The Pricing and Welfare Implications of Non-anonymous Trading

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Abstract

A key distinction between over-the-counter markets and centralized exchanges is the non-anonymity of the transactions. In this paper, we develop a model of non-anonymous trading and compare its prices, liquidity, and efficiency of asset allocations against a baseline with anonymous transactions. The non-anonymity improves the market liquidity by reducing the concerns for adverse selection. More specifically, it allows the market participants to learn valuable information about their counterparties through repeated interactions and consequently enables them to form trading relationships. However, it could harm the market liquidity by increasing the dealers' bargaining power, as the dealers learn more about their clients' liquidity needs. Our theory predicts that the bid-ask spread is smaller in non-anonymous markets, and more so for bonds with low credit-ratings, and at times of high uncertainty. The non-anonymity improves the allocative efficiency for assets with high volatility, with higher degree of asymmetric information, and with less interest among liquidity traders. Using a novel dataset of U.S. corporate bond trades, we find confirming evidence that for high-yield bonds, the bid-ask spread for non-anonymous orders is 20% smaller than that for anonymous orders, while no such price improvement is observed for investment-grade bonds. By examining the waiting times and execution probabilities in our dataset, we present evidence that differentiates our channel from search-based theories.

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1 Introduction

Large quantities of financial assets are being traded in over-the-counter (OTC) markets. In these markets, one of the most salient, and at the same time ignored features is the non-anonymity of the trades. The non-anonymity allows the market participants to learn valuable information about their counterparties through repeated interactions and consequently enables them to form trading relationships, as is prevalent in OTC markets.[1] At the same time, we also see trades happening anonymously on electronic trading platforms, through all-to-all trading protocols. In these trades, participants do not see the identity of each other. Given the prevalence of two types of trading mechanisms, we study how the non-anonymity feature impacts the market liquidity, especially during the time of market turmoil, when both liquidity and adverse selection concerns are utmost. We develop a simple model with predictions about the pricing differences between anonymous and non-anonymous transactions, which we verify in a novel dataset of US corporate bond market. Furthermore, the model has implications for welfare and regulations aiming to improve the liquidity and resiliency of financial markets.

In order to study the pricing and welfare implications of non-anonymous trading, we employ a two-period model of Glosten and Milgrom (1985), with the main distinction that the market makers can privately and imperfectly learn about the type of their counterparty after completing a trade and use the information in making personalized quotations. In this environment, there are two types of traders in the market – informed traders and liquidity traders. Liquidity is provided by some risk-neutral and deep-pocketed "market makers." The informed traders have private information regarding the payoff of the asset traded, while the liquidity traders engage in transactions merely for private benefits.[2]

[1]See Di Maggio, Kermani, and Song (2017), Afonso, Kovner, and Schoar (2013), Hendershott, Li, Livdan, and Schürhoff (2017) and Bräuning and Fecht (2016).

[2]Informed trading is prevalent in corporate bond market, as documented by Kedia and Zhou (2014) and Wei and Zhou (2016).

This setup generates adverse selection concerns, which ensues a positive cost of liquidity provision for the market makers. We compare the prices and welfare in two scenarios: (1) An OTC market, where the traders can be identified and linked across periods. The fundamental assumption is that the market makers can learn about their clients' trading motives, beyond their observable characteristics, through multiple interactions. (2) As our baseline, we also consider a centralized exchange market, where it is not possible to identify the counterparties and their trading motive. Thus, all trades take place anonymously and at the same price.

We find that the OTC market yields a higher welfare, in terms of the extent of liquidity needs served, and a narrower bid-ask spread for the liquidity traders compared to the centralized exchange when the adverse selection concern is more severe. It is more likely the case during the time of market turmoil (Di Maggio, Kermani, and Song, 2017), and for non-investment grade bonds, even during normal times. In particular, we identify two opposite channels through which non-anonymous trading impacts the welfare. On the one hand, it alleviates the concerns for adverse selection by allowing market makers to learn about their counterparties' trading motive. As a result, the market makers can offer a lower bid-ask spread to the counterparties they perceive as liquidity traders. On the other hand, the market makers obtain some information monopoly power over their counterparties, which enables them to cream-skim the liquidity traders with offering little price improvement. Particularly, the cream-skimming amplifies the adverse selection among the traders with no trading relationship and increases their bid-ask spread, which deteriorates the outside option of the ones with a trading relationship. This channel pushes up the spread for all traders and pushes down the welfare. We show that the positive channel dominates for assets with a high level of volatility, asymmetric information, or speculative demand.

This finding informs the policy debate on moving certain assets traded in OTC markets to centralized exchange platforms by emphasizing the economic value created by trading relationships, especially during the time of market turmoil.[3] In particular, our results challenge the belief that OTC markets are less desirable and reduce social welfare, through enabling big market makers to exert monopoly power over smaller traders. Our framework also recognizes this market inefficiency. However, the welfare improvement comes from relationship formation and the reduction in adverse selection concerns. If trading relationships can be formed successfully over time and market makers can learn about their clients' trading motives through repeated interactions, this would allow the market makers to offer a better price to the liquidity traders, which increases the market liquidity and trading volume. That said, our result indicates that a welfare-improving policy should seek to balance out the market makers' market power with their relationship-building incentives, instead of completely eliminating the relationship-building opportunities by moving the assets to centralized exchanges.

We test our model predictions using a novel dataset of U.S. corporate bond transactions that separates non-anonymous and anonymous orders. Our dataset covers transactions conducted between Jan 1st - June 30th 2019 on one of the largest electronic trading platforms. Relative to the average trades in TRACE, trades in our dataset are smaller and more concentrated on higher rated bonds. On this platform, users (both clients and dealers) can choose to trade anonymously or non-anonymously. Our model predicts that relationship traders receive a significant price improvement only for riskier asset classes. Consistent with our model's prediction, for junk-grade bonds, we find that the bid-ask spread for non-anonymous orders is 20% narrower than that for anonymous ones, suggesting relationship traders receive a sizeable price improvement on their transaction of junk-grade bonds. Conversely, for investment-grade bonds, no sign of the price improvement is observed. This empirical finding confirms the pricing prediction of our model that the price improvement for relationship traders could be large or negligible depending on the asset

[3]For instance, as indicated in the annual report of *Financial Stability Board* in 2017, "It is important that authorities have in place a framework in which they regularly assess these [OTC] markets and that allows them to move transactions to organised trading platforms where appropriate"

characteristics.

Another novel feature of our dataset is that it also has information on the unexecuted orders and the waiting time for the executed ones, along with if the orders were placed anonymously or non-anonymously. These features allow us to further highlight the importance of asymmetric information by differentiating our channel from search-based theories of relationship trading, as examined by Hendershott, Li, Livdan, and Schuerhoff (2019), among others. In particular, those theories predict that lower execution probability and longer waiting time in a market, which indicate higher search frictions in that market, should lead to larger bid-ask spreads. Informing on the magnitudes, our results show that one minute increase in the waiting time only increases the half-spread by 0.015 bps, and the average waiting time is about 30 minutes, implying a small economic impact of the waiting time on the prices. It is important to note that we are not ruling out the search costs being an important factor in other segments of the OTC market (e.g. block trades), since our sample is only representative of a subgroup. We emphasize that in our sample, asymmetric information is an important factor in explaining the spreads.

Furthermore, we find a non-monotone relationship between the fraction of non-anonymous trades and asset's payoff uncertainty, both theoretically and empirically. More specifically, as the credit-rating of a bond worsens, the fraction of non-anonymous trades first decrease then increase. This non-monotonicity is predicted by our model. In the model, as payoff uncertainty increases, the issue of asymmetric information becomes more severe; this makes trading with stranger customers more costly, hence increases the fraction of non-anonymous trades. However, higher uncertainty also implies wider bid-ask spreads, which reduces liquidity-driven trades more than information-driven trades, as liquidity traders have a higher price-elasticity in their demand. Since most non-anonymous trades are with liquidity traders, this channel decreases the fraction of non-anonymous trades. The two opposing forces generate a non-monotone relationship, as confirmed in our data.

The implications of our findings are not restricted to OTC markets and carries over to other trading venues with some extent of non-anonymity. An example is dark pools, in which the venue owner is able to monitor the trading behavior of the participants. Dark pools are an important source of liquidity for institutional investors, as they lower their price impact in their block-size transactions. However, the cheaper liquidity is also attractive to speculators, such as hedge funds. As such, to preserve the liquidity, participants with suspicious trading patterns should be detected and their access should be restricted by the venue owners. Thus, the non-anonymity is crucial for the investors' access to a cheaper liquidity. That said, our theory puts forward an explanation of why such exclusive trading venues exist and how they contribute to a higher overall market liquidity.

Literature Review

Earlier studies have explored some pricing and welfare implications of non-anonymous trading. Lee and Wang (2017) discuss the implications of the market makers' ability to price-discriminate based on publicly observable characteristics. Glode and Opp (2016) investigate the role of intermediation chains when the market participants have dispersed information about asset valuations. Nonetheless, neither of those studies examine the endogenous formation of trading relationships, which are pervasive in financial markets.

Multiple papers have empirically shown the prevalence of persistent relationships in OTC markets (Di Maggio, Kermani, and Song (2017); Afonso, Kovner, and Schoar (2013); Bräuning and Fecht (2016)). Hendershott, Li, Livdan, and Schuerhoff (2019) study the pricing implications of dealer-client relationships as a means of reducing clients' search cost. Our results complement theirs as they study the cross-section of prices offered to insurance companies, who presumably mostly trade non-anonymously, while we study the price differences between non-anonymous and anonymous orders. Hau, Hoffmann, and Langfield (2019) show dealers discriminate against unsophisticated clients in these relationships. We focus on another degree of heterogeneity among clients, i.e. informed vs uninformed clients.

In addition to asymmetric information, two other main frictions in OTC markets are search costs and dealers' inventory costs. Starting from Duffie, Gârleanu, and Pedersen (2005), there is an extensive literature explaining patterns observed in OTC markets building on search frictions (Duffie, Gârleanu, and Pedersen (2007), Vayanos and Weill (2008), Lagos and Rocheteau (2009) etc). Wang (2018) develops a network model showing the value of relationship when there is inventory costs. The role of the dealers' inventory costs in the liquidity of OTC markets has been examined both theoretically (Hugonnier, Lester, and Weill, 2018; Yang and Zeng, 2019) and empirically (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Bao, O'Hara, and Zhou, 2018). By focusing on the search costs, Vogel (2019) examines the welfare implications of the policies that advocate moving the assets traded OTC to a "hybrid market" that simultaneously allows for both centralized and over-the-counter transactions. Relatedly, Dugast, Üslü, and Weill (2019) study the welfare implications of those policies by focusing on the inventory costs of bank-affiliated dealers. Here, we focus on the friction of asymmetric information and show empirical evidence that market participants endogenously respond to the friction by forming trading relationships. We also discuss the policy implications of the trading relationships.

The rest of the paper is organized as follows: Section 2 lays out the model setup. Section 3 analyzes the equilibrium prices and allocations. We also examine the welfare implications of non-anonymous trading and relationship formation in that section. Section 4 provides the comparative statics with respect to the parameters of the model. Section 5 describes our data and empirical findings. Section 6 concludes.

2 A Model of Relationship Trading

Consider an economy with two periods ($t = 1, 2$) and a risky asset with a random payoff at the end of each period. The asset payoff $\tilde{v}_t$ is either $v_a > 0$ or $-v_a$, equally likely and i.i.d across the periods.

The economy is populated with a unit measure of risk-neutral traders and a large measure of market makers. There are two types of traders: A fraction μ of the traders are *liquidity traders* (the set is denoted by L), who earn a private benefit, or incur a private cost, from holding the asset at the end of a period. This private component of the demand may arise from some exogenous endowment shock (Vayanos, 1999), heterogeneity in preferences (Vives, 2011), manipulation motives (Zhang, 2018), or some exogenous hedging demand (Diamond and Verrecchia, 1981). Following the literature (as in Glosten and Milgrom (1985) and Lee and Wang (2017)), we assume that liquidity trader $l \in L$ obtains an exogenous private benefit $b_{l,t} \sim_{i.i.d} U(-1, 1)$ from holding one unit of the asset at the end of period $t \in \{1, 2\}$, where $b_{l,t}$'s and $\tilde{v}_t$'s are independent.[4]

The rest of the traders are *informed* (the set is denoted by I) and receive a binary and imperfect signal $\tilde{s}_t \in \{1, -1\}$ about $\tilde{v}_t$ at the beginning of period t. The signal is perfectly correlated across the informed traders and is correct with probability $q > \frac{1}{2}$, that is:

$$P(\tilde{s}_t = v_a | \tilde{v}_t = v_a) = P(\tilde{s}_t = -v_a | \tilde{v}_t = -v_a) = q$$

The informed traders receive no private benefit from a trade, and they trade solely based on speculative motives.

Each trader j, facing the bid and ask prices available at time t, decides whether to buy one

[4] Note that we do not assume that the liquidity traders assign a larger weight to the private component compared to the common component of the asset's payoff. In fact, we assume that the liquidity traders have no private information about the asset's payoff, and consequently, their expected value of the common component is zero. Therefore, their demand for the asset is totally driven by the private component, when they face a positive bid-ask spread.

unit of the asset ($x_t^j = 1$), hold and make no trade ($x_t^j = 0$), or sell one unit of the asset ($x_t^j = -1$), where x_t^j represents the change in the trader's asset position in period t.

The traders choose the best available offer. If multiple best offers are available, to simplify the exposition, we assume they break the tie in favor of their previous market maker; if this is the first time they are trading, then they randomly choose one of the market makers with the best offer.[5]

Finally, the traders do not change types from the first to the second period and they discount the payoff in the second period by β. Therefore, the total payoff of liquidity trader l is:

$$u^l(x_1^l, x_2^l; b_{l,1}, b_{l,2}) = x_1^l(v_1 + b_{l,1} - m_{l,1}) + \beta x_2^l(v_2 + b_{2,1} - m_{l,2}) \tag{1}$$

,where $m_{l,t}$ is the monetary transfer paid/received if she trades at period t.

The informed traders' utility function is similar to that of the liquidity traders, without the private benefit terms.

$$u^i(x_1^i, x_2^i) = x_1^i(v_1 - m_{i,1}) + \beta x_2^i(v_2 - m_{i,2}) \tag{2}$$

All trades are carried out by some infinitesimal and competitive market makers. The market makers post competitive and public bid and ask prices bid_t and ask_t at the beginning of each period. In period $t = 2$, following the public offers, each market maker can offer specific bid and ask prices to the counterparties they traded with at $t = 1$, if any. In fact, by so doing, they can attract the counterparties that are more likely to be a liquidity trader based on the private information they obtained from their interaction. We elaborate on the private information later. Finally, the market makers also have linear utility functions

[5]As we discuss in the proof of Proposition 1, an equilibrium might fail to exist in absence of this tie-breaking rule.

over monetary outcomes and discount the second period by the same rate β.

As follows, we differentiate non-anonymous trading mechanisms (such as over-the-counter markets) from anonymous ones (such as centralized exchanges) by the feasibility (or lack thereof) of linking a counterparty from one trade to another. That said, we analyze the welfare and pricing implications of non-anonymous trading by comparing the equilibrium outcomes in the following two parallel specifications of the trading arrangements:

Centralized Exchange (CE)

A salient feature of centralized exchanges is that the identity of a trade counterparty, along with her trading motive, is unknown. Therefore, due to the presence of traders with superior information, the traders with liquidity-driven motives are adversely selected; hence they need to buy the asset at a premium or need to sell it at a discount.[6] To model the anonymity, we simply assume that the market makers cannot learn anything about the identity or type of the counterparty, before or after the trade. Therefore, forming trading relationships is not possible and the market makers need to break even *period by period*.

Over-the-Counter Markets (OTC)

In contrast to centralized exchanges, traders can disclose their identity in OTC markets. Therefore, the traders with liquidity-driven motives can have multiple interactions with the same dealer, and by doing so, they can partially convey their trading motives and consequently, differentiate themselves from the ones with speculative motives.

[6] Generally speaking, asymmetric information is not the only cause of adverse selection in financial markets. For instance, traders with faster trading technologies, also, impose a negative externality on the other traders, as discussed by Budish, Cramton, and Shim (2015). Our model adopts the informational foundation of the adverse selection. However, its implication can be extended to other causes of the adverse selection as well.

To model learning based on a transaction, we assume that the market makers receive an imperfect and binary signal $t^j \in \{\tilde{l}, \tilde{i}\}$ about the type of their counterparty j, once the trade is completed. In particular,

$$P(t^j = \tilde{l} | j \in L) = p_L > \frac{1}{2} \qquad P(t^j = \tilde{i} | j \in I) = p_I > \frac{1}{2}$$

The signals are independent across the traders conditional on their type.[7] Upon receiving signal t^j, the market maker may make personalized offers $(ask_2^R(t^j), bid_2^R(t^j))$ to the trader in the second period. The personalized offers are made after the public offers, which are publicly observable. We denote the lowest ask and highest bid prices that are publicly offered by the market makers by (ask_2^S, bid_2^S).[8] Given the posted offers, each trader decides whether to trade and whom to trade with. Note that if a trader is perceived as an informed trader (if $t^j = \tilde{i}$ is received), then the market maker would not trade with j even at the public prices. Therefore, in equilibrium, traders with signal $\tilde{i}$ need to find a new market maker to trade with. Conversely, the market makers are willing to trade again with the counterparty if signal $t^j = \tilde{l}$ is received, because she is more likely to be a liquidity trader compared to an average trader accepting the public prices. They do so by offering a price improvement, which is determined endogenously and can be either negligible or strictly positive, depending on the type of equilibrium, as we see later. We call these traders "relationship traders," since they are the ones who endogenously have multiple interactions with the same market maker. We also label these trades as "non-anonymous" traders. We refer to the other traders as "non-relationship traders," and the trades are labelled as "anonymous" trades. This characterisation is based on the traders' behavior in the second period.

[7]The learning process is modeled in a reduced form way. The signal could come from comparing the direction of trade with the final payoff of the asset. It could also be capturing soft information conveyed through the transaction.

[8]Note that there would be no trade at higher ask or lower bid prices, if there is any offered by the market makers. Therefore, for brevity in the exposition, we do not incorporate them in our analysis.

3 Equilibrium

As follows, we solve for and compare the equilibrium bid and ask prices in CE and OTC specifications. In short, we show that non-anonymous trading leads to the formation of trading relationships, for a range of parameters. In OTC specification, the market makers offer a significantly lower bid-ask spread to their relationship trader, only for sufficiently large values of v_a, i.e. when there is high uncertainty regarding the payoff of the asset. The welfare might be strictly higher or lower in OTC specification compared to CE specification. The details on the possible equilibrium outcomes of non-anonymous trading are provided in Proposition 1.

We first solve for the bid and ask prices in CE specification in Lemma 1. In our analysis of OTC specification, we use these prices as our benchmark.

Lemma 1. *In CE specification, the bid and ask prices, in both periods, are:*

$$ask^{CE} = \frac{1 - \sqrt{1 - 4\mu(1-\mu)(2q-1)v_a}}{2\mu}, \qquad bid^{CE} = -ask^{CE} \tag{3}$$

In CE specification, the bid and ask prices are fixed at $-ask^{CE}$ and ask^{CE}. All market makers break even period by period, since personalized offers are not allowed. Due to the positive bid-ask spread, only liquidity traders with an absolute private benefit of $|b| > ask^{CE}$ engage in a transaction and the others' liquidity needs remain unserved. Now, in Proposition 1, we study the equilibrium prices and transactions in OTC specification.

Proposition 1. *Suppose the interactions are sufficiently informative about the type of the counterparty. More precisely, assume the following condition holds:*

$$ask^{CE} < 1 - \frac{1 - p_I}{p_L} \tag{4}$$

Then, we are in an OTC equilibrium, i.e. there are some "relationship traders" in the *second period. compared to the CE baseline, all market makers offer a smaller bid-ask spread in the first period and a larger public bid-ask spread in the second period, that is:*

$$bid_2^S < bid^{CE} < bid_1 < 0 < ask_1 < ask^{CE} < ask_2$$

Depending on the parameters, there are two types of equilibria:

- ***Type 1 equilibrium**: The market makers give no discount to the the relationship traders. In this case, the spread offered to all traders in the second period is larger than the CE baseline:*

  $$bid_2^R(\tilde{l}) = bid_2^S < bid^{CE} < bid_1 < 0 < ask_1 < ask^{CE} < ask_2^S = ask_2^R(\tilde{l})$$

  In this case, liquidity traders with $|b_{l,1}| > ask_1$ trade in the first period, and with $|b_{l,2}| > ask_2^S$ in the second period.

- ***Type 2 equilibrium**: The market makers offer a strictly smaller bid-ask spread to the relationship traders compared to the publicly posted one. In comparison to the CE baseline, the public bid-ask spread is larger, while the spread offered to the relationship traders can be either larger or smaller, depending on the parameters.*

  $$ask_2^R(\tilde{l}) \gtrless ask^{CE} < ask_2^S \qquad bid_2^R(\tilde{l}) \gtrless bid^{CE} > bid_2^S$$

  In this case, there are liquidity traders with $|b_{l,1}| < ask_1$ that are willing to trade at a loss in the first period, in anticipation of the smaller spread associated with the trading relationships in the second period.

Proposition 1 states that trading relationships are formed when the interactions are sufficiently informative. When condition 4 does not hold, no trading relationship is formed, and the prices and trading outcomes are exactly the same as the CE baseline. The market makers offer price improvements to the relationship traders and earn a positive profit. However, the price improvement could be either negligible (such as a tick size) as in type-1 equilibrium, or significant as in type-2 equilibrium.

The interaction of two opposite forces determines the amount of the price improvement for the relationship traders. On the one hand, the market makers learning about their counterparties' type reduces the adverse selection, making them more willing to offer a lower bid-ask spread to the perceived liquidity traders (the ones with $t^j = \tilde{l}$). On the other hand, the signal is privately observed by the market makers, granting them a local information monopoly power over their counterparties. Therefore, the market makers offer a bid-ask spread above their break-even spread and (weakly) below the publicly offered bid-ask spreads. Since the market makers face a spread-elastic demand for liquidity, they may or may not find it optimal to fully squeeze their relationship traders with offering their outside option, namely the public bid-ask spread. The reason that the market makers may not want to fully squeeze their customers is because of the uniformly distributed private value for liquidity. The trader's private value is unobservable for the market maker and effectively gives them a downward sloping demand curve. Setting higher bid-ask spread means less quantity traded. As such, the market makers trade off higher profit per trade with more trades, and may find the optimal spread to be much lower than the public offers. Therefore, depending on the parameters, The liquidity traders may or may not get more favorable prices in a non-anonymous trading arrangement, despite their improved opportunity to signal their type.

Proposition 1 implies that relationship-building motives, in addition to the changes in the information environment, also impact the prices and trading outcomes. In anticipation of the gains from being in a trading relationship, the market makers are willing to incur a loss in the first period to increase the chance of relationship formation. They do so by lowering their spread in the first period ($ask_1 < ask^{CE}$). Likewise, the liquidity traders also have relationship-building motives in a type-2 equilibrium, as the relationships are associated with a sizeable price improvement. Particularly, they might be willing to make a loss in their trade in $t = 1$, by trading at $\underline{b} < ask_1$, to reduce their bid-ask spread in the second period. This increases the measure of liquidity traders trading, and hence the trading volume, in the first period.

3.1 Welfare Implications of Non-anonymous Trading

We examine the welfare implications of non-anonymous trading in this section. In particular, we identify the channels through which non-anonymous trading increases or decreases social welfare. The social welfare in our model is closely linked to market liquidity, since the only social gain from trade is to fulfill the traders' liquidity need, and the rest is mere monetary transfers. We examine whether non-anonymous trading improves market liquidity and analyze how it depends on the asset characteristics and screening technology.

As mentioned above, to compute the social welfare generated in equilibrium, we only need to account for the private component of the liquidity traders who successfully traded. In fact, the gain and losses due to the common component are merely transfers. Specifically

$$W^{CE} = \frac{1 - (ask^{CE})^2}{2} \mu(1 + \beta) \tag{5}$$

$$\begin{aligned} W^{OTC} = &\frac{\beta}{2} \left[(1 - \underline{b})\mu p_L (1 - (ask_2^R)^2) + [(1 - \underline{b})\mu(1 - p_L) + \underline{b}\mu](1 - (ask_2^S)^2) \right] \\ &+ \frac{1 - \underline{b}^2}{2} \mu \end{aligned} \tag{6}$$

,where $\underline{b}$ is the threshold that all liquidity traders with $|b_{l,1}| > \underline{b}$ engage in a trade in the first period.

Proposition 2. *The welfare comparisons in the three cases are:*

- *When condition (4) does not hold,* $W^{OTC} = W^{CE}$

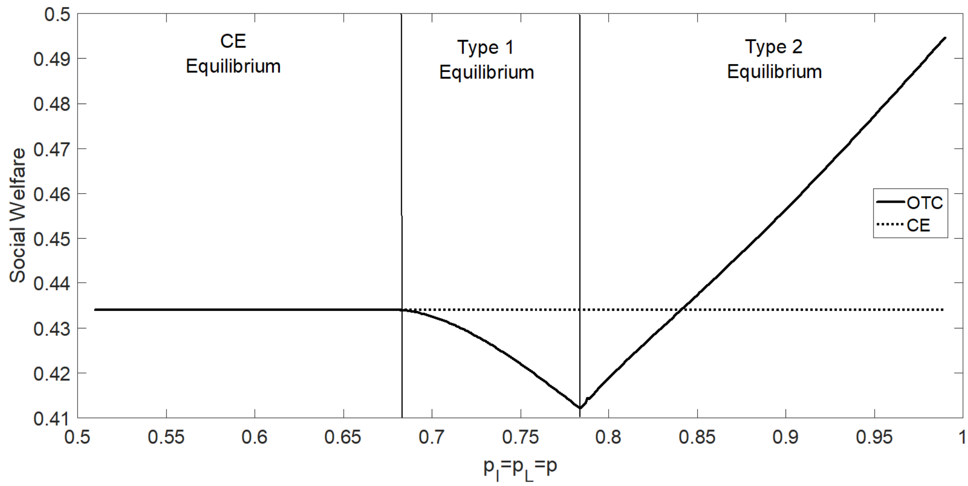

Figure 1: Welfare gain from non-anonymous trading for different precision levels of the screening technology

- *In a type-1 equilibrium,* $W^{CE} < W^{OTC}$
- *In a type-2 equilibrium,* W^{OTC} *could be higher or lower than* W^{CE}*, depending on the parameters.*

Proposition 2 shows that the OTC market yields a higher social welfare only in type-2 equilibrium. A type-2 equilibrium is obtained when the asset volatility (v_a), the information advantage of the informed investors (q), and the precision of the market makers' screening technology (p_L, p_I) are sufficiently high. Figure 1 illustrates how the welfare gain from non-anonymous trading depends on the type of equilibrium and the precision of the market makers' screening technology.

The non-anonymity in trades impacts the social welfare through three different channels. Most importantly, the non-anonymity reduces the adverse selection by providing more information about the trader's trading motive to the market makers. As a result, the market makers break even at a lower bid-ask spread, compared to the CE baseline. Nevertheless, this effect improves the social welfare only in type-2 equilibria. In a type-1 equilibrium, the market makers' information monopoly completely erodes the potential economic gain from the reduced adverse selection and even further distorts the allocative efficiency, as we discuss next.

The non-anonymity hurts the social welfare by increasing the adverse selection against the liquidity traders with no trading relationship. To see this in Proposition 1, note that in the second period, the publicly offered bid-ask spread is larger than the spread for the CE baseline ($ask_2^R > ask^{CE}, bid_2^R < bid^{CE}$) in both type 1 and type 2 equilibria. The intuition is that since the market makers attract away the perceived liquidity traders from the public offers, the pool of remaining traders has a smaller fraction of liquidity traders. The elevated adverse selection among the non-relationship traders hurts the relationship traders as well, by deteriorating their outside option, and consequently, pushing up their spreads. As such, in a type-1 equilibrium, the social surplus in the second period is strictly less than the CE baseline and in a type-2 equilibrium, it depends on the parameters.

Finally, the "relationship-building" channel makes both market makers and liquidity traders more willing to incur initial costs to build and benefit from a trading relationship. To see this in Proposition 1, the market makers earn a positive rent from trading with a relationship trader in both type-1 and type-2 equilibria. Therefore, in the first period, they are willing to lower their bid-ask spread to increase the chance of finding a counterparty and potentially building a trading relationship. This improves the liquidity in the first period. Similarly, the liquidity traders might also strictly benefit from building a trading relationship, as is the case in a type-2 equilibrium. That implies they are willing to accept a slightly larger bid-ask spread, compared to the CE baseline, to benefit from a lower bid-ask spread in the next period, yielding $\underline{b} < ask_1$ in a type-2 equilibrium. This observation resembles the incentives of a borrower and lender to form a lending relationship when there is uncertainty about the borrower's type, as extensively discussed by Sharpe (1990) and Rajan (1992), among others.

Summing up, it is the combination of the three aforementioned forces that connects the non-anonymity to the welfare, which work in different directions. That being said, it is generally unclear whether switching to an anonymous trading platform is welfare improving or deteriorating.

4 Comparative Statics

In this section, we look at how different parameters affect prices, fraction of non-anonymous vs anonymous trades, as well as overall welfare in the economy. We focus on the asset volatility v_a, the precision of the screening technology p_I and p_L, the degree of information asymmetry q, as well as the fraction of liquidity traders in the market μ. Figure 2 -5 illustrate the results for prices, welfare comparison, and fraction of non-anonymous trades. When the bid-ask spread for relationship trades in the second period overlaps with that for non-relationships trades, we are in a type-1 equilibrium; when the two bid-ask spread diverges in the second period, we are in a type-2 equilibrium.

Figure 2 displays a non-monotone relationship between the precision of the screening technology (p_I, p_L) and the welfare and bid-ask spread in the second period. This non-monotonicity emerges since the presence of the screening technology has two opposite impacts on the market makers' pricing behavior. Clearly, it reduces the market makers' adverse selection concerns for their relationship traders, which lowers their cost of liquidity provision, narrowing the bid-ask spread. However, the more subtle impact is that the screening technology increases the fraction of informed trades among the non-relationship traders. It increases the bid-ask spread offered to the non-relationship traders, which deteriorates the outside option of the relationship traders, causing the market makers to widen the spread even for the relationship traders. This squeezes out more liquidity traders in the relationship trades, hence the fraction of non-anonymous trades first decreases. When the screening technology is sufficiently precise, the market makers do not squeeze the re-

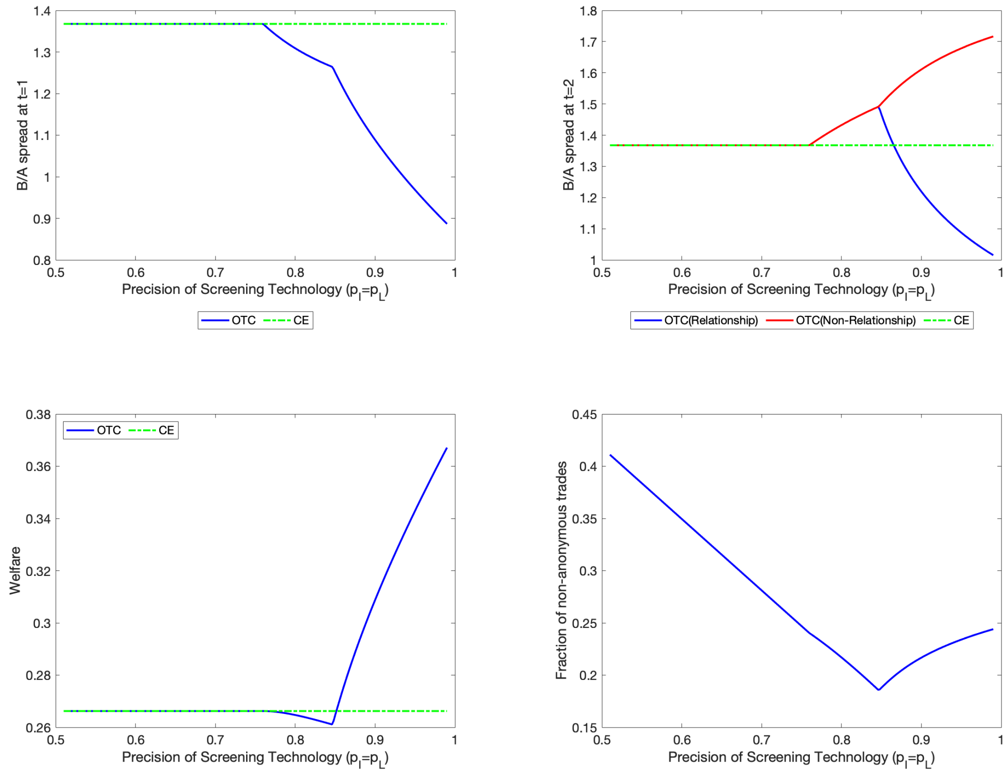

Figure 2: Comparative statics of the welfare and bid-ask spreads with respect to precision of signal

lationship traders to their outside option. In this case, the negative welfare effect is not as strong. Hence, we see in the figure that welfare is increasing when screening technology is sufficiently precise. Correspondingly, the fraction of non-anonymous trades starts to increase.

As shown in Figure 3, the spreads in the first period are decreasing and the welfare is increasing in μ, the fraction of liquidity traders, both for OTC and CE specifications. In the second period, the spread is smaller in the CE equilibrium as well as for the relationship trades. But for non-relationship trades, the probability of those being informed trades increases, which increases the bid-ask spread. For small values of μ, when the concern for

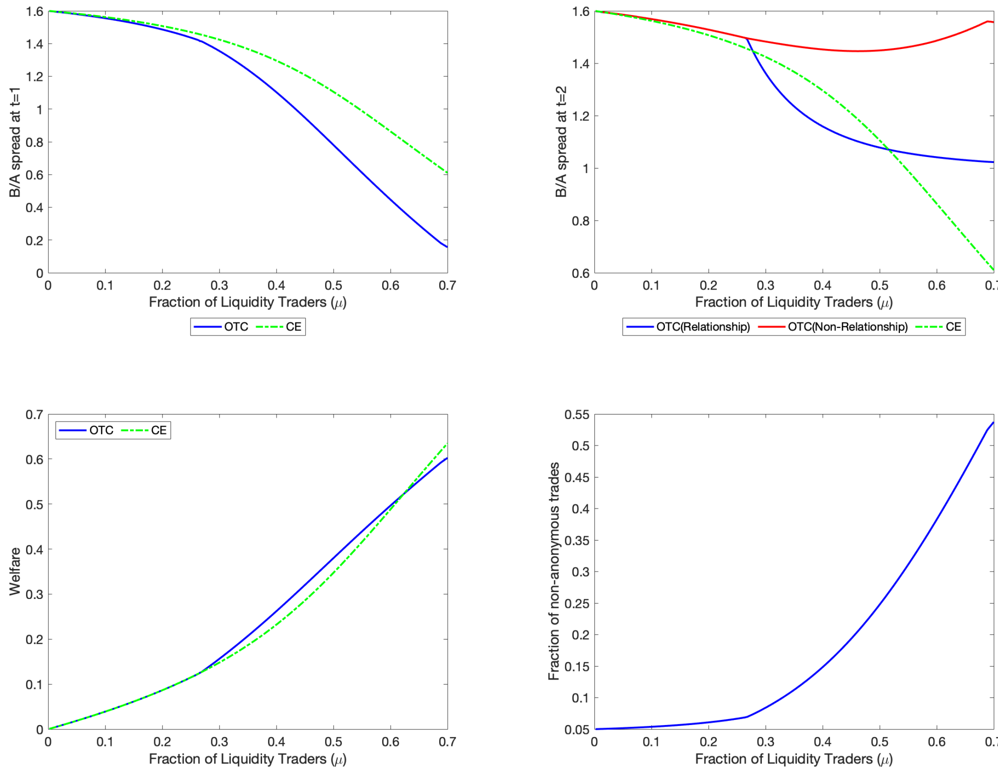

Figure 3: Comparative statics of the welfare and bid-ask spreads with respect to fraction of liquidity traders.

adverse selection is more severe, the non-anonymous trading arrangement yields a higher social welfare and more favorable prices for the relationship traders. This result has an important implication for riskier assets, such as junk-grade bonds. These assets typically have a smaller investor base, partly due to the regulations restricting many institutional investors to invest in safer asset classes. This result suggests that moving these assets to centralized exchanges might make the access to liquidity even harder for the issuing firms and entities, as the anonymity would make the transactions more opaque, which exacerbates the concerns for asymmetric information and adverse selection. Regarding the fraction of non-anonymous trades, as they are mostly conducted with liquidity traders, the more liquidity traders there are, the higher the fraction of non-anonymous trades.

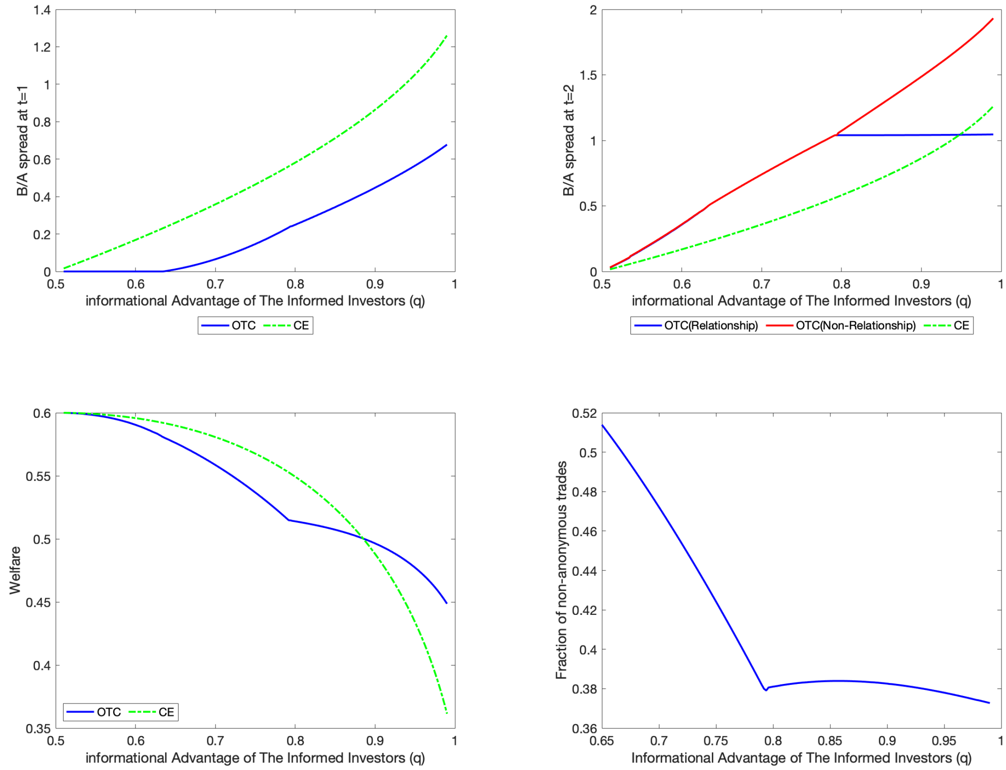

Figure 4: Comparative statics of the welfare and bid-ask spreads with respect to degree of information advantage.

As for the degree of asymmetric information (q), its price and welfare effects are shown in Figure 4. All spreads monotonically increase with q, due to the stronger adverse selection effect. Everything else equal, when q is small, OTC market is in type-1 equilibrium. It migrates to the type-2 equilibrium for sufficiently large values of q. The gap between non-relationship and relationship spreads widens when information becomes more asymmetric, consistent with earlier empirical findings (e.g., See Di Maggio, Kermani, and Song (2017)). Moreover, although welfare in both cases decreases with q, the welfare in the OTC market decreases at a slower pace because learning about counterparties becomes more and more valuable. Eventually, when q is large, welfare in the OTC market surpasses that in the centralized exchange. This is intuitive – relationship is valuable precisely when there is a serious concern about adverse selection. Since the concern for adverse selection is heightened in crisis periods, our results here imply that relationship trading is especially valuable both for liquidity traders and for social welfare during the times of market turmoil. Moreover, as spread increases, it dis-proportionally affects liquidity traders more. As less liquidity traders choose to participate in the market, the fraction of non-anonymous trades drops. Lastly, in Figure 5, we see the spreads are rising and welfare is falling with the asset volatil-

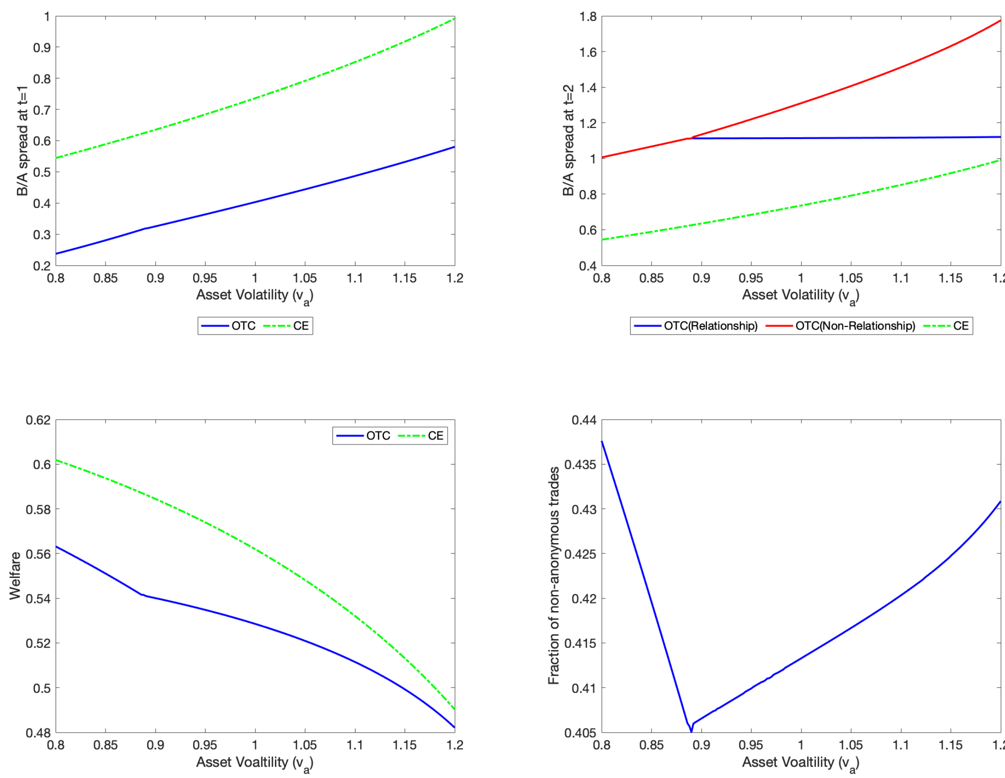

Figure 5: Comparative statics of the welfare and bid-ask spreads with respect to payoff uncertainty.

ity. Interestingly, the relationship traders receive no price improvement for small values of v_a and the welfare is strictly lower than the CE baseline. As shown in the empirical section, in fact in US corporate bond market, we see non-anonymous orders receive no price improvement for investment-grade bonds, whereas the price improvement is positive and significant for junk-grade bonds. As such, data suggests that the non-anonymity is crucial for the liquidity of junk-grade bonds. Similar to before, there are always two opposing forces at play when determining the change in fraction of non-anonymous trades: increase in the volatility increases the spread, which discourages liquidity traders from participating in the market more so than informed traders. As a result, the fraction of non-anonymous trades decreases. But when assets are more volatile, the increase in the spread for anonymous trades is larger than that for non-anonymous trades, which increases the fraction of non-anonymous trades. Hence we see a non-monotone relationship between fraction of non-anonymous trades and asset volatility. We show this is consistent with the data in Section 5.2.2.

5 Empirical Findings

The goal of this section is to empirically verify the pricing implications of our model. Particularly, we study the bid-ask spreads for non-anonymous and anonymous orders in US corporate bond market. For junk-grade bonds, we find a significantly smaller bid-ask spread for the non-anonymous orders, whereas in the case of investment-grade bonds, the non-anonymous orders receive either no or little price improvement. This empirical observation is consistent with our finding that relationship traders receive a price improvement only for assets whose payoff is sufficiently volatile. Furthermore, consistent with our theory, we find that the non-anonymous trades constitute a larger share of the transactions for bonds with a lower credit-rating, for larger traders, and when the market uncertainty measures, such as VIX, are higher. As follows, we first describe our data and empirical methods in Section 5.1, then we report the empirical findings in Section 5.2.

5.1 Data

Our data includes a subset of transactions of US corporate bonds traded on one of the largest electronic trading platforms over the first six months of 2019. It contains 8.6% of the total transactions reported to TRACE over this time period. The platform offers two types of trading protocols: request for quotes (RFQ) and open trading. In RFQ, clients send trading request to one or more dealers, usually the ones that they have relationship with from past interactions; clients then wait for the quotes sent back by the dealers, and choose the best one they want to trade with. The identities of both sides are available to each other through this RFQ process. Conversation with market participants implies there is little room for negotiation, but the quotes that the dealers provide is specific to each client. These trades are what we consider as non-anonymous trades. In open trading, all traders can post quotes to and trade with everyone on the platform, but no one's identity is revealed. These are what we call anonymous trades. Table 1 summarises the comparison of anonymous and non-anonymous trades in our sample, along with all trades reported in TRACE.

Investment Grade

	Our Sample		TRACE
	A	NA	
Number(K)/(%) of Transactions	204.2 /27.8%	484.1/65.9 %	3910.0/92.2 %
Number(K)/(%) of client-dealer transactions	121.2/17.0%	356.3 /49.9%	2070.6/53.0 %
Number(K)/(%) of interdealer transactions	61.3 /8.6%	89.9/12.6%	1322.1/33.8%
Ave. Daily Trading Volume ($M of face value)	552.0/22.9 %	1743.4/72.2%	28830.4/78.4 %
Ave. Trade Size ($K of face value)	335.2	446.6	914.3
Ave. bid/ask spread (one-way, bps)	14.3	15.1	16.7
Number(K)/(%) of Orders	361.0/71.0%	1241.7/20.7%	NA
Fraction of Executed Orders	56.6 %	39.0%	NA
Ave. Waiting Time (mins)[9]	22	36	NA

High Yield

	Our Sample		TRACE
	A	NA	
Number (K)/(%) of Transactions	4.6 /0.7%	41.3 /5.6%	329.3 /7.8%
Number (K)/(%) of client-dealer transactions	2.2 /0.3%	22.0 /3.1%	163.9 /3.9%
Number (K)/(%) of interdealer transactions	2.3 /0.3%	15.4 /2.1%	112.7 /2.7%
Ave. Daily Trading Volume ($M of face value)	11.4 /0.5 %	106.6 /4.4 %	7960.5 /21.6%
Ave. Trade Size ($K of face value)	306.6	319.8	2997.7
Ave. bid/ask spread (one-way, bps)	23.6	19.6	30.8
Number (K)/(%) of Orders	11.1 /0.6%	134.1 /7.7%	NA
Fraction of Executed Orders	41.4%	30.8%	NA
Ave. Waiting Time (mins)[10]	14	15	NA

Table 1: This table reports the key statistics of our sample of transactions and TRACE, for the period between 2019/01/02 and 2019/06/28. "A" represents the set of orders in our sample that are submitted in the anonymous and all-to-all "open" market. "NA" represents the orders submitted through the RFQ system (Request For Quotation), in which the parties' identities are disclosed to their counterparties. The average half-way bid-ask spreads are calculated based on the estimation of linear model (7), without using the controls, a methodology used by Schultz (2001) and Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), among others. The last three rows indicate the number (percentage) of orders, the fraction executed in the platform, and their average waiting time (conditional on execution), for anonymous/non-anonymous orders and investment grade/high yield bonds, respectively.

Eyeballing the numbers in Table 1, we see our sample is a good representative of the transactions reported at TRACE in several aspects, such as the ratio between the number of transactions of investment-grade and high-yield bonds, or the ratio between client-dealer and interdealer transactions. Nevertheless, trading size among our sample is smaller than the average trading size in TRACE, for both investment-grade and high-yield bonds. Moreover, there are relatively more investment-grade trades in our sample compared to that in

TRACE. Both of these features are expected, as the trades conducted on electronic trading platforms are known to be smaller with higher ratings. It suggests that our sample misses a considerable fraction of block-size high-yield transactions. To insulate our empirical results against this difference between our sample and the universe of US corporate bond transactions, we directly control for the trade sizes and ratings in all of our empirical analysis. Moreover, we expect the effect we find here to be even stronger for block trades, since the concern of asymmetric information is more severe for larger quantities of trade.

For each realised transaction in our sample, we have information on its price, quantity, bond characteristics (e.g., the bond cusip, issuer, coupon rate, credit rating), and most importantly, whether the trade initiator disclosed its identity or not. This feature allows us to study the price differences between non-anonymous and anonymous transactions for different types of bonds. Moreover, the dataset contains information on whether a trade order is executed and waiting time between request and execution, conditional on execution. We will use these information to separate our channel from alternative theories of relationship trading, such as "search-based" theories examined by Hendershott, Li, Livdan, and Schuerhoff (2019), among others.

5.2 Empirical Results

5.2.1 Spreads

We match the trades in our dataset with those in TRACE, based on CUSIP and execution time (in seconds). The matching rate is 16.9%. We construct "trade-pairs" using every two consecutive intra-day trades of a given bond in the TRACE dateset. We then regress the price changes in the "trade-pairs" on the direction of trades, interacted with whether the trade is anonymous and whether the underlying bond is investment-grade or junk bonds, along with other control variables. More specifically, we estimate the coefficients in the following linear model.

$$
\begin{aligned}
&\log P_{i,t+1} - \log P_{i,t} = \alpha + \beta(\mathbb{I}^{Buy}_{i,t+1} - \mathbb{I}^{Buy}_{i,t}) + \beta_{Anon}(\mathbb{I}^{Buy}_{i,t+1} - \mathbb{I}^{Buy}_{i,t})(\mathbb{I}^{Anon}_{i,t} + \mathbb{I}^{Anon}_{i,t+1}) \\
&+ \beta_{Junk}\mathbb{I}_{i \text{ is Junk}}(\mathbb{I}^{Buy}_{i,t+1} - \mathbb{I}^{Buy}_{i,t}) + \beta_{Anon,Junk}(\mathbb{I}^{Buy}_{i,t+1} - \mathbb{I}^{Buy}_{i,t})(\mathbb{I}^{Anon}_{i,t} + \mathbb{I}^{Anon}_{i,t+1})\mathbb{I}_{i \text{ is Junk}} \\
&+ Control + \varepsilon_{i,t} \qquad (7)
\end{aligned}
$$

In the equation above, our dependent variable $\log P_{i,t+1} - \log P_{i,t}$ is the percentage price change between two consecutive trades of bond i. The binary variable $\mathbb{I}^{Buy}_{i,t}$ equals to 1 if a client buys the bond from a dealer in this transaction; it equals to 0 if the trade direction is the opposite (inter-dealer transactions are dropped). Similarly, binary variable $\mathbb{I}^{Anon}_{i,t}$ equals to 1 if the trade is conducted anonymously; otherwise it equals to 0. Lastly, binary variable $\mathbb{I}_{i \text{ is Junk}}$ indicates whether the bond is junk-grade (B or BB) or investment grade (A, AA, AAA, or BBB). Controls typically include bond fixed effect at the CUSIP level and quantity of the trades. Note that our dependent variables is constructed based on "trade-pairs" identified in TRACE, but we only include "trade-pairs" in which at least one trade is included in our sample; otherwise, we have no information on whether the trade is executed anonymously or non-anonymously. Moreover, since TRACE does not report the trade size if it exceeds one million dollars, we exclude them as well to be able to control for the impact of trade size in the prices.

The main variables of interest are β_{Anon} and $\beta_{Anon,Junk}$. Compared with investment grade bonds, junk bonds have higher degree of uncertainty in their payoff, hence there is more concern for asymmetric information among market participants. In particular, our theory predicts that $\beta_{Anon,junk} > 0$ and $\beta_{Anon} \simeq 0$.

Table 2 presents our first empirical result. For investment-grade bonds, the half-spread for the non-anonymous orders is slightly less than the anonymous orders, even after controlling

[9] Conditional on execution

[10] Conditional on execution.

Table 2

	Dependent variable:				
	Half-spread				
	(1)	(2)	(3)	(4)	(5)
$\Delta\mathbb{I}_{i,t}^{Buy}$	11.058***	11.050***	11.562***	9.139***	5.455***
	(0.072)	(0.072)	(0.072)	(0.367)	(0.316)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × # anonymous	−1.807***	−1.773***	−1.222***	−1.232***	0.151*
	(0.109)	(0.109)	(0.109)	(0.109)	(0.081)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × junk-rated	6.548***	6.536***	0.219	0.143	0.264
	(0.315)	(0.315)	(0.328)	(0.328)	(0.306)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × junk-rated × # anonymous	4.281***	4.230***	4.621***	4.697***	2.604***
	(0.844)	(0.844)	(0.835)	(0.835)	(0.635)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × log(quantity)		0.087***	−0.067**	−0.065**	−0.125***
		(0.030)	(0.030)	(0.030)	(0.026)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × coupon rate			3.587***	3.588***	2.599***
			(0.060)	(0.060)	(0.053)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × bond age			−0.154***	−0.154***	−0.298***
			(0.023)	(0.023)	(0.021)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × VIX				0.152***	0.054***
				(0.022)	(0.019)
$\Delta\mathbb{I}_{i,t}^{Buy}$ × waiting time					0.015***
					(0.001)
Observations	221,577	221,577	221,577	221,577	107,054
R^2	0.131	0.131	0.149	0.150	0.160
Adjusted R^2	0.131	0.131	0.149	0.149	0.159

Note: *p<0.1; **p<0.05; ***p<0.01

for bond characteristics and the trade size. It implies that relationship clients receive no price improvement compared to anonymous orders for investment-grade bonds.

However, for junk-grade bonds, the non-anonymous orders receive a sizeable price improvement on average. In particular, the half-spread for non-anonymous trades is significantly lower than the anonymous trades. This result suggests that relationship traders receive most of their price improvement on their transactions of junk-grade bonds. It is indeed consistent with the prediction of our model that the price difference only exists for riskier assets, where the concern for asymmetric information is severe. The results are consistent across different specifications.

In column (5), we take one step further to see whether the price differences could be explained by the differences in the waiting times. In fact, as search-based theories of relationship trading would suggest, relationship traders can locate a counter-party for their orders faster, which improves the prices they are offered. We see that more than half of the price improvement remains ($2.6/4.6 \sim 57\%$) even when we control for waiting time in the analysis. Furthermore, the effect of waiting time is economically small compared to the overall effect of anonymous trading. This confirms that our theory of relationship trading, traders form trading relationships to reduce adverse selection, contributes significantly to the price differences.

5.2.2 Fraction of Anonymous-trades

Our theory predicts that the fraction of anonymous trades is non-monotone in uncertainty. To test this empirically, we run a logistic regression of the probability of a trade being executed anonymously on the bond ratings and VIX at the time of trade, which measures the macro-uncertainty.

$$\mathbb{I}_{i,t}^{Anon} = \alpha + \sum_{j \in ratings} \beta_j \mathbb{I}_{i \text{ is rating } j} + \beta_q \log(Q_t) + \beta_{VIX} VIX_t + Control + \epsilon_{i,t} \quad (8)$$

Rating approximates idiosyncratic uncertainty of each bond, whereas VIX approximates aggregate uncertainty. In our model, we do not differentiate idiosyncratic vs aggregate uncertainty. Since both contributes to the uncertainty of bonds' final payoff, our model predicts that fraction of anonymous trades is lower for bonds with low ratings and at times when VIX is high.

Table 3 reports our findings. In general, junk bonds are much more likely to be executed through relationships. Second, VIX also impacts whether trades are more likely to be executed anonymously or not. In a high uncertainty environment, more trades are executed non-anonymously. This observation is consistent with our theory that the trading relationships are more beneficial when the underlying asset is riskier.

Taking a closer look at the coefficient for rating dummies, we see that it is consistent with the non-monotone prediction of our model. For intermediate level of asymmetric information, the dealers widens the bid-ask spreads for both anonymous and non-anonymous orders. It makes it more expensive for liquidity traders to trade and build trading relationships regarding those assets, increasing the fraction of anonymous trades. This finding is robust across multiple specifications.

5.2.3 Waiting Time and Execution Probability

To differentiate our channel with search-based theories of relationship trading, we compare the waiting time and execution probability in the anonymous and non-anonymous markets. Theories built upon search frictions would attribute the higher bid-ask spreads in the anonymous market to higher search frictions in that market, i.e. it takes more time, or even

Table 3

	Dependent variable:			
	non-anonymous			
	(1)	(2)	(3)	(4)
AAA	0.712***	0.581***	0.549***	0.540***
	(0.003)	(0.005)	(0.005)	(0.006)
AA	0.689***	0.560***	0.530***	0.521***
	(0.001)	(0.004)	(0.004)	(0.005)
A	0.700***	0.571***	0.535***	0.526***
	(0.000)	(0.003)	(0.003)	(0.005)
BBB	0.707***	0.574***	0.518***	0.509***
	(0.000)	(0.003)	(0.004)	(0.005)
BB	0.894***	0.760***	0.670***	0.661***
	(0.002)	(0.004)	(0.005)	(0.006)
B	0.948***	0.812***	0.700***	0.691***
	(0.006)	(0.007)	(0.008)	(0.009)
log(quantity)		0.012***	0.009***	0.009***
		(0.0003)	(0.0003)	(0.0003)
coupon rate			0.030***	0.030***
			(0.001)	(0.001)
bond age			−0.011***	−0.011***
			(0.0002)	(0.0002)
VIX				0.001***
				(0.0002)
Observations	734,247	734,247	734,247	734,247
R^2	0.011	0.014	0.020	0.020
Adjusted R^2	0.011	0.014	0.020	0.020

Note: *p<0.1; **p<0.05; ***p<0.01

less likely, to find a counter-party. Whereas, in the non-anonymous market, relationships reduce search costs and lead to lower bid-ask spreads. We run the following regressions to see if it is indeed true that the anonymous market has higher search frictions. We interpret longer waiting time and lower execution probability as higher search frictions.

$$\begin{aligned}
\text{Waiting time}_{i,t} =& \alpha + \beta_{Anon}\mathbb{I}^{Anon}_{i,t} + \beta_{Junk}\mathbb{I}_{i \text{ is Junk}} + \beta_{Anon,Junk}\mathbb{I}^{Anon}_{i,t}\mathbb{I}_{i \text{ is Junk}} \\
& + Controls + \epsilon_{i,t} \qquad (9) \\
\mathbb{I}_{\text{failed-to-execute}i,t} =& \alpha + \beta_{Anon}\mathbb{I}^{Anon}_{i,t} + \beta_{Junk}\mathbb{I}_{i \text{ is Junk}} + \beta_{Anon,Junk}\mathbb{I}^{Anon}_{i,t}\mathbb{I}_{i \text{ is Junk}} \\
& + Controls + \epsilon_{i,t} \qquad (10)
\end{aligned}$$

Waiting time is the time between order request and execution. It is measured in minutes, and is only available for trades that are executed. Furthermore, we only include trades whose waiting time is more than five minutes, to rule out pre-arranged trades, as observed by Schultz (2017) and Goldstein and Hotchkiss (2020), among others. We label an order as failed-to-execute if we could not identify that trade in TRACE. A small fraction of orders can be filled partially. By our labelling rule, partially-filled orders are also classified as failed-to-execute. We think this is reasonable, because the order is not satisfied as initially requested. Even if one considers this classification to be extreme, the fraction of orders that can be partially filled is less than 0.5% and we do not expect it to be driving our results.

Tables 4 and 5 present our findings. For investment grade bonds, we see lower execution probability for anonymous trades but shorter waiting time conditional on being executed successfully. The reason that anonymous trades might be answered in a shorter time frame is because anonymous trade requests are essentially sent to everyone active on the platform; this larger potential counterparty pool could reduce search frictions. For junk bonds, the waiting time for anonymous and non-anonymous orders is virtually the same, and the difference in execution probability between anonymous and non-anonymous trades is actually smaller than that for investment grade bonds. This implies that the difference in spreads should be smaller in junk bonds than in investment-grade bonds[11], which contradicts with what we find in the previous section. It suggests that execution probabilities cannot explain the differences observed in the prices. On the contrary, this result is fully consistent with our theory that more favorable prices are offered to relationship trades because the concern for asymmetric information, typically more severe for junk-grade bonds, is reduced.

[11] Here we are referring to a diff-in-diff measurement. More specifically, denote the difference in spreads for investment-grade bonds as ΔBA_{inv}, denote the difference in spreads for junk bonds as ΔBA_{junk}. Our previous finding indicates $\Delta BA_{junk} - \Delta BA_{inv} > 0$. This contradicts with what search theories would predict, given the empirical differences in execution probability.

Table 4

	Dependent variable:			
	Waiting Time (mins)			
	(1)	(2)	(3)	(4)
junk-rated	−19.583***	−19.954***	−31.853***	−32.057***
	(0.336)	(0.331)	(0.350)	(0.349)
anonymous	−13.751***	−12.320***	−11.044***	−11.045***
	(0.163)	(0.161)	(0.160)	(0.160)
junk-rated × anonymous	13.856***	11.746***	14.312***	14.413***
	(1.092)	(1.078)	(1.069)	(1.068)
log(quantity)		4.834***	4.291***	4.293***
		(0.036)	(0.036)	(0.036)
coupon rate			7.286***	7.284***
			(0.070)	(0.070)
bond age			−1.742***	−1.742***
			(0.026)	(0.026)
VIX				0.672***
				(0.027)
Observations	662,944	662,944	662,944	662,944
R^2	0.014	0.040	0.056	0.057
Adjusted R^2	0.014	0.040	0.056	0.057
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5

	Dependent variable:			
	Chance of execution			
	(1)	(2)	(3)	(4)
junk-rated	-0.688^{***}	-0.540^{***}	-0.328^{***}	-0.328^{***}
	(0.021)	(0.023)	(0.023)	(0.023)
non-anonymous	0.526^{***}	0.669^{***}	0.660^{***}	0.661^{***}
	(0.004)	(0.005)	(0.005)	(0.005)
log(quantity)		-0.700^{***}	-0.694^{***}	-0.694^{***}
		(0.001)	(0.002)	(0.002)
junk rated × non-anonymous	-0.048^{**}	-0.129^{***}	-0.091^{***}	-0.092^{***}
	(0.022)	(0.024)	(0.024)	(0.024)
coupon rate			-0.137^{***}	-0.137^{***}
			(0.002)	(0.002)
bond age			-0.013^{***}	-0.013^{***}
			(0.001)	(0.001)
VIX				0.004^{***}
				(0.001)
Observations	1,574,297	1,574,297	1,574,297	1,574,297
Log Likelihood	−1,016,812.000	−871,920.100	−867,211.400	−867,196.100
Note:				*p<0.1; **p<0.05; ***p<0.01

6 Conclusion

In this paper, we analyze the pricing and welfare implications of non-anonymous trading and identify under what conditions it improves the market liquidity and efficiency of allocations. The non-anonymity feature allows the market participants to learn valuable information about their counterparties through repeated interactions and consequently enables them to form trading relationships. We find the non-anonymity feature improves the liquidity (reduces bid-ask spreads) for riskier assets, assets with a high level of asymmetric information, and/or assets whose investor-base are more populated with informed traders.

We test the model predictions using a novel dataset on U.S. corporate bond trades. We find that relationship traders receive a substantial price improvement in their transactions of riskier bonds, such as junk-grade bonds (about 20%), whereas the price improvement disappears for less riskier ones, such as investment-grade bonds. We also confirm the fraction of anonymous trades behave as the model predicts, i.e. it first decrease then increase with asset payoff uncertainty. Lastly, we present evidence that supports our channel of relationship building but is inconsistent with search-based theories.

Our paper contributes to the policy debate of whether it is welfare-improving to move OTC markets to centralised exchanges. The estimated size of price-improvement of staying in OTC markets is both economically and statistically significant. However, given our sample skews towards smaller trades on average and the fact we are also ignoring other liquidity benefits of centralised market (for example, price transparency), we cannot make welfare claims on the entire market. It would be interesting to construct a richer model that takes into account trading size, the benefit of relationships and other liquidity concerns to structurally quantify the cost and benefit of the two types of market structures. We leave that to future work.

The implications of our findings are not restricted to OTC markets and carries over to other trading venues that have some degree of non-anonymity. For instance, dark pools constitute another example of the importance of the non-anonymity in liquidity provision. Dark pools are an important source of liquidity for institutional investors, as they lower their price impact in their large transactions. However, the cheaper liquidity is also attractive to the speculators, such as hedge funds. As such, to preserve the liquidity, participants with suspicious trading patterns should be detected and their access should be restricted by the venue owners. That of course requires the participants to revel their identity. Our theory marks a novel justification for the emergence of exclusive trading venues.

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