The Impact of Central Clearing on the Interest Rate Swaps Market

ARNOB L. ALAM

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.

1 Background

1.1 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]. 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

[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.

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.

1.2 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]. When counterparties clear their trade through a

[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.

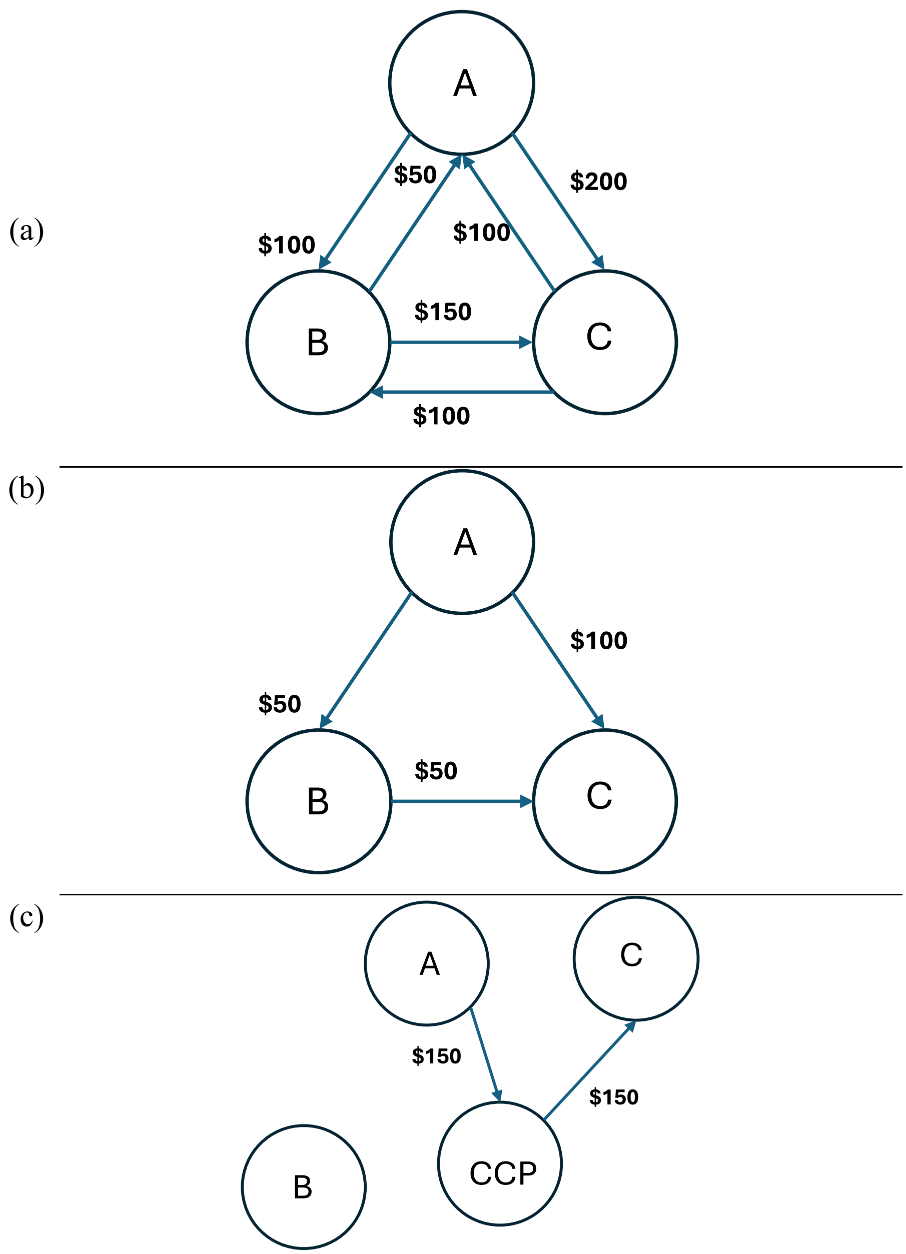
clearinghouse, they must put up collateral (initial margin) and contribute to a default fund. In case the risk position of the counterparty changes, it can be required to put up additional collateral (variation margin). The CCP also has default fund contributions of other members, its own equity (CCP 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 **Error! Reference source not found.**a, 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 **Error! Reference source not found.**b. 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. **Error! Reference source not found.**c 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).



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.

1.3 Regulatory Background

1.3.1 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 1 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.

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

1.3.2 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 2 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.

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.

1.4 Review of Literature

1.4.1 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.

1.4.2 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.

1.4.3 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.

1.4.4 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).

1.4.5 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.

2 Theory

2.1 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):

$$PV_{fixed\ leg} = \sum_{i=0}^{T} \frac{CF}{(1+r_i)^{t_i}} \tag{1}$$

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

The present value of the floating leg is:

$$PV_{floating\ leg} = \sum_{i=0}^{T} \frac{CF_i}{(1+r_i)^{t_i}} \tag{2}$$

where: CF_i is the floating leg payment at period i, 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:

$$PV = PV_{floating\ leg} - PV_{fixed\ leg} \tag{3}$$

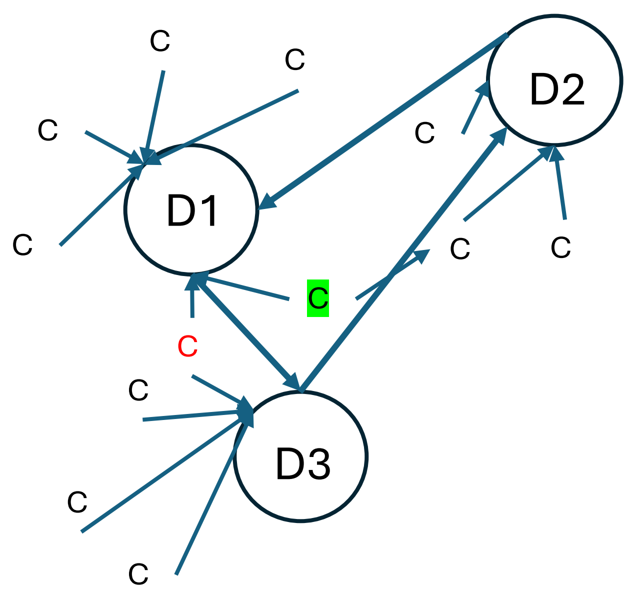
(The counterparty's value is given by a similar formula, but with the signs reversed on the right-hand side.)

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 (PV) 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 CF in (3) such that the present values of both legs equal. The payments are discounted using the same LIBOR yield curve.

2.2 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 S_i represents the survival probability of the counterparty at period i, the expected present value of the fixed leg is:

$$PV = \sum_{i=0}^{T} \frac{CF_i \cdot S_i}{(1 + r_i)^{t_i}} \tag{4}$$

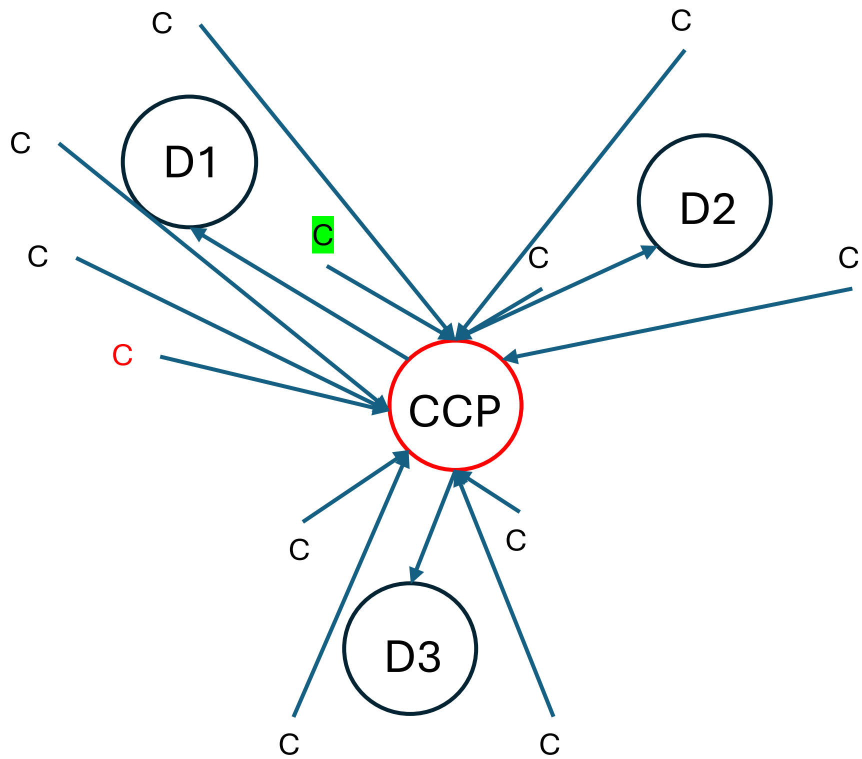
The fixed rate payment CF needs to account for the modified PV of the floating leg.

(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).

2.3 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.

2.4 Model of Liquidity (Bid-Ask Spreads)

2.4.1 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, M of the N 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 λ. If there is a liquidity shock, a liquidity trader (liquidity demander) receives an inventory of quantity L with probability $\frac{1}{2}$ (or a short position of size $-L$ 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 $U(w) = -\exp(-\alpha \cdot w)$, where w is the trader's wealth and α 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 $p = 1 + z$, where $z \sim \mathbb{N}(0, \sigma^2)$.

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

$$w = p(L - Q) + Q \cdot p_b^* \tag{5}$$

where $L - Q$ is the net position of the trader in the risky asset at the end of the game and $(Q \cdot p_b^*)$ is the cash from selling Q units of the risky asset at the best (highest) bid price p_b^*. The liquidity trader will maximize expected utility $\mathbb{E}[U(w)] = \mathbb{E}[-\exp\alpha\big((L - Q)p + Q \cdot p_b^*\big)]$. The optimal quantity is:

$$Q^* = \frac{1}{a \cdot \sigma^2}(p_b^* - 1) + L \tag{6}$$

where I have used the fact that $\mathbb{E}[\exp z], z \sim N(\mu, \sigma^2) = \exp\left(\mu + \frac{\sigma^2}{2}\right)$

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

$$w = (I_1 + Q^*)p - p_1^b Q \tag{7}$$

where: p_1^b is the bid price set by dealer 1, Q^* is the size of the market order and I_1 is their random inventory position (a number between $[-R, R]$). If dealer 1 does not have the best price, they receive:

$$w = I_1 p$$

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

$$p_{r,1}^b = \frac{\alpha\sigma^2}{2}(Q^* + 2I_1) \tag{8}$$

$$p_{r,1}^b = \alpha\sigma^2(L + 2I_1) - 1 \tag{9}$$

where the price is subscripted with r 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):

$$p_{r,1}^a = \alpha\sigma^2(L - 2I_1) - 1 \tag{10}$$

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

$$p_{r,i}^b = \alpha\sigma^2(L + 2I_i) - 1 \tag{11}$$

$$p_{r,i}^a = \alpha\sigma^2(L - 2I_i) - 1$$

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 $[-R, R]$. 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:

$$p_1^b = p_{r,1}^b + \alpha \cdot \sigma^2 \frac{(R - I_1)}{2} \tag{12}$$

Similarly, the optimal ask quote is:

$$p_1^a = p_{r,1}^a + \alpha \cdot \sigma^2 \frac{(R + I_1)}{2} \tag{13}$$

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

$$p_i^a = p_{r,i}^a + \alpha \cdot \sigma^2 \frac{(R + I_i)}{2} \tag{14}$$

$$p_i^b = p_{r,i}^b + \alpha \cdot \sigma^2 \frac{(R - I_i)}{2}$$

The observed bid ask spread is:

$$S = \max[p_i^b] - \min[p_i^a] \tag{15}$$

Note: Under competition with many dealers, the second term on the RHS of (14) becomes $\left[\alpha \cdot \sigma^2 \frac{(R \pm I_i)}{N}\right]$ and approaches 0 as $N \to \infty$. 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:

$$u(w) = \begin{cases} \frac{w^{1-\gamma}}{1-\gamma}, \gamma \neq 1 \\ \ln w, \gamma = 1 \end{cases}$$

The final wealth of the liquidity trader is given by:

$$w(Q) = Q \cdot p_b + (L - Q) \cdot (1 + z) = Q(p_b - 1) + (L + Q)z$$

Let $\mu_w = \mathbb{E}[w(Q)]$ 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 μ_w by a second-order Taylor series approximation:

$$u(w) \approx u(\mu_w) + (w - \mu_w)u'(\mu_w) + \frac{1}{2}(w - \mu_w)^2 u''(\mu_w)$$

Then

$$\mathbb{E}[u(w)] \approx u(\mu_w) + \frac{1}{2}u''(\mu_w)\mathbb{E}[(w-\mu_w)^2]$$

Where I have used $\mathbb{E}[w-\mu_w] = 0$

Since $\mathbb{E}[(w-\mu_w)^2] = (L-Q)^2\sigma^2$. We have:

$$\mathbb{E}[u(w)|w=\mu_w] \approx \frac{\mu_w(Q)^{1-\gamma}-1}{1-\gamma} - \frac{\gamma}{2}\mu_w(Q)^{-\gamma-1}(L-Q)^2\sigma^2$$

where I write $\mu_w = \mu_w(Q)$ 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:

$$d\frac{\mathbb{E}\left[u\left(w(Q)\right)\right]}{dQ} = 0$$

We can solve this to obtain Q*:

$$Q^* = L + \frac{(p_b-1)\mu_w(Q)^{2\gamma+1}}{\gamma\sigma^2}$$

This is like the optimal order quantity we derived under CARA

$$Q_{CARA} = \frac{1}{\alpha\sigma^2}(p_b-1) + L$$

With an additional $\mu_w^{2\gamma+1}$ 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 I_1, $I_1 \sim Unif(-R,R)$. If they posts the best bid price, their wealth at the end of the period is:

$$w = (I_1+Q)(1+z) - p_b^1 Q$$

If they do not trade, their wealth will be:

$$w^{NT} = I_1(1+z)$$

At some price $p_{b,r}^1$ the dealer will be indifferent between trading and not trading. This will occur when $u\left(w(p_{b.r}^1)\right) = u(w^{NT})$.

Let μ_w be the expected wealth $\mathbb{E}\left[(1+Q)(1+z) - p_{b,r}^1 Q\right] = I_1 + Q\left(1-p_{b,r}^1\right)$

The second order Taylor-series expansion about μ_w is:

$$u(w)|w=\mu_w \approx u(\mu_w) + (w-\mu_w)u'(\mu_w) + \frac{1}{2}(\mu_w - w)^2 u''(\mu_w)$$

Taking expectations:

$$\mathbb{E}[u(w)|w = \mu_w] \approx \mathbb{E}[u(\mu_w)] + \frac{1}{2}(w - \mu_w)^2 u''(\mu_w)$$

Using the fact that $\mathbb{E}[w - \mu_w]^2 = (I_1 + Q)^2\sigma^2$ we obtain:

$$\mathbb{E}[u] \approx \frac{I_1 + Q\left(1 - P_{b,r}^1\right)^{1-\gamma} - 1}{1-\gamma} + \frac{1}{2}(I_1 + Q)^2\sigma^2(-\gamma(I_1 + Q\left(1 - p_{b,r}^1\right)^{-\gamma-1}$$

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

$$\mathbb{E}[u(w_{NT})] \approx \frac{\left(w_{NT}^{1-\gamma} - 1\right)}{1-\gamma} - \frac{\gamma}{2} I_1^2 \sigma^2 w_{NT}^{-\gamma-1}$$

We can substitute $w_{NT} = I_1(1 + z)$ and $w = (I_1 + Q)(1 + z) - p_b^1 Q$ into the expressions above and set $\mathbb{E}[u(w)|w = \mu_w] = \mathbb{E}[u(w_{NT})]$. We obtain the reservation price:

$$p_{b,r}^1 \approx \frac{\gamma\sigma^2}{2}\mu_w(p_{r,b}^1)$$

We cannot solve for $p_{b,r}^1$ 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.

2.4.2 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: $p = (1 + z + y), y \sim N(0, \delta^2)$. The analysis remains essentially the same, but the optimal market order size, reservation quotes, and optimal quotes now become:

$$Q^* = \frac{1}{a \cdot (\sigma + \delta)^2}(p_b - 1) + L \tag{16}$$

$$p_{r,i}^{b} = \alpha(\sigma + \delta)^2(L + 2I_i) - 1 \quad (17)$$

$$p_{r,i}^{a} = \alpha(\sigma + \delta)^2(L - 2I_i) - 1 \quad (18)$$

$$p_i^a = p_{r,i}^a + \alpha \cdot (\sigma + \delta)^2 \frac{(R + I_i)}{2} \quad (19)$$

$$p_i^b = p_{r,i}^b + \alpha \cdot (\sigma + \delta)^2 \frac{(R - I_i)}{2} \quad (20)$$

The optimal order size is reduced from $Q^* \propto \frac{1}{\sigma^2}$ to $Q^* \propto \frac{1}{(\sigma+\delta)^2}$, the reservation quotes are increased from $p_r \propto \sigma^2$ to $p_r \propto (\sigma + \delta)^2$ 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.

2.5 Model of Price Volatility

2.5.1 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 σ_ϵ^2:

$$OF_t \sim N(0, \sigma_\epsilon^2) \quad (21)$$

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

$$P_{t+1} = P_t + \alpha \cdot OF_t \quad (22)$$

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

The expression for the volatility in this case is:

$$vol = \sqrt{Var(P_{t+1} - P_t)} = \alpha \cdot \sigma_\epsilon \quad (23)$$

2.5.2 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:

$$OF_{t+1} = \rho OF_t + \epsilon_{t+1} \tag{24}$$

Where: $\epsilon_{t+1} \sim N(0, \sigma_\epsilon^2)$

The expression for the price change becomes:

$$\Delta P_t = (P_{t+1} - P_t) = \alpha OF_{t+1} \tag{25}$$

$$vol = \sqrt{Var(\Delta P_t)} = \alpha^2 Var(OF_{t+1}) \tag{26}$$

$$Var(OF_t) = \frac{Var(\epsilon_{t+1})}{1-\rho^2} = \frac{\sigma_e^2}{1-\rho^2} \tag{27}$$

$$vol = \alpha\sigma_\epsilon\sqrt{\frac{1}{1-\rho^2}} \tag{28}$$

where I have used the fact $Var(OF_{t+1}) = Var(OF_t)$ on the 3rd line and that $Var(\epsilon_{t+1}) = \sigma_\epsilon^2$.

3 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 $Y_i(1)$ denote the outcome for unit i when treated, and $Y_i(0)$ denote the outcome when untreated. The causal effect on unit i is represented by $Y_i(1) - Y_i(0)$. Since both outcomes cannot be observed simultaneously, I focus on estimating the Average Treatment Effect (ATE), $\mathbb{E}[Y(1) - Y(0)]$, by identifying an appropriate control group to estimate the counterfactual $Y_i(0)$.

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 contract characteristics (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.

3.1 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:

$$Y_{i,t} = \alpha + \beta_1 * Treatment_i + \beta_2 Post_t + \delta(Treatment_i \times Post_t) + X_i'\Gamma + \epsilon_{it} \tag{29}$$

where Y_{it} is the swap premium for swap i at time t, $Treatment_i$ is an indicator variable equal to 1 if the swap is denominated in USD (treatment group) and 0 otherwise (control group), $Post_t$ is an indicator variable equal to 1 for the period after the mandate was implemented, and $X_{i,t}$ 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 X_i 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 $treatment \times time$ 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

$$Y_i = \alpha + \beta_1 * Treatment_i + \beta_2 Time + \delta(Treatment \ \times Time) + X'_{i,t}\Gamma + \epsilon_{it}$$

where: $Treatment$ is an indicator variable of whether the contract is in the control group (currency is CAD) or treatment group (currency is USD) and $time$ 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 3 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.

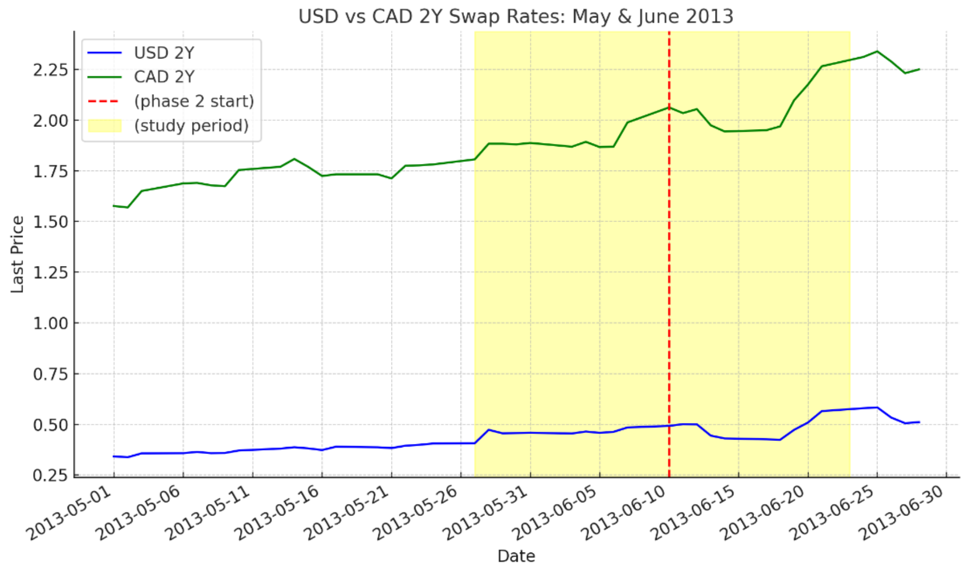
Pre-trend Analysis

	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.

Finally, I test the validity of the parallel trends assumption using a placebo difference-in-differences. Table 4 shows the results from a placebo difference-in-differences regression. I pick the 20 trading days before the study period. I create a "placebo" difference-in-differences, as if there was a transition to clearing mandate on the 11th trading day. 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.

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.



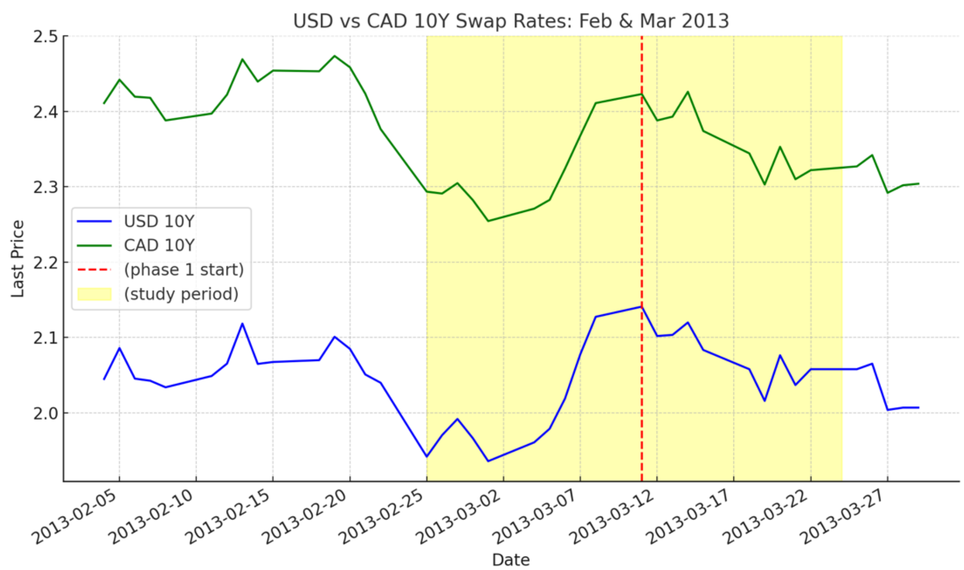


Table 4 Placebo DiD results. The placebo DiD is the same type of DiD analysis described in the identification strategy section, but during a period where there was no variation in central clearing requirements. I examine the 20 trading days before the study period of each phase and perform a "placebo" analysis as if the central clearing mandate had been implented on the the eleventh trading day.

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

R^2	0.0020	0.0136
Adjusted R^2	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

3.2 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:

$$spread = \frac{bid - ask}{\frac{bid + ask}{2}} \tag{30}$$

where the numerator $(bid - ask)$ is the "raw" spread and the denominator $\frac{bid+ask}{2}$ 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 a proxy common in the literature: the Roll measure. The measure, proposed by Roll (1984) estimates the effective spread using the time series of observed prices under assumptions of market efficiency:

$$Roll = 2 \cdot \sqrt{-cov(\Delta p)} \tag{31}$$

where $cov(\Delta p)$ 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:

$$Amihud_t = \frac{|R_t|}{Volume_t} = \frac{|P_{t-1} - P_t|}{Volume_t} \tag{32}$$

where R_t is the return on an asset at time t and $Volume_t$ is the total volume of contracts traded (calculated as the sum of the gross notional contract value in period t). 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 a daily Amihud illiquidity measure for US and Canadian 2-year, 5-year, and 10-year contracts for each trading date (using the contract notional as the swap equivalent of the volume and using the 1-period difference in the fixed rate of contracts with same characteristics as the return on the asset).

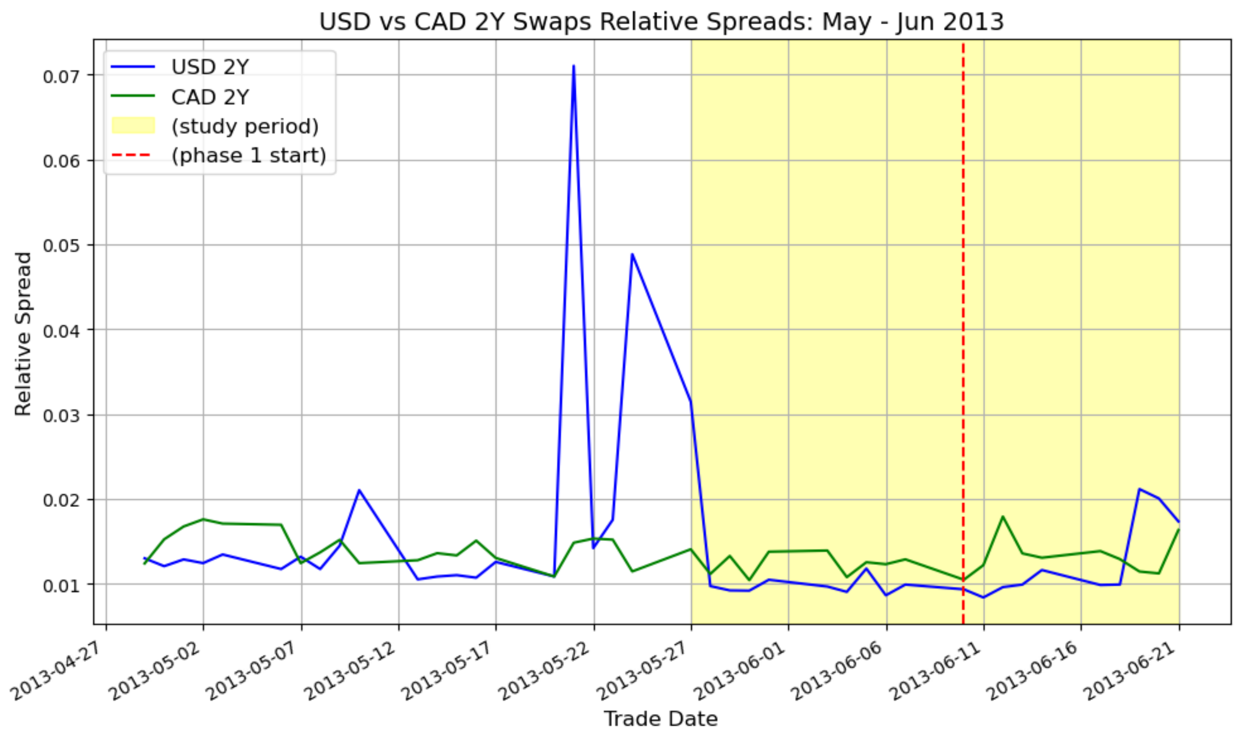
For each liquidity measure discussed above, I run a difference-in-differences model:

$$Y_{i,t} = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \delta(Treatment_i \times Post_t) + \Gamma X_{i,t}\epsilon_{i,t} \tag{33}$$

where $Y_{i,t}$ is the liquidity measure of interest, $Treatment_i$ is an indicator variable for whether the observation is in the treatment (US-dollar denominated market) or control (Canadian-dollar denominated market) group, $Post_t$ is an indicator variable for whether the observation is in the post- or pre implementation period. δ is the parameter of interest and $X_{i,t}$ are control variables (return on equities and equity market volatility).

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 2-year contracts and 10-year contracts in phase 1 and phase 2 respectively (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 2-year and 10-year USD and CAD interest rate swaps contracts for phase 1 and 2 respectively (other tenors show similar trends). Note that due to the limitation previously discussed (negative covariance or days with limited trading volume), 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 again for 2-year and 10-year USD and CAD interest rate swaps contracts in phase 1 and phase 2 respectively. 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, the Amihud liquidity measure is not computable for each tenor for each day (for example, if there are less than 5 observations for a given contract specification on a given day). There is not enough data to conclude whether the parallel trend assumptions hold for the Amihud illiquidity measure.

Figure 5 Pre-trends for Relative bid-ask spreads 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.



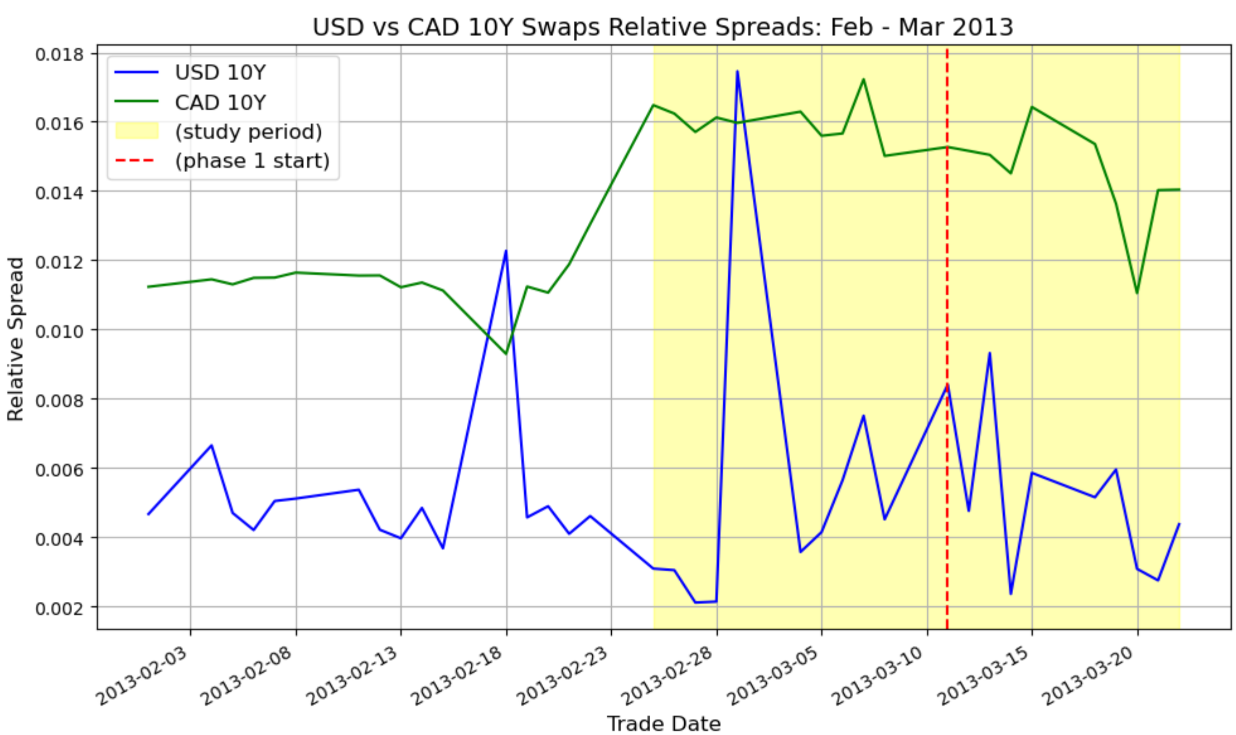
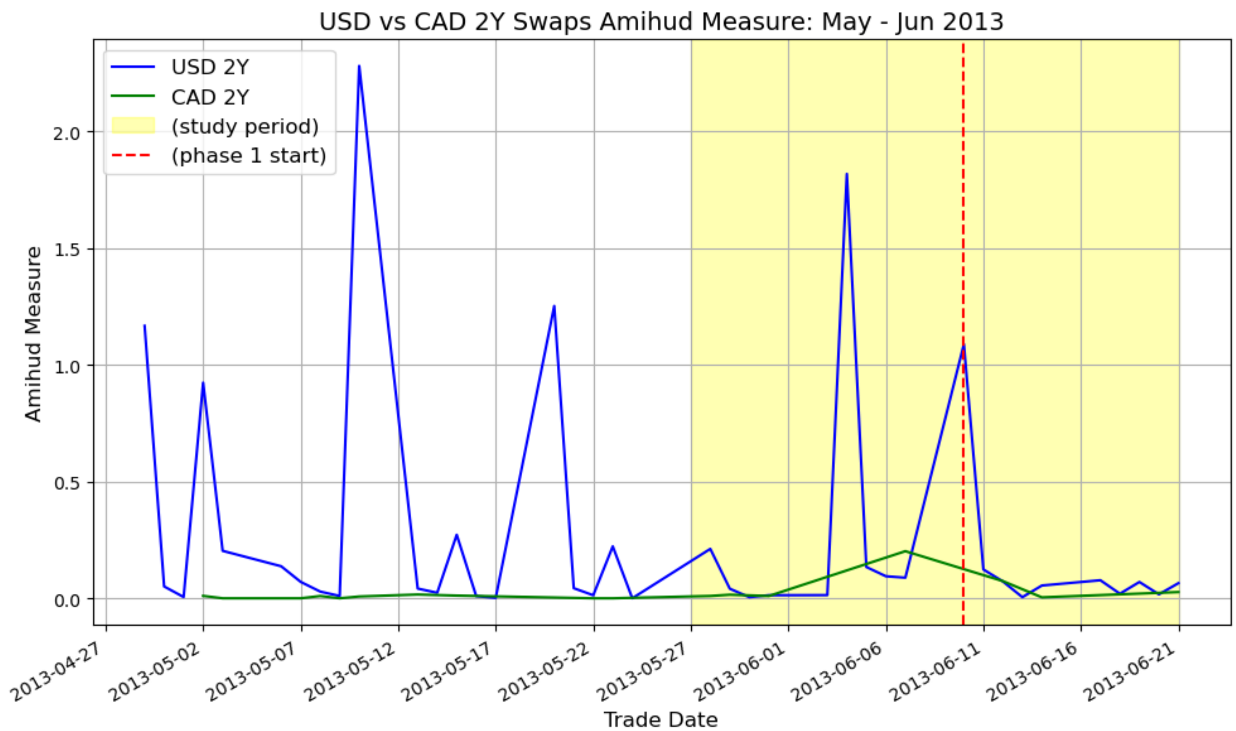


Figure 6 Pre-trends for Roll's Measure for 2-year swaps during phase 2 and 10-year swaps during phase 1 of the clearing mandate implementation. Red, dashed veritcal line indicates when the clearing mandate went into effect. Highlighted area is the period of study and the pre-trend is to the left of highlighted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



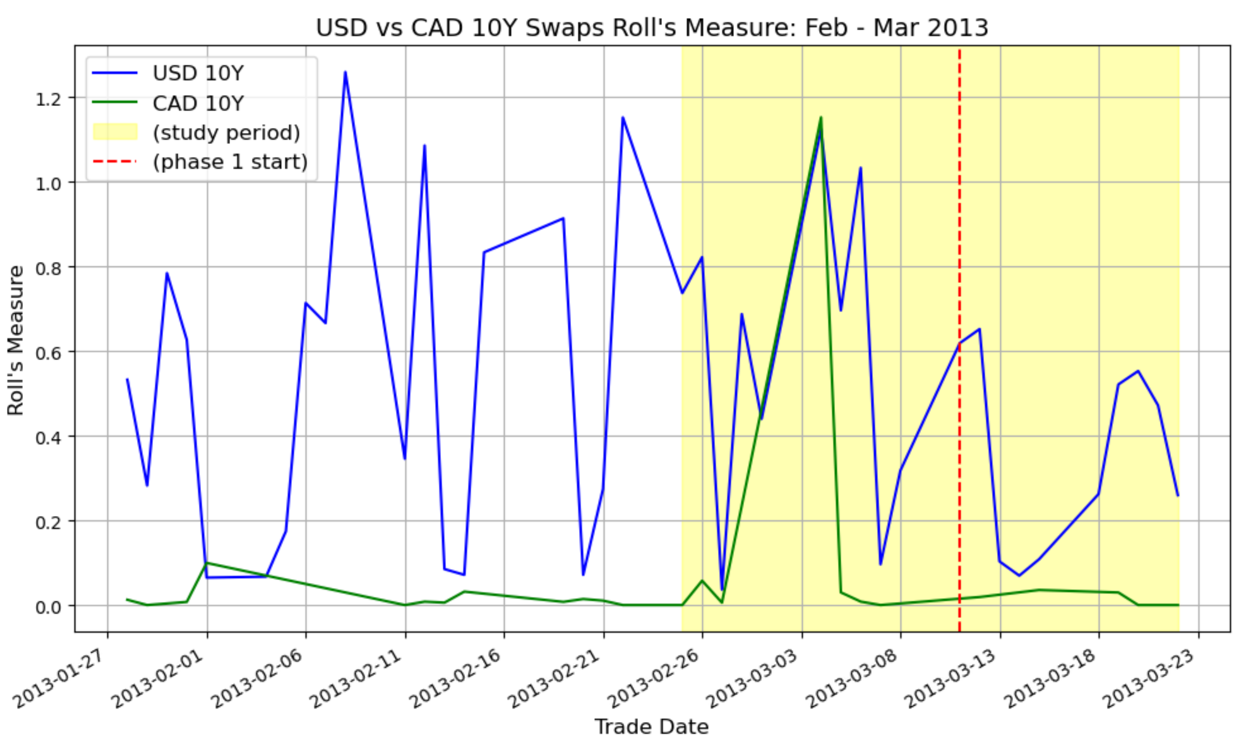
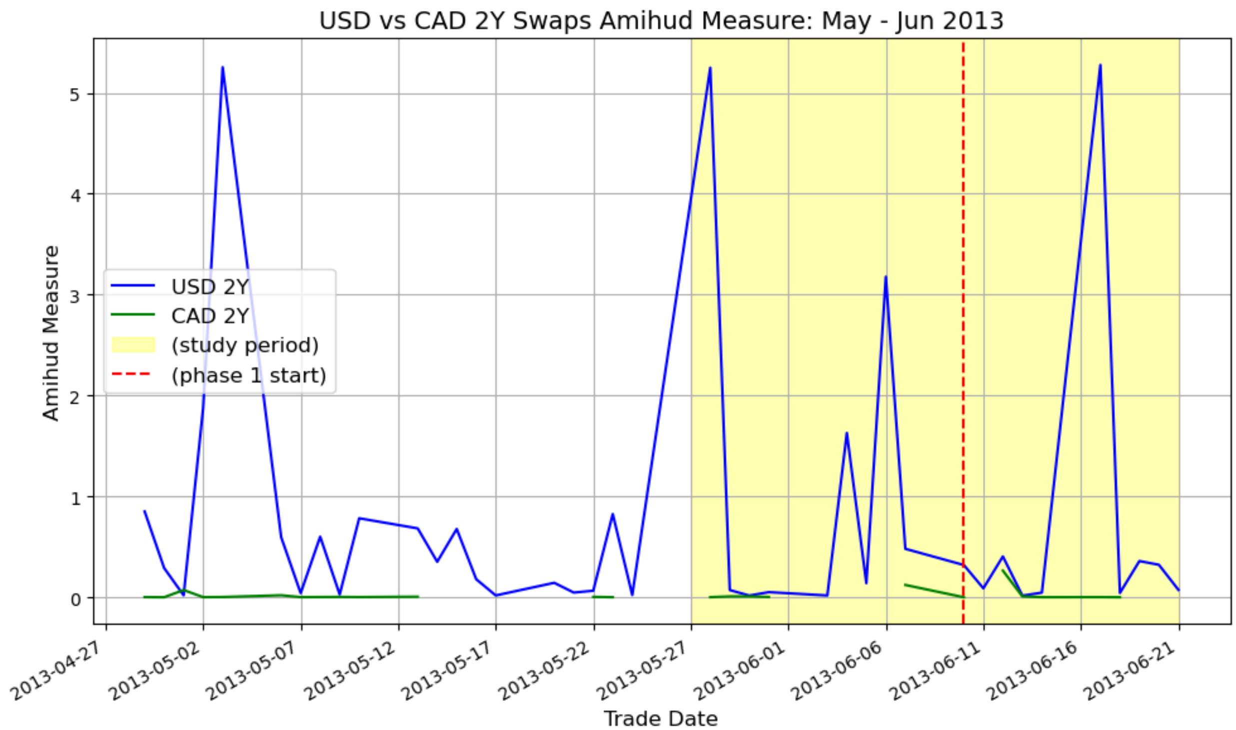
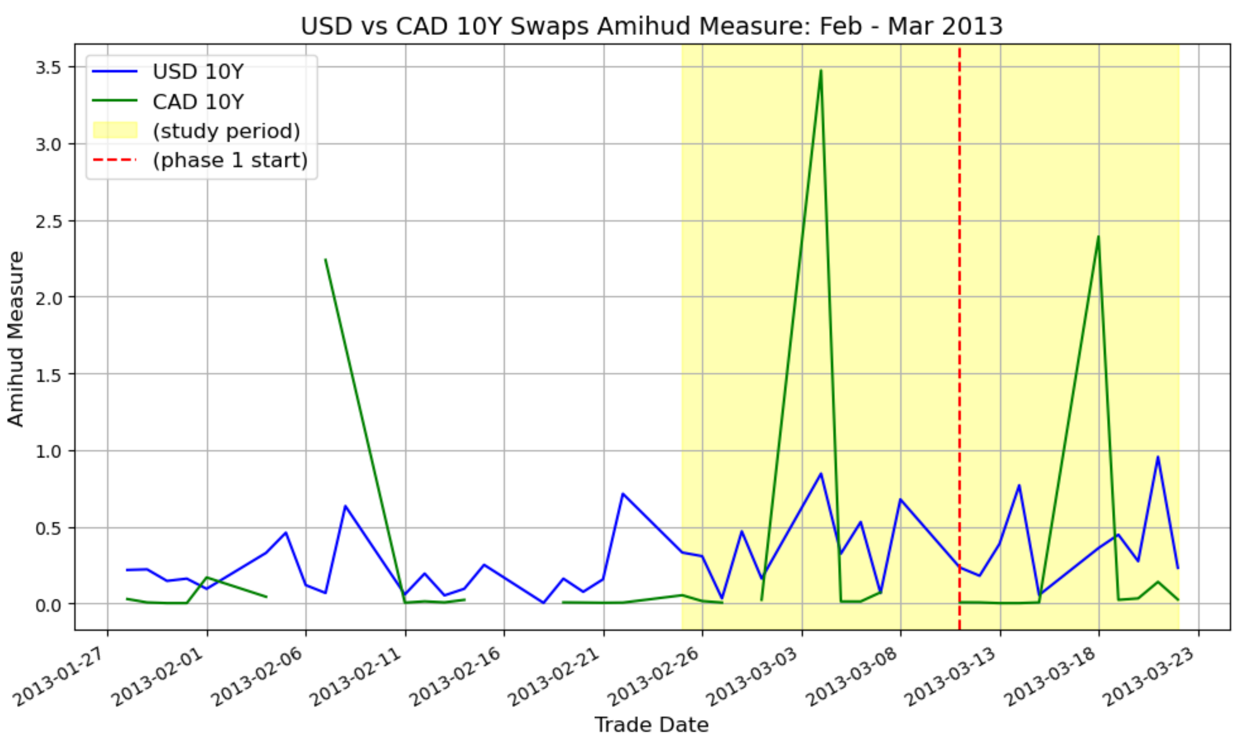


Figure 7 Pre-trends for Amihud Illiquidty Measure for 2-year swaps during phase 2 and 10-year swaps during phase 1 of the clearing mandate implementation. Red, dashed veritcal line indicates when the clearing mandate went into effect. Highlighted area is the period of study and the pre-trend is to the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





3.3 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 $[t-1, t]$ is defined as:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{34}$$

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

$$RV_t = \sum 252 \cdot (r_t)^2 \tag{35}$$

where: n 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 observations when less than 5 contracts with a given specification are traded on a given day). 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]. 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 60 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:

---

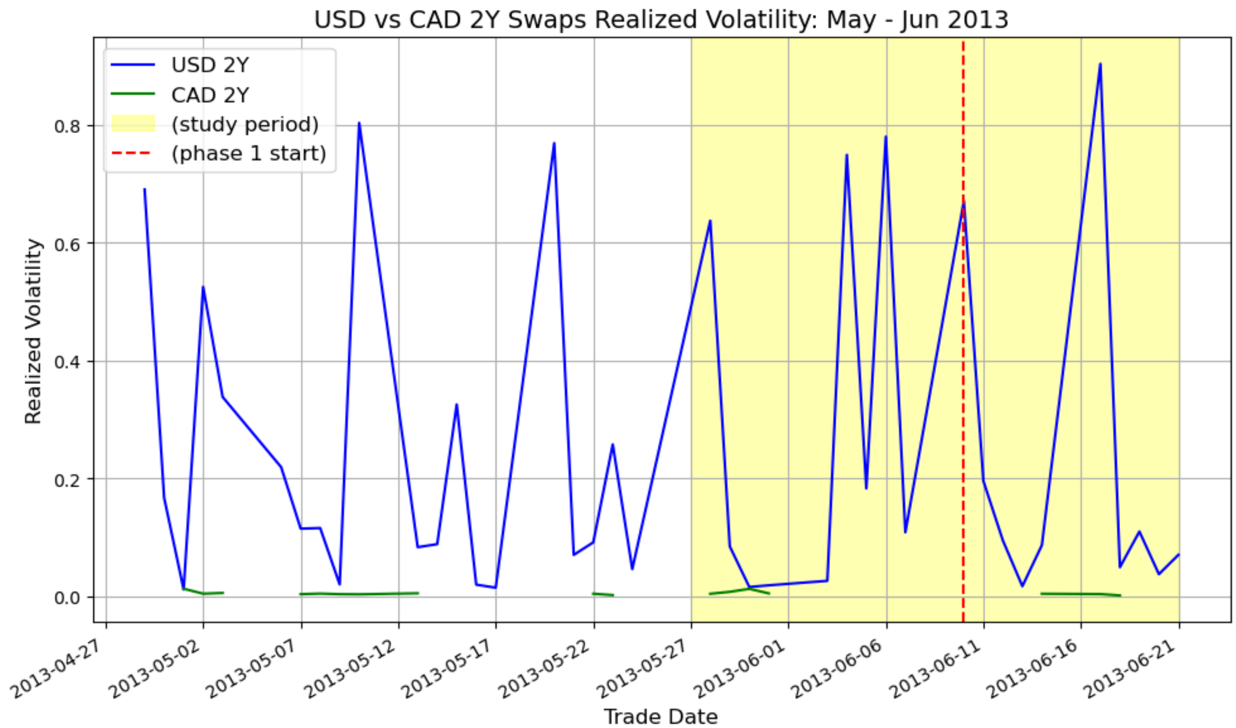
[3] I exclude discussion regarding the data availability of US-dollar denominated contracts. In general, there are enough contracts traded for each trading day and contract specification that a realized volatility measure can be calculated for each. The availability of data for the US market is not a limiting factor in my analysis.

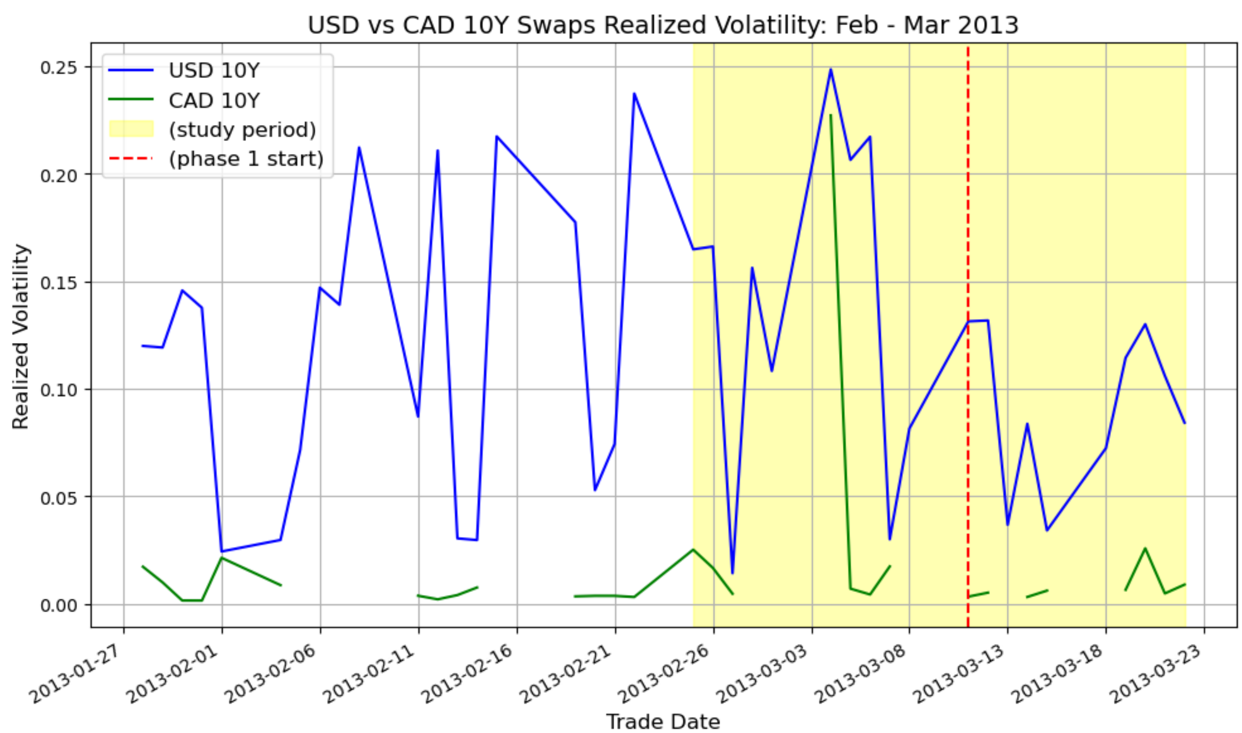
$$RV_{i,t} = \beta_0 + \beta_1 Treatment_i + \beta_2 Period_t + \delta(Treatment_i \times Period_t) + X'_{i,t}\Gamma + \epsilon_{i,t} \qquad (36)$$

where $RV_{i,t}$ is the realized volatility for contract specification i in period t and the rest of the variables are as described in the liquidity section. δ (the interaction between group and pre/post-treatment period) is the parameter of interest. I use the same controls (equity market returns and equity market volatility) as in the liquidity section.

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, 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 Pre-trends for Realized Volatility 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.





4 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 specifically 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 twenty-day trading window around the implementation of each phase (Feb 25 – Mar 22 for phase 1, May 27 – Jun 21 for phase 2 and Aug 26 – Sep 20 for phase 3).

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 for USD, GBP and JPY denominated contracts, or EURIBOR for EUD denominated contracts). It also specified "negative" characteristics, where swaps having the specified characteristics do not need to be cleared. These characteristics included 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 unobserved characteristics, such as early termination clauses, conditional notional amounts, etc. In an appendix, I show that my results are robust to including these outliers.

As discussed in the background section, clearinghouses originated organically in equities trading. Several clearinghouses were already operating in the interest rate swaps space prior to the implementation of the CFTC mandate (for example, LCH.Clearnet SwapClear launched in 1999, and Japan Securities Clearing Corporation offered limited interest rate swaps clearing services as well). Prior to the 2008 financial crisis, there was limited use of these clearinghouses, and risks were usually managed bilaterally. Following the 2008 financial crisis, many swaps market participants moved to voluntary central clearing regime. Before the regulation is passed, voluntary clearing in USD-denominated swaps is around 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 5 shows sample data for CAD and USD yield curves on September 11, 2013. Note that futures rates need to have a convexity adjustment applied to them since futures payoffs differ from payoffs for other instruments. The values reported in the table have this convexity adjustment applied. Values between the “pillars” (observed 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.

Table 5 Sample data for construction of USD and CAD swaps curves. The "short end" of the curve is based on observed deposit rates (such as the overnight Canadian Call Loan Rate and the 1-month and 2-month Canadian Offer Rate). The "medium leg" of the curve is constructed using data from futures contracts (note that a convexity adjustment needs to be applied to quoted futures prices due to differences in settlement between swaps and futures) and the "long end" of the curve is constructed using data from observed interest rate swaps.

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

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 (other reference rate indexes included the Federal Funds Rate T-Bill Rate, and FIFMA rate), 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 are priced differently than the most standardized contracts. Table 6 shows the notional value and number of trades captured in my data, by clearing status and reference floating leg rate.

Table 7 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[4]. The leftmost column shows the statistics of 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 (as described earlier). 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 fixed rate). When receiving the fixed rate (and paying the floating leg), the dealer is likely to require a

[4] This is ~39% of USD contracts in phase 1, 22% of USD contracts in phase 2, and 11% of contracts in phase 3; it is also 52% of CAD contracts in phase 1 and 3 and 44% of CAD contracts in phase 2

premium over the fair price. When paying the fixed rate, the dealer is likely to require 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 6 Number of contracts and notional values by clearing status and reference rate for USD and CAD IR swaps contracts (for entire dataset prior to any filtering). Data are presented for each phase and pre- and post- period separately. Note the increase in clearing for USD contracts after the implementation of phase 1 (from 61% to 77%) and phase 2 (from78% to 90%).

Pre-Phase 1 (Feb 25- Mar 8)

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 (Mar 11 – Mar 22)

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 (May 27 – Jun 7)

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 (Jun 10 – Jun 21)

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 (Aug 26 – Sep 6)

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 (Sep 9 – Sep 20)

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 7 Selected contarct characteristics. The "Main Dataset" reported in column 1 is the dataset used in the main body of the dissertation. This dataset is filtered to only include observations that use USD LIBOR or CAD CDOR as the reference rate, are not voluntarily cleared, are not zero-coupon swaps and are within 50-bps of "fair rate" for the swap reported by Bloomberg. Column 2 shows the same dataset except the 50-bps within Bloomberg reported fair-value is removed.

	Main Dataset	**No 50-bps filter**
	Trading Day	**Trading Day**
Monday	4,096	4,246
Tuesday	5,372	5,558
Wednesday	**6,733**	**7,020**
Thursday	6,001	6,243
Friday	5,008	5,244
	Trading Session	**Trading Session**
Morning	7,193	7,419
Mid-Day	**7,845**	**8,266**
Afternoon	7,684	7,974
After Hours	4,488	4,652
	Capped	**Capped**
Capped	18,837	19,727
Not Capped	8,373	8,584
	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	16,000,000	15,000,000
Median	50,000,000	50,000,000
3rd Quartile	100,000,000	100,000,000
Max	260,000,000	260,000,000
Mean	56,426,143	55,650,025

5 Results

5.1 Pricing

For analyzing the impact of the clearing mandate on prices, I compare USD denominated contracts using LIBOR as the floating rate index, against CAD denominated contracts using the CDOR as the floating rate index. The USD LIBOR contracts are subject to the CFTC clearing mandate (USD denominated contracts using a different floating rate index such as the Federal Funds Rate are not subject to the clearing mandate, but these contracts can be voluntarily cleared. Contracts using other reference rates than CDOR or USD LIBOR are excluded in this analysis).

Table 8 lists the difference-in-differences results for the swap premium, pooling data from all phases. Column 1 shows a basic model without any controls for contract characteristics. 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).

The clearing mandate causes a ~14 bps rise in premia across the three phases in this model per the basic model. In the more advanced model with additional controls for contract characteristics, premia rise by ~13 bps. These results are qualitatively in line with the theoretical model, that reducing the riskiness of the contract increases its price.

Examining the control variables, beginning with the trading day and using Wednesday as the reference level, I note that there is a 1.0-3.0 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). 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). Although statistically significant, the magnitudes of the effects are small, ranging from 0.03 to 3 bps.

Table 9 shows the result of a difference-in-differences analysis on each phase separately. In phase 1, there is a ~5.3 bps increase in premia after the implementation of the mandate. As noted previously, there was a 16% increase in the cleared volume following implementation of phase 1. In phase 2, there was an additional ~2.6 bps increase in premia. In phase 3, premia increased by ~16 bps. These results generally hold to the idea that as more of the market is cleared, there is a perceived reduction in counterparty risk and swap premia rise. The results are consistent with the pooled difference-in-differences, with most of the effect occurring during the third phase of the mandate.

Table 10 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 now serve as the treatment group. The clearing mandate did not apply to Swiss Franc (CHF) denominated contracts, and these contracts now serve 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 8 DiD results for prices pooling all phases together. Column 1 shows results for a basic DiD model without controlling for any covariates. Column 2 cotrols for contract charatceristics such as the tenor (in years), (log) notional value, whether notional is capped, whether the swap was traded on an eelctronic swap execution facility, the trading session and the trading day.

Difference-in-Differences Regression Results

	Dependent variable: Premium	
	Basic Model	Full 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
R^2	0.0283	0.0444
Adjusted R^2	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 9 Difference-in-Dfferences results for prices by each phase separately. This analysis uses the same "full model" described earlier (controlling for contract charatceristics). There is a 5.3 bps increase in premia in phase 1, a 2.7 bps increase in premia in phase 2 and a 16.2 bps increase in premia in phase 3.

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
R^2	0.025	0.109	0.179
Adjusted R^2	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 10 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
R^2	0.0168	0.0580

Adjusted R^2	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:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5.2 Liquidity

As noted previously, liquidity is a broad concept with several measures. I begin by examining the impact of the central clearing mandate on the relative bid-ask spread prevalent at the end of the trading day, a measure of the trading cost (at least at the closing) scaled to the price of the contract. Table 11 shows the results of a difference-in-differences regression for this measure. In the full model, I include the contract tenor as a control variable, as the relative bid-ask spread varies significantly with the contract tenor (for example, the median relative bid-ask spread in the dataset for Canadian 2-year contract was 0.015% while for a 10-year contract was 0.012%. For US contracts, the median relative bid-ask spread was 0.01% for 2-year contracts and 0.003% for the much more heavily traded 10-year contracts). 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, these variables did not vary during the short period studied, and cannot be controlled for. Two control variables that proxy financial market conditions are added to the full model: a measure of equity market volatility and a measure for equity market return. For the volatility measure, I use the CBOE Volatility Index (CBOE VIX) and the TSX 60 VIX Index, which measure the 30-day expected realized variance of the S&P 500 Index and its Canadian equivalent respectively. The Canadian VIX index was launched in April 2021, but S&P provides hypothetical historical values. For equity market returns, I use the returns of the S&P 500 and the S&P/TSX Composite.

The difference-in-differences results suggest that the clearing mandate does not impact liquidity as measured by relative bid-ask spreads. In the theory section, I argued that we should expect reductions in counterparty risk to cause a narrowing of the bid-ask spread, as the spread is charged by dealers to offset their expected losses from holding inventory, and a reduction in counterparty risk reduces these expected losses. However, the spread is also driven by supply and demand conditions in the market (i.e. the quantity and market order size discussed in the theory section). A reduction in riskiness of interest rate swaps increase their demand. If the swaps market is monopolistic (that is, new swaps dealers face barriers to entry), then incumbent dealers can choose not to adjust their bid-ask spreads and pocket the additional profits from the higher demand.

I examine two additional measures of liquidity. Roll's measure is an estimate of bid-ask spreads that might have prevailed during the trading day and is obtained from transaction data (price and trade time). The relative bid-ask spread above is based only on the last quote and is likely indicative of liquidity costs at the end of the trading day. Table 12 shows the results of a difference-in-differences regression for this measure. The contract tenor as well as the equity market volatility and equity market return variables from the previous discussion are included as control variables in the full model. Like the relative bid-ask spread, Roll's measure does not show a significant change in trading costs due to the clearing mandate.

The Amihud measure is an estimate of the average price impact (by what percentage prices change for a given order of size). I use the notional contract amount as the "order size" and the (log) difference in the fixed rate between two trades as the (percent) change in price. I express the results in percent change per million dollar of order quantity for easier interpretation. Table 13 show the results for the Amihud measure difference-in-differences analysis. The Amihud measure shows a statistically significant but small (0.36% change in price/million dollars)

Table 11 Difference-in-differenes analysis of Relative Bid-Ask Spreads. The dependent variable is the Relative Bid-Ask Spread from the last quote of the trading day. For the full model, control variables are the contract tenor, relevant stock market (TSX or S&P 500) returns and volatility. Stock market returns are calculated as the percent change from the previous trading day's adjusted closing price (where adjustments are made for dividends, stock splits and other rights offers). The volatility measures are the CBOE VIX and TSX 60 VIXI indices.

Relative Bid-Ask Spread DiD Analysis

	Dependent variable:	
	Relative Spread	
	Simple Model	Full Model
	(1)	(2)
Group	-0.005***	-0.005***
	(0.001)	(0.001)
Period	0.0001	-0.0001
	(0.001)	(0.001)
Tenor (2Y)		0.006***
		(0.001)
Tenor (5Y)		0.003***
		(0.001)
Equity Return		-0.056*
		(0.031)
Volatility		-0.0003**
		(0.0001)
Group*Period	-0.001	-0.001
	(0.001)	(0.001)
Constant	0.014***	0.016***
	(0.001)	(0.002)

Observations	360	351
R^2	0.204	0.486
Adjusted R^2	0.198	0.476
Residual Std. Error	0.005 (df = 356)	0.004 (df = 343)
F Statistic	30.459^{***} (df = 3; 356)	46.369^{***} (df = 7; 343)
Note:		*p**p***p<0.01

Table 12 Difference-in-differenes analysis of Roll's Measure. The dependent variable is the daily Roll's Measure (a proxy of the bid-ask spread during the trading day). Control variables are the contract tenor, relevant stock market (TSX or S&P 500) returns and volatility. Stock market returns are calculated as the percent change from the previous trading day's adjusted closing price (where adjustments are made for dividends, stock splits and other rights offers). The volatility measures are the CBOE VIX and TSX 60 VIXI indices.

Roll's Measure DiD Analysis

	Dependent variable:	
	Roll's Measure	
	Simple Model	Full Model
	(1)	(2)
Group	0.368^{***}	0.377^{***}
	(0.041)	(0.040)
Period	0.040	0.042
	(0.063)	(0.062)
Tenor (2Y)		-0.113^{***}
		(0.042)
Tenor (5Y)		0.044
		(0.040)
Equity Return		4.289^{*}
		(2.591)
Volatility		-0.009
		(0.011)
Group * Period	-0.139^{*}	-0.133^{*}
	(0.079)	(0.078)
Constant	0.069^{**}	0.213
	(0.032)	(0.159)

Observations	551	548
R^2	0.149	0.183
Adjusted R^2	0.144	0.173
Residual Std. Error	0.393 (df = 547)	0.387 (df = 540)
F Statistic	31.924*** (df = 3; 547)	17.303*** (df = 7; 540)
Note:		*p**p***p<0.01

Table 13 Difference-in-differenes analysis of Amihud's Illiquidity Measure. The dependent variable is Amihud's Measure (expressed in absolute % change in the fixed rate of the contract per a million dollar of notional value traded). Control variables are the contract tenor, relevant stock market (TSX or S&P 500) returns and volatility. Stock market returns are calculated as the percent change from the previous trading day's adjusted closing price (where adjustments are made for dividends, stock splits and other rights offers). The volatility measures are the CBOE VIX and TSX 60 VIXI indices.

Amihud Measure DiD Analysis

	Dependent variable:	
	Amihud Illiquidity Measure	
	Simple Model	Full Model
	(1)	(2)
Group	0.348^{***}	0.367^{***}
	(0.068)	(0.068)
Period	0.362^{***}	0.364^{***}
	(0.099)	(0.098)
Tenor (2Y)		0.018
		(0.072)
Tenor (5Y)		0.206^{***}
		(0.070)
Equity Return		12.328^{***}
		(4.469)
Volatility		0.025
		(0.019)
Group * Period	-0.365^{***}	-0.386^{***}
	(0.133)	(0.132)
Constant	0.106^{**}	-0.344
	(0.051)	(0.280)

Observations	641	635
R^2	0.048	0.077
Adjusted R^2	0.043	0.066
Residual Std. Error	0.733 (df = 637)	0.727 (df = 627)
F Statistic	10.674^{***} (df = 3; 637)	7.445^{***} (df = 7; 627)
Note:		*p**p***p<0.01

5.3 Price Volatility

Table 14 shows the results of the price volatility difference-in-difference regression (pooling all phases together). Price volatility (as measured by realized volatility) is higher for USD contracts compared to their counterpart, but there does not appear to be a time tend over the study period. There are also statistically significant differences in volatility by contract tenor,. The treatment effect (parameter of interest) does not appear to be affected by the clearing mandate: clearing did not reduce volatility in US swaps pricing.

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 (June-July 2015). 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. Table 15 shows the results of a DiD 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 period.

Table 14 differnce-in-difference analysis of volatility of the fixed rate for USD and CAD interest rate swaps contracts

Daily volatility DiD Analysis

	Dependent variable:	
	Realized Volatility	
	Simple Model	Full Model
	(1)	(2)
Group	0.067***	0.095***
	(0.020)	(0.018)
Period	0.009	0.018
	(0.024)	(0.021)
Equity Mkt Return		0.906
		(0.704)
Equity Mkt Volatility		0.003
		(0.003)
Tenor 15Y		-0.053**
		(0.024)
Tenor 1Y		0.240***
		(0.025)
Tenor 2Y		0.047**
		(0.021)
Tenor 30Y		-0.070***
		(0.023)
Tenor 3Y		-0.038*
		(0.022)
Tenor 4Y		-0.052**

		(0.023)
Tenor 5Y		0.043^{**}
		(0.020)
Tenor 6Y		-0.053^{**}
		(0.024)
Tenor 7Y		-0.036
		(0.024)
Tenor 8Y		-0.067^{***}
		(0.024)
Tenor 9Y		-0.074^{***}
		(0.024)
Group * period	0.002	-0.006
	(0.027)	(0.024)
Constant	0.027	-0.029
	(0.017)	(0.047)
Observations	829	829
R^2	0.031	0.247
Adjusted R^2	0.028	0.232
Residual Std. Error	0.161 (df = 825)	0.143 (df = 812)
F Statistic	8.935^{***} (df = 3; 825)	16.612^{***} (df = 16; 812)
Note:	*p**p***p<0.01	

Table 15 Difference-in-difference analysis of price volatility during second Grexit referendum

Difference-in-Differences Analysis of Volatility During GREXIT

	Dependent variable:
	Volatility (Daily Return)
Period	-0.002
	(0.087)
Group	0.012
	(0.090)
Period x Group	-0.016
	(0.119)
Constant	0.039
	(0.065)
Observations	104
R^2	0.001
Adjusted R^2	-0.029
Residual Std. Error	0.300 (df = 100)
F Statistic	0.018 (df = 3; 100)
Note:	*p**p***p<0.01

6 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.

Abadie, Alberto. 2005. "Semiparametric Difference-in-Differences Estimators." *The Review of Economic Studies* 72 (1): 1–19.

Allen, Franklin, and Douglas Gale. 2000. "Financial Contagion." *Journal of Political Economy* 108 (1): 1–33. https://doi.org/10.1086/262109.

Allen, Franklin, and Douglas M. Gale. 2007. "An Introduction to Financial Crises." SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.1008311.

Azad, A. S. M. Sohel, Victor Fang, and Chi-Hsiou Hung. 2012. "Linking the Interest Rate Swap Markets to the Macroeconomic Risk: The UK and Us Evidence." *International Review of Financial Analysis* 22 (April):38–47. https://doi.org/10.1016/j.irfa.2012.03.001.

Bebchuk, Lucian A., and Itay Goldstein. 2011. "Self-Fulfilling Credit Market Freezes." *The Review of Financial Studies* 24 (11): 3519–55. https://doi.org/10.1093/rfs/hhr086.

Benos, Evangelos, Wenqian Huang, Albert J. Menkveld, and Michalis Vasios. 2019. "The Cost of Clearing Fragmentation." SSRN Scholarly Paper ID 3502465. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=3502465.

Benos, Evangelos, Richard Payne, and Michalis Vasios. 2020. "Centralized Trading, Transparency, and Interest Rate Swap Market Liquidity: Evidence from the Implementation of the Dodd–Frank Act." *Journal of Financial and Quantitative Analysis* 55 (1): 159–92. https://doi.org/10.1017/S0022109018001527.

Bernstein, Asaf, Eric Hughson, and Marc Weidenmier. 2019. "Counterparty Risk and the Establishment of the New York Stock Exchange Clearinghouse." *Journal of Political Economy* 127 (2): 689–729. https://doi.org/10.1086/701033.

Biais, Bruno. 1993. "Price Formation and Equilibrium Liquidity in Fragmented and Centralized Markets." *The Journal of Finance* 48 (1): 157–85. https://doi.org/10.1111/j.1540-6261.1993.tb04705.x.

Bicksler, James, and Andrew H. Chen. 1986. "An Economic Analysis of Interest Rate Swaps." *The Journal of Finance* 41 (3): 645–55. https://doi.org/10.2307/2328495.

Bolandnazar, Mohammadreza. 2020. "The Market Structure of Dealer-to-Client Interest Rate Swaps." SSRN Scholarly Paper 3752367. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.3752367.

Boudiaf, Ismael Alexander, Immo Frieden, and Martin Scheicher. 2024. "The Market Liquidity of Interest Rate Swaps." SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.4745740.

Brunnermeier, Markus K. 2009. "Deciphering the Liquidity and Credit Crunch 2007-2008." *Journal of Economic Perspectives* 23 (1): 77–100. https://doi.org/10.1257/jep.23.1.77.

Capponi, Agostino, and Martin Larsson. 2015. "Price Contagion through Balance Sheet Linkages." *The Review of Asset Pricing Studies* 5 (2): 227–53. https://doi.org/10.1093/rapstu/rav006.

Cifuentes, Rodrigo, Gianluigi Ferrucci, and Hyun Song Shin. 2005. "Liquidity Risk and Contagion." *Journal of the European Economic Association* 3 (2–3): 556–66. https://doi.org/10.1162/jeea.2005.3.2-3.556.

Diamond, Douglas W., and Philip H. Dybvig. 1983. "Bank Runs, Deposit Insurance, and Liquidity." *Journal of Political Economy* 91 (3): 401–19. https://doi.org/10.1086/261155.

Diamond, Douglas W., and Raghuram G. Rajan. 2011. "Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes *." *The Quarterly Journal of Economics* 126 (2): 557–91. https://doi.org/10.1093/qje/qjr012.

Duffie, Darrell, and Haoxiang Zhu. 2011. “Does a Central Clearing Counterparty Reduce Counterparty Risk?” *Review of Asset Pricing Studies* 1 (1): 74–95.
Gai, Prasanna, and Sujit Kapadia. 2010. “Contagion in Financial Networks.” *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 466 (2120): 2401–23. https://doi.org/10.1098/rspa.2009.0410.
Golan, Amos. 2017. *Foundations of Info-Metrics: Modeling and Inference with Imperfect Information*. New York, NY: Oxford University Press.
Golan, Amos, George Judge, and Jeffrey M. Perloff. 1996. “A Maximum Entropy Approach to Recovering Information From Multinomial Response Data.” *Journal of the American Statistical Association* 91 (434): 841–53. https://doi.org/10.2307/2291679.
Greenwood, Robin, Augustin Landier, and David Thesmar. 2015. “Vulnerable Banks.” *Journal of Financial Economics* 115 (3): 471–85. https://doi.org/10.1016/j.jfineco.2014.11.006.
Heckman, James J., Hidehiko Ichimura, and Petra E. Todd. 1997. “Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme.” *The Review of Economic Studies* 64 (4): 605–54. https://doi.org/10.2307/2971733.
Jackson, Matthew O., and Agathe Pernoud. 2021. “Systemic Risk in Financial Networks: A Survey.” *Annual Review of Economics* 13 (1): 171–202. https://doi.org/10.1146/annurev-economics-083120-111540.
Kiyotaki, Nobuhiro, and John Moore. 1997. “Credit Cycles.” *Journal of Political Economy* 105 (2): 211–48. https://doi.org/10.1086/262072.
Kleist, Karsten von, and C. Mallo. 2011. “OTC Derivatives Market Activity in the Second Half of 2010.” Bank of International Settlements. https://www.bis.org/publ/otc_hy1105.pdf.
LaLonde, Robert J. 1986. “Evaluating the Econometric Evaluations of Training Programs with Experimental Data.” *The American Economic Review* 76 (4): 604–20.
Liu, Jun, Francis A. Longstaff, and Ravit E. Mandell. 2006. “The Market Price of Risk in Interest Rate Swaps: The Roles of Default and Liquidity Risks.” *The Journal of Business* 79 (5): 2337–59. https://doi.org/10.1086/505237.
Loon, Yee Cheng, and Zhaodong Ken Zhong. 2014. “The Impact of Central Clearing on Counterparty Risk, Liquidity, and Trading: Evidence from the Credit Default Swap Market.” *Journal of Financial Economics* 112 (1): 91–115. https://doi.org/10.1016/j.jfineco.2013.12.001.
McPartland, John W. 2009. “Clearing and Settlement of Exchange Traded Derivatives.” *Chicago Fed Letter* 267 (2). https://fraser.stlouisfed.org/files/docs/historical/frbchi/policydiscussion/frbchi_policy_2009-02.pdf.
Minton, Bernadette A. 1997. “An Empirical Examination of Basic Valuation Models for Plain Vanilla U.S. Interest Rate Swaps.” *Journal of Financial Economics* 44 (2): 251–77. https://doi.org/10.1016/S0304-405X(97)00005-6.
Pirrong, Craig. 2011. “The Economics of Central Clearing: Theory and Practice.”
Rochet, Jean-Charles, and Jean Tirole. 1996. “Interbank Lending and Systemic Risk.” *Journal of Money, Credit and Banking* 28 (4): 733–62. https://doi.org/10.2307/2077918.
Roll, Richard. 1984. “A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market.” *The Journal of Finance* 39 (4): 1127–39. https://doi.org/10.1111/j.1540-6261.1984.tb03897.x.

Skarr, Doug, and Kristin Szakaly-Moore. 2007. “Understanding Interest Rate Swap Math & Pricing.” California Debt and Investment Advisory Commission. https://www.treasurer.ca.gov/cdiac/publications/math.pdf.

Smith, Clifford W., Charles W. Smithson, and Lee Macdonald Wakeman. 1988. “The Market for Interest Rate Swaps.” *Financial Management* 17 (4): 34–44. https://doi.org/10.2307/3665765.

Sun, Tong-sheng, Suresh Sundaresan, and Ching Wang. 1993. “Interest Rate Swaps: An Empirical Investigation.” *Journal of Financial Economics* 34 (1): 77–99. https://doi.org/10.1016/0304-405X(93)90041-9.

Appendix A Contract Characteristics

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

Table 16 Contract characteristics for common contracts

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.

Appendix B Robustness Tests

This appendix provides several robustness tests to my analysis. Firstly, in the main body of the dissertation, in the analysis of the clearing mandate on swap pricing, I filtered out observations that were +/- 50 bps from the Bloomberg terminal calculated fair rate. I now present an alternate version of tables Table 8 and Table 9, now including these outliers. Overall, there were 1,101 such outliers (representing about 4% of the overall dataset). Results continue to be very similar to the results found in the main dissertation. In this borader dataset, clearing causes a 12-bps rise in swaps prices for USD contracts in the overall dataset. Most control variables also show similar results to what is found in the main dissertation. The notable exceptions are tenor (where a one-year increase in the tenor is now associated with a 0.03 bps increase in the premium instead of a 4-bps decrease) and Friday trading (which is now associated with a 0.95 bps increase in the premium rather than a -0.78-bps decrease). The group difference (that is the difference in baseline premium for USD over CAD contracts) also becomes not statistically significant. Note that the effect of these control variables is small (less than 1 bps).

Table 17 Difference-in-differences results after including all pricing 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
R^2	0.0139	0.0182
Adjusted R^2	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

Table 18 Difference-in-differnces results after including pricing outliers. By phase analysis.

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
R^2	0.025	0.036	0.073
Adjusted R^2	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

Also, as is sometimes done in literature, I drop observations on the first trading day of each phase that the clearing mandate went into force (to mitigate the effects of program implementation effects). Results continue to show similar patterns as found in the main body of the dissertation. The mandate causes a 12-bps rise in premiums for US-contracts after implementation. Control variables show similar sign and magnitude as is discussed in the main body of the paper.

Table 19 Difference-in-differences results excluding the first day the treatment went into effect

Difference-in-Differences Regression Results

	Dependent variable: Premium	
	Basic Model	Advanced Model
	(1)	(2)
Group	-0.8889*	-0.7596
	(0.4942)	(0.4928)
Period	-11.4254***	-11.1961***
	(0.7048)	(0.7007)
Tenor		0.0305***
		(0.0089)
Log Notional		0.6367***
		(0.0693)
Capped		-0.7166***
		(0.1920)
SEF		0.4531
		(2.5989)
Morning Session		-0.9881***
		(0.1916)
Afternoon Session		-1.1930***
		(0.1877)
Off Hours		-1.2874***

		(0.2193)
Monday		2.6462***
		(0.2662)
Tuesday		2.3934***
		(0.2081)
Thursday		2.7678***
		(0.2016)
Friday		0.9347***
		(0.2137)
Group * Period	12.0888***	11.5072***
	(0.7234)	(0.7226)
Constant	-0.2415	-11.9859***
	(0.4742)	(1.2767)
Observations	25,613	25,613
R^2	0.0175	0.0335
Adjusted R^2	0.0174	0.0330
Residual Std. Error	11.4106 (df = 25609)	11.3196 (df = 25598)
F Statistic	152.0776*** (df = 3; 25609)	63.4120*** (df = 14; 25598)
Note:		*p**p***p<0.01

Finally, given the low R^2 values of some of the regression results, I try alternative regression specifications. Table 20 shows the results of a model with second-order terms for the continuous control variables tenor and notional. Although these higher order terms are statistically significant, the model still suffers from the same low R^2 as the model used in the main body of the dissertation. The overall conclusion remains the same (clearing causes a 13-bps increase in premium for USD contracts). Control variables also show similar signs and magnitudes as in the main body of the dissertation.

Table 20 Difference-in-differences with alternative model specifications

Difference-in-Differences Regression Results

	Dependent variable: Premium
	Advanced Model
Group	-0.6567
	(0.4897)
Period	-13.3189***
	(0.6611)
$Tenure^2$	0.0007***
	(0.0003)
$(Ln\ notional)^2$	0.0235***
	(0.0021)
Capped	-1.0574***
	(0.1883)
SEF	0.7100
	(2.5202)
Morning	-1.0268***
	(0.1843)
Afternoon	-1.2300***
	(0.1814)
Off Hours	-1.3042***
	(0.2125)
Monday	1.5552***
	(0.2245)
Tuesday	2.3847***
	(0.2071)

Thursday	2.7650***
	(0.2006)
Friday	0.9402***
	(0.2125)
Group * Period	13.4560***
	(0.6840)
Constant	-7.6601***
	(0.7760)
Observations	27,210
R^2	0.0441
Adjusted R^2	0.0436
Residual Std. Error	11.2629 (df = 27195)
F Statistic	89.5578*** (df = 14; 27195)
Note:	*p**p***p<0.01

Appendix C 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:
    a. time-varying confounders: factors that change over time and affect the treatment and control group differently can bias the estimates.
    b. endogenous selection: assignment into the treatment group might be associated with unobserved factors affecting the outcome.
    c. 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:

$$Y_{it} = \alpha + \beta D_i + \gamma T_t + \delta(D_i \times T_t) + \epsilon_{it}$$

where: Y_{it} is outcome Y for individual i at time t), D_i is a group indicator ($D_i = 1$ for the treatment group, $D_i = 0$ for the control group), T_t is a period indicator ($T_t = 1$ for the post-treatment period, $T_t = 0$ for the pre-treatment time period). $\alpha, \beta, \gamma, \delta$ are parameters (δ is the parameter of interest, the effect of the treatment and ϵ_{it} 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*), δ is no longer a consistent estimator of the treatment effect.

The traditional DiD model can be expanded so that:

$$Y_{it} = \alpha + \beta D_i + \gamma T_t + \delta(D_i \times T_t) + T_t \times Z_i'\Gamma + \sigma\epsilon_{it}$$

where: Z_i is a vector of covariates and Γ 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 D_i is correlated with factors affecting the outcome Y_{it}), 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 $Y(1) - Y(0)$ 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 T units are observed, where each unit is either selected into treatment or not. Let

$$p_i = Prob(D_i = 1|x_i, \beta) = F(x_i'\beta)$$

be the probability of observing unit $i \in [1,2, \dots T]$ in the treatment state, conditional on covariates x_i (of dimension $1 \times K$) and unknown parameters β (of dimension $K \times 1$). If we have noisy data, we can write

$$y_i = F(\cdot) + e_i = p_i + e_i$$

where p_i denotes the unknown and unobservable probability of selection and e_i is a noise component for each observation contained in $[-1, 1]$. To proceed, we must reparametrize the error component:

$$e_i = \sum_h v_{ih} w_{ih}$$

where $\sum_h w_h = 1$ are an H-dimensional vector of weights and v_i are the H-dimensional support space. (Golan, Judge, and Perloff 1996) suggest $v_i = \left[-\frac{1}{\sqrt{T}}, \frac{0,1}{\sqrt{T}}\right]$ and thus $H = 3$.

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

$$\max_{p,w}\left(-\sum_i p_i \ln p_i - \sum_{ijh} w_{ijh} \ln w_{ijh}\right)$$

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

$$\sum_i y_i x_{ik} = \sum_i x_i p_i + \sum_{ih} x_i v_h w_{ih}$$

and the adding up constraints

$$\sum_h w_i = 1$$

$$\sum_{j \in [0,1]} p_{ij} = 1$$

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

$$\mathcal{L} = -\boldsymbol{p} \ln p - \boldsymbol{w}' \ln \boldsymbol{w} + \boldsymbol{\lambda}'(\boldsymbol{X}'\boldsymbol{p} + \boldsymbol{X}'\boldsymbol{V}\boldsymbol{w} - \boldsymbol{X}'\boldsymbol{y}) + \boldsymbol{\mu}'(1 - I_T\boldsymbol{p}) + \boldsymbol{\rho}'(1 - \mathbf{1}'w)$$

where $\boldsymbol{\lambda}. \boldsymbol{\mu}, \boldsymbol{\rho}$ are Lagrange multipliers and $\beta = -\lambda$.

The first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial p_i} = -\ln p_i - 1 - \sum_k \lambda_k x_{ik} - \mu_i = 0$$

$$\frac{\partial \mathcal{L}}{\partial w_{ih}} = -\ln w_{ih} - 1 - \sum_k \lambda_k x_{ik} v_h - \rho_i = 0$$

$$\frac{\partial \mathcal{L}}{\partial w_k} = \sum_i y_i x_{ik} - \sum_i x_{ik} p_i - \sum_k x_{ik} v_h w_{ih} = 0$$

$$\frac{\partial \mathcal{L}}{\partial u_i} = 1 - \sum_{j \in 0,1} p_j = 0$$

$$\frac{\partial \mathcal{L}}{\partial \rho_i} = 1 - \sum_h w_{ih} = 0$$

From which we obtain the estimated probability distributions:

$$\widehat{p_i} = \frac{\exp\left(-\sum \widehat{\lambda_k} x_{ik}\right)}{\sum_{j \in (0,1)} \exp\left(-\sum_k \widehat{\lambda_k} x_{ik}\right)}$$

and

$$w_{ih} = \frac{\exp\left(-\sum_k x_{ik} \widehat{\lambda_k} v_h\right)}{\sum_h \exp\left(-\sum_k x_{ik} \widehat{\lambda_k} v_h\right)}$$

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 y_i by:

$$\rho_{0i} = \frac{D_i - p_{ij}}{\widehat{p_{ij}} \cdot \left(1 - \widehat{p_{ij}}\right)}$$

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

1. Reparametrize the β_ks and the error terms as $\beta_k = \sum_m z_{km} p_{km}$ and $\epsilon_i = \sum_j w_{ij} v_j$ where z_k is a $1 \times M$ vector (the discrete support space), p_k is a $M \times 1$ vector of weights, v_j is a $1 \times N$ vector (the discrete error support) and w_{ij} is a set of weights (that dd up to 1).
2. Maximize the entropy of $H_{p,w} = -\sum_i p_i \ln p_i - \sum_i w_i \ln w_i$ subject to the data constraint

$$\sum x_{ik} p_i \rho_0 + \sum v_i w_i \rho_0 - y_i \rho_0 = 0$$

   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).

Simulation

I simulate the performance of this estimator using the following data generating process. For the baseline case, I create a dataset of $n = 500$ observations. Each observation i has observable covariates X_{i1} and X_{2i} and unobservable $u_i \sim \mathbb{N}(0,1)$. Selection into treatment is governed by the selection equation, simulating both selection on observable and selection on unobservables:

$$D_i = \begin{cases} 1 \; if \; Unif(0,1) < logit(3X_{1i} - 5X_{2i} - 2u_i) \\ \qquad\qquad 0, otherwise \end{cases}$$

We observe the outcomes twice: once in the pre period and once in the post period. The outcome process is governed by the equation

$$Y_{pre,i} = 1 + 0.3X_{1i} + 0.3X_{2i} + 0.2D_i + \epsilon_{pre,i}$$

$$Y_{post,i} = 3 + 0.3X_{1i} + 0.3X_{2i} + (1.5 + 0.5X_{1i})D_i + \epsilon_{post,i}$$

This equation induces some difference in the "pre" outcome between treatment and control groups. In addition, there is some heterogeneity in treatment outcomes based on the realized value of X_{1i}. The true Average Treatment Effect on the Treated (ATT) is 2.0.

I generate data using this process 5,000 times. Figure 9 shows the results of the simulation for the baseline case, compared against an uncorrected/naïve difference-in-differences and Abadie's matching estimator using logit for the first stage. Table 21 summarizes these results. Note that the uncorrected difference-on-differences is not a consistent estimator of the treatment effect under the circumstances of selection into treatment and heterogenous treatment effects (both causing violation of the parallel trends assumption). Abadie's method, using either logistic regression or

GME for the first stage perform better, with the GME method having much smaller variance (std. dev.) and mean squared error.

Figure 9 Comparison of GME matching estimator performance, in comparison to matching based on logit and an uncorrected difference-in-differences

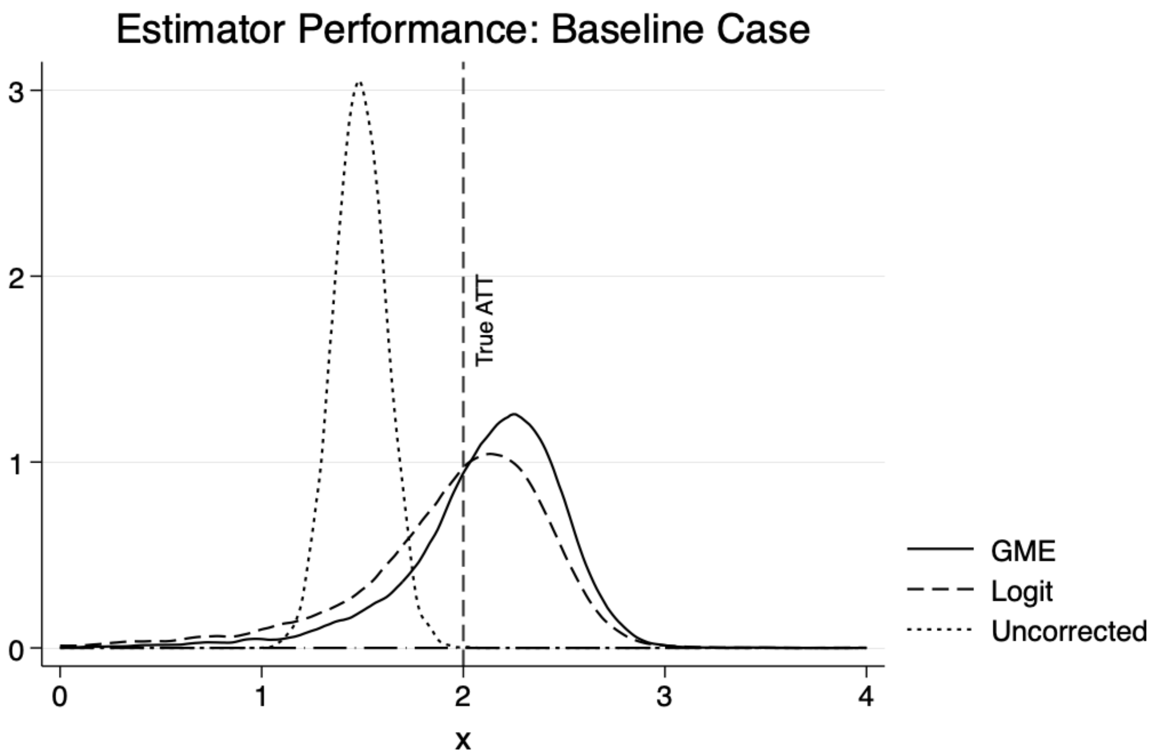


Table 21 Summary of Estimator Performance

	Baseline Performance		
	Bias	Std. Dev	MSE
Abadie (Logit)	-.1147202	.8791705	.7861014
Abadie (GME)	.0797839	.5604687	.3204907
Traditional DiD	-.5119547	.1295395	.2788781

To test the small sample performance, I reduce the size of the simulated dataset from $N = 500$ to $N = 25$. Figure 10 and Table 22 show the results. Now, the GME-based matching estimator clearly outperforms a logit-based first stage, with a lower bias, variance and MSE.

Figure 10 Small Sample Performance of Abadie's Estimator

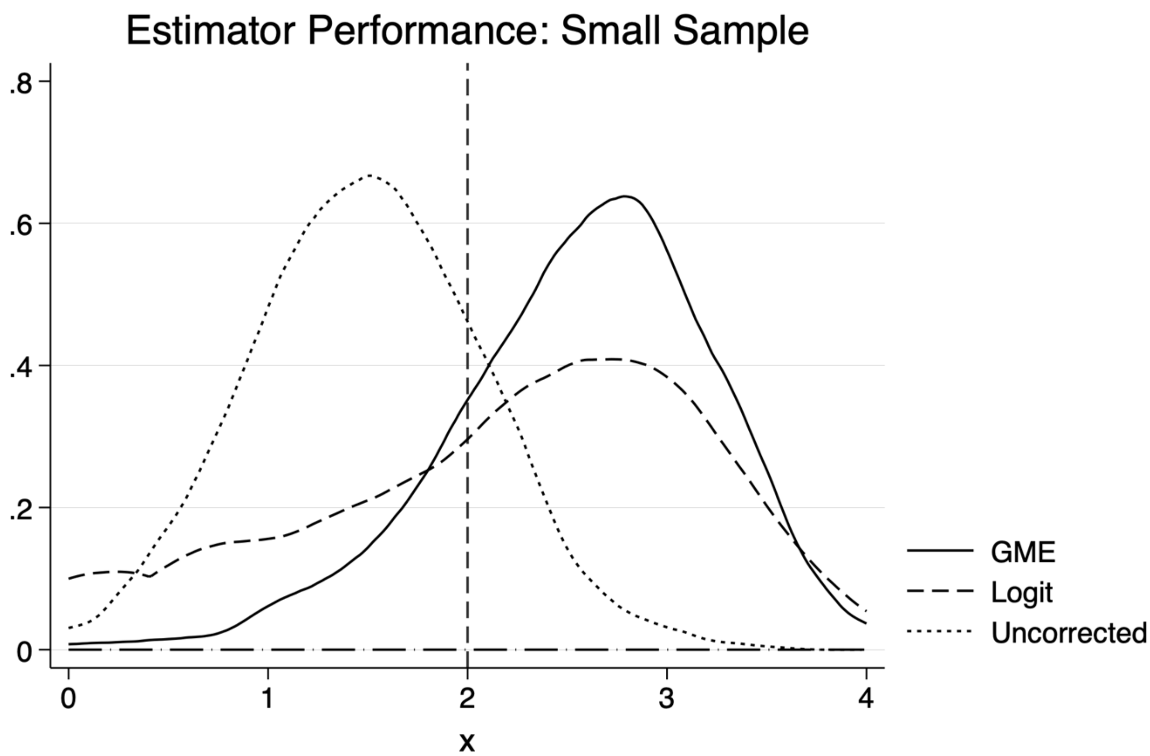


Table 22 Small Sample Performance of Abadie's Estimator

	Small Sample Performance		
	Bias	Std Dev	MSE
Abadie (Logit)	.1169992	1.279985	1.652051
Abadie (GME)	.564807	.683304	.7859113
Traditional DiD	-.5137796	.5946682	.6175997

To test the impact of an ill-conditioned design matrix, I modify the data-generating process as follows:

$$X_{3,i} = X_{1i} + X_{2i} + u_i$$

$$u_i \sim \mathbb{N}(0, 0.001)$$

$$Y_{pre,i} = 1 + 0.3X_{1,i} + 0.3X_{2,i} + 0.2D_i + X_{3,i} + \epsilon_{pre,i}$$

$$Y_{post,i} = 1 + 0.3X_{1,i} + 0.3X_{2,i} + (1.5 + 0.5X_{1i})D_i + X_{3,i} + \epsilon_{post,i}$$

That is, the design matrix now has an additional column X_3 that is nearly a linear combination of X_1 and X_2. Figure 11 and Table 23 shows how the estimators perform under these circumstances. The performance is very similar to the baseline case, with the GME based method still outperforming a logit first stage and the traditional difference-in-differences estimator.

Figure 11 Performnce of Abadie's estimator when the design matrix is ill-conditioned

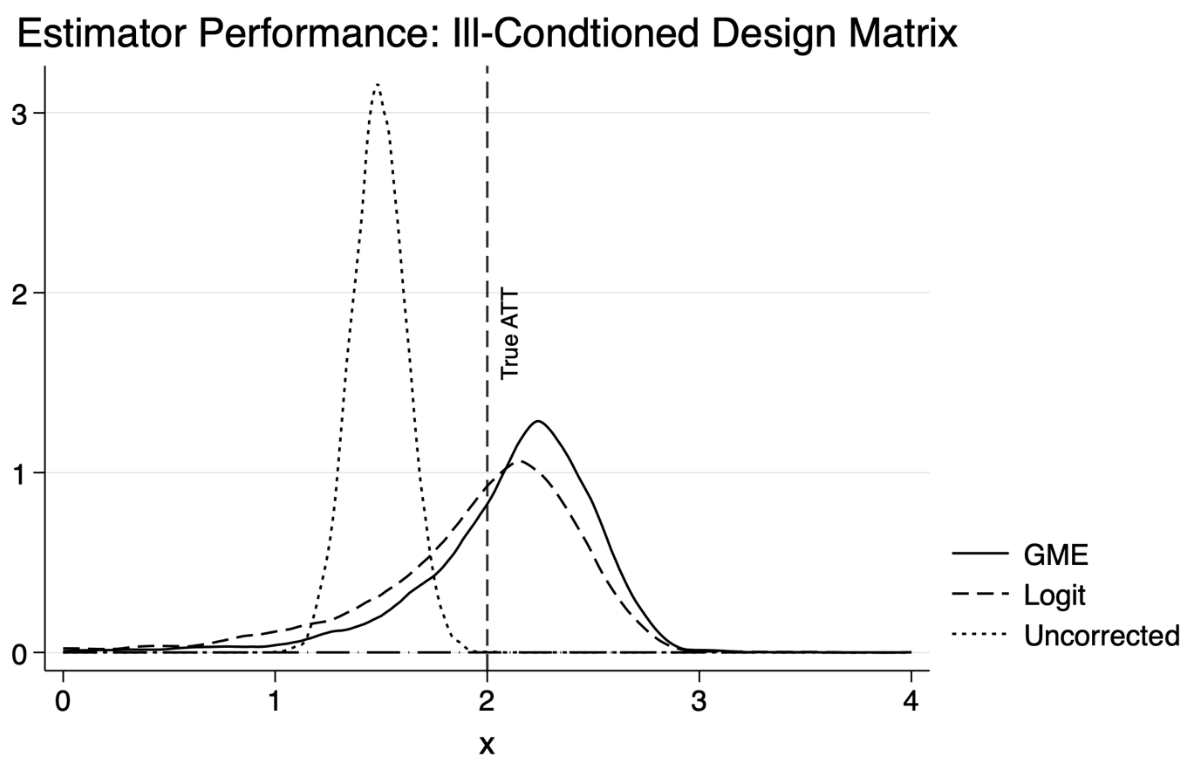


Table 23 Ill-Performance of Abadie's estimator when the design matrix is ill-conditioned

	Ill-Conditioned Data Performance		
	Bias	Std. Dev	MSE
Abadie(Logit)	-.1448158	2.065859	4.288745
Abadie(GME)	.0646625	1.160147	1.350122
Traditional DiD	-.5113141	.1286859	.2780022

Finally, I test the case when there is some heteroskedasticity/correlation between covariates and the error. I modify the data generating process as follows:

$$\epsilon_{pre,i} = \mathbb{N}(0.5\, X_{1i}, 1)$$

$$\epsilon_{post,i} = \mathbb{N}(0.5\, X_{1i}, 1)$$

The results are shown in Figure 12 and Table 24. The GME-based first-stage estimator clearly outperforms the Logit-based one, in terms of bias, variance and mean squared error. In summary, the GME-based first stage estimator outperforms a logit-based method in all cases simulated, with the outperformance especially pronounced in the case of small samples and heteroskedasticity.

Figure 12 Estimator performance when covariates are correlated wth errors

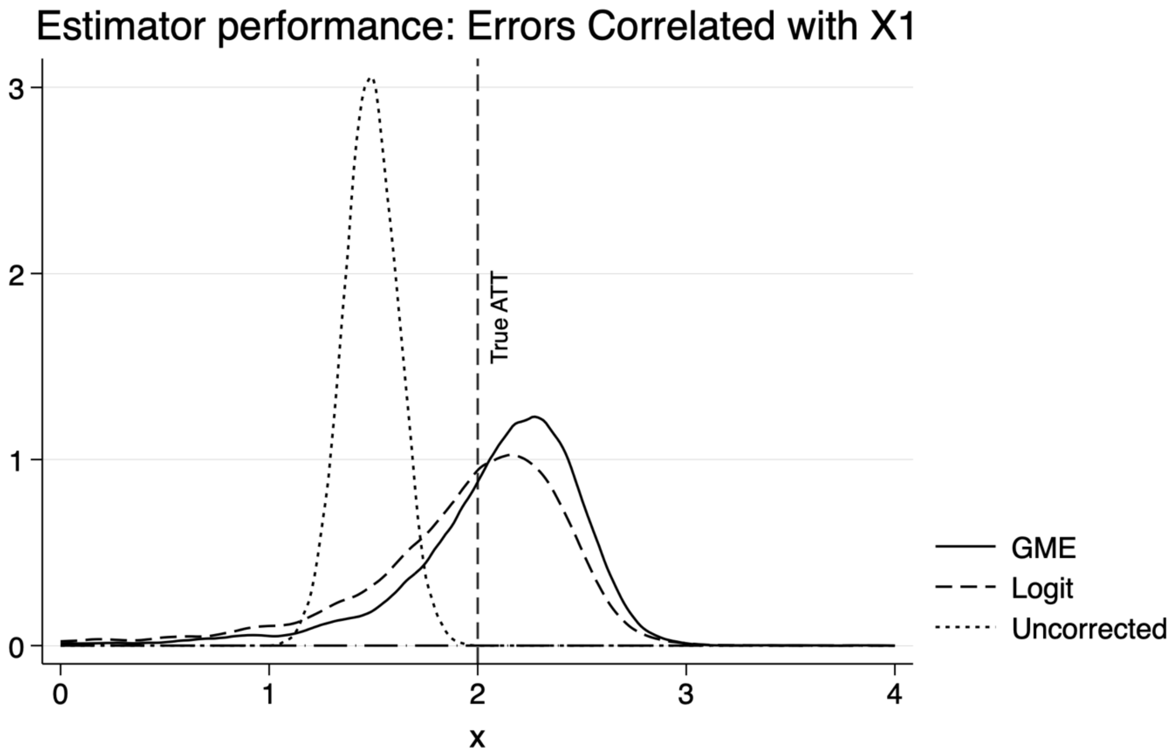


Table 24 Estimator Performance when covariates are correlated with errors

	Heteroskedasticity Performance		
	Bias	Std. Dev.	MSE
Abadie (Logit)	-.1560549	1.163898	1.379011
Abadie (GME)	.052799	.6806262	.4660398
Traditional DiD	-.512848	.1297478	.2798475

Real World Data

I now apply this method to a real-world dataset. I use the data provided by LaLonde (1986) for his evaluation of the impact of the National Supported Work (NSW) demonstration. The data is readily available in many software packages as well as through the NBER website. The NSW program randomly assigned individuals to a treatment or control group. Those in the treatment group received “supported work” where participants were employed at construction, service or similar industries in a supportive but performance-oriented work environment. LaLonde examines the data for male and female participants separately. For the male group, the outcome of interest is the 1978 real earnings due to participation in the program (or earnings growth from baseline 1975 wages in a difference-in-differences context). Since we have data from a control group, the difference in mean 1978 earnings between the experimental and control group is an unbiased estimator of the treatment effect. LaLonde asks what if researchers used an alternative control group to analyze the data instead of the actual control group. He constructs several sets of control groups: one based on the Current Population Survey (CPS), one based on the Panel Study of Income Dynamics (PSID), with additional datasets further sub-setting these to match demographic and pre-treatment earnings characteristics to more closely match that of program participants. A part of LaLonde’s results is reproduced here for reference.

Table 25 LaLonde's Analysis of NSW program effects on male participants (abbreviated)

Comparison Group	Treatment Less Comparison Group Earnings		Difference-in-Differences: Difference in Earnings Growth 1975-1978 Less Comparison Group	
	Unadjusted	Adjusted[5]	Without Age	With Age
Controls	\$886	\$798	\$847	\$856
	(476)	(472)	(560)	(558)
CPS-1	-\$8,870	-\$4,416	\$1,714	\$195
	(562)	(557)	(452)	(441)

[5] The exogenous variables used in the regression adjusted equations are age, age squared, years of schooling, high school dropout status and race

Note that naïve difference in 1975 earnings between the CPS comparison group and the treatment group recovers a large negative impact of participating in the program. Using the experimental control group as our reference, we know participation in the program is associated with a ~$886 increase in earnings. The large negative impact obtained when using the CPS as the comparison group is likely due to differences in demographic characteristics between the treatment group and the CPS population. Column 2 attempts to adjust for some demographic characteristics such as educational attainment, race and age. However, the estimate of the program's effect continues to be negative, likely due to uncontrolled (and unobservable) differences between the two groups. Columns 3 and 4 show the results of a Difference-in-Differences type estimation (using 1975 earnings as a baseline). Column 4 controls for age (and age squared) in the DiD estimate. The CPS group shows wildly different impact of program participation when age is controlled for (which is inconsistent with our findings for the experimental control group).

I now apply Abadie's matching method, using the GME based first stage described earlier. I obtain standard errors through bootstrap. Table 26 shows the results. Note that the estimate of the program's effect is now much closer to one obtained from using the experimental control group. The standard error of the estimate is also similar.

Table 26 LaLonde's Analysis of CPS population with matching

Comparison Group	Difference-in-Differences: Difference in Earnings Growth 1975-1978 Less Comparison Group
	Without Age
Controls	$847 (560)
CPS-1 with Abadie's method	$575 (562)

In conclusion, through simulation I show that Abadie's matching method (especially when using GME first stage to estimate the selection equation) performs well in recovering the impact of treatment when the narrow parallel trends assumption is violated (due to selection or heterogenous treatment effects. However, the parallel trends assumption is still maintained after conditioning on treatment and covariates). The GME-based method performs especially well when there is heteroskedasticity or small sample sizes. In addition, I apply the method to a well-known dataset (once where we have an experimental control group to verify our result). I show the Difference-in-Differences with matching estimator performs much better in estimating the treatment effect than traditional DiD.