Corporate Bond Market Post-Trade Transparency and Dealer Behavior*

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December 12, 2017

Abstract

I study how mandatory post-trade transparency affected dealers’ trading activity and liquidity in the secondary U.S. corporate bond market. Using the TRACE dataset with a novel variable identifying different dealers in the market, I document a large degree of heterogeneity in dealers’ trading patterns. I exploit the gradual nature of the implementation of the reform and employ a difference-in-difference framework to estimate a heterogeneous response to the reform across the market. The introduction of post-trade transparency reduced the estimated bid-ask spreads of peripheral dealers by about 24 basis points, while spreads of core dealers remained unaffected. The trading volume of high-yield bonds fell by 6.7% for core dealers, and by an insignificant amount for peripheral dealers. There was no effect on dealers’ capital commitment and inventory behavior. To rationalize these findings, I propose a dynamic model of trade with asymmetric information and search that gives rise to endogenous heterogeneity in dealers’ trading activity and explains the empirical evidence. Furthermore, I outline mechanisms through which transparency affects the market. Small increases in transparency may have an ambiguous effect on transaction costs and trading speed, while large increases unambiguously reduce transaction costs but may either increase or reduce search costs. I characterize conditions under which transparency is welfare-improving and welfare-worsening, and point to difficulties in interpreting welfare consequences of transparency from empirical evidence.

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*I am extremely grateful to Monika Piazzesi and Pablo Kurlat for their support and guidance as my advisors, as well as Darrell Duffie and Victoria Vanasco for assistance as part of my dissertation committee. I also thank Eran B. Hoffmann, Chris Bruegge, Tram Nguyen, Juan Rios, Martin Schneider, John B. Taylor, Diego Torres Patino and seminar participants for helpful comments. I am especially grateful to Susan Taylor for tremendous help and persistence in the process of obtaining the TRACE Data, as well as to FINRA’s team for assistance and cooperation. Financial support for the Academic Corporate Bond TRACE Data from Stanford Department of Economics is gratefully acknowledged. All errors are mine.

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1 Introduction

As opposed to stocks that trade on exchanges, U.S. corporate bonds trade in an over-the-counter (OTC) market, which is a decentralized market consisting of a large number of dealers who exhibit a substantial amount of heterogeneity in their trading activity. The dealers’ primary role is to intermediate trade between market participants. An investor desiring to trade a bond needs to conduct a costly and time-consuming search in order to locate and contact a dealer able to stand as a counterparty for the trade. Prices are generally set through a bargaining process that reflects each trader’s alternative to immediate trade. The U.S. corporate bond market was opaque until 2002, in the sense that no information about a trade executed between two participants was disclosed to others. I study the effect of an increase in post-trade transparency in the secondary corporate bond market on dealers’ trading activity and measures of market liquidity. While previous literature has studied this topic, my primary focus is on the differential effect of the reform with respect to dealers’ importance and activity in the intermediation process, which is of interest in light of the large degree of heterogeneity among intermediaries in the market. I find a significantly different response in transaction costs and volume between two groups: one, a small fraction of highly active dealers, and the other, a large number of dealers who trade less frequently and with a smaller number of trading partners. I do not find any significant changes in the dealers’ inventory behavior. I then propose a theoretical model with search, bargaining, and asymmetric information that can rationalize these findings. Further implications of the model with respect to the effects of transparency are explored.

The U.S. corporate bond market went through a significant change in July 2002 when a reform implemented by Financial Industry Regulatory Authority (FINRA) led to a public disclosure of the information about the prices and quantities of individual transactions in selected bonds. FINRA required all the registered dealers to report their transactions on a timely basis through the Trade Reporting and Compliance Engine (TRACE) program. FINRA then, within a 75-minute window following the trade, publicly released information about prices and volume of completed bond trades for a selected sample of bonds. Over the following three years, the reform gradually expanded to other bonds; three major samples, distinguished by issue size and credit quality, became transparent at different points in

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1 See, for example, Bessembinder et al. (2006), Goldstein et al. (2006) and Edwards et al. (2007) for the effect on bid-ask spreads, Asquith et al. (2013) for the effect on trading volume and price dispersion, and Bessembinder et al. (2016) for the effect on capital commitment.
time. In parallel, the reporting lag fell. By July 2005, the transaction information was available to all the market participants within 15 minutes after the trade. Six months later, the information became public in real time. The average daily volume in the market was roughly $18 billion at the time (SIFMA, 2017), constituting a dramatic increase in information available to market participants.

Regulators and academics have been divided over the merits of transparency in over-the-counter markets. On the positive side, it has been argued that TRACE enhances the integrity of the corporate bond market and creates a level playing field for all investors. This happens because uninformed retail investors are able to obtain a fair price through price discovery (NASD, 2005a). Pagano and Röell (1996) show in a theoretical model that greater transparency generates lower costs for uninformed traders on average across trade sizes. Furthermore, post-trade transparency in OTC markets improves dealers’ ability to share risk by reducing adverse selection in the interdealer market (Naik et al., 1999). In a related problem regarding pre-trade price transparency in OTC markets, Duffie et al. (2014) show that benchmarks increase market participation of investors in two ways: by reducing their informational disadvantage relative to dealers, and by eliminating incentives to shop around and incur costs due to trading delays. Furthermore, benchmarks improve efficiency by matching investors with the most low-cost dealers.

On the negative side, Naik et al. (1999) point out that the overall effect of transparency may still be ambiguous because dealers fail to extract any information rents in the interdealer market from the information acquired upon trading with investors, and this translates into higher cost of trading for investors. It has also been shown in an experimental setting that larger trade disclosure reduces dealers’ incentives to compete for order flow, which increases bid-ask spreads and benefits dealers at the expense of traders (Bloomfield and O’Hara, 1999). Jamieson (2006) notes that small dealers may be adversely affected due to large compliance costs. Finally, Holmstrom (2015) points out that debt is designed to be informationally insensitive, and thus market transparency may not have the desired positive effects. On contrary, Holmstrom (2015) argues that negative effects of additional release of information may prevail, such as the adverse impact on risk sharing (as in Hirshleifer (1971)) or possibility of triggering runs in the context of the short-term debt.

I use the recently released database, Academic Corporate Bond TRACE Data, which,
in addition to the information on prices and volume of all transactions in corporate bonds reported to TRACE, contains a variable on "reporting party and contra party with unique masked identified for each FINRA member dealer ID." This allows me to study the effect of transparency on dealers’ trading activity and market liquidity, recognizing that the drastic heterogeneity in dealers’ behavior that I document may be met with a heterogeneous response to the reform. Previous studies of the effect of the same reform could not address these issues, as the data did not contain identities of parties involved in trade.

In my empirical strategy, I exploit the fact that the reform took place in stages for different types of bonds over a three-year period. There were four major samples, Phase 1, Phase 2, Phase 3A and Phase 3B, characterized by different issue sizes, credit quality, and dates at which they became transparent. I estimate the changes in the variables of interest for the bonds currently undergoing the reform relative to the bonds that are already transparent. This is a difference-in-difference framework, which allows me to isolate the effect of the reform from other unobserved shocks to the bond market, under the assumption that the bonds used as controls follow the same time pattern. A similar difference-in-difference approach is used in Edwards et al. (2007) for estimating the effect of TRACE on transaction costs of Phase 2 bonds, and in Asquith et al. (2013) for estimating the effect of TRACE on trading volume and price dispersion for each phase of the reform.

The distinguishing feature of my paper is that I allow for the effect of the reform to vary across dealers of different importance in market, where dealers’ importance is represented by their centrality in the trading network. I find that increased post-trade transparency generally affects trading with clients, but I find no evidence of any effect in the interdealer market. In addition, the reform has a differential effect across the trading network. In my main specification, the reform reduces estimated bid-ask spreads of the peripheral dealers by 24 basis points on average across different samples, while there is no evidence of change in the spreads of the core dealers. The volume of trade was affected only for the high yield bonds as in Asquith et al. (2013), declining by 3.5% on average across all the dealers. Looking across different dealer, the volume fell by 6.7% percent for the central dealers, and by an insignificant amount for the peripheral dealers. I further document that there was no effect of transparency on the dealers’ capital commitment and inventory behavior.

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2FINRA (2017a)
3I provide tests of this assumption and show that there is no evidence against it.
4There is a mild, but statistically insignificant increase in the spreads of the central dealers.
which is in line with Bessembinder et al. (2016) for the average market effect.\footnote{Bessembinder et al. (2016) do not investigate heterogeneity across the trading network.}

Having documented the facts and estimated the effects, I ask what frictions can explain the documented response to the introduction of the reform. In that regard, I propose a dynamic model of trade in an over-the-counter market with segmentation, search, and bargaining, populated by asymmetrically informed agents. There are dealers who intermediate the trade, and traders, undistinguishable by dealers, who may trade for either liquidity reasons or in order to profit from private information not yet reflected in the asset price. Dealers costlessly choose the rate at which they are to be contacted by the traders searching for them, and traders choose what type of dealers, represented by their matching rates, to search for. While dealers can select among a continuum of matching rates, the stationary equilibrium consists of only two types of dealers: a fraction of dealers who choose the maximal possible matching rate, and the remaining fraction who select a strictly smaller rate. This is due to the fact that liquidity traders are heterogeneous in terms of their initial search cost and thus choose to either search for fast/core dealers (i.e. if they have high search costs) at the expense of higher transaction costs due to high adverse selection, or to search for slower dealers (i.e. if they have low search costs) and benefit from lower bid-ask spreads.

An increase in transparency is taken to mean that the private information held by informed traders becomes public at a faster rate. This generates three distinct effects. First, there is a reduction in adverse selection across the market, as private information disappears at a faster rate and fewer informed traders are able to trade before their informational advantage is gone. This effect puts a downward pressure on bid-ask spreads and trading volume by both types of dealers. Second, informed traders’ preference for immediacy, and thus for trading with core dealers, becomes stronger, putting an upward pressure on bid-ask spreads and volume of core dealers, with an opposite effect on peripheral dealers. Third, liquidity traders trade in larger numbers with peripheral dealers due to a relative decrease in their bid-ask spreads, further lowering spreads of peripheral dealers and thus attracting informed investors to trade with them. This equilibrium response can have ambiguous effects on transaction costs with both types of dealers, but also on search costs, speed of trading and volume. The resulting outcome and welfare consequences depend on the initial composition of informed and liquidity traders searching for each type of
dealers, on the distribution of liquidity traders’ search costs, and on the magnitude of the change in transparency. A small increase in transparency can have an ambiguous effect on both transaction costs and speed of trading, while a sufficiently large increase necessarily reduces bid-ask spreads, but may either speed up or slow down matching with dealers. Interestingly, if liquidity traders have low search costs or are patient enough, transparency may be harmful for liquidity traders and dealers. This is because traders with low search costs are easily induced to move to trade with peripheral dealers, after which liquidity can get trapped in the market with the slow matching rate even when transparency reduces adverse selection to a great extent.

Liquidity in the secondary corporate bond market does not only concern the participants in the market, but on the contrary, has far reaching consequences for the whole economy. The cost of bond issuance, and consequently a firm’s decision on capital structure and activities such as default or investment, are directly affected by liquidity of bonds in the secondary market. This is of great importance, as bonds have become the primary source of firm debt financing, constituting over 60% of all credit market instruments at the end of 2016, up from 37% in 1985. To put things into perspective, the share of bank loans over the same period fell from 25% to less than 12%. There is a large literature in corporate finance outlining various channel through which debt financing allows for an optimal capital structure and efficient amount of investment, including decreasing agency costs between shareholders and managers, reducing conflicts between insiders and outside investors created by information asymmetries, or as a commitment tool in a strategic interaction with competitors and consumers. As bonds are increasingly more used as a source of debt financing for corporations in the United States, a well-functioning secondary bond market plays a very important role in bringing the economy closer to an efficient allocation.

While my analysis documents the effect of post-trade transparency in the secondary U.S. corporate bond market and highlights the importance of understanding the relevant

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6See, for example, Chen et al. (2007), Bao et al. (2011), He and Milbradt (2014), Chen et al. (2016), and Davis et al. (2017).

7Financial Accounts of the United States, Table L.102

8Financial Accounts of the United States, Table L.102

9See, for example, Jensen and Meckling (1976), Jensen (1986), Harris and Raviv (1990) and Bolton and Freixas (2000).

10See, for example, Ross (1977), Leland and Pyle (1977), Myers and Majluf (1984), Myers (1984) and Hart and Moore (1994).

11See, for example, Titman (1984), Brander and Lewis (1986) and Maksimovic (1988).
frictions in and structure of the market, the insights are likely to also be important in other over-the-counter markets. Difficulties in assessing the value of securities in several OTC markets during the 2008 financial crisis have inspired numerous proposals\textsuperscript{12} that have led to similar transparency reforms being implemented in the market for securitized products starting in March 2010, and in the market for OTC swaps starting in December 2012. There are also various proposals to implement a TRACE-like reform for the European corporate bonds (Learner, 2011), as well as the U.S.Treasury market. European corporate bonds and Treasury bonds differ substantially in terms of liquidity and scope for disagreement about the value, lying at opposite ends of the spectrum relative to the U.S. corporate bonds. It is thus expected that transparency will play a very different role in the secondary markets for these securities.

**Related Literature.** This project relates to and complements several strands of literature. There are four main empirical studies of the impact of TRACE on the U.S. corporate bond market, differing in terms of the methodology, focus of interest, and scope of the reform. Bessembinder et al. (2006) estimate the effect of Phase 1 on transaction costs using a structural model and report a reduction in transaction costs ranging from 4.9 to 7.9 basis points. Goldstein et al. (2006) use a controlled experiment involving 120 BBB Phase 2 bonds, and find declines in transaction costs for actively traded bonds, but find no evidence of a reduction in transaction costs for inactively traded bonds or for very large trades. They also find no effect of the reform on trading volume. Edwards et al. (2007) examine transaction costs for Phase 2 bonds and report that transparency lowers transaction costs by anywhere from 0 to 12 basis points, depending on the trade size and model specification. For the sake of comparison, I estimate the effect of transparency omitting controls for dealers’ market activity, and find a 1 to 5 basis point decline in bid-ask spread for Phase 2 and Phase 3A bonds, respectively, but with no statistical significance. Asquith et al. (2013) study the effect of transparency on price dispersion and trading activity using data on all four major transparency changes. They find that transparency decreases trading volume for high-yield bonds and reduces price dispersion for all bonds. In my estimation, a statistically significant decline in trading volume occurs only for high-yield bonds, which is in line with Asquith et al. (2013). It is important to note that none of the four studies controls for the structure of the market, nor do any assess the heterogeneity of

\textsuperscript{12}See, for example, the Squam Lake Report (French et al., 2010).
the impact of transparency across dealers of different levels of activity in the market, since
the data did not contain identifiers for any market participants. The effect on daily price
dispersion studied in Asquith et al. (2013) is a step in the direction of understanding how
heterogeneous the effect is, but a decrease in price dispersion is consistent with different
ways in which individual dealers could be affected. Controlling for the structure of the
market is particularly important if, for instance, transparency causes the volume to move
from one type of dealer to another, or if different dealers start trading different sets of
bonds. If the outcome changes across dealers, which is shown to be the case in this paper,
then the effect of transparency will not be properly identified. Furthermore, estimates of
dependent variables, such as bid-ask spreads can be seriously biased if they vary across
dealers and that is not taken into account.

Another related, emerging strand of literature explores the structure of OTC markets
using newly available trading data. Among the most relevant papers are Li and Schürhoff
(2014) for municipal bonds, Hollifield et al. (2016) for securitized products, and Di Maggio
et al. (2017) for corporate bonds. Interestingly, all three papers document a persistent
core-periphery structure of the trading network in the corresponding markets, but with
somewhat different relationships between dealers’ activity and bid-ask spreads. Di Maggio
et al. (2017) use the same dataset as used in this paper, but for the post-reform period,
from 2005 to 2011.

Several papers study the effect of transparency on financial markets from a theoretical
perspective. Pagano and Röell (1996) find that transparency lowers average transaction
costs for uninformed traders. Naik et al. (1999) show that the effect may be ambiguous:
on the one hand, post-trade transparency in OTC markets improves dealers’ ability to
share risk by reducing adverse selection in the interdealer market; one the other hand,
dealers are more likely to fail to extract any information rents in the interdealer market
from the information acquired upon trading with investors, and this translates into higher
cost of trading for investors. In a related problem, Duffie et al. (2014) study pre-trade price
transparency in OTC markets by considering the effect of benchmarks. They show that
benchmarks can raise social surplus by increasing the volume of beneficial trade, improving
the matching efficiency and reducing search costs.

There is a growing field of theoretical studies on OTC markets that analyzes the impact
of search frictions on asset prices, starting with seminal papers such as Duffie et al. (2005,
Explaining the emergence of heterogeneous market makers and their role on financial markets is a relatively new topic, explored in Neklyudov (2012), Wang (2016), Weill et al. (2016) and Farboodi et al. (2017), among others. All of these papers focus primarily on search frictions and do not address the role of market transparency on trading outcomes. This paper attempts to fill this void in the literature.

Layout. The rest of the paper is organized as follows. Section 2 presents additional background on TRACE. Section 3 describes the data sources and construction of the main variables. Section 4 provides the descriptive statistics. Section 5 presents the empirical strategy, main results and robustness checks. Section 6 lays out the theoretical model following the empirical evidence. Section 7 concludes.

2 Institutional Background

TRACE overview and history outlined in this section can be found in NASD (2005b) and in Asquith et al. (2013).

TRACE started on July 1, 2002, requiring broker-dealers to report transaction information in TRACE-eligible securities\textsuperscript{13} to FINRA\textsuperscript{14} on a timely basis. Immediately upon receipt, FINRA disseminated transaction information, consisting of prices and quantities,\textsuperscript{15} for selected bonds to the public. Public dissemination of transaction information was implemented in three phases, distinguished by issue size and credit quality of bonds included for dissemination. Table 1 outlines the timeline of the reform. The initial time window in which a transaction was required to be reported to FINRA was 75 minutes, dropping to 45 minutes on October 1, 2003, to 30 minutes on October 1, 2004, and to 15 minutes on July 1, 2005. Finally, starting on January 9, 2006, no delay in reporting was permitted. The first phase, Phase 1, went into effect on July 1, 2002, and included investment-grade debt securities with an initial issue size of $1 billion or greater. I refer to this set of bonds

\textsuperscript{13}A "TRACE-eligible security" is any US dollar-denominated debt security that is depository-eligible and registered by the SEC, or issued pursuant to Section 4(2) of the Securities Act of 1933 and purchased or sold pursuant to Rule 144a.

\textsuperscript{14}The name of the regulatory agency at the time was the National Association of Security Dealers (NASD), changing name to the Financial Industry Regulatory Agency (FINRA) in 2007. It excludes debt that is not depository-eligible, sovereign debt, development bank debt, mortgage- and asset-backed securities, collateralized mortgage obligations, and money market instruments.

\textsuperscript{15}Trade size reports were censored at $1,000,000 for high-yield bonds and $5,000,000 for investment grade bonds.
as Phase 1 bonds. In addition, 50 non-investment-grade (high-yield) securities that were previously disseminated under FIPS2 were transferred to TRACE. This set of 50 securities did not remain constant and was updated on several occasions. The number of TRACE-eligible securities with publicly disseminated trades under TRACE during the second half of 2002 was approximately 520.

It was not clear at the time how the reform would unfold, and whether it would expand to other bonds, primarily because there was a large disagreement between different parties about whether transparency was beneficial or not. The main arguments for the introduction of TRACE revolved around protecting less-experienced market participants through price discovery. The expectation of the proponents of TRACE was that more transparency would encourage more participation by retail investors, which would increase market liquidity and thus benefit everyone (NASD, 2005a). Opponents on the other hand, mainly organized around prominent dealers and institutional traders, argued that transparency would narrow bid-ask spreads, reducing dealers’ willingness to hold inventories and intermediate trade, thus making the market less liquid (Mullen, 2004; Decker, 2007).


<table>
<thead>
<tr>
<th>Date</th>
<th>Information</th>
<th>Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 1, 2002</td>
<td>Dealers required to report to FINRA within 75 minutes</td>
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<tr>
<td></td>
<td>Investment grade bonds having an initial issue of $1 billion or greater</td>
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<tr>
<td></td>
<td>50 High-Yield bonds disseminated under Fixed Income Pricing System (FIPS); Ended on July 14, 2004</td>
<td>Phase 1</td>
</tr>
<tr>
<td>March 3, 2003</td>
<td>Bonds rated A- or higher with an initial issue of $100 million or greater; 50 High-Yield bonds</td>
<td>Phase 2</td>
</tr>
<tr>
<td>April 14, 2003</td>
<td>120 investment grade bonds rated BBB</td>
<td>Phase 2</td>
</tr>
<tr>
<td>October 1, 2003</td>
<td>Dealers required to report to FINRA within 45 minutes</td>
<td></td>
</tr>
<tr>
<td>October 1, 2004</td>
<td>Dealers required to report to FINRA within 30 minutes</td>
<td></td>
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<tr>
<td></td>
<td>All bonds with rating of BBB- or higher</td>
<td>Phase 3A</td>
</tr>
<tr>
<td>February 7, 2005</td>
<td>All bonds with rating of BBB- or lower; Eligible for delayed dissemination</td>
<td>Phase 3B</td>
</tr>
<tr>
<td>July 1, 2005</td>
<td>Dealers required to report to FINRA within 15 minutes</td>
<td></td>
</tr>
<tr>
<td>January 9, 2006</td>
<td>Dealers required to report to FINRA within immediately</td>
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Table 1: TRACE Timeline

Notes. Information available at NASD (2005b). Date is the date at which the reform described in the Information column took place. Information describes a reform. Bonds subject to delayed dissemination are certain infrequently traded non-investment grade bonds (with trading, size, and rating criteria described by Rule 6250(b) in NASD (2004)).
The first expansion of TRACE by FINRA was confirmed on November 21, 2002. The SEC approved the expansion on February 28, 2003, and Phase 2 went into effect on March 3, 2003. Public dissemination was expanded to include transactions in smaller investment-grade issues, which consisted of all investment-grade TRACE-eligible securities with an original issue size of at least $100 million par value or greater, rated A3/A- or higher. I refer to these bonds as Phase 2 bonds. In addition, on April 14, 2003, under the scope of the same phase, dissemination began for 120 investment-grade securities rated BBB. As Phase 2 was implemented, the number of disseminated bonds increased to approximately 4,650 bonds.

Phase 3, approved by the SEC on September 2, 2004, was implemented in two parts: Phase 3A and Phase 3B. Phase 3A went into effect on October 1, 2004, and it included all bonds not already disseminated that were not eligible for delayed dissemination. Phase 3B, effective on February 7, 2005, included the remaining TRACE-eligible securities. Bonds eligible for delayed dissemination were bonds that traded infrequently and were rated BB or below, as well as some bonds following the offering, rated BBB or below. For such bonds, dissemination was delayed for transactions that were over $1 million, and the length of the delay was up to several days, depending on the exact credit rating of the bond in question.\(^\text{17}\) At this point, approximately 99% of all public transactions and 95% of par value in the TRACE-eligible securities market were disseminated immediately upon receipt. Starting in January 9, 2006, all transactions in public TRACE-eligible securities have been disseminated immediately upon receipt.

3 Data

In this section, I describe the data sources that I combine for the empirical analysis. I also define and describe the construction of the main variables used in the analysis. Additional details are provided in Appendix A.

\(^{17}\)See NASD (2004) for more details.
3.1 Academic Corporate Bond TRACE Data

The primary source of data for this paper is the Academic Corporate Bond TRACE Data, released to the academic community on February 27, 2017.\footnote{The data can be purchased upon completion of a written agreement between FINRA and the academic institution. More details can be found at http://www.finra.org/industry/trace-historic-academic-data.} The data used for this paper spans the period from July 1, 2002 through December 31, 2005. This period covers all the major transparency reforms in the U.S. corporate bond market, as Phase 3B, the last major phase of TRACE, concluded in February 2005. While dissemination was taking place for only a subset of the bonds throughout most of the period, FINRA required dealers to report all transactions taking place in the market, opening a path for subsequent studies of the reform. The data consist of historic transaction-level data on all transactions in corporate bonds reported to TRACE. Besides the price and quantity traded, the dealers involved in a transaction were required to report additional information, such as the following: whether they were acting as a buyer or seller; the type of the counterparty, which could be either a client or another dealer; execution date and time; bond identity; commission; principal or agency capacity. In addition, the data contain variables with transaction-level information on "reporting party and contra party with unique masked identifiers for each FINRA member dealer ID" (FINRA, 2017a). This is the distinguishing feature of the dataset used in this paper relative to the Historical TRACE Data, which was released in March 2010. The access to masked identifying information regarding the dealer reporting each transaction allows me to analyze the architecture of the market, control for the market structure during the estimation of the effects of transparency, and assess heterogeneity of the effect across dealers of different trading activity in the market.

In order to perform my main empirical analysis, the data needed to be processed from the raw form along many dimensions. I eliminated all bonds not contained in the Mergent Fixed Income Securities Database (FISD), bonds with an equity-like component, bonds not identified to belong to any of the major three phases, and bonds having an issue size of less than $10,000. In addition, I removed trades that were cancelled or reversed, agency trades, trades with par value of less than $1,000, trades with the execution date within 90 days of the offering date or 1 year of the maturity date, as well as trades with missing or erroneous data. Each trade in the interdealer market should, in theory, be reported twice, by the dealers from both ends of the trade. Due to errors in reporting, which were
perhaps occurring at a larger stale at this initial stage of the reform, I was not able to match 39.2% of trades in the interdealer market. Consequently, I dropped the trades that do not have a corresponding match. While interdealer trades are used to form the trading network and compute measures of dealer centrality, the main results in the paper concern trades with clients, which are not affected by the elimination of matched trades in the interdealer market. Finally, I removed dealers that are not present in the market for at least 2 months and that do not trade for at least 20 days and 10% of days in the market over the entire three-and-a-half-year period. These dealers contribute to an insignificant amount of volume in the market. The resulting sample consists of 12,909,797 transactions in 19,219 bonds with 530 dealers. The steps taken towards processing the data, including the matching algorithm for the interdealer trades, are described in more detail in Appendix A, with corresponding numbers of bonds and trades remaining after every step outlined in Table 8.

**Phase Identification**

The TRACE data do not come with any variable indicating a bond’s phase. However, there is a variable indicating whether a particular trade was disseminated or not. I used this information, together with a phase starting date and criterion for a bond’s dissemination phase presented in Table 1, to recover the phase of each bond. Details are provided in Appendix A.19

**3.2 Mergent Fixed Income Securities Database (FISD)**

The Mergent Fixed Income Securities Database (FISD) is a comprehensive database of publicly offered U.S. bonds. It includes information on characteristics of bond issuers and bond issues, including issuer industry, maturity date, issue date, issue amount, coupon rate, as well as credit ratings from the major credit rating agencies at the time: S&P, Moody’s, Fitch, and Duff and Phelps. To assign a credit rating to a bond, I first use the S&P value if it exists, then attempt to assign a value from the following agencies in order:

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19I contacted FINRA to obtain their listings of the bonds included at the start of Phases 2, 3A, and 3B, but have not received any response regarding this inquiry. I expect that I will be able to obtain these listing in the future in order to have a more accurate procedure for phase identification. The characteristics of bonds assigned to each phase in this paper are very similar to the ones in Asquith et al. (2013), who obtained the FINRA listings and used them for phase identification, which can be seen from comparing Table 2 from this paper, to their Table 2.
Moody’s, Fitch, and Duff and Phelps. If no values exist from any of these agencies, I classify it as unrated. I convert credit rating values to numerical values as in Asquith et al. (2013), with details in Appendix A.

3.3 Definition and Construction of Variables

There are two sets of variables of interest that require construction. The first set consists of measures of market liquidity and dealer trading activity at the bond-dealer level, on which the effect of transparency is studied: bid-ask spread, volume, and inventory change. The second set of variables consists of the measures of dealers’ importance in the market, represented by dealers’ centrality in the trading network.

Measures of market liquidity and dealer trading activity

The bid-ask spread is defined as the difference between the dealer’s sell and buy price as a percentage of the buy price. Because prices in most over-the-counter markets are generally set through bargaining and depend on the outside options of counterparties involved (as is the case in the U.S. corporate bond market), bids and asks are not posted anywhere and thus the data on spreads does not exist. One way to estimate bid-ask spreads from the transaction data is employed in Di Maggio et al. (2017): look at two trades occurring within a short period of time from each other with the same type of counterparty (i.e. dealer or client) in opposite directions (i.e. one buy and one sell), conducted by a particular dealer in the same bond. With this information, compute the spread for the given quantity by using per-unit prices of the two trades as a bid and ask. While this method could produce a precise measure of the bid-ask spread, it comes at costs (as pointed out in Di Maggio et al. (2017)). Since corporate bonds do not trade frequently, the types of transactions necessary for estimating spreads as described above are not very frequent. In addition, bond-dealer pairs in these transactions could be a lot more skewed towards more liquid bonds and more central dealers. This is particularly worrisome for my analysis as, for instance, Phase 3B bonds are high-yield bonds that can be very illiquid. Furthermore, if some dealers adjust their inventories by trading in the interdealer market following a trade with a client, which is often the case for peripheral dealers, estimates of spreads for such dealers can be very sparse. To address these concerns, I considered the following related method. For any transaction conducted by a given dealer, I computed the average price of
the bond traded in the opposite direction by other similar dealers with the same type of counterparty in the same week. I then used the price of the original transaction and the computed price to estimate the spread. Two dealers were considered to be similar if they were both either central or peripheral dealers\textsuperscript{20} at a point in time.\textsuperscript{21} I show that the two methods produce bid-ask spreads with correlation coefficient over 80% over the subsample on which both measures exist. In unreported results I confirm that the main regression estimates of the two methods are similar over the subsample on which both measures exist.\textsuperscript{22} The second method, however, allows for the estimates over a substantially larger number of transactions.

The volume is defined as the daily trading volume in dollars of par value at the bond-dealer level. In order to reduce the skewness, I transformed volume by first adding 1 and then taking logarithm. I added 1 in order to deal with days in which a dealer does not trade a particular bond.\textsuperscript{23}

The next variable looks at the inventory behavior. Because inventories are not reported in the TRACE data, I constructed a variable that considers changes in inventories. In particular, I constructed a variable defined as the absolute daily change in a bond inventory as a percentage of daily trading volume. If the trading volume is 0, then the variable takes a missing value for that date. This variable represents the percentage of the trading activity in a given bond carried into the overnight inventory, and has an interpretation of dealers’ willingness to allow customer trades to shift their inventory away from the beginning-of-day level. A similar variable is used in Bessembinder et al. (2016), but defined over portfolios rather than individual bonds. Following Bessembinder et al. (2016), I denote this variable as capital commitment. I take this name with some reservation, as daily changes in inventories generally depend on the entire market dynamics, not only dealer’s commitment to commit capital for intermediation.

Trading network and measures of dealer centrality

In order to control for dealers’ importance in the market, as well as to assess how

\textsuperscript{20}Definitions of central and peripheral dealers are provided in subsequent paragraphs of this section.

\textsuperscript{21}A similar measure was considered by Di Maggio et al. (2017) in their robustness checks, but without matching the dealers by similarity.

\textsuperscript{22}That does not necessarily mean that the reported estimates of the two methods are similar, as the second method produces estimates for a larger number of transactions.

\textsuperscript{23}In unreported results, I find that adding numerous other small constants produces nearly identical results.
heterogeneous the effect of transparency is, I computed several measures of dealer centrality. I first built a trading network at any date as an undirected graph as follows. Each dealer present in the market was represented by a node in the graph, and an edge was formed between two dealers if they traded during the past two months.\textsuperscript{24} I also included the representative client as a node, and an edge/link between a dealer and the representative client was formed in the same way.\textsuperscript{25} I considered two types of graphs: a weighted graph, if each edge is weighted by the number of trades between the two dealers over the past two month; and an unweighted graph, if each edge is assigned the same weight, normalized to 1.\textsuperscript{26}

I computed two measures of dealer centrality in the trading network. Degree centrality of a node is defined as the sum of the edge weights over the edges containing a given node, normalized by the number of nodes on a given date.\textsuperscript{27} Eigenvector centrality is a more global measure of centrality. It assigns a score of the overall importance of a dealer in the network, such that a dealer’s score is proportional to the (link weighted) sum of trading partners’ scores. Therefore, links to high-scoring dealers contribute more to a dealer’s score. I generally used unweighted degree centrality in graphs, as it has an easy interpretation, while I used weighted eigenvector centrality in the main statistical analysis because, as a more global measure, eigenvector centrality better reflects a dealer’s position in the trading network, since weights contain information about the strength of a trading relationship between two dealers.\textsuperscript{28} A dealer is a core dealer on a given date if he is among top 30 dealers by weighted eigenvector centrality on that date, and a peripheral dealer otherwise. Following Li and Schürhoff (2014), I applied an empirical cumulative distribution function transformation to eigenvector centrality in order to reduce the impact of skewness and outliers, while at the same time normalizing the centrality between 0 and 1. Furthermore, because eigenvector centrality scores are relative rather than absolute, this transformation facilitates the interpretation of economic magnitudes.

\textsuperscript{24}A similar method is employed in Li and Schürhoff (2014).
\textsuperscript{25}A network without the representative client has very similar properties. Furthermore, centralities of networks built from trades of bonds from different phases have pairwise correlation coefficients exceeding 95%. As a consequence, I focus on one trading network that considers transactions in all bonds.
\textsuperscript{26}In the case of a weighted graph, I weight down links with the representative client in order to account for the deletion of unmatched transactions in the interdealer market.
\textsuperscript{27}If the graph is unweighted, degree centrality is simply the number of links containing a given node. If the graph is weighted, it is simply the number of trades between a given node/dealer and other dealers.
\textsuperscript{28}The correlation coefficient between degree and eigenvector centrality (separately for weighted and unweighted graphs) across dealers over the considered time period is above 95%, while the correlation coefficient between weighted and unweighted measures of the same type is above 70%.
4 Summary Statistics

In this section I provide summary statistics and document the structure of the market.

Table 2 shows bond characteristics by phase. Phase 1 bonds have the largest issue size by far, followed by Phase 2 bonds. Phase 3A bonds have the smallest issue size, orders of magnitude smaller than Phase 1 bonds. The number of bonds in each phase is inversely related to the issue size. Phase 1 and 2 bonds have excellent credit quality, followed by Phase 3A bonds, which constitute the remaining investment grade bonds. Phase 3B bonds are the high-yield bonds, with drastically worse credit quality than the bonds belonging to the other three phases. Maturity at issue and coupon rates are more comparable across the phases.

<table>
<thead>
<tr>
<th></th>
<th>Phase 1</th>
<th>Phase 2</th>
<th>Phase 3A</th>
<th>Phase 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Bonds</td>
<td>401</td>
<td>2,518</td>
<td>13,191</td>
<td>3,360</td>
</tr>
<tr>
<td>Size at Issue ($M)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>1,505</td>
<td>325</td>
<td>82</td>
<td>178</td>
</tr>
<tr>
<td>median</td>
<td>1,250</td>
<td>200</td>
<td>11.31</td>
<td>150</td>
</tr>
<tr>
<td>Age at Phase Start</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>1.46</td>
<td>5.33</td>
<td>3.32</td>
<td>6.08</td>
</tr>
<tr>
<td>median</td>
<td>1.12</td>
<td>5.01</td>
<td>1.86</td>
<td>5.93</td>
</tr>
<tr>
<td>Maturity at Issue</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>9.64</td>
<td>14.97</td>
<td>11.03</td>
<td>11.4</td>
</tr>
<tr>
<td>median</td>
<td>9.28</td>
<td>10.02</td>
<td>9.98</td>
<td>9.65</td>
</tr>
<tr>
<td>Rating at Phase Start</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>A</td>
<td>A/A+</td>
<td>A-/BBB+</td>
<td>CCC+</td>
</tr>
<tr>
<td>median</td>
<td>A</td>
<td>A+</td>
<td>A</td>
<td>B-</td>
</tr>
<tr>
<td>Fixed Coupon Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>6.59</td>
<td>6.87</td>
<td>5.77</td>
<td>8.79</td>
</tr>
<tr>
<td>median</td>
<td>6.62</td>
<td>6.88</td>
<td>5.8</td>
<td>8.62</td>
</tr>
<tr>
<td>number</td>
<td>361</td>
<td>2,121</td>
<td>11,833</td>
<td>3,109</td>
</tr>
</tbody>
</table>

Table 2: Bond Characteristics by Phase

Notes. Bond characteristics are from FISD. Bond ratings are the most recent ratings before the Phase starts. To assign a rating, following Asquith et al. (2013), I use the S&P value if it exists, otherwise the Moody’s value, otherwise the Fitch value, and otherwise the Duff and Phelps value. Mean ratings are computed by converting each rating to a number (AAA=22, AA+=21, ..., and D=1) and then converting it back to a letter rating.

Figure 1 plots the trading network using the transaction data from July 1, 2002 to December 31, 2005. Red circles or nodes represent different dealers, with the exception of
Notes. The figure is built using transaction data from September 2002 to December 2005. Each node is a dealer firm or a representative client. Each line represents a transaction between the two nodes. Darker lines indicate a higher number of transactions between the two nodes. The plot is generated using multidimensional scaling based on the criterion that the more trade links exist between two dealers, the closer is their location on the map.

one node for the indistinguishable clients. There is a link between two nodes if a direct trade occurs between them, and darker lines indicate a higher number of transactions between the two nodes. The plot is generated using multidimensional scaling based on the criterion that the more trade links exist between two dealers, the closer is their location on the map. This naturally places more active and interconnected dealers in the center of the network while the less active ones are increasingly further away from the center. The network exhibits a definite core-periphery structure, with a small fraction of highly interconnected dealers accounting for the majority of all transactions, and of several hundred, much less active, peripheral dealers. Di Maggio et al. (2017) provide a similar plot of the trading network in the U.S. corporate bond market for years 2005-2011. Exploring further heterogeneity among intermediaries in the market, Figure 2 illustrates the non-randomness of trading relations between dealers. It plots the empirical cumulative distribution of degree centrality as a fraction of the number of nodes (black line with steps), where each data point is identified by a dealer and business day, and the trading network is built using the trades over the past two months. As a comparison, Figure 2 also plots the degree distribution of a random trading network (the blue line) with the same average degree.\footnote{A random graph is a graph in which each link is formed with fixed probability, independently of other
the graph that the degree distribution of the random graph is much more concentrated, as its cumulative distribution function quickly moves from 0 to 1 over a small range of values for degree centrality. The degree distribution of the actual trading network is substantially more spread out, with a large number of dealers having their degree centrality close to 0 and with a sizable fraction of dealers having fairly large degree (i.e. over 10% of dealers trade with over 15% of other dealers in the market over the past two months).

Table 3 demonstrates a high persistence of the market structure. In particular, a core dealer today is still a core dealer in two months with probability of 94%, while a peripheral dealer remains peripheral with probability of 99.7%. Table 4 reports summary statistics for measures of market liquidity and dealer trading activity, as well as for the variables describing the structure of the market. I report statistics for all trades combined (columns (1)-(3)), but also for trades with clients (columns (4)-(6)) and in the interdealer market (columns (7)-(9)) separately. In addition, I show results across all dealers combined, as well as separately for core and peripheral dealers. I report means, with standard deviations in parentheses. Volume is the daily dealer volume (in dollars of par) averaged across dealers and business days. An average daily volume per dealer in the market is $8,636,000.
An average core dealer has over 25 times larger daily volume than an average peripheral dealer. Peripheral dealers trade in the interdealer market relatively more than the core dealers. Trade size is averaged across transactions. It can be seen that trade size is comparable across dealers of different centrality ranks in their transactions with clients, with an average trade size between core dealers and clients equal to $497,000, and between peripheral dealers and clients equal to $537,000. Peripheral dealers make larger trades in the interdealer market on average. I report bid-ask spread averaged across transactions, both equal- and value-weighted. The equal-weighted average bid-ask spread is larger because bid-ask spread is generally decreasing in trade size. In both cases, the bid-ask spread is substantially larger for the trades with clients than in the interdealer market regardless of the dealers’ centrality rank.\(^{30}\) Note also that core dealers generally have larger spreads for their trades with clients. The magnitudes of the estimated spreads in Table 4 are in line with the literature.\(^{31}\) Capital commitment is averaged across dealers, bonds, and business days. Thus, for a dealer who trades a particular bond on a given day, 76.9% of the daily volume is accounted for by the dealer’s inventories. Capital commitment is larger for core dealers than for peripheral ones, suggesting that core dealers are more willing to absorb customer order imbalances into their own inventories.\(^{32}\) As degree centrality suggests, an average dealer trades with about 5.6% of other dealers over the past

\(^{30}\)Note that some values of the estimated bid-ask spread in the interdealer market are negative. This happens because dealers trade against each other, and thus if one type of dealer has a positive estimated spread for the trades with the other type, then the other type will have a negative estimated spread.

\(^{31}\)See, for instance, Adrian et al. (2016) for average spreads with equal weighting, and Bessembinder et al. (2006) and Edwards et al. (2007) for value-weighted spreads for Phase 1 and Phase 2 bonds, respectively.

\(^{32}\)Since core dealers intermediate trade in a larger number of bonds than peripheral dealers, it could still be the case that overall inventories experience a smaller absolute change for core dealers. In unreported results I find that the absolute change in total inventories as a fraction of total dealer’s daily volume is indeed on average smaller for core dealers.
<table>
<thead>
<tr>
<th>Counterparty</th>
<th>Dealer Centrality Rank</th>
<th>All Dealers</th>
<th>Core</th>
<th>Peripheral</th>
<th>All Dealers</th>
<th>Core</th>
<th>Peripheral</th>
<th>All Dealers</th>
<th>Core</th>
<th>Peripheral</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>All Trades</td>
<td></td>
<td></td>
<td>Trades with Clients</td>
<td></td>
<td></td>
<td>Interdealer Trades</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td>Volume (in thousands)</td>
<td>8,636</td>
<td>73,216</td>
<td>2,825</td>
<td>(92,749)</td>
<td>6,263</td>
<td>60,672</td>
<td>1,308</td>
<td>2,471</td>
<td>12,543</td>
<td>1,553</td>
</tr>
<tr>
<td>Trade Size (in thousands)</td>
<td>505</td>
<td>476</td>
<td>592</td>
<td>(2,376)</td>
<td>504</td>
<td>497</td>
<td>537</td>
<td>510</td>
<td>394</td>
<td>649</td>
</tr>
<tr>
<td>Bid-Ask Spread (ew)</td>
<td>1.426</td>
<td>1.56</td>
<td>0.993</td>
<td>(2.14)</td>
<td>1.97</td>
<td>1.976</td>
<td>1.933</td>
<td>0.028</td>
<td>-0.0835</td>
<td>0.166</td>
</tr>
<tr>
<td>Bid-Ask Spread (vw)</td>
<td>0.511</td>
<td>0.601</td>
<td>0.301</td>
<td>(1.493)</td>
<td>0.705</td>
<td>0.736</td>
<td>0.572</td>
<td>0.0152</td>
<td>-0.0616</td>
<td>0.071</td>
</tr>
<tr>
<td>Capital Commitment</td>
<td>0.769</td>
<td>0.803</td>
<td>0.683</td>
<td>(0.401)</td>
<td>0.017</td>
<td>0.0688</td>
<td>0.029</td>
<td>0.0152</td>
<td>-0.0616</td>
<td>0.071</td>
</tr>
<tr>
<td>Degree Centrality</td>
<td>0.0564</td>
<td>0.192</td>
<td>0.0443</td>
<td>(0.0822)</td>
<td>0.017</td>
<td>0.0688</td>
<td>0.029</td>
<td>0.0152</td>
<td>-0.0616</td>
<td>0.071</td>
</tr>
<tr>
<td>Dealers in Market</td>
<td>359</td>
<td>30</td>
<td>331</td>
<td>(83)</td>
<td>359</td>
<td>30</td>
<td>331</td>
<td>359</td>
<td>30</td>
<td>331</td>
</tr>
<tr>
<td>Dealers Trading</td>
<td>215</td>
<td>30</td>
<td>186</td>
<td>(50)</td>
<td>187</td>
<td>30</td>
<td>159</td>
<td>173</td>
<td>29</td>
<td>146</td>
</tr>
<tr>
<td>Days in Market</td>
<td>575</td>
<td></td>
<td></td>
<td>(246)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days Trading</td>
<td>209</td>
<td></td>
<td></td>
<td>(277)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Summary Statistics

Notes. The table reports averages of important variables conditional on dealer centrality rank and type of counterparty, using transaction data from September 2002 to December 2005. Degree Centrality is number of trading counterparties over past 2 months divided by the number of dealers. Capital Commitment is absolute value of daily change in inventories as a fraction of daily volume. Days in Market is the number of business days between the first and last trade a dealer makes during the sample period. Days Trading is number of days during which a dealer makes at least one trade. Unit of observation for "Dealer in Market" and "Dealers Trading" is business day. Unit of observation for "Volume" and "Degree Centrality" is (business day,dealer). Unit of observation for "Capital Commitment" is (business day, bond, dealer). Unit of observation for "Trade Size" and "Bid-Ask Spread" is transaction. Unit of observation for "Days in Market" and "Days Trading" is dealer. "ew" and "vw" stand for equal-weighted and value-weighted, respectively. Numbers larger than 10 are rounded to the closest integer. Standard deviations are in parentheses.
two months. Average degree centrality for a core dealer 0.192, while a peripheral one it is 0.0443. There are on average 359 dealers present in the market on any given day\(^\text{33}\), while on average 215 dealers trade on any given day. The core dealers trade on every business day.

5 Empirical Analysis

In this section I describe the empirical strategy and present the main results.

5.1 Empirical Strategy

My main empirical strategy is a difference-in-difference framework, where I estimate the differential effect of transparency on the variables of interest for a sample of bonds undergoing a change in their dissemination status (i.e. treatment phase) relative to the bonds not experiencing the change during a particular phase. A simple before-and-after comparison is not sufficient to attribute the changes to dissemination alone because market liquidity and dealer activity vary over time. Before going into the main specification, I start with estimating a standard difference-in-difference model that ignores any heterogeneities across the market participants, as in Asquith et al. (2013)\(^\text{34}\):

\[
y_{ijt} = \gamma \text{Post}_t + \lambda \text{Disseminate}_i \times \text{Post}_t + \beta X_{it} + \eta_i + \epsilon_{ijt}
\]

where \(y_{ijt}\) is the outcome of bond \(i\) and dealer \(j\) at date \(t\) (i.e. bid-ask spread, volume, and capital commitment), \(\text{Post}_t\) is an indicator for dates \(t\) during which transaction information for the treated bonds is disseminated to the market, \(\text{Disseminate}_i\) is an indicator for whether bond \(i\) changes dissemination status, \(X_{it}\) is the vector of bond specific and possibly time-varying controls, such as credit rating, maturity, age, coupon rate, trade size, buy/sell indicator, etc, \(\eta_i\) is a constant which may vary across bonds (i.e. allowing for bond fixed effects), and \(\epsilon_{ijt}\) is the error term. I refer to the specification in Equation (1) as ”Average Effect”, since dealer heterogeneity is not taken into account. Since there are repeated

\(^{33}\)After very inactive dealers have been filtered out, as described in Appendix A.

\(^{34}\)Since the literature on the effect of transparency in the bond market has not dealt with heterogeneity across the market due to data limitations, this is a natural starting point.

\(^{35}\)Controls such as trade size and buy/sell indicator apply if a unit of observation is a transaction, which is the case when the outcome variable is bid-ask spread.
observations per bond and per dealer, the standard errors are always, in this and future specifications, clustered by bond and by dealer.

In Equation (1), the bond-fixed effects term $\eta_i$ accounts for the pre-existing difference between bonds (i.e. before the change in the dissemination status of the treatment phase bonds). Any time-varying changes in the market liquidity, and any potential effect of transparency that affects the entire market, is captured by the time effect $\gamma_i$.

The coefficient of interest is $\lambda$, which estimates the direct effect of transparency on the outcomes of the bonds belonging to the treatment phase. Including bond fixed effects is particularly important because changes in the outcome variables could be due to a change in the composition of the bonds traded by dealers at the start of a phase, as dealers could be, for instance, less willing to trade riskier bonds. If the bonds are not held constant (i.e. if bond fixed effects are omitted), then any changes in the outcome variable due to the change in the composition of the traded bonds will be wrongly attributed to TRACE.

I next move onto the main empirical specification. In particular, I build onto the specification in Equation (1) to assess the extent to which transparency heterogeneously affects different dealers. In particular, the main specification that I estimate is the following:

$$y_{ijt} = (\gamma_i Post_t + \lambda_i Disseminate_i \times Post_t + \delta Disseminate_i + \alpha) \times Core_{jt}$$

$$+ (\gamma_p Post_t + \lambda_p Disseminate_i \times Post_t) \times (1 - Core_{jt}) + \beta X_{it} + \eta_i + \epsilon_{ijt} \tag{2}$$

where $Core_{jt}$ is an indicator for a core dealer at time $t$. I refer to the specification in Equation (2) as ”Differential Effect”, since dealer heterogeneity is taken into account.

In Equation (2), the bond-fixed effects term $\eta_i$ accounts for pre-existing difference between bonds, the term $\alpha$ captures pre-existing differences between core and peripheral dealers, and the term $\delta$ accounts for any additional pre-existing differences in the outcome of the treated bonds between core and peripheral dealers. Time-varying changes in the market liquidity are captured by time effects $\gamma_c$ and $\gamma_p$ for core and peripheral dealers, respectively. The coefficients of interest are $\lambda_c$ and $\lambda_p$, which estimate the direct effect of transparency on the outcomes of the bonds belonging to the treatment phase for core and peripheral dealers, respectively.

The time-effect term $\gamma Post_t$, can be replaced by a more general term, $\gamma_t$, that captures time-effects at a finer partition of time, such as a day or week. I explore these changes and show that the results are unchanged.
For completeness and robustness, I also estimate a specification that takes into account dealers’ full centrality instead of the binary classification into core and peripheral dealer groups:

\[ y_{ijt} = (\gamma \text{Post}_t + \lambda \text{Disseminate}_i \times \text{Post}_t + \delta \text{Disseminate}_i + \alpha) \times \text{Centrality}_{jt} + \gamma_0 \text{Post}_t + \lambda_0 \text{Disseminate}_i \times \text{Post}_t + \beta X_{it} + \eta_i + \epsilon_{ijt} \]  

(3)

where \( \text{Centrality}_{jt} \) is the empirical cumulative distribution function transformation of the weighted eigenvector centrality, as explained in Section 3. This specification is also referred to as the ”Differential Effect”.

In Equation (3), the bond-fixed effects term \( \eta_i \) accounts for pre-existing difference between bonds, the term \( \alpha \) captures pre-existing differences between dealers of different centrality, and the term \( \delta \) accounts for any additional pre-existing differences in the outcome of the treatment phase bonds between dealers of different centrality. Time-varying changes in market liquidity are captured by time effects \( \gamma_0 \) and \( \gamma \). The coefficients of interest are \( \lambda_0 \) and \( \lambda \), which estimate the direct effect of transparency on the outcomes of the bonds belonging to the treatment phase, where \( \lambda_0 + \lambda C \) is the estimate for a dealer with centrality \( C \).

In order to estimate Equations (1), (2) and (3), following Asquith et al. (2013), choices need to be made regarding the estimation window surrounding the phase start date and regarding the control sample. On the one hand, since corporate bonds trade infrequently (and especially so when traded by the same dealer), it is important to have a longer estimation window in order to capture a sufficient number of transactions by each dealer in each bond. On the other hand, the longer the estimation window, the more likely it is that changes in the outcome variables due to market trends will be misattributed to the effect of transparency. I use an estimation window covering 60 days before and after the phase start date.\(^{37}\) The second decision is about the choice of the control sample. I include in the control sample all bonds that have already gone through the reform and have been transparent for some time. Such bonds are least likely to be affected by the dissemination of the new sample of bonds, as the information about their transaction data is already

\(^{37}\)In their analysis of the impact of TRACE on the average volume per bond, and on price dispersion, Asquith et al. (2013) use a 90-day estimation window. My results become even stronger when a 90-day window is used. I report here more conservative estimates, obtained by using a shorter, 60-day, window. I find using a 60-day window more convenient.
available.

I estimate Equations (1), (2) and (3) separately for Phase 2, Phase 3A and Phase 3B. Following Asquith et al. (2013), I also provide a pooled estimate for the effect of dissemination that uses data on all three phases. Note that the effect of Phase 1 cannot be estimated, as the data prior to the introduction of TRACE does not exist. For the cases in which the outcome variables are bid-ask spread and volume, I estimate the effects separately for trades with clients and in the interdealer market, since these two types of trades have different properties, as documented in Table 4.

A difference-in-difference framework requires a parallel trend assumption, which requires that in the absence of the transparency change, the outcomes of the treated and control bonds would have changed by the same amount. Thus, any deviation between the change in the outcomes of the treated sample and the outcomes of the control sample is attributed to the reform. This does not mean that control bonds must have the same characteristics as treated bonds, but only the same time trends. While time trends cannot be observed under the counterfactual, the assumption of parallel trends can be tested for the time window before the phase start date. I conduct such test for each outcome variable and under each specification (i.e. for Equations (1), (2) and (3)), and I show that there is no evidence against the parallel trend assumption. The description of the tests and results is presented in Appendix B.

There are several other assumptions required in order for the models in this section to provide causal effects of transparency. First, transparency and its consequences must not have been fully anticipated by market participants. If dealers and investors had knowledge about timing and effect of transparency in advance, they could have responded before dissemination started taking place. As Asquith et al. (2013) point out, this seems unlikely as there was a large uncertainty about whether transparency expansion would take place, and even when an expansion was announced, the start date would often be revealed no more than several days in advance.\textsuperscript{38} Furthermore, it is not clear what an early response would consist of and whether it was at all possible before information on transaction data started being released to the market. If there was an early response, the results in this paper would understate the true impact of the reform. The second important assumption is that the effect of earlier phases was contained within the sample of the disseminated bonds, and

\textsuperscript{38}For instance, the SEC approved the expansion for Phase 2 on February 28, 2003, and the phase was effective on March 3, 2003.
did not affect nontransparent bonds to the extent that their future dissemination would have no effect on the outcome variables. This would happen, for instance, if the entire effect of transparency on the market occurred at the start of Phase 1. This seems unlikely since bonds belonging to different phases differ substantially in terms of credit quality and issue size, as well as other characteristics such as maturity and coupon rate (see Table 2); as such, they are priced by different factors. To the extent that earlier phases have an effect on bonds yet to become transparent, my estimates understate the true impact of TRACE, and thus provide a lower bound on the effect of transparency across the market. It is also possible that control bonds are affected through general equilibrium effects, i.e. if transparency directly affects demand for treated bonds, then demand for control bonds could be affected if there are complementarities or substitutabilities between treated and control bonds. Since bonds belonging to distinct phases differ substantially across many dimensions, it is likely that they are of interest to different investors, and that they play distinct roles in investors’ portfolios. Thus, the change in demand for control bonds should be negligible.

5.2 Results

Tables 5, 6, and 7 report estimates of the impact of TRACE on bid-ask spread, volume, and capital commitment, respectively. The first four columns in Tables 5 and 6 (i.e. columns (1)-(4)) report estimates using transactions with clients, while the last four columns (i.e. columns (5)-(8)) report estimates for the interdealer market. No such division exists for capital commitment. Columns (1) and (5) in Tables 5 and 6 and column (1) in Table 7 show estimates for the pooled sample across all phases, and the remaining columns report estimates for individual phases. Panel A in each table provides the Average Effect estimate from Equation (1), and panels B and C report the Differential Effect estimates from Equations (2) and (3), respectively.

One general conclusion that can be drawn from Tables 5 and 6 is that there are no consistently significant effects of TRACE on bid-ask spreads and trading volume in the interdealer market. Focusing on Table 5 (i.e. for bid-ask spread), for the trades with

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39 In Table 6 for the trading volume, variables are averaged over all business days in the before and in the after window due to computing limitations. This is because any bond-dealer-date triple is an observation for any bond traded by a particular dealer at least once throughout the sample period, since no trading in a particular bond counts as 0 volume.
Table 5: Difference-in-Difference Estimation: Bid-Ask Spread

<table>
<thead>
<tr>
<th>Counterparty</th>
<th>Client</th>
<th>Dealer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>Pooled</td>
<td>Phase 2</td>
</tr>
<tr>
<td>Disseminate x Post</td>
<td>-0.00833</td>
<td>-0.0102</td>
</tr>
<tr>
<td></td>
<td>(0.0492)</td>
<td>(0.0629)</td>
</tr>
<tr>
<td>Disseminate x Post x Core</td>
<td>0.0303</td>
<td>0.0139</td>
</tr>
<tr>
<td></td>
<td>(0.0497)</td>
<td>(0.0634)</td>
</tr>
<tr>
<td>Disseminate x Post x Peripheral</td>
<td>-0.235**</td>
<td>-0.125</td>
</tr>
<tr>
<td></td>
<td>(0.0885)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>p-value (Core=Peripheral)</td>
<td>0.0035</td>
<td>0.225</td>
</tr>
<tr>
<td>Disseminate x Post</td>
<td>-1.357***</td>
<td>-0.659</td>
</tr>
<tr>
<td></td>
<td>(0.343)</td>
<td>(0.363)</td>
</tr>
<tr>
<td>Disseminate x Post x Centrality</td>
<td>1.412***</td>
<td>0.675</td>
</tr>
<tr>
<td></td>
<td>(0.370)</td>
<td>(0.373)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,672,870</td>
<td>520,071</td>
</tr>
<tr>
<td>Mean Before (Core)</td>
<td>2.145</td>
<td>1.763</td>
</tr>
<tr>
<td>Mean Before (Peripheral)</td>
<td>2.114</td>
<td>1.302</td>
</tr>
<tr>
<td>Mean Before (All)</td>
<td>2.14</td>
<td>1.702</td>
</tr>
</tbody>
</table>

Notes: A unit of observation is a transaction. OLS regressions include standard difference-in-difference regressors (see specifications), in addition to controls for buy/sell, rating, maturity, age, coupon rate, (log) trade size, and bond fixed effects. The dependent variable is bid-ask spread. Disseminate is an indicator for whether the bond changes dissemination status. Post is an indicator for dates during which transaction information for the treated bond is disseminated to the market. Centrality is dealer eigenvector centrality rank of the trading network weighted by the number of trades over the last two months, normalized between 0 and 1, and computed at each date. A core dealer is a dealer among top 30 dealers by centrality. A peripheral dealer is a dealer who is present in the market but not a core dealer. Robust standard errors clustered at the bond and dealer level are in parenthesis immediately below the estimates. ***, **, * indicate significance at 1, 5, and 10%.
<table>
<thead>
<tr>
<th>Counterparty Sample</th>
<th>Client Pooled</th>
<th>Client Phase 2</th>
<th>Client Phase 3A</th>
<th>Client Phase 3B</th>
<th>Dealer Pooled</th>
<th>Dealer Phase 2</th>
<th>Dealer Phase 3A</th>
<th>Dealer Phase 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td><strong>Panel A: Average Effect (Eq. (1))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disseminate x Post</td>
<td>-0.000815</td>
<td>0.0772</td>
<td>-0.0185</td>
<td>-0.0357***</td>
<td>0.0000482</td>
<td>0.0211</td>
<td>-0.00128</td>
<td>-0.0120*</td>
</tr>
<tr>
<td></td>
<td>(0.0159)</td>
<td>(0.0614)</td>
<td>(0.0194)</td>
<td>(0.0103)</td>
<td>(0.00506)</td>
<td>(0.0206)</td>
<td>(0.00563)</td>
<td>(0.00473)</td>
</tr>
<tr>
<td><strong>Panel B: Differential Effect (Eq. (2))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disseminate x Post x Core</td>
<td>-0.00832</td>
<td>0.261</td>
<td>-0.0414</td>
<td>-0.0666***</td>
<td>0.0109</td>
<td>0.108</td>
<td>0.00639</td>
<td>-0.0176*</td>
</tr>
<tr>
<td></td>
<td>(0.0455)</td>
<td>(0.256)</td>
<td>(0.0543)</td>
<td>(0.0201)</td>
<td>(0.0108)</td>
<td>(0.0617)</td>
<td>(0.00846)</td>
<td>(0.00693)</td>
</tr>
<tr>
<td>Disseminate x Post x Peripheral</td>
<td>0.00176</td>
<td>0.0109</td>
<td>-0.00675</td>
<td>-0.0154*</td>
<td>-0.00545</td>
<td>-0.00280</td>
<td>-0.00572</td>
<td>-0.00918</td>
</tr>
<tr>
<td></td>
<td>(0.00618)</td>
<td>(0.0195)</td>
<td>(0.00761)</td>
<td>(0.00690)</td>
<td>(0.00465)</td>
<td>(0.0169)</td>
<td>(0.00686)</td>
<td>(0.00511)</td>
</tr>
<tr>
<td>p-value (Core=Peripheral)</td>
<td>0.819</td>
<td>0.315</td>
<td>0.519</td>
<td>0.00653</td>
<td>0.125</td>
<td>0.0664</td>
<td>0.221</td>
<td>0.202</td>
</tr>
<tr>
<td><strong>Panel C: Differential Effect (Eq. (3))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disseminate x Post</td>
<td>0.00198</td>
<td>-0.0992</td>
<td>0.0199</td>
<td>0.0113</td>
<td>-0.00331</td>
<td>-0.0133</td>
<td>-0.00403</td>
<td>0.00255</td>
</tr>
<tr>
<td></td>
<td>(0.0249)</td>
<td>(0.0930)</td>
<td>(0.0315)</td>
<td>(0.0119)</td>
<td>(0.00537)</td>
<td>(0.0201)</td>
<td>(0.00649)</td>
<td>(0.00438)</td>
</tr>
<tr>
<td>Disseminate x Post x Centrality</td>
<td>-0.00592</td>
<td>0.348</td>
<td>-0.0755</td>
<td>-0.0907*</td>
<td>0.00645</td>
<td>0.0682</td>
<td>0.00532</td>
<td>-0.0283**</td>
</tr>
<tr>
<td></td>
<td>(0.0786)</td>
<td>(0.301)</td>
<td>(0.0975)</td>
<td>(0.0380)</td>
<td>(0.0164)</td>
<td>(0.0737)</td>
<td>(0.0139)</td>
<td>(0.0108)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,974,664</td>
<td>280,666</td>
<td>808,834</td>
<td>885,164</td>
<td>1,974,664</td>
<td>280,666</td>
<td>808,834</td>
<td>885,164</td>
</tr>
<tr>
<td>Mean Before (Core)</td>
<td>0.337</td>
<td>0.446</td>
<td>0.316</td>
<td>0.261</td>
<td>0.0899</td>
<td>0.121</td>
<td>0.089</td>
<td>0.0411</td>
</tr>
<tr>
<td>Mean Before (Peripheral)</td>
<td>0.0611</td>
<td>0.064</td>
<td>0.0596</td>
<td>0.0636</td>
<td>0.0583</td>
<td>0.0435</td>
<td>0.0658</td>
<td>0.0484</td>
</tr>
<tr>
<td>Mean Before (All)</td>
<td>0.178</td>
<td>0.211</td>
<td>0.171</td>
<td>0.151</td>
<td>0.0717</td>
<td>0.0731</td>
<td>0.0759</td>
<td>0.0452</td>
</tr>
</tbody>
</table>

Table 6: Difference-in-Difference Estimation: Volume

Notes: A unit of observations is (dealer, bond, date). Variables are averaged over before and after windows for each period due to computing limitations. OLS regressions include standard difference-in-difference regressors (see specifications), in addition to controls for bond rating, maturity, age, coupon rate, and bond fixed effects. The dependent variable is log(volume+1). Disseminate is an indicator for whether the bond changes dissemination status. Post is an indicator for dates during which transaction information for the treated bond is disseminated to the market. Centrality is dealer eigenvector centrality rank of the trading network weighted by the number of trades over the last two months, normalized between 0 and 1, and computed at each date. A core dealer is a dealer among top 30 dealers by centrality. A peripheral dealer is a dealer who is present in the market but not a core dealer. Robust standard errors clustered at the bond and dealer level are in parenthesis immediately below the estimates. ***, **, * indicate significance at 1, 5, and 10%.
Panel A: Average Effect (Eq. (1))

<table>
<thead>
<tr>
<th></th>
<th>Pooled (1)</th>
<th>Phase 2 (2)</th>
<th>Phase 3A (3)</th>
<th>Phase 3B (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disseminate x Post</td>
<td>0.00693</td>
<td>-0.000128</td>
<td>0.0103</td>
<td>0.0154</td>
</tr>
<tr>
<td></td>
<td>(0.00435)</td>
<td>(0.00468)</td>
<td>(0.00675)</td>
<td>(0.00954)</td>
</tr>
</tbody>
</table>

Panel B: Differential Effect (Eq. (2))

<table>
<thead>
<tr>
<th></th>
<th>Pooled (1)</th>
<th>Phase 2 (2)</th>
<th>Phase 3A (3)</th>
<th>Phase 3B (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disseminate x Post x Core</td>
<td>0.00724</td>
<td>-0.00258</td>
<td>0.0138</td>
<td>0.00731</td>
</tr>
<tr>
<td></td>
<td>(0.00600)</td>
<td>(0.00470)</td>
<td>(0.00946)</td>
<td>(0.0108)</td>
</tr>
<tr>
<td>Disseminate x Post x Peripheral</td>
<td>0.00321</td>
<td>0.00242</td>
<td>-0.00189</td>
<td>0.0328</td>
</tr>
<tr>
<td></td>
<td>(0.00961)</td>
<td>(0.00947)</td>
<td>(0.0163)</td>
<td>(0.0227)</td>
</tr>
<tr>
<td>p-value (Core=Peripheral)</td>
<td>0.747</td>
<td>0.613</td>
<td>0.462</td>
<td>0.322</td>
</tr>
</tbody>
</table>

Panel C: Differential Effect (Eq. (3))

<table>
<thead>
<tr>
<th></th>
<th>Pooled (1)</th>
<th>Phase 2 (2)</th>
<th>Phase 3A (3)</th>
<th>Phase 3B (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disseminate x Post</td>
<td>0.0351</td>
<td>-0.00695</td>
<td>0.0348</td>
<td>0.115</td>
</tr>
<tr>
<td></td>
<td>(0.0384)</td>
<td>(0.0400)</td>
<td>(0.0620)</td>
<td>(0.0735)</td>
</tr>
<tr>
<td>Disseminate x Post x Centrality</td>
<td>-0.0305</td>
<td>0.00697</td>
<td>-0.0275</td>
<td>-0.106</td>
</tr>
<tr>
<td></td>
<td>(0.0424)</td>
<td>(0.0422)</td>
<td>(0.0685)</td>
<td>(0.0798)</td>
</tr>
</tbody>
</table>

Observations: 1,445,873 344,021 522,572 579,280

Mean Before (Core): 0.8 0.848 0.778 0.785
Mean Before (Peripheral): 0.675 0.731 0.669 0.533
Mean Before (All): 0.766 0.82 0.747 0.713

Table 7: Difference-in-Difference Estimation: Capital Commitment

Notes: A unit of observation is (dealer, bond, date), restricted to days on which dealer trades a given bond. OLS regressions include standard difference-in-difference regressors (see specifications), in addition to controls for bond rating, maturity, age, coupon rate, and bond fixed effects. The dependent variable is capital commitment. Disseminate is an indicator for whether the bond changes dissemination status. Post is an indicator for dates during which transaction information for the treated bond is disseminated to the market. Centrality is dealer eigenvector centrality rank of the trading network weighted by the number of trades over the last two months, normalized between 0 and 1, and computed at each date. A core dealer is a dealer among top 30 dealers by centrality. A peripheral dealer is a dealer who is present in the market but not a core dealer. Robust standard errors clustered at the bond and dealer level are in parenthesis immediately below the estimates. ***, **, * indicate significance at 1, 5, and 10%.

The estimates for the average effect in Panel A (i.e. Equation (1)) are generally small and insignificant. The sign and magnitude of the estimate for Phase 2 are in line with the literature, but my estimate is not statistically significant. This could be due to differences in estimation methodology, both for the bid-ask spread and parameter for the effect of transparency. Moving on to Panel B, which provides estimates for Equation (2), the effect remains insignificant for core dealers (though mildly positive), while it is consistently negative for peripheral dealers. The pooled estimate implies a reduction in the bid-ask spread for peripheral dealers by 23.5 basis points. The estimates are more negative and more statistically significant for later phases, suggesting that the effect is stronger for bonds with lower credit quality. The F-test for the equality of the effect...
for core and peripheral dealers is rejected at the 1% significance level. The same picture is painted in Panel C, which reports estimates for Equation (3). The effect is negative for the dealers with the lowest centrality score (which can be inferred from the estimate for Disseminate); meanwhile, the effect is less and less negative as the centrality score increases (which can be seen from the interaction term), and it settles around 0 or a slightly positive value for the dealer with the highest centrality (i.e. with Centrality = 1).

Moving on to Table 6 (i.e. for trading volume), and focusing again on the trades with clients, it can be observed that all three panels suggest that the effect is only present for Phase 3B, which consists of the lowest quality bonds. There is a 3.57% reduction in the trading volume on average across the market (i.e. Panel A) for Phase 3B bonds. Panel B reports a 6.66% reduction for core dealers and a much smaller and less significant fall for peripheral dealers in the amount of 1.54%. Panel C confirms the findings from Panel B: the lowest centrality dealers experience no significant change in the trading volume, and the effect is more and more negative as dealers’ centrality increases.

Table 7 shows no evidence of the effect of TRACE on dealers’ capital commitment. Therefore, conditional on trading a bond on a given day, the percentage of the trading activity in the bond carried into the overnight inventory is not affected by transparency.

6 Theory

In this section I propose a model that can explain the empirical facts documented in the previous section, and analyze mechanisms through which increased transparency can affect the market and agents involved. It is a dynamic model of trade in an over-the-counter market with segmentation, search, and bargaining, populated by asymmetrically informed agents. There are dealers who intermediate the trade, and traders, undistinguishable by dealers, who may trade for either liquidity reasons or in order to profit from the private information not yet reflected in the asset price. Dealers costlessly choose the rate at which they are to be contacted by the traders searching for them, and traders choose what type of dealers, represented by their matching rates, to search for. An increase in transparency

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40 Asquith et al. (2013) also find evidence of a decrease in the trading volume only for Phase 3B, but do not look at differential effect across the market.

41 Bessembinder et al. (2016) also find no evidence of the effect of TRACE on capital commitment by looking at the average effect and using several different definition for capital commitment.
is taken to mean that the duration of private information held by informed traders falls. I consider stationary equilibria and analyze how the outcome, comprising of bid-ask spread and volume, among others, responds to the change in the level of transparency.

6.1 Setup

The model is set in continuous time with no terminal period, with a fixed probability space \((\Omega, \mathcal{F}, \Pr)\) and a filtration \(\{\mathcal{F}_t : t \geq 0\}\) satisfying the usual conditions.

*Assets*

There is a unit mass of risky assets provided perfectly elastically. The value of a generic asset evolves as a compound Poisson jump process with arrival rate \(\phi\). Positive and negative jumps occur with equal probability, and all have a size normalized to 1. The Poisson jump process is independent across assets.

*Agents and Markets*

There is a continuum of three types of agents: liquidity (L) and informed (I) traders, and dealers (D). All agents are infinitely lived, with time preferences determined by a constant discount factor \(r\).

Trading occurs in an over-the-counter (OTC) market characterized by segmentation, and search and bargaining frictions. Trade is intermediated by a unit mass of dealers, who are always present in the market and stand ready to trade assets at agreed upon prices. Dealers initially hold at least one unit of each risky asset, to which they assign value \(v(t)\) at time \(t\). The OTC market consists of a continuum \([\underline{\Lambda}, \bar{\Lambda}]\) of markets, with \(\underline{\Lambda} > 0\), such that a trader in market \(\lambda \in [\underline{\Lambda}, \bar{\Lambda}]\) finds a dealer in that market at rate \(\lambda\), as long as there are some dealers present in that market. Thus, for a given positive masses \(\mu\) and \(\mu'\) of dealers and traders in market \(\lambda\), respectively, a particular dealer is contacted with intensity \(\lambda \frac{\mu'}{\mu}\).\(^{42}\)

Each dealer continuously and costlessly chooses the market in which to operate, taking into account trading volume and expected surplus per trade in each market. Traders, upon arriving to the market, direct their search towards a particular market, taking into

\(^{42}\)If there is a measure zero of dealers, then the matching rate is unbounded. This never happens in an equilibrium, but it plays a role in considering profitable deviations.
account speed of matching and prices in each market. Dealers in a market with the high
value of $\lambda$ are interpreted as more central dealers, while the dealers in markets with the
low value of $\lambda$ are interpreted as more peripheral dealers. This assumption is meant to
represent the fact that more central dealers have larger presence in the market, pick up
the phone faster, are easier to learn of, and are more likely to hold any particular asset in
their inventory. The assumption is in line with anecdotal evidence that suggests that core
dealers provide immediacy to other dealers and traders in the market.

Liquidity traders arrive to the market at the rate normalized to 1. A liquidity trader
assigns value $v(t) + \delta$ at time $t$ to the corresponding asset, where $\delta$ is a random variable with
a symmetric probability distribution over its support $\{-1, 1\}$, the value of which is fixed
at the arrival for a given trader. $\delta$ is independent across bonds and traders. Each liquidity
trader departs after trading 1 unit of the asset. In order to prevent outcomes in which all
trade happens with the same type of dealers due to liquidity externalities, I assume that
liquidity traders are heterogeneous in terms of their initial search cost, until they become
familiar with the market, which happens when they meet the first dealer. For simplicity, I
represent this cost in terms of impatience, and thus a liquidity trader with cost $\beta$ discounts
time at rate $r + \beta$ until the first dealer is met, after which $\beta$ drops to 0 if the trader chooses
to search for another dealer to trade with instead. This assumption, may, for instance,
proxy for traders’ experience in the market. I assume that each liquidity trader is assigned
a cost $\beta$ at the time of the entry, which is distributed according to an atomless cumulative
distribution function $F$ (with corresponding probability density function $f$) with support
$[0, \infty)$, and is independent across traders.

Every jump in the value of an asset is observed in real time only by one new trader,
an informed trader, who values a generic risky asset at $v(t)$ at time $t$. Such trader sub-
sequently joins the market and searches for an opportunity to trade and profit from the
private information. Information about each jump is revealed to the public at intensity
$\rho \geq 0$. Here $\frac{1}{\rho}$, for $\rho > 0$ (and $\infty$, for $\rho = 0$), represents the expected duration of private
information, and I assume that an increase in market transparency reduces the expected
duration of private information (or increases $\rho$, in other words). An informed trader leaves
the market either after trading 1 unit of the asset, or after the information becomes public,
whichever happens first.
Bargaining

When a dealer and trader meet, they bargain over the price. The bargaining problem is the one of one-sided incomplete information, in which the dealer is uninformed about the size of the trade surplus and about the time discount factor of the counterparty, both of which depend on whether the counterparty is an informed or liquidity trader. If the dealer trades with a liquidity trader, the size of the trade surplus is 1, and the trader discounts time at rate $r$. This is because the idiosyncratic component of the search cost (i.e. $\beta$) disappears when the first dealer is met. If the dealer trades with an informed trader, the size of the trade surplus is 0, and the trader discounts time at rate $r + \rho$ (as demonstrated in the results section), which is due to the fact that informational advantage disappears at rate $\rho$. As a solution to the bargaining problem, I consider an outcome of an alternating offer bargaining game with one-sided incomplete information, analyzed in Appendix D, in which the informed party may have one of the two values for the discount factors, as in Rubinstein (1985), but in which the size of the surplus also varies depending on the type of the informed party, in the same manner as in the current model. While there are a continuum of sequential equilibria to the bargaining game, I show that under an intuitive restriction on off-equilibrium beliefs, there is a unique pooling equilibrium in which bargaining concludes in the first period and the price resembles the outcome of a complete information alternating offer bargaining game between a more patient informed party and the uninformed party with the reservation value equal to the expected value of the asset at the time of the contact by a counterparty. There are also non-pooling equilibria (i.e. separating or hybrid), depending on parameters. I apply the outcome of the pooling equilibrium as the solution to the bargaining problem in the current model. Let $q$ denote trader’s bargaining power. I refer the reader to Appendix D for the analysis of the bargaining game.

6.2 Equilibrium

Because the problem is symmetric with respect to buying and selling assets, I assume without loss of generality that traders are buyers and dealers are sellers.

Let $\theta \in \Theta$ denote an exogenous type of an agent in the market, with $\Theta = \{I, D, (L, \beta) : \beta \in [0, \infty)\}$, where $I$ stands for an informed trader, $D$ for a dealer, and $(L, \beta)$ for a liquidity trader with initial search cost $\beta$. Let $x^\theta(t) \in [\underline{\lambda}, \bar{\lambda}]$ denote the market in which a particular
agent of type $\theta$ chooses to trade at time $t$, and let $\mu^\theta_\lambda(t)$ denote the mass of agents of type $\theta$ in market $\lambda$ at time $t$, and let $\mu^\theta(t) \equiv \int_\lambda^\bar{\lambda} \mu^\theta_\lambda(t)d\lambda$ denote the mass of agents of type $\theta$ in the OTC market at time $t$. Furthermore, let $\mu^\theta_\lambda(t) \equiv \int_0^\infty \mu^{(L,\theta)}_\lambda(t)dF(\beta)$, which denotes the total mass of liquidity traders in market $\lambda$ at time $t$. Let $\mathbb{E}_t[v(t)]$ denote the expected value of a generic bond at time $t$ conditional on the public information up to time $t$ and let $p_\lambda(t)$ denote the ask price for such bond charged by dealers in market $\lambda$ at time $t$. Note that it is assumed that $p_\lambda(t)$ is the same across traders for a given market, which is justified by the existence of a pooling equilibrium (shown in Proposition 1 below). Finally, let $s_\lambda(t) \equiv p_\lambda(t) - \mathbb{E}_t[v(t)]$, which is a half of the bid-ask spread.

Before defining the equilibrium, a remark is in order. Because dealers start with at least one unit of each bond, a dealer never runs out of a positive measure of bonds. Thus, there are no gains from trade in the interdealer market for the purpose of rebalancing inventories. It is possible that dealers could attempt to use information obtained from trading with traders to profit in the interdealer market, but because there are no gains from trade, this leads to full sharing of information, and thus private information cannot be used to profit in the interdealer market. In addition, because there are a continuum of bonds, the probability that a dealer matches with a trader attempting to trade any particular bond is 0. Thus, dealer’s learning from trading with traders does not affect the outcome of the model. The equilibrium is defined as follows:

**Definition 1.** A Stationary Perfect Bayesian Equilibrium (SPBE) is given by a collection of masses $\mu^\theta_\lambda \geq 0$, spreads $s_\lambda \in \mathbb{R}_+$, market choices $x^\theta \in [\underline{\lambda}, \bar{\lambda}]$, and beliefs $\eta_\lambda \equiv \text{Pr}(\theta = I|x^\theta = \lambda) \in [0, 1]$ for $\lambda \in [\underline{\lambda}, \bar{\lambda}]$, $\theta \in \Theta$ such that:

- **Market choice** $x^\theta$ maximizes the utility of agent of type $\theta$, for all $\theta \in \Theta$;

- **Belief** $\eta_\lambda$ satisfies Bayes’ rule for every $\lambda \in [\underline{\lambda}, \bar{\lambda}]$ such that $\text{Pr}(x^\theta = \lambda) > 0$:

$$\eta_\lambda = \frac{\mu^I_\lambda}{\mu^I_\lambda + \mu^L_\lambda} \quad (4)$$

- **Masses** $\{\mu^\theta_\lambda\}_{\lambda \in [\underline{\lambda}, \bar{\lambda}]}$, satisfy following laws of motion:

$$\phi = \int_\lambda^\bar{\lambda} (\lambda + \rho)\mu^I_\lambda d\lambda \quad (5)$$

$$f(\beta) = \int_\lambda^\bar{\lambda} \lambda \mu^{(L,\beta)}_\lambda d\lambda \quad \text{for } \beta \in [0, \infty)$$

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• Spread $s_{\lambda}$ is an outcome of the bargaining game for every $\lambda$ with $\mu_{\lambda}^\theta > 0$ for $\theta = D$ and some $\theta \in \Theta \setminus \{D\}$;

Equations (5) state that arrivals and departures of agents of a particular type offset each other. The left-hand sides specify the arrival rates: $\phi$ for informed traders, and $f(\beta)$ for liquidity traders with discount $\beta$. For the right-hand sides, note that informed traders depart either when they meet a dealer and trade, which happens at rate $\lambda$, or when the information they possess becomes public, which happens at rate $\rho$, while liquidity traders depart only after buying a unit of the asset, which happens at rate $\lambda$.

In order to establish if a particular stationary outcome is a SPBE, it must be the case that there are no profitable deviations by any agent. In order to assess deviations, I assume that strategies of agents already present in the market satisfy inertia, as in Perry and Reny (1993) or Bergin and MacLeod (1993), meaning that agents cannot change their strategies in an infinitesimal\textsuperscript{43} interval immediately after each time $t$. This means that, if a dealer or a mass of dealers choose to move to a new market at time $t$, traders that have just arrived to the market at time $t$ can respond to their strategy instantly, while the other dealers and traders already searching can do so only after an infinitesimal period of time.\textsuperscript{44} This allows for assessing optimality of strategies by checking for profitability of deviations over an infinitesimal period of time.\textsuperscript{45}

As is often the case in games with incomplete information, there may exist multiple equilibria because beliefs off the equilibrium path are not uniquely determined as Bayes’ rule cannot be applied to zero-probability events. In the current context, if some dealers were to deviate from the equilibrium market choice to another market, then whether some newly arriving traders find it optimal to search for these dealers depends on the dealers’ beliefs about the identity of the traders searching for them. Without any further restrictions, dealers could form beliefs that would deter any trader from searching there, even though such beliefs would never be consistent with Bayes’ rule if some traders found it optimal to search in that market (which could occur under different dealers’ beliefs).

I make the following restriction on beliefs of dealers, assumed throughout:

\textsuperscript{43} An infinitesimal is a concept from nonstandard analysis, based on the hyperreal numbers $^{*}\mathbb{R}$, an ordered field extension of the real numbers that contains both nonzero infinitesimals and infinities.

\textsuperscript{44} A discrete-time game equivalent would be an infinitely repeated game in which at every stage dealers and searching traders move simultaneously, followed by newly arriving traders.

\textsuperscript{45} A discrete-time game equivalent is the one-shot deviation principle.
Assumption 1. Consider market $\lambda$ in which no trade takes place in a SPBE, and suppose that an infinitesimal mass of dealers moves to market $\lambda$ at time $t$ over an infinitesimal period of time. Let $\tilde{x}^I(\eta)$ and $\tilde{x}^{(L,\beta)}(\eta)$ denote optimal actions with respect to the market choice of newly arriving agents $I$ and $(L, \beta)$, respectively, over an infinitesimal period of time given such a history and belief $\eta$ of dealers in market $\lambda$. Let $M \equiv \{ \eta \in [0, 1] : \tilde{x}^I(\eta) = \lambda \} \cup \{0\}$ and $m^* \equiv \sup M$. If there exists $\epsilon > 0$ and $\beta \in (0, \infty)$ such that $\tilde{x}^{(L,\beta)}(m^* + \epsilon) = \lambda$, then $\eta = m^*$.

Assumption 1 states that dealers’ beliefs about traders’ arriving to market $\lambda$ cannot exceed the most pessimistic belief that can ever be justified. Assuming $\eta > m^*$ does not seem sensible, since under such assumption, the only types of traders who will ever choose to search in market $\lambda$ are liquidity traders, which is inconsistent with $\eta > m^* \geq 0$. Assumption 1 is thus conservative in eliminating equilibria, as dealers take a very conservative view with respect to their profit opportunities in markets that are closed.\textsuperscript{46}

6.3 Results

Equilibrium characterization

In what follows I characterize a SPBE. I use the notation $p_\lambda$ and $E[v]$ for $p_\lambda(t)$ and $E_v[v(t)]$, respectively, omitting the time subscript. The following proposition describes price $p_\lambda$ and spread $s_\lambda$ in market $\lambda$ that carries positive volume of trade in a SPBE, using the pooling equilibrium outcome of the alternating-offer bargaining game outlined in Appendix D:

**Proposition 1.** For any market $\lambda$ with $\mu^I_\lambda > 0$ or $\mu^L_\lambda > 0$ in a SPBE:

$$p_\lambda = E[v] + s_\lambda \quad (6)$$

$$s_\lambda = \frac{q(r + \lambda)\eta + (1 - q)r}{r + q\lambda} \quad (7)$$

\textsuperscript{46}Assumption 1 is related to the Intuitive Criterion proposed by Cho and Kreps (1987). There are two differences. First, the Intuitive Criterion puts structure on beliefs when the informed player deviates from the equilibrium strategy following the equilibrium play, while Assumption 1 puts structure on beliefs when the informed player deviates from the equilibrium strategy following a deviation by the uninformed player. Second, the Intuitive Criterion rules out placing positive probability on types what would under no off the equilibrium beliefs profit from certain deviation while some other type would certainly profit from such deviation under some beliefs. In particular, if we were to apply a requirement like the Intuitive Criterion following a deviation by dealers to a new market $\lambda$, then if $\tilde{x}^I(\eta) = 0$ for all $\eta \in [0, 1]$ and $\tilde{x}^{(L,\beta)}(\eta) = 1$ for some $\beta \in [0, \infty)$ and $\eta \in [0, 1]$, the Intuitive Criterion would force $\eta = 0$, and would have no restrictions on beliefs in any other case.
Proof. See Appendix C.

The spread $s_\lambda$ from equation (7) is decreasing in traders’ bargaining power $q$ and matching rate $\lambda$, and increasing in the time discount factor $r$ and the probability that the trader is informed $\eta$. When traders’ have all the bargaining power, i.e. $q = 1$, we have that $s_\lambda = \eta$, which is merely enough to compensate dealers for expected losses incurred due to trading with informed traders. These effects are intuitive and are extensively studies in the search-theoretic over-the-counter market literature (as in, for instance, Duffie et al. (2005)) and the asymmetric information literature (as in Glosten and Milgrom (1985)).

The following theorem asserts that there is a unique SPBE and that the trade occurs in at most two markets in a SPBE:

**Theorem 1.** There exists a unique SPBE. If $\rho > 0$, then $\mu^I_\lambda > 0$ and $\mu^L_\lambda = \frac{1 - F(\rho)}{\lambda} > 0$. Furthermore, there exists $\lambda_0 \in [\underline{\lambda}, \bar{\lambda})$ such that $\mu^L_{\lambda_0} = \frac{F(\rho)}{\lambda_0} > 0$ and $\mu^I_{\lambda_0} = \mu^L_{\lambda_0} < \mu^L_\lambda$. If $\mu^I_{\lambda_0} > 0$, then $\lambda_0 = \underline{\lambda}$. For $\lambda \not\in \{\lambda_0, \bar{\lambda}\}$ and $\theta \in \{L, I\}$, $\mu^\theta_\lambda = 0$.

If $\rho = 0$, then $\mu^I_\lambda = \frac{\phi_\lambda}{\lambda}$, $\mu^L_\lambda = \frac{1}{\lambda}$ and $\mu^\theta_\lambda = 0$ for $\lambda \in [\underline{\lambda}, \bar{\lambda})$ and $\beta \in \{L, I\}$.

Proof. See Appendix C.

Theorem 1 shows that only two types of dealers operate in a SPBE (for $\rho > 0$): the fastest dealers with matching rate $\bar{\lambda}$, which trade with less patient liquidity traders and informed traders; and slower dealers who are more attractive to liquidity traders with lower search costs (i.e. $\beta < \rho$) as they have lower bid-ask spread due to a relatively lower proportion of informed traders searching for them as opposed to searching for the fast dealers. The slow dealers are as slow as necessary to discourage informed traders from searching for them. If some informed traders wish to search for slow dealers no matter how slow the matching process is, then the slow dealers have the lowest possible matching rate, i.e. $\underline{\lambda}$, and are still prone to some adverse selection. This result is in line with the empirical evidence, which documents that the dealer network exhibits a core-periphery structure: dealers are either highly connected, trade very frequently and are easily accessible by other market participants (i.e. core dealers), or trade much less often and with a selected number of counterparties over a limited period of time (i.e. peripheral dealers).

**Comparative statics**

For the remainder of the section, abusing the notation, I use subscript 1 to denote
outcomes occurring in market $\bar{\lambda}$, and subscript 0 for the outcome in the other active market $\lambda_0 \in [\underline{\lambda}, \bar{\lambda})$ (which exists for $\rho > 0$). For a generic market $\lambda \in [\underline{\lambda}, \bar{\lambda}]$, I still use a subscript $\lambda$.\footnote{For instance, I use $\mu^I_\lambda$ and $\mu^I_{\lambda_0}$ instead of $\mu^I_\lambda$ and $\mu^I_{\lambda_0}$ to denote the mass of informed traders in markets $\bar{\lambda}$ and $\lambda_0$, respectively.} In order to relate the model to the empirical results, I analyze how bid-ask spreads (i.e. $s_0$ and $s_1$) and trading volume depend on the level of transparency (i.e. $\rho$). I look at the effect of the marginal change in transparency (i.e. $d\rho$), but also at the limiting case as $\rho \to \infty$. Let $\gamma \equiv \frac{\mu^I_0(\lambda_0+\rho)}{\phi}$, which is the fraction of newly arriving informed traders choosing to search in market $\lambda_0$ (which is populated with slower dealers). Consequently, in any steady state, $1 - \gamma = \frac{\mu^I_\lambda(\lambda+\rho)}{\phi}$, which is the fraction of newly arriving informed traders choosing to search in market $\bar{\lambda}$ (populated with fast/core dealers). Note from Equation (7) that $s_\lambda$ depends on $\rho$ only through the adverse selection term $\eta_\lambda$. In particular:

**Proposition 2.** In the SPBE, $\frac{ds_\lambda}{d\rho} = \frac{q(r+\lambda)}{r+q\lambda} \frac{ds_\lambda}{d\rho}$, and $\frac{ds_0}{d\rho} = \frac{q(r+\lambda_0)}{r+q\lambda_0} \frac{ds_0}{d\rho} - \frac{q(1-\gamma)\eta(1-\gamma_0) d\rho}{r+q\lambda_0}$. If $\eta_1 > \frac{(\bar{\lambda}-\lambda)[(r+\lambda)(r+\Delta)(r+\rho)-(1-\rho)\lambda\bar{\lambda}]}{(r+\lambda)(r+\Delta)(r+\rho)(r+\bar{\lambda})}$, then $\lambda_0 = \underline{\lambda}$, $\frac{d\lambda_0}{d\rho} = 0$, and

$$\frac{d\eta_1}{d\rho} = \eta_1(1-\eta_1) \left( \frac{f(\rho)}{1-F(\rho)} - \frac{1}{\lambda+\rho} \right),$$

(10)

**Proof.** See Appendix C.

Focusing on Equations (8) and (9) for $\frac{d\eta_1}{d\rho}$ and $\frac{d\eta_0}{d\rho}$ when $\lambda_0 = \underline{\lambda}$ (i.e. the slowest market operates), three different factors affecting bid-ask spreads can be observed, outlined in the following expression:

$$\frac{d\eta_1}{d\rho} = \frac{\eta_1(1-\eta_1)}{\gamma \eta_1 + (1-\gamma) \eta_0} \left[ \frac{\gamma(\bar{\lambda}-\lambda)}{(r+\lambda)(r+\Delta)(r+\rho)} \frac{(1-\gamma)\lambda\bar{\lambda}}{(r+\lambda)(r+\Delta)(r+\rho)(r+\bar{\lambda})} - \eta_0 f(\rho) \left( \frac{1}{1-F(\rho)} - \frac{\gamma}{F(\rho)} \right) \right]$$

(8)

and

$$\frac{d\eta_0}{d\rho} = \frac{\eta_0(1-\eta_0)}{\gamma \eta_1 + (1-\gamma) \eta_0} \left[ \frac{(1-\gamma)(\bar{\lambda}-\lambda)}{(r+\lambda)(r+\Delta)(r+\rho)} \frac{\gamma(\bar{\lambda}-\lambda)}{(r+\lambda)(r+\Delta)(r+\rho)(r+\bar{\lambda})} - \eta_1 f(\rho) \left( \frac{1}{1-F(\rho)} - \frac{\gamma}{F(\rho)} \right) \right]$$

(9)

increased impatience
of informed traders

reduction in adverse selection

equilibrium interaction
between liquidity and informed traders
The first term in the brackets is due to an increase in the impatience of informed traders, since their information disappears at a faster rate. This shifts their preferences towards trading more in the fast market (i.e. with core dealers), putting an upward pressure on the spread in market $\lambda$ and downward pressure in market $\Lambda$ (hence the positive sign for $\frac{d\eta_1}{d\rho}$ and negative sign for $\frac{d\eta_0}{d\rho}$). The remaining two terms have the same signs across both markets, and the only difference between the magnitudes is the multiplying term $1 - \eta_1$ for $\frac{d\eta_1}{d\rho}$ and $1 - \eta_0$ for $\frac{d\eta_0}{d\rho}$. The second term is necessarily negative and follows from the reduction in overall adverse selection as private information disappears at a faster rate, lowering the steady state masses of informed traders in both markets, ceteris paribus. The third term captures the interaction between liquidity and informed traders, and can either be positive or negative. The mechanism is as follows. When the rate at which private information disappears (i.e. $\rho$) increases, informed traders’ preferences for trading in the fast market become stronger, which initiates their flight to that market. This is captured by the first term, as already discussed. That puts upward pressure on the bid-ask spread in market $\lambda$ and downward pressure in market $\Lambda$, and hence some patient liquidity traders initially trading in market $\lambda$ start moving to market $\Lambda$. This weakens informed traders’ preferences for trading in the fast market, and in the extreme case they could even revert their initial action and move to search for peripheral dealers in higher proportion than before. The effect is the same across both markets because traders optimally respond until they are indifferent between trading in the two markets. This third term is positive (and thus has a positive effect on bid-ask spreads in the two markets) when a large number of informed traders trade with central dealers, while the large number of liquidity traders trade with peripheral dealers. When that happens, a large enough transition of marginal liquidity traders towards peripheral dealers upon an increase in transparency can cause a large relative decrease in the expected trading surplus with core dealers. This generates incentives for both types of traders to search more for peripheral dealers. As not too many informed traders were trading with peripheral dealers before the change, an arrival of a small number of such traders can cause a large increase in adverse selection and bid-ask spread. Mathematically, if $\frac{1 - \gamma}{1 - F(\rho)} > \frac{\gamma}{F(\rho)}$, and $f(\rho)$ is large enough, a marginal increase in transparency can increase bid-ask spreads in both markets.

The next proposition provides expressions for the percentage change in trading volume (denoted as $Vol$) with respect to $\rho$. 

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Proposition 3. In the SPBE with the active markets $\bar{\lambda}$ and $\lambda_0$

\[
\frac{d\log(\text{Vol}_1)}{d\rho} = \frac{1}{1-\eta_1} \frac{d\eta_1}{d\rho} - \frac{f(\rho)}{1-F(\rho)} \quad (11)
\]

\[
\frac{d\log(\text{Vol}_0)}{d\rho} = \frac{1}{1-\eta_0} \frac{d\eta_0}{d\rho} + \frac{f(\rho)}{F(\rho)} \quad (12)
\]

If $\lambda_0 > \bar{\lambda}$, then

\[
\frac{d\log(\text{Vol}_1)}{d\rho} - \frac{d\log(\text{Vol}_0)}{d\rho} = \eta_1 \left( \frac{f(\rho)}{1-F(\rho)} - \frac{1}{\bar{\lambda}+\rho} \right) - \frac{f(\rho)}{F(\rho)(1-F(\rho))} < 0 \quad (13)
\]

If $\lambda_0 = \bar{\lambda}$, then

\[
\frac{d\log(\text{Vol}_1)}{d\rho} - \frac{d\log(\text{Vol}_0)}{d\rho} = \frac{\bar{\lambda}-\lambda}{(\lambda+\rho+r)(\bar{\lambda}+\rho+r)} - \frac{f(\rho)}{F(\rho)(1-F(\rho))} \quad (14)
\]

Proof. See Appendix C.

If $\lambda_0 > \bar{\lambda}$, then informed traders only trade in the fast market (i.e. with core dealers), in which case a rise in $\rho$ encourages peripheral dealers to increases their matching rate $\lambda_0$, which attracts more liquidity traders to search for them. This leads to a fall in volume in the fast market and increase in the slow market. If $\lambda_0 = \bar{\lambda}$, then there is an additional effect which induces informed traders to trade more in the fast market due to a decrease in the duration of private information, leading to an ambiguous effect on the relative percentage change in trading volumes in the two markets.

Recall that it was documented in the empirical section that bid-ask spreads for peripheral dealers dropped upon introduction of transparency, while no significant change occurred for core dealers. The volume for high-yield bonds, on the other hand, fell for core dealers and remain roughly the same for peripheral dealers. Propositions 2 and 3 enable us to interpret these results in the context of the current model. Observe that transparency causes a fall in the bid-ask spread for peripheral dealers through two separate channels, with the third channel having an ambiguous effect. For core dealers, the first two effects act in opposite directions, with the third channel having an ambiguous effect as in the case for peripheral dealers. Therefore, bid-ask spreads for peripheral dealers experience a large amount of downward pressure due to an increase in transparency, while the effect is rather ambiguous for core dealers. In fact, the following result obtains:

Corollary 1. In the SPBE with $\lambda_0 = \bar{\lambda}$, if $\frac{d\text{Vol}_1}{d\rho} = 0$, then $\frac{d\text{Vol}_0}{d\rho} < 0$ and $\frac{d\log(\text{Vol}_1)}{d\rho} < 0$, while
\[
\frac{d\log(\text{Vol}_0)}{d\rho}
\]
has an ambiguous sign.

Proof. See Appendix C.

In light of Corollary 1, if \( \frac{d\log(\text{Vol}_0)}{d\rho} \approx 0 \), then we have a case that resembles the empirical evidence. The example in Figure 3 illustrates such a case.

Figure 3: Effect of transparency on bid-ask spread and trading volume

Notes: The figure illustrates SPBE outcomes for the range of parameters \( \rho \) in the interval [1, 10]. The cumulative distribution function satisfies \( F(\beta) = 1 - \frac{1}{1+\beta^\alpha} \) for \( \beta \in \mathbb{R}_+ \). The parameters of the model are set as follows: \( \lambda = 0.6, \tilde{\lambda} = 1.6, \phi = 5, r = 0.05, q = 1 \).

While closed form expressions of endogenous variables exist, the effect of transparency on various outcomes may often be ambiguous and difficult to characterize. More specifically, marginal increase in transparency parameter \( \rho \) can lead to an ambiguous effect on spreads, trading volume and welfare in each market, depending on which effect dominates over a specific range of \( \rho \). For this reason, it may be instructive to look at the limiting case when \( \rho \to \infty \), which is interpreted as the highest possible level of transparency. Theorem 1 already characterizes the SPBE for \( \rho = 0 \), which can then be contrasted with the limiting outcome as \( \rho \to \infty \). This comparison may be justified if there are reasons to believe that an increase in transparency in the OTC market is substantial enough to resemble a large increase in \( \rho \) (i.e. from a very low value of transparency parameter \( \rho \) to a very large one).

The next proposition characterizes the SPBE for the case when \( \rho \to \infty \).

Proposition 4. In a SPBE, \( \lim_{\rho \to \infty} \text{Vol}_1 = 0 \) and \( \lim_{\rho \to \infty} \eta_0 = 0 \). If \( 1 - F(\beta) = o(\beta^{-1}) \), then \( \exists \hat{\rho} \) such that \( \lambda_0 = \hat{\lambda} \) whenever \( \rho > \hat{\rho} \), and \( \gamma \to 1 \) and \( \eta_1 \to \frac{(\tilde{\lambda} - \lambda)[r(\lambda + \tilde{\lambda} + r) + q\lambda\tilde{\lambda}]}{\lambda(\lambda + r)(q\lambda + q\tilde{\lambda})} \) as

\[48\]For any two real-valued functions \( g_0 \) and \( g_1 \), \( g_0(n) = o(g_1(n)) \) is defined to mean that \( \forall k > 0, \exists N \) such that \( \forall n > N, |g_0(n)| \leq k|g_1(n)| \).
If $1 - F(\beta) = \omega(\beta^{-1})$,\textsuperscript{49} then $\exists \rho$ such that $\gamma = 0$ whenever $\rho > \hat{\rho}$, and $\lambda_0 \to \bar{\lambda}$ and $\eta_1 \to 0$ as $\rho \to \infty$.

Proof. See Appendix C.

If the survival function, $1 - F(\rho)$, falls fast enough, the transition of liquidity traders to market $\lambda_0$ upon a marginal increase in transparency lowers the relative cost of trading in market $\lambda_0$ over market $\bar{\lambda}$ enough to induce informed traders to also trade in larger numbers in market $\lambda_0$. Thus, as transparency increases, all traders gradually move to market $\bar{\lambda}$, and settle there in the limit as $\rho \to \infty$. As liquidity traders move away from $\bar{\lambda}$ fast enough, informed traders in market $\bar{\lambda}$ always constitute a significant fraction of traders in that market, and thus adverse selection there does not disappear even in the limit as $\rho \to \infty$.

On the other hand, if the survival function falls at a slow enough rate as transparency increases, then the relative cost of trading in market $\lambda_0$ over market $\bar{\lambda}$ does not fall fast enough to outweigh the value of immediacy provided by core dealers to induce informed traders to transition to trading with peripheral dealers. As the fast market remains liquid enough, peripheral dealers are able to increase their matching rate without attracting informed traders and falling victim to adverse selection. In the limit as $\rho \to \infty$, the slow market converges to the fast market, and all dealers move to the core. Note that in this case adverse selection disappears in the limit as $\rho \to \infty$ even in market $\bar{\lambda}$ as the rate at which informed traders die out outweighs the rate at which liquidity traders flee market $\bar{\lambda}$.

Therefore, if liquidity traders have low search costs and weak preference for immediacy, a sufficiently large increase in transparency can lead to an increase in search cost since the matching rate in the OTC market decreases. If liquidity traders have high search costs, transparency can result in a reduction in adverse selection without slowing down the trade execution, which unambiguously benefits liquidity traders and dealers. Note that this limiting result only depends on the distribution of liquidity traders’ search costs, and not on any other parameters. Thus, if $\bar{\lambda}$ is low enough, the welfare loss due to a lower matching rate in the limit can outweigh the gain from a reduction in the bid-ask spread, and thus an increase in transparency can be welfare worsening for liquidity traders. Note that both cases predict the same qualitative behavior over a large enough increase in $\rho$ for the trading volume in markets $\bar{\lambda}$ and $\lambda_0$, and for the bid-ask spread in market $\lambda_0$. The

\textsuperscript{49}For any two real-valued functions $g_0$ and $g_1$, $g_0(n) = \omega(g_1(n))$ is defined to mean that $\forall k > 0, \exists N$ such that $\forall n > N, |g_0(n)| \geq k|g_1(n)|$. 

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behavior of the bid-ask spread in market $\bar{\lambda}$ provides a way of distinguishing whether the first or the second case prevails. In particular, if $1 - F(\beta) = \omega(\beta^{-1})$, then $\eta_1$ falls from $\frac{\phi}{1+\phi}$ at $\rho = 0$ to 0 as $\rho \to \infty$. If $1 - F(\beta) = o(\beta^{-1})$, then $\eta_1$ changes from $\frac{\phi}{1+\phi}$ at $\rho = 0$ to $\frac{(\bar{\lambda}-\Lambda)[r(\bar{\lambda}+\Lambda+r)+q\bar{\lambda}]}{\Lambda(\lambda+r)(q\lambda+r)} > 0$ as $\rho \to \infty$. If $\frac{\phi}{1+\phi} \leq \frac{(\bar{\lambda}-\Lambda)[r(\bar{\lambda}+\Lambda+r)+q\bar{\lambda}]}{\Lambda(\lambda+r)(q\lambda+r)}$, then this case will not result in a decrease in $\eta_1$ and thus in $s_1$, distinguishing if from the previous case. Given a small observed drop in volume, the effect of transparency is not large enough to justify using this asymptotic analysis to interpret the existing empirical evidence.

Panel A: $1 - F(\beta) = o(\beta^{-1})$

(a) Bid-Ask Spread

(b) Volume and Slow Market Matching Rate

Panel B: $1 - F(\beta) = \omega(\beta^{-1})$

(c) Bid-Ask Spread

(d) Volume and Slow Market Matching Rate

Figure 4: Effect of transparency on bid-ask spread and trading volume

Notes: The figure illustrates SPBE outcomes for the range of parameters $\rho$ in the interval [0, 15]. Panel A and Panel B show two different examples, distinguished only by the distribution of search costs, $F$. The cumulative distribution function satisfies $F(\beta) = 1 - \frac{1}{(1+\beta)^\alpha}$ for $\beta \in \mathbb{R}_+$, with $\alpha = 1.5$ for Panel A, and $\alpha = 0.5$ for Panel B. Other parameters of the model are set as follows: $\lambda = 0.8$, $\bar{\lambda} = 1.5$, $\phi = 0.5$, $r = 0.05$, $q = 0.5$. 

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The two cases stated in Proposition 4 are illustrated in Figure 4. Panel A shows an example with search cost distribution $F$ such that $1 - F(\beta) = o(\beta^{-1})$, and Panel B illustrates the case in which the search cost distribution satisfies $1 - F(\beta) = \omega(\beta^{-1})$. Focusing first on Panel A, observe that in market $\bar{\lambda}$ (i.e. fast market with core dealers), initially as $\rho$ moves away from 0, the bid-ask spread first falls, which happens due to an overall reduction in adverse selection in the OTC market, but eventually goes up as liquidity traders flee the market in large numbers. As the bid-ask spread remains high in market $\bar{\lambda}$, some informed traders always trade in market $\lambda_0 = \bar{\lambda}$, and as $\rho$ increases, all the trading volume moves to market $\bar{\lambda}$. In Panel B, initially as $\rho$ moves away from 0, liquidity traders from market $\bar{\lambda}$ move to market $\lambda_0$, and the opposite transition happens for informed traders. Eventually, all the informed traders search in market $\bar{\lambda}$ and bid-ask spread in market $\lambda_0$, $s_0$, falls to $\frac{(1-q)r}{r+q}\lambda_0$, which is the outcome of the bargaining process with complete information. As suggested in the previous section, the distinguishing feature of the two examples is the behavior of the bid-ask spread in market $\bar{\lambda}$ as $\rho$ increases. The spread increases for a sufficiently large increase in $\rho$ in the example in Panel A, while it decreases in the example in Panel B.

Summary

I have shown that in the equilibrium two types of dealers operate, distinguished by their matching rates with traders. A marginal increase in transparency (i.e. a marginal fall in the duration of private information) generates three effects: first, there is an overall decrease in adverse selection as informed traders make fewer trades on average, ceteris paribus; second, informed traders’ preference for immediacy, and thus for trading with core dealers, increases; and third, liquidity traders trade in larger numbers with peripheral dealers due to a relative decrease in bid-ask spreads there, which in turn generates a response by informed traders. The first effect puts downward pressure on bid-ask spreads of both types of dealers. The second effect exerts upward pressure on bid-ask spreads of core dealers and downward pressure on spreads of peripheral dealers. The third effect is ambiguous and has the same effect on the two types of dealers. In general, spreads of peripheral dealers are likely to fall. Whenever some spreads in the OTC market experience a fall, spreads of peripheral dealers must fall and spreads of core dealer cannot fall as much as for peripheral dealers, and could potential move in either direction depending on parameters. This scenario matches the empirical evidence the best. If the inflow of newly
informed traders relative to new liquidity traders is larger for trading with core dealers and a sufficiently large number of liquidity traders transition to trade with peripheral dealers upon a marginal increase in transparency, bid-ask spreads can increase in both markets, and trade execution speed falls for some traders and does not change for others. In this case, the welfare of all types of market participants falls.

Focusing on the limiting case in which the duration of private information tends to 0, adverse selection disappears and dealers become homogeneous in terms of the matching rate. Whether the matching rate ends up being high or low depends on the distribution of search costs of liquidity traders: if they are on the low-cost side, the resulting matching rate in the limit is low and transparency may be welfare-worsening; if the search costs are on the high-cost side, the resulting matching rate in the limit is high, and liquidity traders and dealers unambiguously benefit from transparency. From the empirical perspective, the main distinguishing feature between the two cases is the response of the bid-ask spreads of core dealers to a substantial increase in transparency. The unambiguously welfare-improving case is characterized by a fall in the spreads of core dealers, while the other case allows for a response in any direction, depending on parameters.

7 Conclusion

In this paper I estimate the effect of post-trade transparency on dealers’ trading activity and liquidity in the secondary U.S. corporate bond market. Using a novel dataset with identifiers of dealers in the market, I document a large degree of heterogeneity in dealers’ trading patterns, and highlight a differential response to the reform across the market structure. I show that bid-ask spreads fall for peripheral dealers only, with the effect being larger for bonds with lower credit quality. The fall in trading volume for high-yield bonds is generally concentrated among core dealers. Furthermore, I find no effect on inventory behavior. This differential impact of transparency emphasizes the importance of understanding the market structure and relevant market frictions in designing optimal regulatory policies. I make a step in that direction by proposing a dynamic model of trade with asymmetric information and search that can qualitatively match the empirical evidence. I further outline mechanisms through which transparency affects the market, and

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50FINRA’s Academic Corporate Bond TRACE Data.
characterize conditions for different equilibrium outcomes, which may have contrasting welfare implications. The theoretical analysis points to difficulties in interpreting welfare consequences of transparency from empirical evidence, since it is possible that measurable quantities respond in a similar way under welfare improving and welfare worsening scenarios. Further research is required in this direction.

Liquidity in the secondary corporate bond market does not only concern its participants, but has far reaching consequences for the whole economy. For instance, the cost of bond issuance (and consequently a firm’s decision on capital structure and activities such as default or investment) is directly affected by the liquidity of bonds in the secondary market. In addition, in light of recent research documenting similarities in market structures between different OTC markets, insights from this paper are likely to also be important in other similar markets. This is especially true for markets for securitized products and OTC swaps, which have been subject to similar transparency reforms as a regulatory response to the 2008 financial crisis. There are, however, differences between various OTC securities in terms of liquidity and scope for disagreement about asset values, among other things. Consequently, different frictions may have relevance in different OTC markets, and therefore, the role of transparency may vary across OTC securities. Further research is needed in order to improve our understanding of relevant frictions in different OTC markets, the role of heterogeneity across market participants, as well as the impact of transparency on trading outcomes.
References


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Appendix

A. Data Filters and Variable Construction

Data Filters

In this section I describe the steps applied to the original dataset in order to arrive to the cleaned sample used in the analysis. The steps are outlined in Table 8. In order to arrive to a similar sample as used in the literature, I follow Asquith et al. (2013) everywhere except in the last two steps which use information about dealers’ identifiers. The original sample, from July 1, 2002 to December 31, 2005 contains 28,876,005 trade records in 36,777 bonds, with 1,372 dealers.

I first apply bond specific filters. I eliminate all securities that are not corporate bonds, and furthermore all TRACE bonds that do not match to FISD. Next, I drop bonds with equity-like characteristics, such as convertibles and exchangeables, since their equity component may be included in the bond price. I keep only bonds belonging to Phase 1, 2, or 3, since these bonds constitute treated bonds and most suitable controls, as discussed in the empirical section. Finally, I eliminate bonds with an issue size of less than $10,000, without an existing offering date, or if without a rating on a specific date. I apply several trade specific filters. I remove trades executed on a day different from the reporting day, and trades with the par value of less than $1,000. Next, I exclude canceled and reversed trades. Some trades are reported several times because their transaction information gets modified. I fix modified trades by keeping the most recent update and eliminating intermediate reports. I also exclude agency trades, defined as trades in which a dealer stands between the customer and the contra party, and does not trade for his own account. Following the literature, I also eliminate trades with execution date within 90 days of the offering date, and within 1 year of the maturity date, since it has been documented that trading and liquidity in newly issued bonds, as well as bonds close to maturity, are markedly different from other bond issues.51 I also remove transactions in the week around Christmas and New Year due to irregular trading activity. I next eliminate trades with erroneous data: trades with trade size higher than the issue amount, trades without price data, and trades with negative or zero price. Finally, I eliminate trades in the interdealer market which are not consistent. In particular, each trade in the interdealer market is reported separately by

51See, for example, Green et al. (2006).
<table>
<thead>
<tr>
<th>Step</th>
<th>Trades</th>
<th>Bonds</th>
<th>Dealers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Academic Corporate Bond TRACE Data (Source)</td>
<td>28,876,005</td>
<td>36,777</td>
<td>1,372</td>
</tr>
<tr>
<td>Keep corporate bonds only</td>
<td>27,982,487</td>
<td>31,814</td>
<td>1,360</td>
</tr>
<tr>
<td>Exclude bonds unmatched to FISD</td>
<td>27,742,512</td>
<td>30,599</td>
<td>1,354</td>
</tr>
<tr>
<td>Exclude convertible bonds</td>
<td>25,434,922</td>
<td>29,579</td>
<td>1,341</td>
</tr>
<tr>
<td>Exclude exchangeable bonds</td>
<td>24,992,287</td>
<td>29,320</td>
<td>1,330</td>
</tr>
<tr>
<td>Exclude SEC Rule 144a bonds</td>
<td>24,973,877</td>
<td>28,949</td>
<td>1,330</td>
</tr>
<tr>
<td>Exclude bonds with issue size &lt; 10,000</td>
<td>24,905,301</td>
<td>28,690</td>
<td>1,330</td>
</tr>
<tr>
<td>Exclude bonds without existing offering date</td>
<td>24,905,301</td>
<td>28,690</td>
<td>1,330</td>
</tr>
<tr>
<td>Exclude bonds that are not in Phase 1, 2, or 3</td>
<td>20,415,153</td>
<td>20,703</td>
<td>1,308</td>
</tr>
<tr>
<td>Exclude bond-date pairs without rating</td>
<td>19,989,761</td>
<td>20,485</td>
<td>1,304</td>
</tr>
<tr>
<td>Exclude trades executed on different day than reported</td>
<td>18,675,889</td>
<td>20,444</td>
<td>1,249</td>
</tr>
<tr>
<td>Exclude trades with par value &lt; 1000</td>
<td>18,670,804</td>
<td>20,444</td>
<td>1,249</td>
</tr>
<tr>
<td>Exclude canceled trades</td>
<td>18,352,512</td>
<td>20,385</td>
<td>1,248</td>
</tr>
<tr>
<td>Fix modified trades</td>
<td>18,345,324</td>
<td>20,385</td>
<td>1,248</td>
</tr>
<tr>
<td>Exclude reversed trades</td>
<td>18,345,324</td>
<td>20,385</td>
<td>1,248</td>
</tr>
<tr>
<td>Exclude agency trades</td>
<td>18,056,493</td>
<td>20,383</td>
<td>1,241</td>
</tr>
<tr>
<td>Exclude trades with execution date &lt; offering date + 90 days</td>
<td>17,213,183</td>
<td>20,241</td>
<td>1,228</td>
</tr>
<tr>
<td>Exclude trades with execution date &gt; maturity date - 1 year</td>
<td>16,093,243</td>
<td>19,339</td>
<td>1,219</td>
</tr>
<tr>
<td>Exclude trades with trade size higher than issue amount</td>
<td>16,092,381</td>
<td>19,332</td>
<td>1,219</td>
</tr>
<tr>
<td>Exclude trades without the price data</td>
<td>16,092,381</td>
<td>19,332</td>
<td>1,219</td>
</tr>
<tr>
<td>Exclude trades with price &lt;= 0</td>
<td>16,092,300</td>
<td>19,332</td>
<td>1,219</td>
</tr>
<tr>
<td>Exclude FINRA50 bonds</td>
<td>15,406,291</td>
<td>19,279</td>
<td>1,210</td>
</tr>
<tr>
<td>Exclude week around Christmas and New Year</td>
<td>15,203,849</td>
<td>19,262</td>
<td>1,208</td>
</tr>
<tr>
<td>Exclude unmatched interdealer trades</td>
<td>12,945,268</td>
<td>19,224</td>
<td>1,178</td>
</tr>
<tr>
<td>Exclude infrequent dealers</td>
<td>12,909,797</td>
<td>19,219</td>
<td>530</td>
</tr>
</tbody>
</table>

Table 8: Steps from Original Academic Corporate Bond TRACE Data to Cleaned Sample

Notes: The source contains all transactions from July 2002 to December 2005. Columns refer to the number of trades, bonds and dealers remaining in the sample after the corresponding data cleaning step has been applied. SEC Rule 144A bonds are not covered by TRACE during the sample period. The FINRA50 represent 50 Non-Investment Grade securities disseminated under Fixed Income Pricing System (FIPS2). This list of 50 bonds changes over time with bonds both entering and exiting. Infrequent dealers are dealers who are in the market for less than 2 months total, or who trade less than 20 days or less than 10% of the days in the market.

both dealers participating in the trade. I firstly find trades in the interdealer market that have an exact match with respect to the execution date and time, bond, price, quantity and reporting counterparty. Out of the remaining trades, I match the ones that have the exact match with respect to the execution date (but not time), bond, price, quantity and
reporting counterparty. Finally, out of the remaining trades, I match the ones that have the exact match with respect to the execution date and time, bond, price, and quantity, but one dealer’s report of the counterparty is not consistent (which I consider to be an error), while the other dealer’s report is. This procedure matches 60.8% of trades in the interdealer market, which is certainly on the low side, but could be due to the fact that the program was in the initial stage and dealers were still adjusting to the new rules. While I use interdealer trades to form the trading network and compute measures of dealer centrality, the main results in the paper concern trades with clients, which are not affected by the elimination of matched trades in the interdealer market.

Finally, I apply a dealer specific filter. Here I eliminate dealers who are present in the market for less than 2 months, or who trade for less than 20 days over the sample period, or less than 10% of the days in the market. This eliminates over 50% of dealers, but less than 0.4% of trades. It is possible that these dealers are specialized in intermediating trade in debt securities that exclude corporate bonds, such as asset backed securities.

The resulting sample consists of 12,909,797 transactions in 19,219 bonds with 530 dealers.

*Phase Identification*

I use the transaction data to identify bonds belonging to each phase. This is possible because the dataset contains a variable that reports whether information about a particular trade is disseminated to the market or not. Phase 1 bonds are identified as bonds that have disseminated trades before the beginning of Phase 2, which happens on March 3, 2003. I am able to separate the standard Phase 1 sample from the 50 high-yield bonds included in this phase by using information on ratings and issue size. I identify bonds for Phases 2 by looking at bonds that have non-disseminated trades before Phase 2 becomes effective, and disseminated trades after the effective date and before the beginning of the next phase. There is a sample of 120 investment grade bonds that become transparent between Phase 2 and Phase 3A. I use the listing of these bonds provided on FINRA’s website to exclude them from the sample of bonds identified to belong to Phase 2. The bond samples belonging to Phase 3A and 3B are identified in the same way. Table 2 provides information about bond samples separated by phase.

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52The standard Phase 1 sample consists of investment grade bonds with an initial issue size of $1 billion or greater.
Rating Construction

Bond ratings are from Mergent FISD. Following Asquith et al. (2013), I use the S&P value if it exists, otherwise the Moody’s value, otherwise the Fitch value, and otherwise the Duff and Phelps value. In order to compute mean ratings, as well as for statistical analysis, letter ratings are converted to numerical ratings, starting with value 25 for the highest rating AAA, and decreasing by 1 unit for each marginal downgrade, with value 1 for the lowest rating D.

B. Parallel Trends Tests

In this section I test if the time trends for the outcome variables of control and treated bonds are parallel in the 2-month period before the phase start. The assumption of parallel trends is required for the difference-in-difference framework to be justified. I perform the test for each specification described and implemented in Section 5.\textsuperscript{53} I estimate and report the coefficient on the deviation of the time trend for the outcome of treated bonds from the overall time trend. For the two specifications investigating differential effect of transparency across dealers (i.e. Equations (2) and (3)), I estimate the coefficient on the deviation of the time trend separately for dealers of different centrality, since the underlying assumption of the specifications is that trends are parallel conditional on centrality, with centrality treated as a binary variable in Panel B, and as continuous in Panel C.

The reports are shown in Tables 9, 10 and 11 for the bid-ask spread, trading volume, and capital commitment, respectively. As it can be seen from the three tables, estimates are generally insignificant, and more so for the trades with clients. In addition, magnitudes of the estimates are small, and are orders of magnitude smaller from the estimates reporting the impact of transparency in Tables 5-7, wherever the impact of transparency was found to be significant. Thus, I conclude that the parallel trends assumption holds for each outcome variable and each specification.

\textsuperscript{53}See Equations (1)-(3) for descriptions of the specifications, and Tables 5-7 for their implementations.
### Table 9: Parallel Trends Test: Bid-Ask Spread

<table>
<thead>
<tr>
<th>Counterparty Sample</th>
<th>Pooled (1)</th>
<th>Phase 2 (2)</th>
<th>Phase 3A (3)</th>
<th>Phase 3B (4)</th>
<th>Pooled (5)</th>
<th>Phase 2 (6)</th>
<th>Phase 3A (7)</th>
<th>Phase 3B (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Average Effect (Eq. (1))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Trend x Disseminate</td>
<td>0.00104</td>
<td>-0.0268*</td>
<td>-0.00116</td>
<td>0.00240</td>
<td>-0.000168</td>
<td>-0.000118</td>
<td>-0.00239</td>
<td>-0.0000562</td>
</tr>
<tr>
<td></td>
<td>(0.00182)</td>
<td>(0.0119)</td>
<td>(0.0108)</td>
<td>(0.00190)</td>
<td>(0.00218)</td>
<td>(0.00258)</td>
<td>(0.00179)</td>
<td>(0.000259)</td>
</tr>
<tr>
<td>Panel B: Differential Effect (Eq. (2))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Trend x Disseminate x Core</td>
<td>0.000126</td>
<td>-0.0246</td>
<td>-0.00677</td>
<td>0.00183</td>
<td>-0.00184</td>
<td>-0.0176**</td>
<td>-0.0106</td>
<td>0.000511</td>
</tr>
<tr>
<td></td>
<td>(0.00224)</td>
<td>(0.0133)</td>
<td>(0.0109)</td>
<td>(0.00246)</td>
<td>(0.00200)</td>
<td>(0.00652)</td>
<td>(0.00643)</td>
<td>(0.00217)</td>
</tr>
<tr>
<td>Time Trend x Disseminate x Peripheral</td>
<td>0.00322</td>
<td>-0.0382</td>
<td>0.0273</td>
<td>0.00324</td>
<td>-0.000230</td>
<td>0.0263**</td>
<td>0.00302</td>
<td>-0.00110</td>
</tr>
<tr>
<td></td>
<td>(0.00434)</td>
<td>(0.0203)</td>
<td>(0.0315)</td>
<td>(0.00452)</td>
<td>(0.00145)</td>
<td>(0.00974)</td>
<td>(0.00619)</td>
<td>(0.00158)</td>
</tr>
<tr>
<td>Panel C: Differential Effect (Eq. (3))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Trend x Disseminate</td>
<td>0.0102</td>
<td>-0.105</td>
<td>0.0465</td>
<td>0.00480</td>
<td>-0.00121</td>
<td>0.102*</td>
<td>0.0144</td>
<td>-0.00606</td>
</tr>
<tr>
<td></td>
<td>(0.0184)</td>
<td>(0.0928)</td>
<td>(0.107)</td>
<td>(0.0194)</td>
<td>(0.0114)</td>
<td>(0.0442)</td>
<td>(0.0280)</td>
<td>(0.0127)</td>
</tr>
<tr>
<td>Time Trend x Disseminate x Centrality</td>
<td>-0.0101</td>
<td>0.0816</td>
<td>-0.0504</td>
<td>-0.00281</td>
<td>0.000857</td>
<td>-0.112*</td>
<td>-0.0214</td>
<td>0.00705</td>
</tr>
<tr>
<td></td>
<td>(0.0201)</td>
<td>(0.0996)</td>
<td>(0.111)</td>
<td>(0.0214)</td>
<td>(0.0135)</td>
<td>(0.0483)</td>
<td>(0.0320)</td>
<td>(0.0150)</td>
</tr>
<tr>
<td>Observations</td>
<td>782,527</td>
<td>241,938</td>
<td>272,318</td>
<td>268,271</td>
<td>352,496</td>
<td>77,620</td>
<td>133,062</td>
<td>141,814</td>
</tr>
</tbody>
</table>

Notes: A unit of observation is a transaction. The sample is restricted to the pre-treatment window. Estimates above indicate the deviation of the time trend of the treated sample relative to the control sample. OLS regressions include standard difference-in-difference regressors (see specifications). Panel A regression also includes week fixed effects. Panels B and C include week fixed effect interacted with the centrality ranks corresponding to the specifications. The dependent variable is bid-ask spread. Disseminate is an indicator for whether the bond changes dissemination status. Centrality is dealer eigenvector centrality rank of the trading network weighted by the number of trades over the last two months, normalized between 0 and 1, and computed at each date. A core dealer is a dealer among top 30 dealers by centrality. A peripheral dealer is a dealer who is present in the market but not a core dealer. Robust standard errors clustered at the bond and dealer level are in parenthesis immediately below the estimates. ***, **, * indicate significance at 1, 5, and 10%. 
### Table 10: Parallel Trends Test: Volume

<table>
<thead>
<tr>
<th>Counterparty Sample</th>
<th>Client</th>
<th>Dealer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pooled</td>
<td>Phase 2</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Time Trend x Disseminate</td>
<td>-0.00227</td>
<td>-0.0126</td>
</tr>
<tr>
<td>(0.00346)</td>
<td>(0.0113)</td>
<td>(0.00309)</td>
</tr>
</tbody>
</table>

**Panel A: Average Effect (Eq. (1))**

<table>
<thead>
<tr>
<th>Time Trend x Disseminate x Core</th>
<th>-0.00641</th>
<th>-0.0645</th>
<th>0.00685</th>
<th>0.0283</th>
<th>-0.00486</th>
<th>-0.0366***</th>
<th>0.00233</th>
<th>0.00834</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.0102)</td>
<td>(0.0449)</td>
<td>(0.00791)</td>
<td>(0.0332)</td>
<td></td>
<td>(0.00265)</td>
<td>(0.0109)</td>
<td>(0.00174)</td>
<td>(0.00666)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time Trend x Disseminate x Peripheral</th>
<th>0.000564</th>
<th>0.00333</th>
<th>0.000221</th>
<th>0.0145*</th>
<th>0.00107</th>
<th>0.00337</th>
<th>0.000136</th>
<th>0.00948</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.00157)</td>
<td>(0.00768)</td>
<td>(0.00112)</td>
<td>(0.00631)</td>
<td></td>
<td>(0.000933)</td>
<td>(0.00225)</td>
<td>(0.000975)</td>
<td>(0.00631)</td>
</tr>
</tbody>
</table>

**Panel B: Differential Effect (Eq. (2))**

<table>
<thead>
<tr>
<th>Time Trend x Disseminate</th>
<th>0.00606</th>
<th>0.0361</th>
<th>-0.00336</th>
<th>-0.0115</th>
<th>0.00305*</th>
<th>0.0107**</th>
<th>0.00385</th>
<th>0.00750</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.00529)</td>
<td>(0.0193)</td>
<td>(0.00421)</td>
<td>(0.0187)</td>
<td></td>
<td>(0.00125)</td>
<td>(0.00381)</td>
<td>(0.000865)</td>
<td>(0.00659)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time Trend x Disseminate x Centrality</th>
<th>-0.0164</th>
<th>-0.0970</th>
<th>0.00977</th>
<th>0.0545</th>
<th>-0.00727</th>
<th>-0.0299*</th>
<th>0.000237</th>
<th>0.000811</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.0167)</td>
<td>(0.0556)</td>
<td>(0.0140)</td>
<td>(0.0572)</td>
<td></td>
<td>(0.00436)</td>
<td>(0.0127)</td>
<td>(0.00306)</td>
<td>(0.0103)</td>
</tr>
</tbody>
</table>

**Panel C: Differential Effect (Eq. (3))**

| Observations | 3,306,814 | 632,715 | 1,970,528 | 703,571 | 3,306,814 | 632,715 | 1,970,528 | 703,571 |

Notes: A unit of observations is (dealer, bond, date). The sample is restricted to the pre-treatment window. Variables are averaged over a week for each period due to computing limitations. Estimates above indicate the deviation of the time trend of the treated sample relative to the control sample. OLS regressions include standard difference-in-difference regressors (see specifications). Panel A regression also includes week fixed effects. Panels B and C include week fixed effect interacted with the centrality ranks corresponding to the specifications. The dependent variable is log(volume+1). Disseminate is an indicator for whether the bond changes dissemination status. Centrality is dealer eigenvector centrality rank of the trading network weighted by the number of trades over the last two months, normalized between 0 and 1, and computed at each date. A core dealer is a dealer among top 30 dealers by centrality. A peripheral dealer is a dealer who is present in the market but not a core dealer. Robust standard errors clustered at the bond and dealer level are in parenthesis immediately below the estimates. ***, **, * indicate significance at 1, 5, and 10%.

---

Client

Dealer

Sample

Pooled

Phase 2

Phase 3A

Phase 3B

Pooled

Phase 2

Phase 3A

Phase 3B

(1)

(2)

(3)

(4)

(5)

(6)

(7)

(8)
Panel A: Average Effect (Eq. (1))

<table>
<thead>
<tr>
<th>Sample</th>
<th>Pooled</th>
<th>Phase 2</th>
<th>Phase 3A</th>
<th>Phase 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Trend x Disseminate</td>
<td>-0.000219</td>
<td>-0.00305**</td>
<td>0.0000334</td>
<td>-0.000131</td>
</tr>
<tr>
<td></td>
<td>(0.000245)</td>
<td>(0.00102)</td>
<td>(0.00109)</td>
<td>(0.000251)</td>
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</table>

Panel B: Differential Effect (Eq. (2))

<table>
<thead>
<tr>
<th>Sample</th>
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<th>Phase 2</th>
<th>Phase 3A</th>
<th>Phase 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Trend x Disseminate x Core</td>
<td>-0.0000261</td>
<td>-0.00349**</td>
<td>0.000733</td>
<td>0.0000564</td>
</tr>
<tr>
<td></td>
<td>(0.000294)</td>
<td>(0.00115)</td>
<td>(0.00134)</td>
<td>(0.000293)</td>
</tr>
<tr>
<td>Time Trend x Disseminate x Peripheral</td>
<td>-0.0000167</td>
<td>-0.00345</td>
<td>-0.00113</td>
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<tr>
<td></td>
<td>(0.000567)</td>
<td>(0.00261)</td>
<td>(0.00271)</td>
<td>(0.000592)</td>
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</table>

Panel C: Differential Effect (Eq. (3))

<table>
<thead>
<tr>
<th>Sample</th>
<th>Pooled</th>
<th>Phase 2</th>
<th>Phase 3A</th>
<th>Phase 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Trend x Disseminate</td>
<td>0.0000995</td>
<td>0.000242</td>
<td>-0.000393</td>
<td>0.0000174</td>
</tr>
<tr>
<td></td>
<td>(0.00199)</td>
<td>(0.0119)</td>
<td>(0.0112)</td>
<td>(0.00211)</td>
</tr>
<tr>
<td>Time Trend x Disseminate x Centrality</td>
<td>-0.000259</td>
<td>-0.00339</td>
<td>-0.00113</td>
<td>0.0000841</td>
</tr>
<tr>
<td></td>
<td>(0.00217)</td>
<td>(0.0125)</td>
<td>(0.0120)</td>
<td>(0.00230)</td>
</tr>
</tbody>
</table>

Observations

<table>
<thead>
<tr>
<th>Sample</th>
<th>Pooled</th>
<th>Phase 2</th>
<th>Phase 3A</th>
<th>Phase 3B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>693,973</td>
<td>160,844</td>
<td>271,606</td>
<td>261,523</td>
</tr>
</tbody>
</table>

Notes: A unit of observation is (dealer, bond, date), restricted to days on which dealer trades a given bond. The sample is restricted to the pre-treatment window. Estimates above indicate the deviation of the time trend of the treated sample relative to the control sample. OLS regressions include standard difference-in-difference regressors (see specifications). Panel A regression also includes week fixed effects. Panels B and C include week fixed effect interacted with the centrality ranks corresponding to the specifications. The dependent variable is capital commitment. Time Trend is a number of a week on which transaction takes place. Disseminate is an indicator for whether the bond changes dissemination status. Centrality is dealer eigenvector centrality rank of the trading network weighted by the number of trades over the last two months, normalized between 0 and 1, and computed at each date. A core dealer is a dealer among top 30 dealers by centrality. A peripheral dealer is a dealer who is present in the market but not a core dealer. Robust standard errors clustered at the bond and dealer level are in parenthesis immediately below the estimates. ***, **, * indicate significance at 1, 5, and 10%.

C. Proofs of Theoretical Results from Section 6

Before going into individual proofs, I define value functions and derive Bellman equations used throughout this sections. Let $U^\theta$ denote a value function for an agent of type $\theta$. Then $U^\theta = \sup_{\lambda \in [L, L]} V^\theta_\lambda$, where $V^\theta_\lambda$ denotes a value function of trader of type $\theta$ in market $\lambda$, and satisfies the following Bellman equation, for any $\lambda$ such that $x^D = \lambda$ for some dealer:

$$r V^I_\lambda = \lambda \left( E[v] + 1 - p_\lambda - V^I_\lambda \right) - \rho V^I_\lambda$$  \hspace{1cm} (15)

$$r V^{(L, \beta)}_\lambda = \lambda \left( E[v] + 1 - p_\lambda - V^{(L, \beta)}_\lambda \right) - \beta V^{(L, \beta)}_\lambda \quad \text{for } \beta \in [0, \infty)$$  \hspace{1cm} (16)

$$r V^D_\lambda = \lambda \frac{\mu^L_\lambda + \mu^L_\lambda}{\mu^D_\lambda} (s_\lambda - \eta_\lambda) \quad \text{for } \mu^D_\lambda > 0$$  \hspace{1cm} (17)
Proof of Proposition 1:

Note that when a liquidity trader meets a dealer in market \( \lambda \), his search cost \( \beta \) drops to 0 in market \( \lambda \) by assumption. Thus, every liquidity trader has the same outside option, equal to the value function of a liquidity trader with \( \beta = 0 \) in market \( \lambda \). Let \( V^I_\lambda \) and \( V^{(L,0)}_\lambda \) denote value functions of an informed trader and liquidity trader with \( \beta = 0 \) in market \( \lambda \), as defined in the previous paragraph. Using Equations (15)-(16), it follows that

\[
V^I_\lambda = \frac{\lambda}{\lambda + r + \rho} (E[v] + 1 - p_\lambda) \quad \text{and} \quad V^{(L,0)}_\lambda = \frac{\lambda}{\lambda + r} (E[v] + 1 - p_\lambda), \quad V^I_\lambda \leq V^{(L,0)}_\lambda.
\]

The gains from trade are higher for trader \( I \), i.e.

\[
E[v] + 1 - V^I_\lambda \geq E[v] + 1 - V^{(L,0)}_\lambda , \quad \text{and} \quad \text{trader } I \text{ is less patient, as } r + \rho \geq r.
\]

Hence, the conditions from Appendix D apply, and under the regularity condition on beliefs in Appendix D a unique pooling equilibrium exists, resembling the outcome of a complete information alternating offer bargaining game between trader \((L,0)\) and dealer with the reservation value equal to the expected value of the asset at the time of the contact by the trader. Note that this justifies the initial assumption that both types of traders expect the same price \( p_\lambda \). Price \( p_\lambda \) thus satisfies:

\[
p_\lambda = (1 - q) \left( E[v] + 1 - V^{(L,0)}_\lambda \right) + q(\eta_\lambda(E[v] + 1) + (1 - \eta_\lambda)E[v])
\]

(18)

Using the expression for \( V^{(L,0)}_\lambda \) and solving for \( p_\lambda \) gives Equations (7)-(6). \qed

Proof of Theorem 1:

Equations (5) imply that \( \int_\lambda^\bar{\lambda} \mu^I_\lambda d\lambda > 0 \) and \( \int_\lambda^\bar{\lambda} \mu^L_\lambda d\lambda > 0 \). After substituting out the expression for \( p_\lambda \), and then for \( s_\lambda \) from Equations (6)-(7) into Equations (15)-(17), the value functions \( V^\theta_\lambda \) for \( \theta \in \Theta \) satisfy the following equations:

\[
V^I_\lambda = \frac{q\lambda(\lambda + r)}{(q\lambda + r)(\lambda + r + \rho)}(1 - \eta_\lambda) \quad (19)
\]

\[
V^{(L,\beta)}_\lambda = \frac{q\lambda(\lambda + r)}{(q\lambda + r)(\lambda + r + \beta)}(1 - \eta_\lambda) \quad (20)
\]

\[
V^D_\lambda = \frac{(1 - q)\lambda \mu^I_\lambda + \mu^L_\lambda}{q\lambda + r - \mu^D_\lambda}(1 - \eta_\lambda) \quad (21)
\]

Observe that \( \frac{\partial V^\theta_\lambda}{\partial \lambda} > 0 \), and thus if \( \mu^I_\lambda > 0 \) and \( \mu^L_\lambda > 0 \) for \( \lambda < \lambda' \), it must be the case that \( \eta_\lambda < \eta_{\lambda'} \). The remainder of the proof consists of 3 steps. Lemma 1 shows that at most two markets operate in any SPBE. Lemma 2 establishes that trade always takes place in market \( \bar{\lambda} \). Lemma 3 proves that positive amount of trade must take place in another
market $\lambda \in [\hat{\lambda}, \bar{\lambda}]$ if and only if $\rho > 0$. Lemma 4 shows that if $\mu_{30}^L > 0$, then $\lambda_0 = \hat{\lambda}$. Lemma 5 establishes uniqueness.

**Lemma 1.** In any SPBE, there exist markets $\lambda', \lambda'' \in [\hat{\lambda}, \bar{\lambda}]$ with $\lambda' > \lambda''$ such that $\mu_{\lambda'}^L > 0$ and $\mu_{\lambda''}^L > 0$, and $\mu_0^L = 0$ for any $\theta \in \{I, L\}$ and $\lambda \notin \{\lambda', \lambda''\}$.

**Proof.** The proof is by contradiction. Suppose that there are more than two markets with positive volume of trade in a SPBE. Pick three such markets, $\lambda_1$, $\lambda_2$, and $\lambda_3$, and assume without loss of generality that $\lambda_1 > \lambda_2 > \lambda_3$. Observe first that $\mu_{\lambda_1}^I > 0$, for otherwise $\eta_{\lambda_1} = 0$, implying $V_{\lambda_1}^I > V_{\lambda_2}^I$ and $V_{\lambda_1}^{(L, \beta)} > V_{\lambda_2}^{(L, \beta)}$ for any $\beta \in [0, \infty)$, which violates the optimality condition of either trader $I$ or trader $(L, \beta)$ for some $\beta$. Using an identical argument, with $\lambda_2$ and $\lambda_3$ in the place of $(\lambda_1$ and $\lambda_2)$, respectively, it can be established that $\mu_{\lambda_2}^L > 0$. Therefore, $U^I = V_{\lambda_1}^I = V_{\lambda_2}^I \geq V_{\lambda_3}^I$. There are two possible cases, $U^I = V_{\lambda_3}^I$ or $U^I > V_{\lambda_3}^I$. If $U^I > V_{\lambda_3}^I$, then it is easy to see that $x^{(L, \beta)} = \lambda_1$ for any $\beta > \rho$ and $x^{(L, \beta)} = \lambda_3$ for any $\beta < \rho$. But then $\eta_{\lambda_2} = 1$, and thus $x^I = \lambda_2$ can never be optimal for trader $I$. Therefore, $U^I > V_{\lambda_3}^I$, and $\eta_{\lambda_3} = 0$. Now consider a market $\lambda_3 + \epsilon$ for small enough $\epsilon > 0$ and suppose that a sufficiently small mass of dealers moves to market $\lambda_3 + \epsilon$ over an infinitesimal period of time. Then $U^I > V_{\lambda_3 + \epsilon}^I$ for any belief $\eta_{\lambda_3 + \epsilon}$. But $V_{\lambda_3 + \epsilon}^{(L, \beta)} > V_{\lambda_3}^{(L, \beta)}$ for $\eta_{\lambda_3 + \epsilon} < \delta$ where $\delta > 0$ is small enough, and any $\beta \in [0, \infty)$. Using Assumption 1, it follows that $\eta_{\lambda_3 + \epsilon} = 0$. All the newly arriving liquidity traders who would have previously preferred market $\lambda_3$ now go to $\lambda_3 + \epsilon$. If the mass of dealers there is small enough, their payoff there must exceed dealers’ payoff in other open markets, establishing that this is an profitable deviation (i.e. a deviation by mass zero of dealers leads to unbounded instantaneous profits per dealer). This is a contradiction, and thus no more than two markets can have positive volume of trade in any SPBE.

Clearly at least one market must have positive volume. If it is only one market, say market $\lambda'$, then it must be the case that $\mu_{\lambda'}^L > 0$ and $\mu_{\lambda'}^L > 0$. Therefore, suppose there are two distinct markets, $\lambda'$ and $\lambda''$ with $\lambda' > \lambda''$ such that $\mu_{\lambda'}^L + \mu_{\lambda'}^L > 0$ and $\mu_{\lambda''}^L + \mu_{\lambda''}^L > 0$. By the argument as in the previous paragraph, it must be the case that $\mu_{\lambda'}^L > 0$. If $\mu_{\lambda'}^L = 0$, then $\eta_{\lambda'} = 1$ and $\eta_{\lambda''} < 1$, implying $V_{\lambda'}^I > V_{\lambda''}^I$, which cannot happens since $\mu_{\lambda'}^L > 0$. Therefore, $\mu_{\lambda'}^L > 0$. If $\mu_{\lambda''}^L = 0$, then $\mu_{\lambda''}^L > 0$ and $\eta_{\lambda''} = 1$, implying $V_{\lambda'}^I > V_{\lambda''}^I$, which violates optimality of trader $I$ since $\mu_{\lambda''}^L > 0$. Therefore, $\mu_{\lambda''}^L > 0$. 

**Lemma 2.** In any SPBE, $\mu_{\lambda}^I > 0$ and $\mu_{\lambda}^L > 0$. 

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Proof. Observe that if \( \mu^I_\lambda + \mu^L_\lambda > 0 \), then Lemma 1 implies that \( \mu^L_\lambda > 0 \) and \( \mu^I_\lambda > 0 \). Aiming for a contradiction, suppose that \( \mu^I_\lambda + \mu^L_\lambda = 0 \). Consider market with largest \( \lambda \) such that \( \mu^I_\lambda + \mu^L_\lambda > 0 \). By Lemma 1, \( \mu^I_\lambda > 0 \) and \( \mu^L_\lambda > 0 \). Suppose that an infinitesimal mass of dealers moves to market \( \bar{\lambda} \). Take \( m^* = \sup \{ \eta \in [0, 1] : \bar{x}^I(\eta) = \bar{\lambda} \} \cup \{0\} \), as defined in Assumption 1 for market \( \bar{\lambda} \). Then \( 0 < m^* < 1 \): \( m^* < 1 \) since trader \( I \) has positive utility in market \( \lambda \), and \( 0 < m^* \) since \( \eta_\lambda > 0 \). Then for any liquidity trader \( (L, \beta) \) with \( \beta > \rho \), there exists \( \delta > 0 \) such that market \( V^I_{\lambda}(L, \beta) \big|_{\eta_\lambda=m^*+\delta} > V^I_{\lambda}(L, \beta) \), since \( \beta > \rho \) and \( V^I_{\lambda} \big|_{\eta_\lambda=m^*} = V^I_{\lambda} \) by definition of \( m^* \). Thus, Assumption 1 implies that \( \eta_{\bar{\lambda}} = m^* \) and sufficiently small mass of dealers can make arbitrarily large profits by deviating to market \( \bar{\lambda} \) and trading with newly arriving traders \( (L, \beta) \) with \( \beta > \rho \). This contradicts the definition of a SPBE. Therefore, \( \mu^I_\lambda > 0 \) and \( \mu^L_\lambda > 0 \).

**Lemma 3.** In any SPBE, \( \mu^I_\lambda = \frac{1-F(\rho)}{\lambda} > 0 \), and there exists \( \lambda_0 \in [\underline{\lambda}, \bar{\lambda}] \) such that \( \mu^L_{\lambda_0} = \frac{F(\rho)}{\lambda_0} \geq 0 \). If \( \rho = 0 \), then \( \mu^I_{\lambda_0} = 0 \), and if \( \rho > 0 \) then \( \frac{\mu^I_{\lambda_0}}{\mu^L_{\lambda_0}} < \frac{\mu^I_\lambda}{\mu^L_\lambda} \).

**Proof.** Aiming for a contradiction, suppose that \( \mu^L_\lambda = 0 \) and \( \rho > 0 \) for any \( \lambda \in [\underline{\lambda}, \bar{\lambda}] \). Since by Lemma 2, \( \mu^I_\lambda > 0 \) and \( \mu^L_\lambda > 0 \), it follows that \( \mu^I_\lambda = 0 \) for any \( \lambda \in [\underline{\lambda}, \bar{\lambda}] \). Suppose that an infinitesimal mass of dealers moves to market \( \bar{\lambda} - \epsilon \), for small enough \( \epsilon > 0 \). Take \( m^* = \sup \{ \eta \in [0, 1] : \bar{x}^I(\eta) = \bar{\lambda} - \epsilon \} \cup \{0\} \). By optimality of trader \( I \), \( m^* < 1 \), and for sufficiently small \( \epsilon \), \( m^* > 0 \). Then for any liquidity trader \( (L, \beta) \) with \( \beta < \rho \), there exists \( \delta > 0 \) such that \( V^I_{\lambda-\epsilon}(L, \beta) \big|_{\eta_\lambda=m^*+\delta} > V^I_{\lambda}(L, \beta) \), since \( \beta < \rho \) and \( V^I_{\lambda-\epsilon} \big|_{\eta_\lambda=m^*} = V^I_{\lambda} \) by definition of \( m^* \). Therefore, Assumption 1 implies that \( \eta_{\bar{\lambda}-\epsilon} = m^* \) and sufficiently small mass of dealers can make arbitrarily large profits by deviating to market \( \bar{\lambda} - \epsilon \) and trading with newly arriving traders \( (L, \beta) \) with \( \beta < \rho \). But this contradicts the definition of a SPBE. Consequently, there exists \( \lambda_0 \in [\underline{\lambda}, \bar{\lambda}] \) such that \( \mu^L_{\lambda_0} > 0 \). An argument in Lemma 1 shows that \( V^I_{\lambda} = V^I_{\lambda_0} \) (because \( V^I_{\lambda} < V^I_{\lambda_0} \) violates informed traders’ optimality condition, and \( V^I_{\lambda} > V^I_{\lambda_0} \) violates dealers’ optimality condition). But this implies that \( V^I_{\lambda}(L, \beta) > V^I_{\lambda_0}(L, \beta) \) for \( \beta > \rho \) and \( V^I_{\lambda_0}(L, \beta) < V^I_{\lambda}(L, \beta) \) for \( \beta < \rho \). Then the law of motion from equations (5) implies that \( \mu^I_\lambda = \frac{1-F(\rho)}{\lambda} \) and \( \mu^L_{\lambda_0} = \frac{F(\rho)}{\lambda_0} \).

It is easy to see that \( \eta_{\lambda_0} < \eta_{\bar{\lambda}} \), because otherwise it would not be optimal for any trader to search in market \( \lambda_0 \). This implies that \( \frac{\mu^I_{\lambda_0}}{\mu^L_{\lambda_0}} < \frac{\mu^I_\lambda}{\mu^L_\lambda} \).

To show that \( \mu^I_\lambda = 0 \) when \( \rho = 0 \) for any \( \lambda \in [\underline{\lambda}, \bar{\lambda}] \), suppose, aiming for a contradiction, that \( \mu^I_\lambda > 0 \) for some \( \lambda \in [\underline{\lambda}, \bar{\lambda}] \), and \( \rho = 0 \). We know by Lemma 2 that \( \mu^I_\lambda > 0 \) and thus \( V^I_{\lambda} \geq V^I_{\lambda_0} \). But this implies that \( V^I_{\lambda}(L, \beta) > V^I_{\lambda_0}(L, \beta) \) for any \( \beta > \rho = 0 \). Thus, at most
mass 0 of liquidity traders (i.e. the ones with $\beta = 0$) could optimally search in market $\lambda$, contradicting the hypothesis that $\mu^L_\lambda > 0$. Thus $\mu^L_\lambda = 0 = \frac{F(\rho)}{\lambda}$ for any $\lambda \in [\underline{\lambda}, \bar{\lambda})$. Note that this implies that also $\mu^I_\lambda = 0$ for any $\lambda \in [\underline{\lambda}, \bar{\lambda})$. The law of motion then implies that $\mu^L_\lambda = \frac{1}{\lambda} = \frac{1-F(\rho)}{\lambda}$, and $\mu^I_\lambda = \frac{\phi}{\lambda}$.

Lemma 4. If $\mu^I_{\lambda_0} > 0$, then $\lambda_0 = \bar{\lambda}$.

Proof. Suppose that $\mu^I_{\lambda_0} > 0$, and aiming for a contradiction assume that $\lambda_0 > \bar{\lambda}$. The argument follows the same steps as previous lemmas. Suppose that an infinitesimal mass of dealers moves to market $\lambda_0 - \epsilon$, for small enough $\epsilon > 0$. Take $m^* = \sup\{\eta \in [0, 1] : \bar{x}^I(\eta) = \lambda_0 - \epsilon\} \cup \{0\}$. By optimality of trader $I$, $m^*_I < 1$, and for sufficiently small $\epsilon$, $m^* > 0$. Then for any liquidity trader $(L, \beta)$ with $\beta < \rho$, there exists $\delta > 0$ such that market $V^{(L, \beta)}_{\lambda_0 - \epsilon}\{\eta_{\lambda_0 - \epsilon} = m^* + \delta\} > V^{(L, \beta)}_{\lambda_0}$, since $\beta < \rho$ and $V^{I}_{\lambda_0 - \epsilon}\{\eta_{\lambda_0 - \epsilon} = m^*\} = V^{I}_{\lambda_0}$ by definition of $m^*$. Therefore, Assumption 1 implies that $\eta_{\lambda_0 - \epsilon} = m^*$ and sufficiently small mass of dealers can make arbitrarily large profits by deviating to market $\lambda_0 - \epsilon$ and trading with newly arriving traders $(L, \beta)$ with $\beta < \rho$. But this contradicts the definition of a SPBE. Therefore, $\mu^I_{\lambda_0} > 0$ implies $\lambda_0 = \bar{\lambda}$.

Lemma 5. There is a unique SPBE.

Proof. Let $\gamma^I$ and $\gamma^L$ denote the fractions of newly arriving informed and liquidity traders choosing to search in market $\lambda_0$, respectively. By the results outlines in previous lemmas, the remaining fractions search in market $\bar{\lambda}$. The laws of motion then imply that masses in a SPBE satisfy: $\mu^I_\lambda = \frac{\gamma^I_{\lambda_0}}{\lambda_0 + \rho}$, $\mu^L_\lambda = \frac{(1-\gamma^I_{\lambda_0})}{\lambda_0 + \rho}$, $\mu^L_{\lambda_0} = \frac{\gamma^L_{\lambda_0}}{\lambda_0}$, and $\mu^I_{\lambda_0} = \frac{(1-\gamma^L_{\lambda_0})}{\lambda_0}$. By the argument in Lemma 3, $\gamma^L = F(\rho)$. If $\gamma^I$ is unique, the uniqueness is established. By Lemma 3, if $\rho = 0$, then $\gamma^I = 0$, so the result follows. So, suppose that $\rho > 0$. By Lemma 4, $\lambda_0 = \bar{\lambda}$ whenever $\gamma^I > 0$. Let $V^I_\lambda$ be as defined in equation (19), with $\eta_\lambda$ implied by stationary masses when $\gamma^L = F(\rho)$ and $\gamma^I \in [0, 1]$. Then $\gamma^I$ constitutes a SPBE if $V^I_\lambda - V^I_{\bar{\lambda}} = 0$ for either $\gamma^I > 0$ and $\lambda = \bar{\lambda}$, or $\gamma^I = 0$ and $\lambda \in [\underline{\lambda}, \bar{\lambda})$. Observe that $V^I_\lambda - V^I_{\bar{\lambda}}$ is increasing in $\gamma^I$ and decreasing in $\lambda$, and thus the two cases can never happen simultaneously. Therefore, if a solution exists, it must be unique. If $\gamma^I = 1$, then $V^I_\lambda - V^I_{\bar{\lambda}} > 0$ for any $\lambda < \bar{\lambda}$. If $\gamma^I = 0$ and $\lambda < \bar{\lambda}$ is close enough to $\bar{\lambda}$, then $V^I_\lambda - V^I_{\bar{\lambda}} < 0$. Thus, a solution must exist. This completes the proof.

Proof of Proposition 2:
I first prove the second part of the proposition concerning Equation (10). By Theorem 1, if
\( \lambda_0 > \underline{\lambda} \), then \( \mu_0^I = 0 \) and thus \( \eta_0 = 0 \). By the arguments outlined in the proof of Theorem 1, it must be the case that \( V_1' = V_0' \) (i.e., an informed trader is indifferent between the two operating markets). A necessary condition for the indifference is \( V_1' > V_\underline{\lambda} \) when \( \eta_\underline{\lambda} = 0 \). But this condition is also sufficient because, if it holds, then there exists \( \lambda \in (\underline{\lambda}, \bar{\lambda}) \) such that \( V_1' = V_\lambda' \). Simplifying \( V_1' > V_\lambda' \) with \( \eta_\lambda = 0 \) implies \( \eta_1 < \frac{\phi \lambda}{\phi \lambda + (1 - F(\rho)) (\lambda + \rho)} \) (where the second equality follows from using expressions for the stationary masses). Taking derivative with respect to \( \rho \) gives Equation (10).

Now suppose that \( \eta_1 > \frac{\phi \lambda}{\phi \lambda + (1 - F(\rho)) (\lambda + \rho)} \). The arguments from the previous paragraph imply that \( \lambda_0 = \underline{\lambda} \) and \( \mu_0^I > 0 \). Note that by continuity it follows that \( \lambda_0 = \underline{\lambda} \) in a neighborhood around \( \rho \). We have that \( \eta_1 = \frac{\mu_1^I}{\mu_1^I + \mu_0^I} = \frac{(1 - \gamma) \phi \lambda}{(1 - \gamma) \phi \lambda + (1 - F(\rho)) (\lambda + \rho)} \) and \( \eta_0 = \frac{\mu_0^I}{\mu_1^I + \mu_0^I} = \frac{\gamma \phi \lambda}{\phi \lambda + F(\rho) (\lambda + \rho)} \). Taking derivatives of \( \eta_1 \) and \( \eta_0 \) with respect to \( \rho \), as well as totally differentiating \( V_1' = V_0' \) with respect to \( \rho \), yields the following equations, respectively

\[
\begin{align*}
\frac{d\eta_1}{d\rho} &= \frac{\partial \eta_1}{\partial \rho} \frac{\partial \gamma}{\partial \rho} + \frac{\partial \eta_1}{\partial \gamma} \frac{\partial \rho}{\partial \rho} \\
\frac{d\eta_0}{d\rho} &= \frac{\partial \eta_0}{\partial \rho} \frac{\partial \gamma}{\partial \rho} + \frac{\partial \eta_0}{\partial \gamma} \frac{\partial \rho}{\partial \rho} \\
- \frac{1}{\lambda + \rho + r} - \frac{1}{1 - \eta_1} \left( \frac{\partial \eta_1}{\partial \rho} + \frac{\partial \eta_1}{\partial \gamma} \frac{\partial \gamma}{\partial \rho} \right) &= - \frac{1}{\lambda + \rho + r} - \frac{1}{1 - \eta_0} \left( \frac{\partial \eta_0}{\partial \rho} + \frac{\partial \eta_0}{\partial \gamma} \frac{\partial \gamma}{\partial \rho} \right)
\end{align*}
\]

where \( \frac{\partial \eta_1}{\partial \gamma} = \frac{\eta(1 - \eta)}{1 - \gamma} \), \( \frac{\partial \eta_0}{\partial \gamma} = \frac{\eta(1 - \eta)}{\gamma} \), \( \frac{\partial \eta_1}{\partial \rho} = \left( \frac{f(\rho)}{1 - F(\rho)} - \frac{1}{\lambda + \rho} \right) \eta_1 (1 - \eta_1) \), and \( \frac{\partial \eta_0}{\partial \rho} = - \left( \frac{f(\rho)}{F(\rho)} + \frac{1}{\lambda + \rho} \right) \eta_0 (1 - \eta_0) \). Substituting these expressions in Equations (22)-(24) and solving, leads to expressions for \( \frac{d\eta_1}{d\rho} \) and \( \frac{d\eta_0}{d\rho} \) in Equations (8) and (9).

**Proof of Proposition 3:**

Trading volume satisfies

\[
\begin{align*}
V_{0} &= \lambda_0 \left( \frac{\gamma \phi}{\lambda_0 + \rho} + \frac{F(\rho)}{\lambda_0} \right) \\
V_{1} &= \bar{\lambda} \left( \frac{(1 - \gamma) \phi}{\lambda + \rho} + \frac{1 - F(\rho)}{\lambda} \right)
\end{align*}
\]
Taking logs and using expressions for \( \eta_0 \) and \( \eta_1 \),

\[
\log Vol_0 = -\log(1 - \eta_0) + \log(F(\rho))
\]

(27)

\[
\log Vol_1 = -\log(1 - \eta_1) + \log(1 - F(\rho))
\]

(28)

Taking derivatives with respect to \( \rho \) gives Equations (11) and (12).

If \( \lambda_0 > \lambda \), then \( \frac{d\eta_0}{d\rho} = 0 \) and \( \frac{d\eta_1}{d\rho} \) satisfied Equation (10). Taking the difference between Equations (11) and (12) leads to Equation (13). The expression is negative because \( \eta_1 < 1 \) and \( f(\rho) > 0 \).

If \( \lambda_0 = \lambda \), then we can totally differentiate \( \log(V_{I0}) = \log(V_{I1}) \) (where \( V_{I0} \) and \( V_{I1} \) are informed trader’s value functions in markets \( \lambda \) and \( \bar{\lambda} \), respectively) with respect to \( \rho \) to obtain

\[
\frac{1}{1-\eta_1} \frac{dn_1}{d\rho} - \frac{1}{1-\eta_0} \frac{dn_0}{d\rho} = \frac{\lambda - \bar{\lambda}}{(\lambda + \rho + r)(\lambda + \rho + r)}.
\]

Substituting this expression after taking the difference between Equations (11) and (12) leads to Equation (14).

Proof of Corollary 1:

Suppose that \( \frac{dn_1}{d\rho} = 0 \). Then, using Proposition 2, it follows that \( \frac{dn_0}{d\rho} = 0 \), and it is easy to see that \( \frac{dn_0}{d\rho} < 0 \). Since \( \lambda_0 = \lambda \), it follows that \( \frac{d\lambda_0}{d\rho} \geq 0 \), implying that \( \frac{dn_0}{d\rho} < 0 \). Since \( \frac{dn_0}{d\rho} = 0 \), Proposition 3 implies that \( \frac{d\log Vol_0}{d\rho} = \frac{d\log Vol_1}{d\rho} - f(\rho) < 0 \). Finally, \( \frac{d\log Vol_0}{d\rho} \) has an ambiguous sign.

Proof of Proposition 4:

Since \( Vol_1 = \bar{\lambda} \left( \frac{(1-\gamma)\phi}{\lambda + \rho} + \frac{1-F(\rho)}{\lambda} \right) \), with \( \gamma \in [0, 1] \), it is easy to see that \( \lim_{\rho \to \infty} Vol_1 = 0 \).

Also, \( \eta_0 = \frac{\gamma \phi \lambda_0}{\gamma \phi \lambda_0 + F(\rho)(\lambda_0 + \rho)} \), implying that \( \lim_{\rho \to \infty} \eta_0 = 0 \).

From Theorem 1, we know that \( \gamma < 1 \) for any \( \rho \in \mathbb{R}_+ \). Since an informed investor is indifferent between trading in markets \( \bar{\lambda} \) and \( \lambda_0 \), it follows that \( V_{I1} = V_{I0} \) which is equivalent to

\[
\frac{q \bar{\lambda}(\bar{\lambda} + r)}{(q \lambda + r)(\lambda + r + \rho)}(1 - \eta_1) = \frac{q \lambda_0(\lambda_0 + r)}{(q \lambda_0 + r)(\lambda_0 + r + \rho)}(1 - \eta_0)
\]

(29)

with \( \eta_1 = \frac{(1-\gamma)\phi \bar{\lambda}}{(1-\gamma)\phi \lambda + (1-F(\rho))(\lambda + \rho)} \) and \( \eta_0 = \frac{\gamma \phi \lambda_0}{\gamma \phi \lambda_0 + F(\rho)(\lambda_0 + \rho)} \). Using the condition that \( \gamma = 0 \).
whenever \( \lambda_0 > \lambda \), we can solve for \( \gamma \) to get

\[
\gamma = \max \left( \frac{F(\rho) \left[ \phi \lambda \xi(\rho, \lambda) - (1 - F(\rho)) \left( (\lambda + \rho) \xi(\rho, \lambda) - (\lambda + \rho) \xi(\rho, \lambda) \right) \right]}{\phi [F(\rho) \lambda \xi(\rho, \lambda) + (1 - F(\rho)) \lambda \xi(\rho, \lambda)]}, 0 \right)
\]

(30)

where \( \xi(\rho, \lambda) \equiv \frac{\lambda(\lambda + r)(\lambda + \rho)}{(\lambda + r)(\lambda + r + \rho)} \). Observe that \( \lim_{\rho \to \infty} = \frac{\lambda(\lambda + r)}{\lambda + r} \). If \( \lim_{\rho \to \infty} \rho(1 - F(\rho)) = 0 \), then it can be seen from the expression for \( \gamma \) that \( \gamma \to 1 \), and \( \lambda_0 = \lambda \) whenever \( \gamma > 0 \). In that case, we can use the expression for \( \gamma \) to show that \( \frac{1 - \gamma}{(\lambda + \rho)(1 - F(\rho))} \to \frac{(\lambda - \Delta) r (\lambda + \Delta + r) + q \lambda \Delta}{\phi \lambda \Delta (\lambda + r) (\lambda + r + \rho)} \)

as \( \rho \to \infty \). Using this result in the expression for \( \eta_1 \), it follows that \( \eta_1 \to \frac{(\lambda - \Delta) r (\lambda + \Delta + r) + q \lambda \Delta}{\lambda (\lambda + r)(\lambda + r + \rho)} \)

as \( \rho \to \infty \). If \( \lim_{\rho \to \infty} \rho(1 - F(\rho)) = \infty \), then \( \exists \hat{\rho} \) such that \( \gamma = 0 \) for \( \rho > \hat{\rho} \). In that case, it is easy to see that \( \lim_{\rho \to \infty} \eta_1 = 0 \), and then from the indifference condition for informed traders, \( V_1^I = V_0^I \), it follows that \( \lim_{\rho \to \infty} \lambda_0 = \hat{\lambda} \).

D. The Bargaining Problem

Consider the following discrete-time infinitely-repeated alternating offer bargaining game between two players, with incomplete information. Player \( A \) owns one unit of a good, and the bargaining is over the price \( P \in \mathbb{R}_+ \) (in the units of the numeraire) at which the good is to be sold to player \( B \). There are two possible states of the world, determined at the start of the game, that define players’ valuations for the good, as well as the discount factor of player \( B \). In particular, with probability \( \alpha \) state 0 occurs, meaning that the values of the good for players \( A \) and \( B \) are \( v_0 > 0 \) and \( u_0 > 0 \), respectively, and the time discount factor of player \( B \) is \( \delta_0 \in (0, 1) \). Otherwise, state 1 occurs, and the corresponding values are \( v_1 > 0 \) and \( u_1 > 0 \), and the time discount factor of player \( B \) is \( \delta_1 \in (0, 1) \). Player \( A \) has a fixed time discount factor \( \beta \in (0, 1) \). The following assumptions are made: \( \beta \geq \delta_0 \), \( \delta_1 \geq \delta_0 \), \( u_0 \geq u_1 \), \( u_0 - v_0 < 0 < u_1 - v_1 \), and \( u_1 > \alpha v_0 + (1 - \alpha) v_1 \). The game is the one of incomplete information. Player \( B \) knows the state, while player \( A \) does not.

The game starts in period \( t = 0 \), in which one of the players makes an offer \( P \), and the other player either accept, ”\( Y \)”, or rejects, ”\( N \)”, the offer. If in period \( t \), player \( i \in \{ A, B \} \) makes an offer, and player \( \neg i \) rejects the offer, then in period \( t + 1 \) player \( \neg i \) makes an offer and player \( i \) makes a decision on whether to accept or reject that offer. If the offer is accepted, the game is over, player \( A \) receives \( P \) units of the numeraire in exchange for the good, and player \( B \) receives the good in exchange for \( P \) units of the numeraire. In that case, the payoffs to players \( A \) and \( B \) in states 0 and 1 are \( (P - v_0, u_0 - P) \) and \( (P - v_1, u_1 - P) \),

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respectively. Otherwise, the game continues to period $t + 1$.

Let $\Sigma$ denote the set of all strategies available to the player who starts the bargaining. Formally, $\Sigma = \{\sigma | \sigma = \{\sigma^t\}_{t=0}^{\infty}, \sigma^t : \mathbb{R}_+^{t-1} \rightarrow \mathbb{R}_+ \text{ if } t \text{ is even, } \sigma^t : [0, 1]^t \rightarrow \{Y, N\} \text{ if } t \text{ is odd}\}$. For example, $\sigma^2(P^0, P^1)$ is player’s offer at time 2 assuming that he offered $P^0$ in period 0, the other player rejected it and offered $P^1$, which was rejected by the first player. Similarly, $\sigma^3(P^0, P^1, P^2, P^3)$ is player’s decision on whether to accept $P^3$ assuming that all the previous offers were rejected. Note that mixed strategies are not allowed. $\Xi$ is the set of all strategies of a player whose first move is a response to the other player’s offer. Let $\Omega$ denote the set of all belief systems of player $A$. Formally, let $T_A$ and $T_B$ denote the set of periods at which players $A$ and $B$ make offers if the game is not over, respectively. $\Omega$ is a sequence $\alpha = \{\alpha^t\}_{t \in T_B \cup \{-1\}}$ such that $\alpha^{-1} = \alpha_0$, and for any $t \in T_B$, $\alpha^t : \mathbb{R}_+^t \rightarrow \mathbb{R}$, where $t = -1$ is the period before the beginning of the game. Thus, $\alpha^t(P^0, P^1, ..., P^t)$ is player $A$’s belief that that the state of the world is 0, after the sequence of rejected offers $(P^0, P^1, ..., P^{t-1})$, and after player $B$ made offer $P^t$. Let $P^t = (P^0, ..., P^t)$.

Let $(\sigma, \xi_0, \xi_1)$ denote a triplet of strategies for player $A$, and player $B$ in states 0 and 1, if player $A$ makes the first offer. Define $U_A(\sigma, \xi_0, \xi_1, P^t)$ as the expected period $t + 1$ payoff to player $A$ given strategies $(\sigma, \xi_0, \xi_1)$ and history $P^t$, and define $U_{B,0}$ and $U_{B,1}$ similarly. Let $(\sigma_0, \sigma_1, \xi)$ denote a triplet of strategies for player $B$ in states 0 and 1, and player $A$, respectively, if player $B$ makes an offer first. Define $U_A$, $U_{B,0}$ and $U_{B,1}$ for this case in the same manner as above.

In what follows I analyze the game in which player $A$ makes the first offer. The results for the other case naturally follow from the results and discussion of the first case.

**Definition E.** A sequential equilibrium consists of a triplet of strategies and a sequence of beliefs, $(\sigma, \xi_0, \xi_1, \alpha)$ such that, each player’s strategy is an optimal response for other players’ strategies and belief system $\alpha$, and belief system $\alpha$ is the limit point of sensible beliefs (i.e. beliefs consistent with the Bayes’ rule) associated with totally mixed strategies converging to $(\sigma, \xi_0, \xi_1)$. The restriction on beliefs is equivalent to the following requirements:

(a) If $\xi_0^{t-1} = \xi_1^{t-1} = N$, and $\xi_0^t = \xi_1^t = P^t$, then $\alpha^t = \alpha^{t-2}$;

(b) If $\alpha^{t-2} \in (0, 1)$, $\xi_0^{t-1} = N$, $\xi_0^t = P^t$, and either $\xi_1^{t-1} = Y$ or $\xi_1^t \neq P^t$, then $\alpha^t = 1$;

(c) If $\alpha^{t-2} \in (0, 1)$, $\xi_1^{t-1} = N$, $\xi_1^t = P^t$, and either $\xi_0^{t-1} = Y$ or $\xi_0^t \neq P^t$, then $\alpha^t = 0$. 

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In games of incomplete information, there are generally multiple equilibria due to a lack of restrictions on beliefs off the equilibrium path. I make several assumptions on the belief system and equilibrium strategies in order to guarantee a uniqueness of the equilibrium of interest. The existence of the equilibrium is not affected by the assumptions to follow.

The first assumption is similar to one in Rubinstein (1985):

**Assumption E1.** For any equilibrium sequence of rejected offers $\mathbf{P}^{t-2}$, if $\sigma^{t-1} = \mathbf{P}^{t-1}$, $\xi_{0}^{t-1} = Y$ and $\xi_{1}^{t-1} = Y$, then $\alpha^{t}(\mathbf{P}^{t}) \leq \alpha^{t-2}(\mathbf{P}^{t-2})$. Furthermore, if $\xi_{1}^{t-1} = N$, $\xi_{0}^{t} > \mathbf{P}^{t}$ and $\xi_{1}^{t} > \mathbf{P}^{t}$, then $\alpha^{t}(\mathbf{P}^{t}) \leq \alpha^{t-2}(\mathbf{P}^{t-2})$.

Assumption E1 means that player $B$’s insistence cannot mean that state 0 is more likely. In particular, if at time $t - 1$ player $B$ is expected to accept the equilibrium offer $\mathbf{P}^{t-1}$, but a rejection is observed, followed by offer $\mathbf{P}^{t}$, then player $A$’s belief that the state is 0 cannot be stronger than before. This is a natural assumption, since player $B$ in state 0 is less patient because $\delta_{0} \leq \delta_{1}$ and $u_{0} \geq u_{1}$. Thus, it can never be optimal for player $B$ to reject an offer in state 0 and accept the same offer in state 1. The second part of the assumption follows the same logic. In addition, I make the following assumption:

**Assumption E2.** For any two histories $\mathbf{P}^{t}$ and $\hat{\mathbf{P}}^{t}$, if $\alpha^{t}(\mathbf{P}^{t}) = \alpha^{t}(\hat{\mathbf{P}}^{t})$, then players’ continuations strategies given histories $\mathbf{P}^{t}$ and $\hat{\mathbf{P}}^{t}$ are the same.

Assumption E2 is a Markovian assumption, making equilibrium strategies invariant to histories that induce the same beliefs. The final assumption is the following:

**Assumption E3.** If $\sigma^{t} = Y$ given belief $\alpha^{t}$ and current offer $\mathbf{P}^{t}$, then $\sigma^{t} = Y$ given $\hat{\alpha}^{t} \leq \alpha^{t}$ and current offer $\mathbf{P}^{t}$. If $\sigma^{t} = \mathbf{P}^{t}$ given belief $\alpha^{t}$, then $\sigma^{t} \leq \mathbf{P}^{t}$ given belief $\hat{\alpha}^{t} \leq \alpha^{t}$.

Assumption E3 puts a consistency requirement on equilibrium strategies of player $A$. In particular, if player $A$ accepts price $\mathbf{P}^{t}$ from player $B$ when he believes that the probability of state 0 is $\alpha^{t}$, then he must also accept price $\mathbf{P}^{t}$ from player $B$ when he believes that the probability of state 0 is at most $\alpha^{t}$. Similarly, if player $A$ requests price $\mathbf{P}^{t}$ when he believes that the probability of state 0 is $\alpha^{t}$, then he should request no more than $\mathbf{P}^{t}$ when the expected reservations value of good for both, player $A$ and $B$, fall.

I now provided the characterization of a particular pooling equilibrium of the bargaining game, and establish a uniqueness among all pooling equilibria under Assumptions E1-E3.

**Theorem E.** The bargaining game has a pooling sequential equilibrium outcome such that
the agreement is reached in the first period, and the price \( P \) satisfies:

\[
P = \frac{1 - \delta_1}{1 - \delta_1 \beta} v_1 + \frac{\delta_1 (1 - \beta)}{1 - \delta_1 \beta} (\alpha v_0 + (1 - \alpha) v_1)
\]  

(31)

If Assumptions E1-E3 hold, this is the unique pooling equilibrium outcome.

Proof. Let \( P \) be defined as in Equation (31). Let \( P' = \beta P + (1 - \beta)(\alpha v_0 + (1 - \alpha) v_1) \) and \( \bar{v} = \alpha v_0 + (1 - \alpha) v_1 \). Because \( u_1 > \bar{v} \), it follows that \( P' < P \). Consider the following set of strategies and beliefs:

- As long as \( \alpha^t = \alpha \), player \( A \) always asks for \( P \), and accepts player \( B \)'s offer \( P_B \) if and only if \( P_B \geq P' \).
- Player \( B \) always offers \( P' \). In state 0, player \( B \) accepts player \( A \)'s offer \( P_A \) if and only if \( P_A \leq \delta_0 P' + (1 - \delta_0) u_0 \). In state 1, player \( B \) accepts player \( A \)'s offer \( P_A \) if and only if \( P_A \leq P \).
- If player \( B \) makes a move at time \( t - 1 \) that does not agree with player \( B \) equilibrium play in either state of the world, then \( \alpha^t = \alpha^{t-1} \).

Let’s check that there are no profitable one-shot deviations. If player \( B \) rejects the offer today, then in the next period he offers \( P' \), which is accepted. It is easy to see that \( u_1 - P_A \geq \delta_1 (u_1 - P') \), for any \( P_A \leq P \), and \( u_0 - P_A \geq \delta_0 (u_0 - P') \) for any \( P_A \leq \delta_0 P' + (1 - \delta_0) u_0 \). Therefore, this deviation cannot be profitable. An offer \( P_B \) by player \( B \) such that \( P_B > P' \) cannot be profitable since \( P_B \) is accepted by player \( A \), and player \( B \)'s payoff is decreasing in the price. An offer \( P_B \) by player \( B \) such that \( P_B < P' \) is rejected by player \( A \), in which case player \( B \) accepts price \( P \) in the next period. In that case player \( B \)'s payoff is \( \delta_i (u_i - P) \) for \( i \in \{0, 1\} \). Since \( P' < P \), it follows that \( u_i - P' > \delta_i (u_i - P) \) or \( i \in \{0, 1\} \), so this cannot be a profitable deviation. If player \( A \) rejects an offer by player \( B \), then he asks for \( P \) in the next period, which is accepted. But \( P_B - \bar{v} \geq \beta (P - \bar{v}) \) for any \( P_B \geq P' \), so this deviation cannot be profitable. An offer \( P_A \) by player \( A \) such that \( P_A < P \) cannot be profitable since \( P_A \) is accepted by player \( B \), and player \( A \)'s payoff is increasing in the price. An offer \( P_A \) by player \( A \) such that \( P_A > \delta_0 P' + (1 - \delta_0) u_0 \) is rejected by player \( B \), in which case player \( A \) accepts price \( P' \) in the next period. In that case player \( A \)'s payoff is \( \beta (P' - \bar{v}) \). But since \( P' < P \), it follows that \( P - \bar{v} > \beta (P' - \bar{v}) \), so this cannot be a profitable deviation. Finally, player \( A \) could ask for \( P_A = \delta_0 P' + (1 - \delta_0) u_0 \) at time \( t \), reject offer \( P' \) at time \( t + 1 \)
and offer \( \hat{P}_A = \frac{1 - \delta_1}{1 - \delta_1 \beta} u_1 + \frac{\delta_1 (1 - \beta)}{1 - \delta_1 \beta} v_1 \) at time \( t + 2 \). In that case player \( B \) accepts offer \( P_A \) at time \( t \) in state 0, but not in state 1, and thus \( \alpha^\tau = 0 \) for any \( \tau \geq t + 1 \). Then player \( B \) accepts \( \hat{P}_A \) at time \( t + 2 \) because \( \hat{P}_A \) is the offer resulting from the unique subgame perfect equilibrium in the full information game when state 1 occurs with certainty. In the case of such deviation, player \( A \)'s expected payoff at time \( t \) is:

\[
\alpha (P_A - v_0) + (1 - \alpha) \beta^2 \left( \hat{P}_A - v_1 \right)
\]

\[
= \alpha \left( \delta_0 P + (1 - \delta_0)u_0 - v_0 \right) + (1 - \alpha) \beta^2 \left( \frac{1 - \delta_1}{1 - \delta_1 \beta} u_1 + \frac{\delta_1 (1 - \beta)}{1 - \delta_1 \beta} v_1 - v_1 \right)
\]

\[
= \alpha \left( \delta_0 (\beta P + (1 - \beta)\bar{v}) + (1 - \delta_0)u_0 - v_0 \right) + \beta^2 \frac{1 - \delta_1}{1 - \delta_1 \beta} (1 - \alpha)(u_1 - v_1)
\]

\[
= \alpha \delta_0 \beta(P - v_0) + \alpha [\delta_0 \beta(v_0 - \bar{v}) + \delta_0 \bar{v} + (1 - \delta_0)u_0 - v_0] + \beta^2 \frac{1 - \delta_1}{1 - \delta_1 \beta} (1 - \alpha)(u_1 - v_1)
\]

\[
= \frac{1 - \delta_1}{1 - \delta_1 \beta} \beta [\delta_0 \alpha(u_1 - v_0) + \beta(1 - \alpha)(u_1 - v_1)] - \delta_0 (1 - \beta)(1 - \alpha)(v_0 - v_1) - (1 - \delta_0)(v_0 - u_0)
\]

\[
< \frac{1 - \delta_1}{1 - \delta_1 \beta} (u_1 - \alpha v_0 - (1 - \alpha)v_1)
\]

\[
= P - \bar{v}
\]

where the inequality come from the fact the \( v_0 > u_0, v_0 > v_1 \), and \( \delta_0 \leq \beta \). Therefore, this is not a profitable deviation.

To establish uniqueness, I rely on Assumptions E1-E3. First observe that the equilibrium strategies and beliefs that support the pooling equilibrium stated in the theorem satisfy Assumptions E1-E3. Now consider any pooling equilibrium. In any pooling equilibrium, each player must accept the other player’s offer by the similar argument as above, for otherwise the offering player has a profitable deviation. Given current belief \( \alpha \), let \( P_A \) denote the offer made by player \( A \), which must be accepted by player \( B \), and let \( P_B \) denote the offer made by player \( B \), which must be accepted by player \( A \). The following inequalities must be satisfied:

\[
P_B - \bar{v} \geq \beta(P_A - \bar{v}) \tag{32}
\]

\[
u_1 - P_A \geq \delta_1(u_1 - P_B) \tag{33}
\]

where \( \bar{v} = \alpha v_0 + (1 - \alpha)v_1 \). Inequality (32) holds because of Assumption E2: if player \( A \) rejects offer \( P_B \), the belief is unchanged, and thus the continuation strategy is unchanged and \( P_A \) will be accepted in the next period. Inequality (33) follows from Assumptions E1
and E3. In particular, upon a rejection of offer $P_A$ by player B, the next period belief $\alpha'$ satisfies $\alpha' \leq \alpha$, by Assumption E1. Since $P_B$ is accepted under belief $\alpha$, it must also be accepted under belief $\alpha'$, by Assumption E3. In addition, the two inequalities must hold with equality. To see why, observe that if player A increases $P_A$ without violating inequality (33), player A’s belief in the next period is the same, and it thus does not affect the continuation strategies of any player. Thus player B will accept the new offer and player A will profit. If player B can lower $P_B$ without violating inequality (32), then player A will still accept the offer since player A does not believe that state 0 is more likely, and thus does not request a price higher than $P_A$ in the next period. But then there is a unique solution to the set of two equalities, which gives rise to the pooling equilibrium characterized in the theorem. \qed