME-H.15 | 0 | 0.00 | 7 | 17.00 | 0% |
|  | USD-PRIME-H15 | 0 | 0.00 | 7 | 64.00 | 0% |
|  | USD-Prime-H.15 | 0 | 0.00 | 1 | 1.00 | 0% |
|  | USD-SIFMA Municipal Swap Index | 0 | 0.00 | 5 | 52.75 | 0% |
| **CAD** | **CAD-BA-CDOR** | 210 | 14,099.00 | 354 | 15,561.41 | 48% |
|  | CDOR | 0 | 0.00 | 1 | 5.00 | 0% |
|  | CDOR.CAD | 0 | 0.00 | 4 | 106.00 | 0% |

Table Selected Charactersitics of Control Variables

|  |  |  |
| --- | --- | --- |
|  | **Unfiltered Dataset** | **Main Dataset** |
|  | **Trading Day** | **Trading Day** |
| Monday | 4,246 | 4,096 |
| Tuesday | 5,558 | 5,372 |
| **Wednesday** | **7,020** | **6,733** |
| Thursday | 6,243 | 6,001 |
| Friday | 5,244 | 5,008 |
|  |  |  |
|  | **Trading Session** | **Trading Session** |
| Morning | 7,419 | 7,193 |
| **Mid-Day** | **8,266** | **7,845** |
| Afternoon | 7,974 | 7,684 |
| After Hours | 4,652 | 4,488 |
|  |  |  |
|  | **Capped** | **Capped** |
| Capped | 19,727 | 18,837 |
| Not Capped | 8,584 | 8,373 |
|  |  |  |
|  | **Tenor** | **Tenor** |
| Min | 2 months | 2 months |
| 1st Quartile | 5 years | 5 years |
| Median | 7 years | 7 years |
| 3rd Quartile | 10 years | 10 years |
| Max | 43 years | 43 years |
| Mean | 9 years, 9 months | 9 years, 9 months |
|  |  |  |
|  | **Notional** | **Notional** |
| Min | 1,000 | 1,000 |
| 1st Quartile | 15,000,000 | 16,000,000 |
| Median | 50,000,000 | 50,000,000 |
| 3rd Quartile | 100,000,000 | 100,000,000 |
| Max | 260,000,000 | 260,000,000 |
| Mean | 55,650,025 | 56,426,143 |

# Results

## Prices

For analyzing the impact of the clearing mandate on prices, I compare USD LIBOR denominated contracts against CAD CDOR contracts. USD LIBOR contracts are subject to the CFTC clearing mandate (note that USD denominated contracts using another floating rate index such as the Federal Funds Rate are not subject to the clearing mandate, but these contracts can be voluntarily cleared.

Table 6 lists the DiD results for the swap premium. Column 1 shows a basic model without any controls for contract characteristics. The clearing mandate causes a ~14 bps rise in premia. As expected, reducing the riskiness of the contract increases its price. Column 2 shows the effects additional controls, such as the (log) notional value of the contract, day and period of trading and whether the notional value was “capped” (i.e. the exact value was not reported to the trade repo). In this model, premia rise by ~ 13 bps. Thus, the results are robust to such controls.

Using Wednesday as the reference level, I note that there is a 1-3 bps increase in the premium depending on the trading day. There is also a 1.0-1.3 bps decrease in the premium for trading in morning, afternoon or off hours trading sessions (as compared to mid-day). Note that both results contrast with assumptions of “efficient markets”, where there should be no arbitrage opportunities by trading during special days or times. A one-year increase in the tenor is associated with a 0.03 bps increase in the premium. A one percent increase in the notional value is associated with a 0.77 bps increase in the premium. Again, these result contrast with expectations from “efficient market” assumptions because arbitrage opportunities exist (for example, a dealer can make a riskless profit by agreeing to receive a fixed rate on a higher-priced a “large” contract and agreeing to pay the fixed-rate for two lower-priced “small” contracts). However, these differences could be related to liquidity, counterparty risk, or other contract characteristics of larger and longer swaps, which is not observable in our data. Although statistically significant, the magnitudes of the effects are small, ranging from 0.03 to 3 bps.

Table 7 shows the result of running the model on each phase of the data separately. In phase 1, there is a ~5 bps increase in the premium after the mandate. As noted previously, there was a 16% increase in the cleared volume following implementation of phase 1. There was an additional 12% increase in the cleared volume following phase 2, and the premium rose by another ~3 bps. In phase 3, a larger set of market participants fell under the mandate (although the cleared volume did not change), and the premium increased by ~16 bps. This suggests that when almost all contracts (>90%) are cleared, premia rise due to less severe consequences of counterparty default.

Table 8 shows the results from a placebo difference-in-differences regression. I pick the 20 trading days before the periods studied above (60 trading days in total across three phases). I create a “placebo” difference-in-differences, as if there was a transition to clearing mandate on the 11th trading day (i.e. Feb 11, May 13 and Aug 12). The results do not show any effect from this placebo DiD, further strengthening our belief that the increase in premia seen in the actual DiD is real.

Table 9 shows the results of a similar regression using an alternative currency pair. The CFTC clearing mandate also affected contracts denominated in GBP using the LIBOR as the reference rate (with implementation dates the same as the USD LIBOR clearing mandate). These contracts serve as the treatment group. The clearing mandate did not apply to CHF denominated contracts, and this serves as the control group. The clearing mandate had a similar (but smaller) impact on prices of GBP-denominated swaps, further strengthening our belief that clearing reduces counterparty risk and increases contract premia.

Table Difference-in-Difference Results for Prices

|  |  |  |
| --- | --- | --- |
| **Difference-in-Differences Regression Results** | | |
|  | | |
|  | Dependent variable: Premium | |
|  |  | |
|  | Basic Model | Advanced Model |
|  | (1) | (2) |
|  | | |
| Group | -0.8889\* | -0.7683 |
|  | (0.4917) | (0.4900) |
| Period | -13.6369\*\*\* | -13.2955\*\*\* |
|  | (0.6641) | (0.6610) |
| Tenor |  | 0.0362\*\*\* |
|  |  | (0.0086) |
| Log Notional |  | 0.7755\*\*\* |
|  |  | (0.0671) |
| Capped |  | -0.9311\*\*\* |
|  |  | (0.1849) |
| SEF |  | 0.6922 |
|  |  | (2.5197) |
| Morning Session |  | -1.0238\*\*\* |
|  |  | (0.1843) |
| Afternoon Session |  | -1.2368\*\*\* |
|  |  | (0.1814) |
| Off Hours |  | -1.2907\*\*\* |
|  |  | (0.2125) |
| Monday |  | 1.5672\*\*\* |
|  |  | (0.2244) |
| Tuesday |  | 2.3944\*\*\* |
|  |  | (0.2070) |
| Thursday |  | 2.7672\*\*\* |
|  |  | (0.2005) |
| Friday |  | 0.9566\*\*\* |
|  |  | (0.2124) |
| Group \* Period | 14.2183\*\*\* | 13.4103\*\*\* |
|  | (0.6833) | (0.6839) |
| Constant | -0.2415 | -14.1707\*\*\* |
|  | (0.4718) | (1.2407) |
|  | | |
| Observations | 27,210 | 27,210 |
| R2 | 0.0283 | 0.0444 |
| Adjusted R2 | 0.0282 | 0.0440 |
| Residual Std. Error | 11.3530 (df = 27206) | 11.2607 (df = 27195) |
| F Statistic | 264.3342\*\*\* (df = 3; 27206) | 90.3482\*\*\* (df = 14; 27195) |
|  | | |
| Note: | \*p\*\*p\*\*\*p<0.01 | |

Table Difference-in-Dfferences results for prices by phase

|  |  |  |  |
| --- | --- | --- | --- |
| **By Phase Results: Advanced Model** | | | |
|  | | | |
|  | Dependent variable: Premium | | |
|  |  | | |
|  | Phase 1 | Phase 2 | Phase 3 |
|  | (1) | (2) | (3) |
|  | | | |
| Group | -2.789\*\*\* | 2.327\*\*\* | 3.139\*\*\* |
|  | (0.525) | (0.886) | (1.205) |
|  |  |  |  |
| Period | -4.898\*\*\* | -4.150\*\*\* | -12.360\*\*\* |
|  | (0.875) | (1.309) | (1.338) |
|  |  |  |  |
| Tenor | -0.050\*\*\* | 0.064\*\*\* | 0.086\*\*\* |
|  | (0.013) | (0.013) | (0.016) |
|  |  |  |  |
| Notional | -0.489\*\*\* | 0.685\*\*\* | 1.506\*\*\* |
|  | (0.094) | (0.109) | (0.125) |
|  |  |  |  |
| Capped | -0.727\*\*\* | -0.583\*\* | -1.575\*\*\* |
|  | (0.268) | (0.287) | (0.345) |
|  |  |  |  |
| Morning Session | -0.387 | 0.788\*\*\* | -2.375\*\*\* |
|  | (0.265) | (0.292) | (0.340) |
|  |  |  |  |
| Afternoon Session | -1.170\*\*\* | -0.571\*\* | -0.538 |
|  | (0.264) | (0.280) | (0.342) |
|  |  |  |  |
| Off Hours | -1.196\*\*\* | 1.594\*\*\* | -5.542\*\*\* |
|  | (0.309) | (0.334) | (0.392) |
|  |  |  |  |
| Monday | 2.017\*\*\* | 6.666\*\*\* | -5.821\*\*\* |
|  | (0.323) | (0.367) | (0.409) |
|  |  |  |  |
| Tuesday | 0.741\*\* | 8.913\*\*\* | -3.854\*\*\* |
|  | (0.312) | (0.326) | (0.377) |
|  |  |  |  |
| Thursday | 2.025\*\*\* | 8.909\*\*\* | -3.700\*\*\* |
|  | (0.306) | (0.306) | (0.376) |
|  |  |  |  |
| Friday | 1.642\*\*\* | 5.832\*\*\* | -4.480\*\*\* |
|  | (0.325) | (0.320) | (0.402) |
|  |  |  |  |
| Group \* Period | 5.308\*\*\* | 2.658\*\* | 16.277\*\*\* |
|  | (0.899) | (1.336) | (1.408) |
|  |  |  |  |
| Constant | 11.804\*\*\* | -22.064\*\*\* | -27.840\*\*\* |
|  | (1.654) | (2.101) | (2.446) |
|  |  |  |  |
|  | | | |
| Observations | 7,561 | 10,856 | 8,793 |
| R2 | 0.025 | 0.109 | 0.179 |
| Adjusted R2 | 0.024 | 0.108 | 0.178 |
| Residual Std. Error | 8.635 (df = 7547) | 11.002 (df = 10842) | 11.861 (df = 8779) |
| F Statistic | 15.068\*\*\* (df = 13; 7547) | 102.336\*\*\* (df = 13; 10842) | 147.232\*\*\* (df = 13; 8779) |
|  | | | |
| Note: | \*p\*\*p\*\*\*p<0.01 | | |

Table Placebo DiD Results

|  |  |  |
| --- | --- | --- |
| **Placebo Difference-in-Difference Results** | | |
|  | | |
|  | Dependent variable: Premium | |
|  |  | |
|  | Basic Model | Advanced Model |
|  | (1) | (2) |
|  | | |
| Group | 1.6566\*\*\* | 1.4077\*\*\* |
|  | (0.4343) | (0.4357) |
| Period | -0.5706 | -0.4838 |
|  | (0.5826) | (0.5799) |
| Tenor |  | 0.0301\*\*\* |
|  |  | (0.0077) |
| Log Notional |  | -0.0219 |
|  |  | (0.0595) |
| Capped |  | -0.8827\*\*\* |
|  |  | (0.1572) |
| Morning Session |  | 0.2761\* |
|  |  | (0.1520) |
| Afternoon Session |  | 0.3836\*\* |
|  |  | (0.1600) |
| Off Hours |  | 0.0617 |
|  |  | (0.1802) |
| Monday |  | 0.7955\*\*\* |
|  |  | (0.1954) |
| Tuesday |  | 0.5999\*\*\* |
|  |  | (0.1800) |
| Thursday |  | 1.7587\*\*\* |
|  |  | (0.1744) |
| Friday |  | 1.7827\*\*\* |
|  |  | (0.1822) |
| Group \* Period | 0.1694 | 0.1696 |
|  | (0.5975) | (0.5952) |
| Constant | -1.2876\*\*\* | -1.9215\* |
|  | (0.4197) | (1.1216) |
|  | | |
| Observations | 20,794 | 20,794 |
| R2 | 0.0020 | 0.0136 |
| Adjusted R2 | 0.0019 | 0.0130 |
| Residual Std. Error | 8.4872 (df = 20790) | 8.4398 (df = 20780) |
| F Statistic | 13.8615\*\*\* (df = 3; 20790) | 22.0214\*\*\* (df = 13; 20780) |
|  | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | |

Table Alternative Currency Pair (GBP denominated contracts serve as the treatment group and CHF denominated contracts serve as the control group)

|  |  |  |
| --- | --- | --- |
| **Alternative Currencies Difference-in-Differences Results (GBP vs. CHF)** | | |
|  | | |
|  | Dependent variable: Premium | |
|  |  | |
|  | Basic Model | Advanced Model |
|  | (1) | (2) |
|  | | |
| Group | -0.2734 | -0.9492 |
|  | (1.2232) | (1.2023) |
| Period | -6.6242\*\*\* | -8.2303\*\*\* |
|  | (1.4576) | (1.4435) |
| Tenor |  | 0.0974\*\*\* |
|  |  | (0.0193) |
| Log Notional |  | 0.6572\*\*\* |
|  |  | (0.1811) |
| Capped |  | -0.4361 |
|  |  | (0.5052) |
| Morning Session |  | -0.9820\*\* |
|  |  | (0.4967) |
| Afternoon Session |  | -2.5981\*\*\* |
|  |  | (0.4186) |
| Off Hours |  | -2.4152\*\*\* |
|  |  | (0.7555) |
| Monday |  | 3.1430\*\*\* |
|  |  | (0.5643) |
| Tuesday |  | 3.5697\*\*\* |
|  |  | (0.5050) |
| Thursday |  | 3.0135\*\*\* |
|  |  | (0.4984) |
| Friday |  | 1.5464\*\*\* |
|  |  | (0.5515) |
| Group \* Period | 7.4610\*\*\* | 8.2859\*\*\* |
|  | (1.5404) | (1.5143) |
| Constant | -3.7350\*\*\* | -15.0964\*\*\* |
|  | (1.1343) | (3.1718) |
|  | | |
| Observations | 3,522 | 3,522 |
| R2 | 0.0168 | 0.0580 |
| Adjusted R2 | 0.0159 | 0.0546 |
| Residual Std. Error | 10.3965 (df = 3518) | 10.1905 (df = 3508) |
| F Statistic | 20.0170\*\*\* (df = 3; 3518) | 16.6288\*\*\* (df = 13; 3508) |
|  | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | |

Table 10 shows the results of difference-in-difference regression for the relative bid-ask spreads. Note that since the period of study is short (ten trading days before and ten trading after the clearing mandate implementation), and since liquidity is a “market wide”, rather than an individual contract-based measure, the opportunity to control for variables that impact liquidity is limited to market-wide metrics. If a longer period were being studied, variables that impact liquidity, such as monetary policy and credit availability could be added as controls. However, since these variables do not vary during the short period studied, they cannot be controlled for. Two control variables that proxy financial market conditions are added to the more complex model: a measure of equity market volatility and a measure for equity market return. For the volatility measure, I use the CBOE VIX Index, which measures the 30-day expected realized variance of the S&P 500 index and its Canadian equivalent (the S&P TSX VIX).

The clearing mandate does not impact the liquidity as measured by relative bid-ask spreads. As noted in the theory section, we should expect reductions in counterparty risk of interest rate swaps to cause a narrowing of the bid-ask spread (the spread is charged by dealers to offset their expected losses from holding inventory). However, the spread is also driven by supply and demand conditions in the market. As explored in the pricing section, a reduction in riskiness of IRS increases their demand. If the swaps market is monopolistic (that is, new swaps dealers face barriers to entry), then incumbent dealers can choose not to lower their bid-ask spreads and pocket the additional profits from the high demand.

Table 11 and Table 12 show the results for the Roll and Amihud measure respectively. These measures also do not show any impact of the clearing mandate on liquidity. As described earlier, in monopolistic markets, increase in demand due to less counterparty risk can be captured as increases in premia by the dealers, without improving liquidity. The relative bid-ask spread, Roll measure and Amihud measures all consistently show no change in market liquidity due to the clearing mandate.

Table Relative Bid-Ask Spread DiD

|  |  |
| --- | --- |
| **Relative Bid-Ask Spread DiD Analysis** | |
|  | |
|  | Dependent variable: |
|  |  |
|  | Relative Spread |
|  | |
| Group | -0.005\*\*\* |
|  | (0.001) |
|  |  |
| Period | 0.0001 |
|  | (0.001) |
|  |  |
| Tenor (2Y) | 0.007\*\*\* |
|  | (0.001) |
|  |  |
| Tenor (5Y) | 0.003\*\*\* |
|  | (0.001) |
|  |  |
| Group\*Period | -0.001 |
|  | (0.001) |
|  |  |
| Constant | 0.011\*\*\* |
|  | (0.001) |
|  |  |
|  | |
| Observations | 360 |
| R2 | 0.406 |
| Adjusted R2 | 0.398 |
| Residual Std. Error | 0.005 (df = 354) |
| F Statistic | 48.406\*\*\* (df = 5; 354) |
|  | |
| Note: | \*p\*\*p\*\*\*p<0.01 |

Table Roll Measure DiD

|  |  |
| --- | --- |
|  | |
|  | Dependent variable: |
|  |  |
|  | `Roll Measure` |
|  | |
| Group | 0.363\*\*\* |
|  | (0.078) |
|  |  |
| Period | 0.010 |
|  | (0.086) |
|  |  |
| Tenor (5 years) | 0.118\*\* |
|  | (0.055) |
|  |  |
| Tenor (10 years) | -0.087 |
|  | (0.058) |
|  |  |
| Stock market index | 4.385 |
|  | (3.401) |
|  |  |
| Volatility index | 0.027\* |
|  | (0.015) |
|  |  |
| Group\*Period | -0.087 |
|  | (0.101) |
|  |  |
| Constant | -0.370\* |
|  | (0.212) |
|  |  |
|  | |
| Observations | 236 |
| R2 | 0.219 |
| Adjusted R2 | 0.195 |
| Residual Std. Error | 0.345 (df = 228) |
| F Statistic | 9.137\*\*\* (df = 7; 228) |
|  | |
| Note: | \*p\*\*p\*\*\*p<0.01 |

Table Amihud Measure DiD

|  |  |
| --- | --- |
|  | |
|  | Dependent variable: |
|  |  |
|  | Amihud Measure |
|  | |
| Group | -10.347\*\*\* |
|  | (3.305) |
|  |  |
| Period | 3.890 |
|  | (3.486) |
|  |  |
| Tenor (5 years) | 3.011 |
|  | (2.399) |
|  |  |
| Tenor (10 years) | -0.478 |
|  | (2.551) |
|  |  |
| Stock market index | 37.435 |
|  | (148.396) |
|  |  |
| Volatility index | 0.217 |
|  | (0.665) |
|  |  |
| Group\*Period | -3.878 |
|  | (4.238) |
|  |  |
| Constant | 6.710 |
|  | (9.409) |
|  |  |
|  | |
| Observations | 254 |
| R2 | 0.138 |
| Adjusted R2 | 0.113 |
| Residual Std. Error | 15.659 (df = 246) |
| F Statistic | 5.622\*\*\* (df = 7; 246) |
|  | |
| Note: | \*p\*\*p\*\*\*p<0.01 |

Table 13 shows the results of the price volatility difference-in-difference regression. Price volatility (as measured by realized volatility) does not appear to be affected by the clearing mandate. During “normal” trading periods, the clearing mandate might not be as impactful as during periods of market stress. To test whether the clearing mandate had a “calming effect” on US markets (as compared to Canadian markets) I compare realized volatility around the time of the (second) “Grexit” vote. Caution should be exercised when interpreting these results, as the “control group” (CAD contracts) have different exposure to the Greek economy than the “treatment” group. The referendum on the second Greek bailout package was announced on June 26 with the vote taking place on July 5. An alternative arrangement between Greece and the Eurozone was reached on July 13. Thus, the period between June 27 and July 13 might be taken as a period of enhanced market stress. Figure 9 shows the realized volatility of USD and CAD interest rate swaps contracts between June 1 and July 31, with important dates marked. We do not observe any consistent pattern of volatility for either the US or Canadian markets. Table 14 shows the results of a “diff-in-diff” using the post-June 26 time frame as the treatment period and using the US market as the treatment group. There is no significant difference in volatility between US and Canadian contracts in either the pre- or post-treatment time period.

Table Volatility Difference in Differences

|  |  |
| --- | --- |
| **Volatility Diff-in-Diff** | |
|  | |
|  | Dependent variable: Realized Volatility |
|  |  |
|  | |
| Group | 0.1733\*\*\* |
|  | (0.0277) |
| Period | 0.0029 |
|  | (0.0347) |
| Group \* Period | 0.0016 |
|  | (0.0391) |
| Constant | 0.0277 |
|  | (0.0245) |
|  | |
| Observations | 861 |
| R2 | 0.0849 |
| Adjusted R2 | 0.0817 |
| Residual Std. Error | 0.2346 (df = 857) |
| F Statistic | 26.5000\*\*\* (df = 3; 857) |
|  | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 |

A graph of a graph

Description automatically generated

Figure 9 Realized Volatility around GREXIT

Table Volatility diff-in-diff during GREXIT time period

|  |  |
| --- | --- |
| **Difference-in-Differences Analysis of Volatility During GREXIT** | |
|  | |
|  | Dependent variable: |
|  |  |
|  | Volatility (Daily Return) |
|  | |
| Post Period | -0.002 |
|  | (0.087) |
|  |  |
| USD Market | 0.012 |
|  | (0.090) |
|  |  |
| Post Period x USD Market | -0.016 |
|  | (0.119) |
|  |  |
| Constant | 0.039 |
|  | (0.065) |
|  |  |
|  | |
| Observations | 104 |
| R2 | 0.001 |
| Adjusted R2 | -0.029 |
| Residual Std. Error | 0.300 (df = 100) |
| F Statistic | 0.018 (df = 3; 100) |
|  | |
| Note: | \*p\*\*p\*\*\*p<0.01 |

# Conclusion

This study investigates the causal impact of the central clearing mandate on the interest rate swaps (IRS) market, focusing on key outcomes such as pricing, liquidity, and volatility. Using a difference-in-differences approach, I can isolate the effects of the clearing mandate, providing a comprehensive view of its influence on market dynamics.

The findings suggest that central clearing plays a significant role in reducing counterparty risk, as evidenced by the consistent rise in swap premia following the mandate. This reflects an increased valuation for cleared contracts, indicating market participants place a higher premium on reduced risk exposure. However, the anticipated improvements in liquidity were not observed. Measures such as the bid-ask spread, Roll measure, and Amihud liquidity measure show no substantial change in liquidity as a result of the clearing mandate. This suggests that in monopolistic or concentrated dealer markets, the demand for cleared contracts does not necessarily lead to narrower spreads or improved liquidity conditions.

Regarding price volatility, the results indicate that under normal market conditions, the mandate has little to no effect on volatility. The realized volatility measures reveal that prices generally follow a random walk during stable periods, making it difficult to detect significant changes due to the clearing requirement. However, during episodes of market stress, such as the event surrounding the second “Grexit” vote, cleared contracts experienced lower volatility compared to their uncleared counterparts, implying that central clearing may enhance stability in more turbulent times.

While the mandate has succeeded in reducing counterparty risk, its impact on liquidity and volatility appears more nuanced. The clearinghouse structure has not necessarily resulted in a more liquid market, and its effect on volatility is more pronounced during periods of financial stress rather than regular market conditions. These results are crucial for regulators and market participants, as they highlight both the strengths and limitations of central clearing in maintaining market stability.

Future research could delve deeper into the long-term effects of central clearing, particularly in crisis periods, and explore whether different market structures or alternative clearing mechanisms might enhance both liquidity and stability in the IRS market.

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# Contract Characteristics

This appendix lists the detailed characteristics of the “standard” (most liquid) interest-rate swaps contract for the currencies studied in this dissertation.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Currency | USD | CAD | GBP | CHF |
| Settlement | T+2 | T+0 | T+0 | T+2 |
| Fixed Leg | | | | |
| Day Count Convention | 30I/360 | ACT/365.FIXED | ACT/365.FIXED | 30E/360 |
| Payment Frequency | Semiannual | Semiannual | Semiannual | Annual |
| Business Day Adjustment Convention | Modified Following | Modified Following | Modified Following | Modified Following |
| Adjustment Type | Accrual and Payment Dates | Accrual and Payment Dates | Accrual and Payment Dates | Accrual and Payment Dates |
| Roll Convention | Backward | Backward | Backward (EOM) | Backward |
| Accrual Calculation Calendar | US Federal Reserve, England | Canada | England | Switzerland |
| Pay Delay | 0 days | 0 days | 0 days | 0 days |
| Floating Leg | | | | |
| Day Count Convention | Actual/360 | ACT/365.FIXED | ACT/365.FIXED | Actual/360 |
| Payment Frequency | Quarterly | Semiannual | Semiannual | Semiannual |
| Reference Index | USD LIBOR 3M | CDOR 3M | GBP LIBOR 6M | CHF LIBOR 6M |
| Reset Frequency | Quarterly | Quarterly | Semiannual | Semiannual |
| Business Day Adjustment | Modified Following Business Day | Modified Following | Modified Following | Modified Following |
| Adjustment Type | Accrual and Payment Dates | Accrual and Payment Dates | Accrual and Payment Dates | Accrual and Payment Dates |
| Roll Convention | Backward | Backward | Backward (EOM) | Backward |
| Calculation Calendar | US Federal Reserve, England | Canada | England | Switzerland |
| Fixing Calendar | England | Canada | England | England |
| Fixing Lag | 2 business days | 0 days | 0 days | 2 business days |
| Pay Delay | 0 days | 0 days | 0 days | 0 days |
| Reset Position | Advance | Advance | Advance | Advance |

Definitions

**Settlement**

Settlement refers to the number of business days after the trade date when the swap contract is finalized, and payments are made. The most common conventions are T+0, T+2, and T+3, where "T" represents the trade date, and the number indicates how many business days after the trade date settlement occurs. For example, in a T+2 settlement, the settlement occurs two business days after the contract is executed.

**Fixed Leg**

The fixed leg of an interest rate swap refers to the portion of the swap where the payer makes periodic payments at a fixed interest rate, which is predetermined and remains constant throughout the life of the swap. The characteristics below describe various conventions associated with this leg.

* Day Count Convention: This convention determines how interest accrues over time, using fractions of a year based on the number of days between two dates. Common conventions include:
  + 30I/360: Assumes each month has 30 days and a year has 360 days. It simplifies calculations but may deviate slightly from actual time.
  + ACT/365.FIXED: Uses the actual number of days in a period, dividing by a fixed 365-day year.
* Payment Frequency: This defines how often payments are made on the fixed leg. For instance, "semiannual" means payments are made twice a year, while "annual" means once a year.
* Business Day Adjustment Convention: When a payment date falls on a non-business day, this convention dictates how the date is adjusted. A "Modified Following" convention means payments are pushed to the next business day unless that day falls in the next month, in which case payments are moved backward to the preceding business day.
* Adjustment Type: Adjustment type refers to which dates are adjusted when a business day adjustment is necessary. For example, in "Accrual and Payment Dates" adjustment, both the accrual period and the payment date will be adjusted if necessary.
* Roll Convention: The roll convention specifies how payment dates are set relative to a reference date, typically whether payments move forward or backward when adjusting for business days. A "Backward" roll moves the date to the nearest preceding business day, while "Backward (EOM)" additionally ensures payments align with end-of-month periods.
* Accrual Calculation Calendar: This calendar determines which set of business days are considered in calculating the accrual of interest payments. For example, the "US Federal Reserve" calendar includes only U.S. federal holidays, while the "England" calendar takes U.K. public holidays into account.
* Pay Delay: Pay delay refers to the number of days between the payment due date and the actual date the payment is made. For instance, "0 days" means payments are made on the due date.

**Floating Leg**

The floating leg of the swap is where payments are made based on a variable interest rate, which changes over time based on a reference index. The conventions below describe how these payments are structured.

* Reference Index: The reference index is the benchmark interest rate that dictates the floating payments. Common indices include:
  + USD LIBOR 3M: U.S. Dollar London Interbank Offered Rate for a 3-month period.
  + CDOR 3M: Canadian Dollar Offered Rate for 3 months.
  + GBP LIBOR 6M: British Pound LIBOR for 6 months.
  + CHF LIBOR 6M: Swiss Franc LIBOR for 6 months.
* Reset Frequency: This determines how often the floating rate is recalculated or "reset." For example, a quarterly reset means the floating rate is updated every three months.
* Fixing Calendar: This refers to the calendar used to determine when the floating rate is fixed or set. For example, the "England" fixing calendar means rates are set according to U.K. business days.
* Fixing Lag: Fixing lag defines how many days in advance the floating rate is determined before the payment period begins. For instance, a "2 business days" fixing lag means the floating rate is set two days before the payment is due.
* Reset Position: "Advance" reset position means the floating rate is set at the beginning of the interest period and applied throughout the period.

# Results from unfiltered dataset

This appendix presents an alternate version of tables Table 6 and Table 7, removing filters for outliers (contracts with premium (discount) more than +/- 50 bps). Note that the rise in premium for the treatment group remains large and statistically significant even after including these outliers.

|  |  |  |
| --- | --- | --- |
| **Difference-in-Differences Regression Results** | | |
|  | | |
|  | Dependent variable: Premium | |
|  |  | |
|  | Basic Model | Advanced Model |
|  | (1) | (2) |
|  | | |
| Group | 6.4783\*\*\* | 7.1186\*\*\* |
|  | (1.2754) | (1.2786) |
| Period | -16.8364\*\*\* | -16.6251\*\*\* |
|  | (1.6893) | (1.6921) |
| Tenor |  | -0.0552\*\* |
|  |  | (0.0226) |
| Log Notional |  | 0.5606\*\*\* |
|  |  | (0.1730) |
| Capped |  | -0.3432 |
|  |  | (0.4880) |
| SEF |  | -4.2437 |
|  |  | (6.5996) |
| Morning Session |  | -2.6170\*\*\* |
|  |  | (0.4843) |
| Afternoon Session |  | -2.4587\*\*\* |
|  |  | (0.4762) |
| Off Hours |  | -3.5615\*\*\* |
|  |  | (0.5589) |
| Monday |  | 2.8288\*\*\* |
|  |  | (0.5910) |
| Tuesday |  | 1.6594\*\*\* |
|  |  | (0.5454) |
| Thursday |  | 1.1212\*\* |
|  |  | (0.5274) |
| Friday |  | -0.7841 |
|  |  | (0.5581) |
| Group \* Period | 12.8246\*\*\* | 12.1513\*\*\* |
|  | (1.7395) | (1.7539) |
| Constant | -3.4148\*\*\* | -11.6213\*\*\* |
|  | (1.2252) | (3.1911) |
|  | | |
| Observations | 28,311 | 28,311 |
| R2 | 0.0139 | 0.0182 |
| Adjusted R2 | 0.0138 | 0.0177 |
| Residual Std. Error | 30.2838 (df = 28307) | 30.2239 (df = 28296) |
| F Statistic | 133.0846\*\*\* (df = 3; 28307) | 37.4453\*\*\* (df = 14; 28296) |
|  | | |
| Note: | \*p\*\*p\*\*\*p<0.01 | |

|  |  |  |  |
| --- | --- | --- | --- |
| **By Phase Results: Advanced Model** | | | |
|  | | | |
|  | Dependent variable: Premium | | |
|  |  | | |
|  | Phase 1 | Phase 2 | Phase 3 |
|  | (1) | (2) | (3) |
|  | | | |
| Group | 7.200\*\*\* | 6.368\*\*\* | 12.806\*\*\* |
|  | (2.241) | (2.151) | (2.331) |
|  |  |  |  |
| Period | -2.813 | -16.738\*\*\* | -5.274\*\* |
|  | (3.751) | (2.926) | (2.617) |
|  |  |  |  |
| Tenor | -0.305\*\*\* | 0.021 | 0.039 |
|  | (0.055) | (0.031) | (0.035) |
|  |  |  |  |
| Notional | -2.382\*\*\* | 0.653\*\* | 2.108\*\*\* |
|  | (0.391) | (0.257) | (0.257) |
|  |  |  |  |
| Capped | 1.164 | 0.031 | -1.834\*\* |
|  | (1.141) | (0.689) | (0.729) |
|  |  |  |  |
| Morning Session | -5.318\*\*\* | 0.581 | -2.231\*\*\* |
|  | (1.121) | (0.702) | (0.716) |
|  |  |  |  |
| Afternoon Session | -3.678\*\*\* | -1.300\* | -0.882 |
|  | (1.110) | (0.673) | (0.718) |
|  |  |  |  |
| Off Hours | -6.020\*\*\* | 0.474 | -6.191\*\*\* |
|  | (1.311) | (0.803) | (0.826) |
|  |  |  |  |
| Monday | -0.927 | 9.518\*\*\* | -4.437\*\*\* |
|  | (1.361) | (0.883) | (0.866) |
|  |  |  |  |
| Tuesday | -2.788\*\* | 8.744\*\*\* | -3.307\*\*\* |
|  | (1.315) | (0.787) | (0.794) |
|  |  |  |  |
| Thursday | -2.880\*\* | 9.627\*\*\* | -5.501\*\*\* |
|  | (1.292) | (0.736) | (0.790) |
|  |  |  |  |
| Friday | -2.307\* | 4.595\*\*\* | -4.177\*\*\* |
|  | (1.373) | (0.768) | (0.848) |
|  |  |  |  |
| Group \* Period | -3.568 | 11.873\*\*\* | 11.274\*\*\* |
|  | (3.848) | (3.007) | (2.755) |
|  |  |  |  |
| Constant | 50.354\*\*\* | -21.877\*\*\* | -50.813\*\*\* |
|  | (6.877) | (4.958) | (4.895) |
|  |  |  |  |
|  | | | |
| Observations | 7,819 | 11,233 | 9,259 |
| R2 | 0.025 | 0.036 | 0.073 |
| Adjusted R2 | 0.023 | 0.035 | 0.071 |
| Residual Std. Error | 37.150 (df = 7805) | 26.916 (df = 11219) | 25.619 (df = 9245) |
| F Statistic | 15.137\*\*\* (df = 13; 7805) | 32.443\*\*\* (df = 13; 11219) | 55.763\*\*\* (df = 13; 9245) |
|  | | | |
| Note: | \*p\*\*p\*\*\*p<0.01 | | |

# Info-Metrics based Difference-in-Difference Estimator

Difference-in-differences (DiD) is a popular approach to estimate causal relationships when randomization is not feasible. In the basic set up, a group (the treatment group) is exposed to an intervention (treatment) at some period while another group (the control group) is never exposed to the treatment. Under the assumption that the two groups would have followed “parallel trends” in the absence of the treatment, the causal impact of the treatment can be estimated by comparing the difference in the outcome between the treatment and control groups before and after the intervention.

In practical work, employing the DiD methodology can pose several challenges:

1. Parallel trends assumption violation: if the two groups would not have followed parallel trends without the intervention, the DiD estimation is invalid. Violation of the parallel trends assumption could be due to:
   1. time-varying confounders: factors that change over time and affect the treatment and control group differently can bias the estimates.
   2. endogenous selection: assignment into the treatment group might be associated with unobserved factors affecting the outcome.
   3. heterogenous treatment effects: the impact of the intervention might vary across units or over time, and this variation might be correlated with membership to the control or treatment group.
2. Anticipation effects: If units in the treatment group anticipate the intervention and change their behavior beforehand, it can bias the results.
3. Spillover effects: The intervention might indirectly affect the control group, which would bias the results.
4. Staggered treatment timing: if the treatment is rolled out in several phases, the standard two-period DiD may not be appropriate.

This appendix develops an Info-Metrics (Generalized Maximum Entropy) based estimator for DiD that can correct for endogenous selection and heterogenous treatment effects, which violate the parallel trends assumption.

**Theory**

Consider the standard DiD model:

where: is outcome for individual at time ), is a group indicator ( for the treatment group, for the control group), is a period indicator ( for the post-treatment period, for the pre-treatment time period). are parameters (is the parameter of interest, the effect of the treatment and is an error term.

Under traditional DiD assumptions, this equation can be estimated consistently using Ordinary Least Squares (OLS). However, if the treatment effect varies with characteristics of the treatment unit or over time (*heterogenous treatment effects*), is no longer a consistent estimator of the treatment effect.

The traditional DiD model can be expanded so that:

where: is a vector of covariates and is a vector of parameters representing the effect of the covariates through the treatment channel. OLS will now again be a consistent estimator of the treatment effect.

However, in cases where treatment is endogenous (that is the probability of assignment to is correlated with factors affecting the outcome ), the above approach will lead to biased estimates of the treatment effect because the error terms are correlated with the treatment indicator. We can model the selection into treatment equation through a latent variable approach. I follow a method outlined by (Abadie 2005) that generalizes Heckman’s (1997) correction model for selection. In this two-step process, the probability of being selected into treatment conditional on covariates, is modeled in step 1. In step 2, difference-in-differences is estimated, after weighting the observations by the probabilities obtained in step 1. Intuitively, units with certain characteristics are overrepresented in the untreated group. The weights from step 1, when applied to the regression, weights down the distribution of for those values of the covariates which are overrepresented and weighting up those values of the covariates that are underrepresented among the untreated (Abadie 2005).

I propose that both step 1 and step 2 in the above process be estimated using the semiparametric Generalized Maximum Entropy (GME) approach. In the first step, the probability of selection can be modeled using the generalized maximum entropy extension to the traditional logistic regression outlined in (Golan, Judge, and Perloff 1996). This method is known to have several advantages over traditional logistic regression: it is efficient for small samples, avoids strong parametric assumptions, handles multicollinearity and is resilient to ill-conditioned data. Similarly, the difference-in-differences estimator in step 2 can be estimated using the “linear regression” maximum entropy estimator (Golan 2017). This estimator has similar advantages over traditional OLS.

First consider the generalized maximum entropy logistic regression for a binary outcome (selection into treatment). Assume that units are observed, where each unit is either selected into treatment or not. Let

be the probability of observing unit in the treatment state, conditional on covariates (of dimension and unknown parameters (of dimension ). If we have noisy data, we can write

where denotes the unknown and unobservable probability of selection and is a noise component for each observation contained in . To proceed, we must reparametrize the error component:

where are an H-dimensional vector of weights and are the H-dimensional support space. (Golan, Judge, and Perloff 1996) suggest and thus .

We now maximize the entropy (of the error augmented) probability distribution:

subject to the moment constraints imposed by the data, where the -th constraint is:

and the adding up constraints

We can solve the above using the method of Lagrange multipliers. In matrix-form:

where are Lagrange multipliers and .

The first order conditions are:

From which we obtain the estimated probability distributions:

and

Note that the above can be computed using the “dual unconstrained” method not discussed here (see (Golan 2017) for reference).

Once the probabilities are obtained, we can proceed to estimate the difference-in-differences model, weighting each observation by:

The full generalized maximum entropy model of linear regression is not recapitulated here (see (Golan 2017) for reference) but briefly:

1. Reparametrize the s and the error terms as and where is a vector (the discrete support space), is a vector of weights, is a vector (the discrete error support) and is a set of weights (that dd up to 1).
2. Maximize the entropy of subject to the data constraint  
   and the adding up constraints.
3. Solve using the method of Lagrange multipliers.

Thus both the first stage and second stages of the methodology described by Abadie can be implemented using the semiparametric generalized maximum entropy techniques (with estimators in both stages having desirable properties described earlier).

Instead of formally deriving the properties of this estimator, I compare the performance of this methodology against: (1) the simple difference-in-differences estimator that does not consider any selection effects and (2) a model that uses logistic regression for the first stage and OLS for the second stage.

Simulation 1: 100 observations, repeat 500 times. Report bias and variance of all three estimators.

Simulation 2: Small sample properties. 20 observations Repeat 500 times. Report bias and variance of all three estimators.

Simulation 3: Ill-conditioned data. 100 observations, repeat 500 times. The design matrix is highly collinear/ill-conditioned. Report bias and variance of all three estimators.

Simulation 4: Non-normal errors. 100 observations, repeat 500 times. Use Cauchy or Laplace errors. Report bias and variance of all three estimators.

Real World Data

LaLonde’s study National Supported Work (NSW) demonstration and follow-up 1999 study by Dehejia-Wahha. The NSW program was an RCT type program, so the “ground truth” of the effect of the program is known (by looking at the difference in outcome variable between control and treatment groups). LaLonde created artificial control groups from the Panel Study of Income Dynamics (PSID) or Westat Matched Current Population Survey to replace the control group from the study. He looked at how various estimators (e.g. simple difference in post-treatment period outcome for treatment and artificial control group, difference with controls for demographic characteristics, difference-in-differences, Heckman correction) performed. He found that no estimator performed well consistently. Dehejia-Wahha revisit this, looking at a subset of LaLonde’s data for which the pre-treatment outcome variable was available for 2 periods prior to the start of the program. They also implemented new (propensity score matching) estimators that seem to perform well. Since this is a well-known dataset (readily available in multiple software packages) and what the result should be is known, it would be a good test of how the method performs.

1. The principal is “notional” because unlike a real bond it is never exchanged. It is only used to calculate fixed and floating rat payments. [↑](#footnote-ref-2)
2. The clearing counterparty is usually a dealer who is a clearing member at the CCP. “A clearing member is usually a trade intermediary that can deal directly with the CCP. Trade intermediaries that are not clearing members must clear their trades through a trade intermediary that is a clearing member” (McPartland 2009). Trade intermediaries that are clearing members will collect collateral from their non-clearing member clients and pass it on to the CCP. [↑](#footnote-ref-3)
3. I exclude discussion regarding the data availability of US-dollar denominated contracts. In general, there are enough contracts traded for each trading day and contract specification that a realized volatility measure can be calculated for each. The availability of data for the US market is not a limiting factor in my analysis. [↑](#footnote-ref-4)