Why Trade Over the Counter?*

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Abstract

Over-the-counter trading dominates in many highly liquid assets. We provide an explanation: OTC trading is privately optimal for traders who are likely uninformed. Traders choose between an exchange and a dealer, who cream-skims those likely uninformed. Closing the OTC market directly causes certain traders to exit, while inducing some others to enter by improving prices on the exchange. Overall, closing the OTC market raises welfare for assets whose trades are *mostly* over the counter, despite reducing aggregate trade volume and widening average bid-ask spread. We predict and document a positive correlation between the market share of exchanges and their quoted spreads.

JEL-Classification: D47, G14, G18, G23

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1 Introduction

Opaque and hard-to-access over-the-counter markets dominate the trading of many assets tradable on transparent and easily accessible exchanges.[1] The typical explanation for this OTC dominance is that certain assets are complex or non-standard. Such assets might attract few traders, and this illiquidity makes trading on exchanges impractical. The illiquidity explanation implies little role for policy intervention in OTC markets—OTC trading occurs where exchanges are comparably inefficient. This argument is frequently cited against regulation of OTC markets (Section 5.2). The illiquidity explanation can clearly account for complex or non-standard assets that are seldom-traded, including high-yield corporate bonds, collateralized debt obligations, and single-name credit default swaps. However, numerous platforms offer exchange trading of standardized swaps, the most liquid derivative, yet 95% of its trades are over the counter (Nagel, 2016). Treasuries, repurchase agreements, and foreign exchange are similarly liquid, exchange-tradable, and mostly traded over the counter.[2] Even among US exchange-listed equities, the majority of dollar volume is traded over the counter for 12% (373) of them (Section 4.1). We provide the first explanation for the OTC dominance of liquid and exchange-tradable assets. In doing so, we show that the equilibrium outcome starkly deviates from the efficient outcome: closing the OTC market would raise welfare for the most OTC-traded assets, such as standardized swaps and Treasuries. This result is novel in the literature, and helps justify the aims of MiFID II and the Dodd-Frank Act to ban or shift trades away from the OTC market.

Our explanation builds on a fundamental feature of OTC markets: the dealers' ability to price discriminate among their customers. Price quotes on an exchange are publicly available to all traders. To trade over the counter, a trader must request quotes from a dealer, which

[1] In our context, "over-the-counter (OTC) markets" consist of all financial markets in which trades are executed nonanonymously between a client and a dealer. This definition includes traditional voice markets in which clients contact dealers one-by-one, and request-for-quote markets in which clients contact multiple dealers at a time. "Exchanges" include all other markets, including limit order books (e.g., stock exchanges), dark pools, and batch auctions.

[2] Treasuries are tradable on several centralized exchanges while EU government bonds are listed on exchanges by regulation (Group of Thirty Working Group on Treasury Market Liquidity, 2021). Examples of widely accessible exchanges include Saxo Bank SaxoTrader for government bonds, Tradeweb Dealerweb for repos, and Refinitiv FXall for foreign exchange, all of which are open to any buy-side trading firms.

reveals her identity and allows the dealer to offer a trader-specific price. This way the dealer can offer a discount to those who pose low adverse selection risk, *cream-skimming* them into the OTC market. To illustrate, between a low-risk insurer and a high-risk hedge fund, the dealer would price discriminate to the insurer's benefit. Consequently, the insurer seeks out the dealer while the hedge fund trades on the exchange. Under our explanation, liquid fixed income assets are OTC dominated because they mainly attract traders who pose low adverse selection risk, including insurers and passive funds.[3]

While cream-skimming explains the OTC dominance of liquid assets, we consider other key elements of financial markets to examine whether cream-skimming is socially efficient. As with prices, trading decisions are endogenous. The traders differ in their gains from trade. Moreover, a dealer cannot perfectly distinguish an informed trader from an uninformed one—sometimes, hedge funds have liquidity needs and insurers trade on proprietary information. Because endogenous trading and imperfect information are crucial for empirics and policy, we incorporate them into our analysis.

We develop a model of venue choice in which traders buy or sell an asset with an uncertain payoff. Uninformed traders have heterogeneous hedging benefits that incentivize them to trade. Informed traders receive imperfect signals about the asset payoff and seek profit. Whether a trader is informed or not is the trader's private information, which is imperfectly indicated by her public label either as *Likely Informed (LI-traders)* or *Likely Uninformed (LU-traders)*. All traders optimally choose between trading on an exchange, with a dealer over the counter, or exit. The venues differ solely in that the dealer can condition his prices on each trader's label. In equilibrium, the LI-traders endogenously choose the exchange and the LU-traders choose the OTC market, and thus the share of OTC trades is increasing in the fraction of the uninformed traders.

[3] In Section 4.3, we cite evidence that trades are rarely informative in corporate bonds and repurchase agreements. Moreover, government bonds are more OTC traded than their futures, and indeed much of the price discovery in government bonds occur in the futures market, not the spot market. Likewise, equity options are more OTC traded than equities, and in fact equity prices predict equity option prices, not the reverse. For index credit default swaps and interest rate swaps, the evidence is mixed on whether their prices lag or lead equity and interest rate futures prices, respectively. The evidence is also mixed for single-name CDS (which is outside the scope of this paper as they are illiquid and has no viable exchange). DeMarzo (2005) would predict a substantially lower adverse selection risk in index CDS than in single-name CDS due to the information destruction effect of pooling.

The efficient outcome is the *opposite* of the equilibrium outcome in our model: closing the OTC market raises utilitarian welfare for assets that are mostly OTC-traded. This result follow from (1) the OTC market share is high for assets that attract relatively few informed traders, in which case (2) welfare is higher without the OTC market. In addition, closing the OTC market can raise welfare while reducing aggregate trade volume and widening the average bid-ask spread. Therefore, neither trade volumes nor spreads are good guides for policy. The dichotomy between the effects on welfare and volume can be stark. Under our baseline model, closing the OTC market always reduces volume whereas it raises welfare if the share of the informed traders is below a single cutoff. We find analogous effects when the traders' labels become less accurate, perhaps as a result of laxer disclosure rules.

Closing the OTC market can raise welfare while reducing aggregate trade volume, because the traders who are pushed out upon closing the OTC market ("exiters") have lower hedging benefits than those who are induced to trade ("entrants"). To elaborate, upon closing the OTC market, the "No-OTC" spread on the exchange S_{N} is higher than the spread the LU-traders would have received over the counter, pushing some of them to exit. Meanwhile, the greater presence of uninformed traders on the exchange reduces its quoted spread *down* to the No-OTC spread S_{N} and induces some, who otherwise would not trade, to do so. Thus, any exiter's hedging benefit must be below the No-OTC spread S_{N} and any entrant's hedging benefit must be above S_{N}—the entrants substitute for the comparably "cheap" exiters. Although aggregate trade volume falls whenever the exiters outnumber the entrants, *cheap substitution* can overturn this negative effect on welfare.

Precisely, closing the OTC market raises welfare if there are few informed traders and harms welfare if there are many. The effect of closing the OTC market on welfare depends on the trade-off between cheap substitution, which raises welfare, and a possible reduction in volume. Cheap substitution is most pronounced with few informed traders, and vanishes with many informed traders. It vanishes here because the entrant's hedging benefits increase while being bounded above by the (constant) spread that would be quoted if all traders were informed, allowing the exiters' relatively lower hedging benefits to "catch up". The reduction in volume turns out to vanish with few informed traders and be the most pronounced with many. Therefore with few informed traders, the effect of cheap substitution dominates and closing the OTC market raises welfare. The reverse is true with many informed traders.

Our model generates a testable empirical prediction that the market share of the exchange and its quoted spread are positively correlated. Adding informed traders worsens adverse selection risk, widening the spreads while relatively more trades occur on the exchange. Hence, both the exchange market share and its quoted spread increase with the share of informed traders. We investigate our prediction using US equities and find a positive correlation between the market share of exchanges and their quoted spreads. Our finding holds in every quintile of equities by dollar volume with ticker-level clustered standard errors and time fixed effects, and is robust to controlling for proxies of liquidity.

The market share of exchanges is a new proxy for the amount of informed trading in our theory, based on the tight link from the informed traders to the exchange market share. It can be calculated from aggregate quantities that are easy to measure. Alternative proxies, including price impact and measures of bid-ask spread, require prevailing prices or frequently observed quotes which are unavailable for many assets.

Whether the OTC market is socially beneficial has become an increasingly relevant question as regulators impose unprecedented restraints on OTC trading. For example, beyond Dodd-Frank and MiFID II, in 2020 the Commodities and Futures Trading Commission banned a practice called "name give-up" in the swaps market, in part to boost trading on exchanges. Most recently, proposals to implement blockchain for financial transactions would reveal traders' identities to selected dealers. Our results speak to the welfare implications of these plans and policies.

We make three contributions to the literature discussed shortly. First, we contribute the first theory to explain the OTC dominance of many liquid and standardized assets. Second, we provide novel guidance for policymakers, namely that closing the OTC market improves welfare for assets with few informed traders. In particular, closing the OTC market improves welfare for OTC-dominated assets. Third, we are the first to theoretically predict and to document a *positive* correlation between the market share of exchanges and their average spread. We do so by showing that the exchange market share is a proxy for informed trading, adding an easy-to-obtain measure of informed trading to the literature.

Most closely related to us are the studies of venue choice between centralized and OTC markets.[4] One strand in this literature abstracts away from adverse selection and focuses on the presence of search frictions (Pagano, 1989, Rust and Hall, 2003) or limited trading capacity (Dugast, Üslü and Weill, 2022) in OTC markets. This strand does not explain why many liquid and standardized assets are OTC dominated.[5] Others, like this paper, have cream-skimming driven by price discrimination (Seppi, 1990, Desgranges and Foucault, 2005).[6] Because private values are homogenous in these models, they cannot feature cheap substitution from which we derive our results on welfare. Seppi (1990) explains why trade sizes over the counter are larger than the sizes on exchanges for a given asset, without explaining why some assets are more often traded over the counter than others. The key parameter of Seppi (1990), the size of an order by a large trader relative to the order size of a small trader, lacks an obvious interpretation for cross-asset prediction. Desgranges and Foucault (2005) examines how a dealer can screen out informed trades over repeated interactions. They show that OTC trading is viable if traders are sufficiently likely to be informed (their Proposition 5). Thereby they would predict a negative relationship between the exchange market share and its quoted spread—the opposite of our prediction.

We belong to the enduring literature that compares centralized and OTC markets. Benveniste, Marcus and Wilhelm (1992), Pagano and Roell (1996), Malinova and Park (2013), Glode and Opp (2019) compare a case with only the exchange against one with just the OTC market. Without endogenous venue choice, this literature cannot explain why certain assets are more OTC-traded than others, and cannot study the effects of removing OTC trading as an option.

Section 2 describes the model then derives its unique equilibrium and empirical predic-

[4]A somewhat-related literature studies the choice between a limit order book and a specialist (who represented exchanges on the trading floor). Ready (1999), Parlour and Seppi (2003) allow the specialist to stop an incoming order, observe the subsequent order flow, then choose whether to execute the order on her own account.

[5]Rust and Hall (2003) is the closest in the strand to explain the OTC dominance of such assets, in particular steel, with the lack of expertise in operating electronic exchanges for steel at the time. This explanation does not apply to the OTC dominance of steel or other liquid assets today.

[6]We are more distantly related to the literature on how traders choose between separate exchanges in the presence of adverse selection (e.g., Hendershott and Mendelson, 2000, Zhu, 2014, Pagnotta and Philippon, 2018, Lee, 2019, Chao, Yao and Ye, 2019, Babus and Parlatore, 2021, Baldauf and Mollner, 2021). In these models, a centralized mechanism determines the price at each exchange.

tions. Section 3 analyzes utilitarian welfare, aggregate trade volume, and quoted spread (1) upon closing the OTC market or (2) as the traders' labels become less accurate. Section 4 documents empirical patterns predicted by our model and summarizes existing stylized facts related to our theory. Section 5 discusses the policy implications of our results. Section 6 concludes with a discussion of some potentially important effects that are not captured by our model.

2 A Model of Venue Choice

We first setup the model, which extends Glosten and Milgrom (1985) with endogenous venue choice and imperfect labels for the types of traders. Later we discuss our assumptions in Section 2.2 and derive the unique equilibrium in Section 2.3.

2.1 Setup

A dealer, a market maker, a mass μ of informed traders, and a mass 1 of uninformed traders, all risk-neutral, trade an indivisible asset in a three-stage game. A trader buys or sells 1 unit, or exits without trading. The dealer acts as the counterparty to the traders and absorbs net demand in an OTC market. The market maker does so on the exchange. The asset is equally likely to pay $v = 1$ or -1 in the last stage.

An informed trader has a private binary signal which equals the true value v with probability $\alpha \in (1/2, 1)$ and $-v$ otherwise. That is, probability α is the precision of the informed traders' signals. Each uninformed trader is equally likely to be a buyer or a seller, and obtains a hedging benefit b_i upon trading in her desired direction. The hedging benefits are uniformly distributed over $[0, 1]$, $b_i \overset{\text{iid}}{\sim} \mathbb{U}[0, 1]$. Whether an uninformed trader is a buyer or a seller and her realized hedging benefit b_i are her private information.

An informed trader is labeled $\ell_i = LI$ with probability θ. An uninformed trader is LI with probability $1 - \gamma$. Otherwise, a trader is LU. LI-traders are "Labeled Informed" and LU-traders are "Labeled Uninformed". The labels are informative, $\theta > 1 - \gamma$, in that an LI-trader is more likely to be informed than an LU-trader. The labels become more informative as their accuracy θ or γ increases. We assume $\theta < 1$ and $\gamma < 1$, so that the labels are imperfectly informative.

In Stage 1, the dealer posts a bid to buy and an ask to sell one unit of the asset to every trader i. The dealer's price can depend on the trader's label $\ell_i \in \{LI, LU\}$. The market maker posts one bid and one ask for all traders. Prices are competitive in each market: the dealer offers the highest bid and the lowest ask to earn a zero expected profit conditional on the label ℓ_i, while the market maker does so unconditionally. That is, the OTC market differs from the exchange in one way, that the dealer observes the label ℓ_i before setting the prices for trader i.

In Stage 2, every trader makes two decisions: *whether* to buy, sell, or not trade, and *where* to trade. Figure 1 summarizes the timing of the model. All distributions, parameters, and the structure of the game are common knowledge.

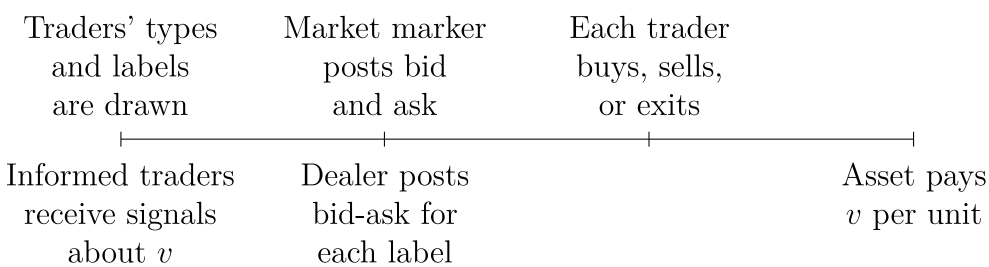

Figure 1: Timing

We impose a tie-breaking rule to pin down a unique equilibrium.

Assumption 1. *If indifferent between trading over the counter or on the exchange, a trader chooses to trade on the exchange.*

Assumption 1 is purely expositional, as our results only require that an otherwise indifferent trader chooses the exchange with a positive probability.[7] The rule is equivalent to imposing a small cost on OTC trades, which can represent the inconvenience of soliciting prices that is absent on exchanges.

[7] Every equilibria that would exist without Assumption 1 are payoff equivalent.

2.2 Discussion

Our setup features competitive prices as defined by Glosten and Milgrom (1985). That prices on exchanges are competitive is a good proxy of reality. However, search friction and dealer market power make OTC prices far from competitive in practice. We assume competitive OTC prices without any search friction to show that, despite making the OTC market artificially efficient, it can nonetheless raise welfare upon closing the OTC market. Granting monopoly power to the dealer would increase the social benefit of closing the OTC market, as the dealer would still cream-skim from the exchange while offering worse-than-competitive prices.

The dealer in the model posts label-dependent prices. In practice, a trader approaches dealers with requests-for-quote (RFQ), and the dealers quote trader-specific prices upon receiving the RFQ. If, in the model, traders must submit an RFQ to trade over the counter, there would be two equilibria: one is the equilibrium solved below. The other is a degenerate equilibrium in which no trader sends an RFQ and no one trades over the counter. This degenerate equilibrium is not a sequential equilibrium, as it can only be supported by the dealer's belief that any trader (LU or LI) requesting a quote is more likely to be informed than its unconditional prior. Such off-equilibrium beliefs are ruled out by the sequential equilibrium refinement. We let the dealer post label-dependent prices instead of responding to an RFQ so that the dealer never faces an off-equilibrium information set, eliminating the degenerate equilibrium.

We interpret a trader's label as a summary statistic of her observable characteristics and reputation. The observables may include the trader's industry (hedge fund versus insurer), marketing or public filings (active versus passive fund), name ("Two-Sigma" versus "AIG"), and any public factoid that is informative about the trader's motive. The labels are imperfectly informative since the true motive behind a trade is not known for certain. This uncertainty is illustrated in the commodities futures market, where the US Commodity Futures Trading Commission classifies traders based on their typical strategies. Cheng and Xiong (2014) find that the trades of "hedgers" often deviate from their label. The hedgers' trades are far more volatile than output, and the volatility is especially high in their short positions. These positions are consistently profitable and uncorrelated with output, which suggests that even the traders who typically hedge sometimes speculate.

We fix the mass of uninformed traders and will vary the mass of informed traders μ in the welfare analysis. This choice ensures that the maximum welfare that can be achieved is fixed and equal to the total hedging benefit of all uninformed traders.

2.3 Equilibrium

A Nash equilibrium consists of the dealer's and the market maker's price setting strategies, and the traders' venue choice and trading strategies. Each trader maximizes her expected profit while the dealer and the market maker offers the highest bid and the lowest ask to earn zero expected profit.

We study the equilibrium without OTC trading, then introduce venue choice. Here, the market maker posts one bid and one ask price symmetrically around zero, and thus his strategy is summarized by the half bid-ask spread s. For brevity, we write "half bid-ask spread" and "spread" interchangeably. The equilibrium spread $S(\beta)$ is the smallest solution to the market maker's zero profit condition

$$\underbrace{s \cdot (1-s)}_{\substack{\text{Profit from} \\ \text{uninformed traders}}} = \underbrace{(2\alpha - 1 - s)^{+} \cdot \beta}_{\text{Loss to informed traders}}, \tag{1}$$

where β denotes the *informed ratio*, the ratio of the mass of informed traders to the mass of uninformed traders who *choose* a given market.[8] Under this No-OTC case, the informed ratio on the exchange is $\beta = \mu/1 = \mu$. The market maker's profit from uninformed traders is $s \cdot (1-s)$. He earns the spread s per trade with an uninformed trader. As each uninformed trader trades if and only if her hedging benefit exceeds the spread s, a mass $(1-s)$ of them actually trade. The market maker's loss to the informed traders is $(2\alpha - 1 - s)^{+} \cdot \beta$ because every informed trader trades if and only if her expected profit $(2\alpha - 1)$ exceeds the spread s. The market maker thereby suffers an expected loss of $(2\alpha - 1 - s)^{+}$ per unit mass of informed traders. The zero-profit condition (1) has a unique solution that we denote as

[8] We say "a trader chooses a market" if the trader would trade in that market were she forced to trade.

$S(\beta)$. Formally, this is Proposition 0 Part (a). Proofs are in Appendix A.

Proposition 0. *(a) If the OTC market is closed, the equilibrium spread on the exchange is the No-OTC spread $S_N = S(\mu)$. (b) If the OTC market is open, every LU-trader chooses the OTC market and receives the OTC spread $S_O = S\left(\frac{1-\theta}{\gamma}\,\mu\right)$ in equilibrium, and every LI-trader chooses the exchange and receives the exchange spread $S_E = S\left(\frac{\theta}{1-\gamma}\,\mu\right)$.*

Part (a) is a standard result of Glosten and Milgrom (1985) and follows from the definition of competitive prices as the highest bid and the lowest ask that satisfy the zero profit condition (1). Part (b) incorporates venue choice by allowing OTC trading. The LU-traders would receive a lower spread alone than if all traders are pooled together. The LI-traders would receive a higher spread alone. Thus, the LU-traders want to separate while the LI-traders wish to pool. To avoid being pooled by the LI-traders, the LU-traders choose the label-dependent OTC spread. The LI-traders, unable to pool over the counter, choose the exchange due to the tie-breaking Assumption 1.[9] Hence in equilibrium, those who are less likely to be informed are cream-skimmed into the OTC market.

2.4 Empirical Predictions

Cream-skimming supplies a battery of testable predictions. As our leading prediction, the assets that mostly attract traders who pose low adverse selection risk (say, insurers and passive funds) have high OTC market shares. Equivalently, most trades are uninformative in OTC-dominated assets. Second, trading costs over the counter are lower than on exchanges. Third, the share of trades on exchanges and the exchanges' quoted spreads are positively correlated, driven by variation in informed trading. Proposition 1 formalizes these predictions.

We let V_{O} denote the equilibrium volume of trades over the counter, V_{E} the trade volume on the exchange, and $V := V_{\mathrm{O}} + V_{\mathrm{E}}$ the aggregate trade volume.[10] Market shares are V_{O}/V

[9] We can relax Assumption 1 to have the traders indifferent between the exchange or the OTC market choose the exchange with probability $\rho > 0$. Then, all LU-traders choose the OTC market, while ρ share of LI-traders choose the exchange and $1-\rho$ share choose the OTC market. All results are unchanged under this relaxed assumption.

[10] Explicitly, $V_{\mathrm{O}} = (1-\theta)\mu + \gamma \cdot (1 - S_{\mathrm{O}})$, $V_{\mathrm{E}} = \theta\mu + (1-\gamma)\cdot(1 - S_{\mathrm{E}})$, $m_{\mathrm{LU}} = (1-\theta)\mu + \gamma$, and $m_{\mathrm{LI}} = \theta\mu + 1 - \gamma$.

over the counter and V_{E}/V on the exchange. The mass of LU-traders is denoted m_{LU} and the mass of LI-traders is m_{LI}.

Proposition 1. *(a) For any given $\underline{O} \in (0,1)$, the set of label accuracies (θ, γ) such that the OTC market share $V_O/V > \underline{O}$ is non-empty and strictly expanding as the mass of informed traders μ decreases. (b) The exchange spread S_E is strictly higher than the OTC spread S_O. (c) Both the exchange spread S_E and its market share V_{E}/V are strictly increasing in the informed mass μ for given label accuracies (θ, γ).*

Part (a) rests on the OTC market share V_{O}/V being strictly decreasing in the mass of informed traders μ, as Part (c) shows. Then high OTC market share is easier to attain with fewer informed traders. An additional, technical argument in Appendix A.1 proves that it is *strictly* easier. Part (b) is a direct consequence of cream-skimming. Part (c) is due to a mechanical increase in the ratio of LI- to LU-traders as the mass of informed traders μ increases. When there are an additional $\mathrm{d}\mu$ mass of informed traders, a mass $\mathrm{d}m_{\mathrm{LI}} := \theta \mathrm{d}\mu$ of them are labeled as Likely Informed and the remaining $\mathrm{d}m_{\mathrm{LU}} := (1-\theta)\mathrm{d}\mu$ as Likely Uninformed. The resulting growth rate in the LI-traders $\mathrm{d}m_{\mathrm{LI}}/m_{\mathrm{LI}}$ is strictly smaller than that for the LU-traders $\mathrm{d}m_{\mathrm{LU}}/m_{\mathrm{LU}}$. Hence, the ratio of LI- to LU-traders increases, which in turn raises the exchange market share V_{E}/V.

We cite evidence related to the predictions of Parts (a) and (b) in Section 4.3. To test Part (c), we require observations to share similar trader label accuracies (θ, γ) while varying substantively in the mass of informed traders μ. We use cross-asset variation within narrowly defined asset classes for this test. Across assets within a narrow asset class (say, Alphabet (GOOG) and Apple (APPL) stocks), the amount of available information about their individual traders (for example, the type of firm, reputation, past disclosures) is similar, so their trader label accuracies are also similar. Meanwhile even within a narrow asset class, a cross-asset variation in the informed mass μ arises from day-to-day changes in the composition of the true types of traders (GOOG might attract more informed traders than AAPL on dates with more news about GOOG). In Section 4.2, our choice of the narrow asset class is US-listed stocks in the same quintile by dollar volume. We document a positive correlation between exchange market share and exchange quoted spreads within every quintile.

3 Welfare, Volume, and Spread

This section analyzes utilitarian welfare, aggregate trade volume, and quoted spread as (1) the OTC market is closed or (2) traders' labels become less accurate.

3.1 Cheap Substitution

Our main result is that closing the OTC market would raise welfare where OTC market share V_{O}/V is high and reduce welfare if the share V_{O}/V is low. *Welfare* W is the sum of all agents' payoffs, which equals the total hedging benefit gained from trade.

Proposition 2. *(a) Closing the OTC market strictly raises welfare if the OTC market share V_O/V is above a single cutoff, and strictly reduces welfare if the share V_O/V is below the single cutoff. (b) For any $\theta_0, \theta_1 \in (1-\gamma, 1), \theta_1 > \theta_0$, lowering label accuracy θ from θ_1 to θ_0 strictly raises welfare if the OTC market share V_O/V is above a single cutoff, and strictly reduces welfare if the share V_O/V is below the single cutoff.*

Proposition 2 provides a simple guide to policy. First, closing the OTC market would raise welfare if OTC market share is high—in our model, high OTC market share is a sign of inefficiency. Second, making labels more accurate, perhaps by requiring greater disclosures, would reduce welfare if OTC share is high and raise welfare if OTC share is low. These predictions are the products of two results: *(i)* OTC market share is increasing in the mass of informed traders μ (Proposition 1) and *(ii)* closing the OTC market raises welfare if the informed mass μ is low and reduces welfare if the mass μ is high (Proposition 3 below). This welfare result stands in stark contrast to our predictions on conventional measures of liquidity: closing the OTC market always reduces aggregate volume V and widens the (OTC and exchange) volume-weighted *average quoted spread*[11]

$$\bar{S} := \frac{V_{\mathrm{E}}}{V} S_{\mathrm{E}} + \frac{V_{\mathrm{O}}}{V} S_{\mathrm{O}}.$$

Proposition 3. *(a) There exists a cutoff $\mu^* > 0$ such that closing the OTC market strictly raises welfare across all mass of informed traders $\mu < \mu^*$ and strictly reduces welfare across all informed mass $\mu > \mu^*$. (b) Closing the OTC market strictly reduces aggregate trade volume V and widens average quoted spread $\bar{S}$ across all informed mass $\mu > 0$.*

Proposition 3 says closing the OTC market would raise welfare for the assets with low informed mass μ, in which most trades are motivated by risk sharing rather than informational advantage. Aggregate trade volume V may yet move in the opposite direction. Aggregate volume V falls and average quoted spread $\bar{S}$ widens upon closing the OTC market, whether doing so raises or reduces welfare. Hence, neither trade volumes nor observed spreads are good indicators of the effects of closing the OTC market on welfare.

Cheap substitution drives the mismatch between volume and welfare, as we illustrate in Figure 2. The 45-degree line marks the hedging benefit of a marginal uninformed trader for a given spread. With the OTC market, the spread on the exchange is S_{E} and the spread over the counter is S_{O}. Upon closing the OTC market, some uninformed LU-traders exit since their spread rises from the OTC spread S_{O} to the No-OTC spread S_{N}. Those exiters' hedging benefits are in the range $[S_{\mathrm{O}}, S_{\mathrm{N}}]$. Meanwhile, the LI-traders' spread falls from the exchange spread S_{E} to the No-OTC spread S_{N}, inducing some uninformed LI-traders to enter. These entrants' hedging benefits are in the strictly higher range $[S_{\mathrm{N}}, S_{\mathrm{E}}]$ than the exiters. In welfare terms, the exiters are "cheap" relative to their substitutes. Cheap substitution imposes a natural upward pressure on welfare upon closing the OTC market: welfare declines only if the reduction in volume is large enough to overcome the positive effect of cheap substitution on welfare.

[11] "Higher aggregate trade volume V" and "lower average quoted spread $\bar{S}$" are interchangeable in our model as competitive prices imply that the aggregate volume V is the inverse of average spread $\bar{S}$

$$\underbrace{V \cdot \bar{S}}_{\text{Revenue}} = \underbrace{(2\alpha - 1) \cdot \mu}_{\text{Gross loss}}.$$

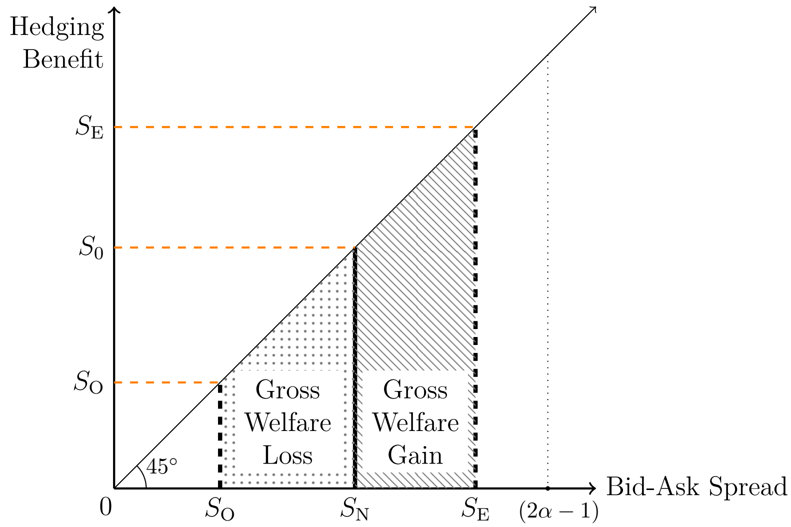

Figure 2: Cheap Substitution

The exiters have lower hedging benefits than the entrants. In welfare terms, the exiters are "cheap" relative to their substitutes.

Figure 3 provides the intuition for why closing the OTC market raises welfare if and only if the mass of informed traders μ is low. (Formal proofs are in in Appendix A.) We know

$$\text{Gross Welfare Loss} = \bar{b}(\text{exiters}) \times m(\text{exiters})$$
$$\text{Gross Welfare Gain} = \bar{b}(\text{entrants}) \times m(\text{entrants}),$$

where $\bar{b}(\text{exiters})$ and $\bar{b}(\text{entrants})$ are the exiters' and the entrants' average hedging benefits, and $m(\text{exiters})$ and $m(\text{entrants})$ are their respective mass. Comparing the gross welfare loss against the gross welfare gain is equivalent to comparing the ratio of average hedging benefits $\bar{b}(\text{exiters})/\bar{b}(\text{entrants})$ to the ratio of the masses $m(\text{entrants})/m(\text{exiters})$. By cheap substitution, $\bar{b}(\text{exiters}) < \bar{b}(\text{entrants})$ and so the benefit ratio $\bar{b}(\text{exiters})/\bar{b}(\text{entrants})$ is less than 1. As the mass of informed traders μ increases, both the entrants' average hedging benefit $\bar{b}(\text{entrants})$ and the exiters' average benefit $\bar{b}(\text{exiters})$ increase. However, the entrants' average benefit $\bar{b}(\text{entrants})$ is the first to feel the pressure from its upper bound $(2\alpha - 1)$ which allows the exiters' average $\bar{b}(\text{exiters})$ to "catch up". Thus, the benefit ratio $\bar{b}(\text{exiters})/\bar{b}(\text{entrants})$ approaches 1 as the informed mass μ increases. That is, cheap substitution is most pronounced with a small informed mass μ and vanishes as the mass μ becomes large. The upper bound $2\alpha - 1$ is the spread that the market maker would quote if all traders were informed.

The reverse is true for the other ratio $m(\text{entrants})/m(\text{exiters})$. The right panel of Figure 3 shows a high informed mass μ, where both the No-OTC spread S_{N} and the exchange spread S_{E} are near the upper bound $2\alpha - 1$. Here the entrants' hedging benefits are constrained into the narrow range $[S_{\text{N}}, S_{\text{E}}]$, tightly limiting the scope for entry. The exiters hence greatly outnumber the entrants $m(\text{entrants}) \ll m(\text{exiters})$, which reduces aggregate volume. On the left with a low informed mass μ, the ratio $m(\text{entrants})/m(\text{exiters})$ approaches 1, because both informed ratios β_{O} ($< \mu$) and β_{E} ($> \mu$) are close to the informed mass μ, in which case

$$\frac{S_{\text{N}} - S_{\text{O}}}{S_{\text{E}} - S_{\text{N}}} \approx \frac{\beta_{\text{N}} - \beta_{\text{O}}}{\beta_{\text{E}} - \beta_{\text{N}}} = \frac{1-\gamma}{\gamma},$$

and both spreads S_{O} and S_{E} are close to the No-OTC spread S_{N}, which implies

$$\frac{m(\text{entrants})}{m(\text{exiters})} \approx \frac{\gamma\, f(S_{\text{N}})\,(S_{\text{N}} - S_{\text{O}})}{(1-\gamma)\, f(S_{\text{N}})\,(S_{\text{E}} - S_{\text{N}})} \approx 1.$$

Altogether, the volume effect is weak with small mass of informed traders μ and strengthens as the mass μ increases. Therefore if the mass μ is small, cheap substitution dominates the volume effect, and causes welfare to rise upon closing the OTC market. The opposite is true if the mass μ is large. This trade-off between cheap substitution and the volume effect is robust to generalizing the distribution of hedging benefits, which we turn to in Section 3.2.

Figure 4 illustrates Proposition 3 with parameters $\gamma = 0.6$, $\theta = 0.9$, and $\alpha = 0.98$. It plots the changes in welfare W, aggregate trade volume V, and average quoted spread $\bar{S}$ upon closing the OTC market, for varying values of the mass of informed traders μ. The changes are positive above the red line. Figure 4 confirms that closing the OTC market always reduces trade volume and widens average spread, while the closure raises welfare if the mass μ is low and reduces welfare if the mass μ is high. The rise and the decline in welfare are on the same order of magnitude. Other OTC frictions not modeled here—such as search frictions or dealers' market power—would further contribute to the rise while reducing the

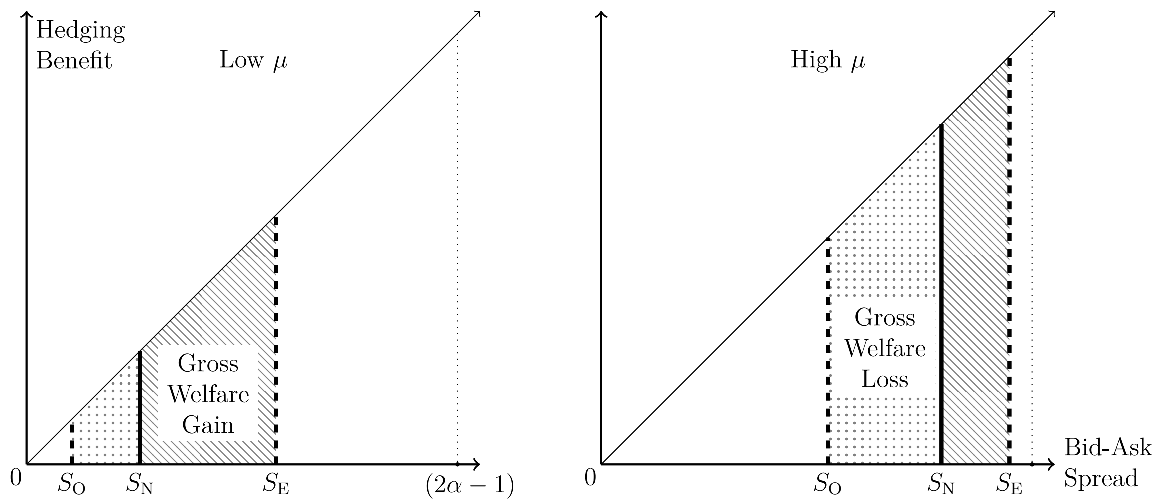

Figure 3: Cheap Substitution is most pronounced at Low Informed Mass μ

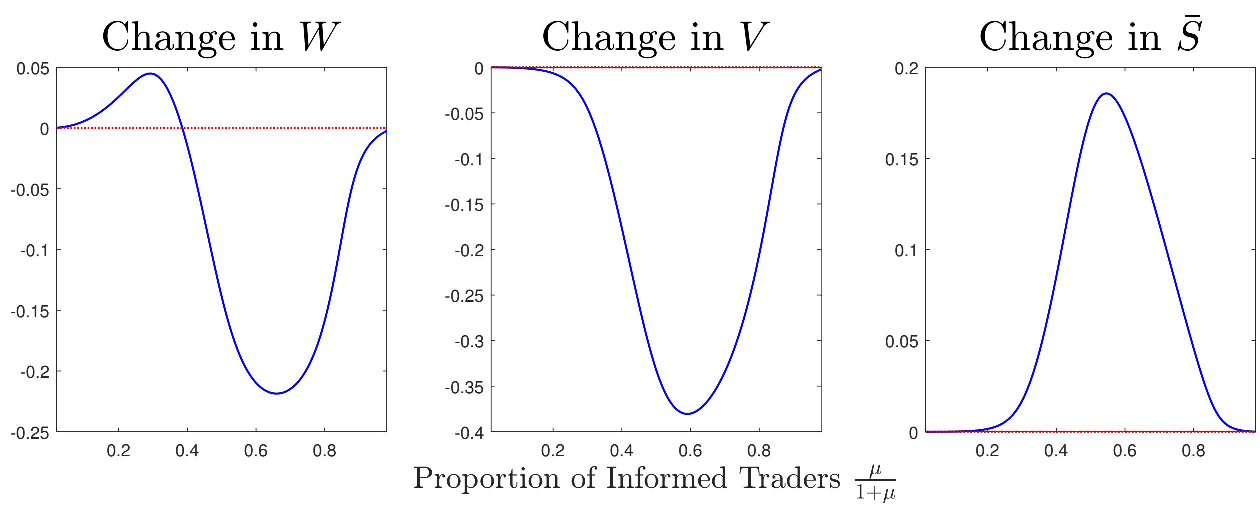

Figure 4: Effects of Closing the OTC Market

decline. Therefore, introducing search frictions or relaxing competitive prices in the OTC market would only reinforce our result, by expanding the range of informed mass μ for which closing the OTC market raises welfare.

We obtain identical results when, instead of closing the OTC market, the traders' labels become less accurate.

Proposition 4. *We suppose that label accuracy θ decreases from θ_1 to θ_0, where $\theta_0 < \theta_1$.*

Then, (a) there exists a cutoff $\mu^*(\theta_0, \theta_1)$ such that welfare is strictly higher across all mass of informed traders $\mu < \mu^*$ and strictly lower across all informed mass $\mu > \mu^*$, and (b) aggregate trade volume V strictly decreases and average quoted spread $\bar{S}$ strictly widens across all informed mass $\mu > 0$.

Making the traders' labels less accurate has the same effect on welfare, volume, and spread as closing the OTC market. Indeed, the latter is an extreme case of the former, as closing the OTC market is equivalent to reducing label accuracy θ from the current level $\theta_1 > 1 - \gamma$ to the uninformative level $\theta_0 = 1 - \gamma$. Proposition 4 applies to recent debates and policy changes on trader anonymity and trade reporting, which we discuss in Section 5.

3.2 General Distributions

Our welfare implications are remarkably sharp. Precisely, closing the OTC market always reduces aggregate volume whereas its effect on welfare hinges on a single cutoff on the mass of informed traders μ^*. Crucial for the result is the behavior of endogenous entry versus exit, which plainly depends on the distribution of hedging benefits. In this section, we show that our welfare implications are robust to most economically relevant distributions.

To do so, we assume that the hedging benefits follow a generic distribution F, $b_i \overset{iid}{\sim} F$, whose support is $[0, 1]$ with a pdf $f(s)$. The pdf $f(s)$ is "regular" in that it is differentiable in some neighborhoods of 0 and $2\alpha - 1$ and that the limits $\lim_{s \downarrow 0} f'(s)$ and $\lim_{s \uparrow 2\alpha-1} f'(s)$ exist.[12] With a general distribution F, the zero-profit condition (1) becomes

$$\underbrace{s \cdot (1 - F(s))}_{\substack{\text{Profit from} \\ \text{uninformed traders}}} = \underbrace{(2\alpha - 1 - s)^+ \cdot \beta}_{\text{Loss to informed traders}} . \tag{2}$$

The left-hand side is changed from $s \cdot (1 - s)$ to $s \cdot (1 - F(s))$ while the right-hand side is unchanged. We define *marginal volume* Δ_V as the decrease in the proportion of uninformed

[12] These limits can be, but need not be, infinite. Most economically relevant pdfs for f are regular. For example, any pdf f continuously differentiable in the support $[0, 1]$ and any beta distribution are regular.

traders who trade upon a marginal increase in the informed ratio β,

$$\Delta_V(\beta) := \underbrace{S'(\beta)}_{\substack{\text{Increase} \\ \text{in spread}}} \cdot \underbrace{f(S(\beta))}_{\substack{\text{Decrease} \\ \text{in trades}}}. \tag{3}$$

Marginal welfare Δ_W is the reduction in welfare per unit mass of uninformed traders upon a marginal increase in the ratio β. It is simply marginal volume Δ_V weighted by the hedging benefit of a marginal uninformed trader $b = S(\beta)$,

$$\Delta_W(\beta) := \underbrace{S(\beta)}_{\substack{\text{Benefit} \\ \text{lost}}} \cdot \underbrace{S'(\beta)f(S(\beta))}_{\Delta_V}. \tag{4}$$

We show that marginal volume Δ_V and marginal welfare Δ_W are well defined in Appendix A.2. We say marginal welfare Δ_W is "n-shaped" if Δ_W is strictly increasing below a cutoff in the ratio β and strictly decreasing beyond the cutoff. Figure 5 illustrates an n-shaped marginal welfare Δ_W.

Proposition 5. *(a) There are two constants $\bar{\mu} > \underline{\mu} > 0$ such that closing the OTC market strictly raises welfare across all mass of informed traders $\mu < \underline{\mu}$ and strictly reduces welfare across all informed mass $\mu > \bar{\mu}$. (b) If marginal welfare Δ_W is n-shaped, there is a single cutoff on the informed mass $\hat{\mu}$ such that closing the OTC market raises welfare across all informed mass $\mu < \hat{\mu}$ and strictly reduces welfare across all informed mass $\mu > \hat{\mu}$. (c) If marginal volume $\Delta_V(\beta)$ is decreasing, closing the OTC market reduces aggregate trade volume V across all informed mass $\mu > 0$. (d) Results equivalent to (a)-(c) hold when label accuracy θ decreases from θ_1 to θ_0, where $\theta_0 < \theta_1$.*

Proposition 5 Part (a) says closing the OTC market raises welfare for low mass of informed traders μ and reduces welfare for high informed mass μ under *any* regular pdf f. Parts (b) and (d) sharpen our policy guidance to a single cutoff on the informed mass μ, around which the effect of closing the OTC market (or less accurate labels) on welfare hinges. Precisely, whenever marginal welfare Δ_W is n-shaped, closing the OTC market raises welfare if and only if the informed mass $\mu < \hat{\mu}$.

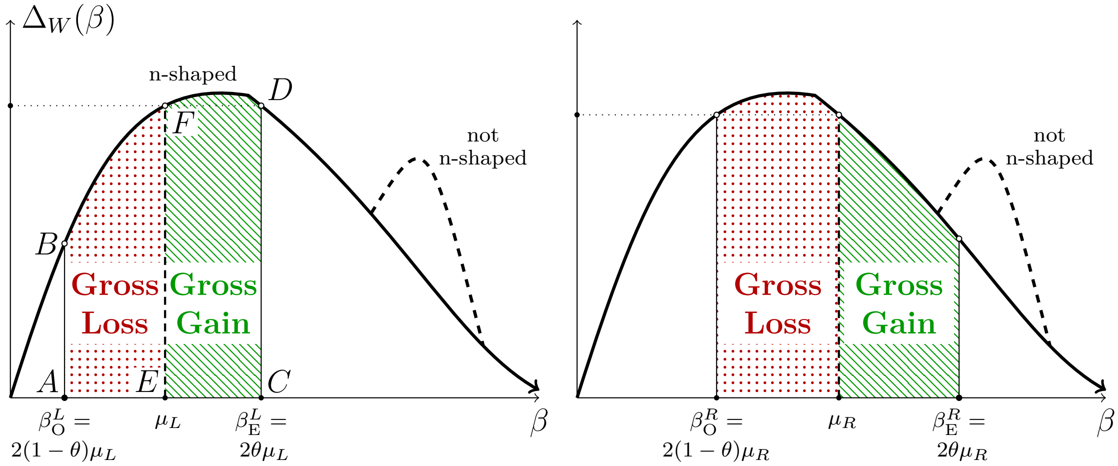

Figure 5: The Effect of Closing the OTC Market on Welfare ($\gamma = 1/2$)

We now outline the proof of Proposition 5 Parts (a)-(b), then argue that most relevant distributions for F would result in an n-shaped marginal welfare Δ_W. We consider the simple example where the label accuracy $\gamma = 1/2$ and marginal welfare Δ_W is n-shaped. Figure 5 plots marginal welfare Δ_W in this example for the informed mass $\mu = \mu_L, \mu_R$. We first focus on the left panel. Here the informed ratio β without the OTC market is some constant μ_L. With the OTC market, the ratio is $\beta_{\mathrm{O}}^L = 2(1-\theta)\mu_L < \mu_L$ over the counter and $\beta_{\mathrm{E}}^L = 2\theta\mu_L > \mu_L$ on the exchange. As the informed ratio without the OTC market μ_L is larger than the ratio β_{O}^L over the counter, the LU-traders would pay a higher spread without the OTC market. The resulting exit by uninformed LU-traders creates a gross welfare loss marked by the red-dotted area between the points $\beta = \mu_L$ and $\beta = \beta_{\mathrm{O}}^L$. Symmetrically, the gross welfare gain from the entry of uninformed LI-traders is marked by the green-lined area between the points $\beta = \mu_L$ and $\beta = \beta_{\mathrm{E}}^L$.

We use Figure 5 to summarize our three-step proof of Proposition 5 Parts (a)-(b). First, we show that under any regular pdf f, marginal welfare $\Delta_W(\beta)$ is increasing over low informed ratio β and decreasing over high ratio β. Intuitively, marginal welfare Δ_W is small if either the hedging benefit of a marginal uninformed trader is small or if few uninformed traders remain at the margin. When the informed ratio β is small enough, the quoted spread is near zero. Hence, the marginal uninformed trader's hedging benefit is small, which implies marginal welfare Δ_W is small. When the informed ratio β is large enough, the spread is wide and very few uninformed traders still trade, meaning marginal welfare Δ_W is again small. Altogether, marginal welfare Δ_W must be increasing from zero around the informed ratio $\beta = 0$ and decreasing to zero over high enough ratio β (regardless of whether marginal welfare Δ_W is n-shaped).

Second, we set the constants μ_L, μ_R such that marginal welfares $\Delta_W(\mu_L) = \Delta_W(\beta^L_{\mathrm{E}})$ and $\Delta_W(\mu_R) = \Delta_W(\beta^R_{\mathrm{O}})$, and show that closing the OTC market causes a net gain in welfare if the informed mass $\mu \leq \mu_L$ and a net loss if the mass $\mu \geq \mu_R$. From the left panel of Figure 5, because the gross welfare gain is uniformly "taller" than the gross welfare loss, the area of gross welfare gain is larger than the area of loss. (The base lengths of the gain and the loss are equal when the label accuracy $\gamma = 1/2$.) This remains to be true if we shift the constant μ_L leftwards, and thus closing the OTC market generates a net welfare gain for all mass $\mu \leq \mu_L$. Similarly on the right panel, the gross welfare loss is uniformly "taller" than the gross welfare gain, which would remain so as we shift the constant μ_R rightwards, thereby closing the OTC market would cause a net welfare loss for all mass $\mu \geq \mu_R$. We do not require marginal welfare Δ_W be n-shaped in this argument to establish Part (a).

Third, the net welfare gain is increasing in the mass of informed traders μ between the constants μ_L and μ_R if marginal welfare Δ_W is n-shaped. From both panels of Figure A.10, when the informed mass μ moves from the lower constant μ_L towards the higher one μ_R, the derivative of the net welfare change with respect to μ is, written geometrically,

$$\underbrace{\left(\theta \cdot ||\overline{CD}|| - \frac{1}{2} \cdot ||\overline{EF}||\right)}_{\text{Derivative of the gross welfare gain}} - \underbrace{\left(\frac{1}{2} \cdot ||\overline{EF}|| - (1-\theta) \cdot ||\overline{AB}||\right)}_{\text{Derivative of the gross welfare loss}}.$$

The derivative is negative for any informed mass μ between μ_L and μ_R, as both segments $\overline{AB}$ and $\overline{CD}$ are shorter than $\overline{EF}$. Thus, increasing the informed mass μ from μ_L to μ_R monotonically reduces the net change in welfare, which ensures a unique cutoff $\hat{\mu} \in (\mu_L, \mu_R)$, establishing Part (b).

In the complete proof in Appendix A.2, we let the label accuracy γ be any value, not 1/2. For any accuracy $\gamma \neq 1/2$, the base lengths of the losses and the gains in Figure 5 differ from one another. It happens that, in calculating welfare, the relative weights on the gross loss and the gain change inversely to keep their base-times-weight equal. Therefore, our comparison of the lengths $\{||\overline{AB}||, ||\overline{CD}||, ||\overline{EF}||\}$ continues to work in establishing Parts (a)-(b) for all values of accuracy γ.

How general are the conditions in Proposition 5? Most economically relevant distributions would result in an n-shaped marginal welfare Δ_W. Proposition 6 states the necessary and sufficient conditions on the distribution F for the resulting marginal welfare Δ_W to be n-shaped and marginal volume Δ_V to be decreasing.

Proposition 6. *(i) Marginal welfare Δ_W is n-shaped if and only if*

$$\frac{(2\alpha-1)(1-F(s))}{sf(s)(2\alpha-1-s)^2} - \frac{1}{2\alpha-1-s} \quad \textit{is U-shaped in } s \in (0, 2\alpha-1). \tag{5}$$

In particular, any beta distribution Beta(a, b) satisfies condition (5).

(ii) Marginal volume Δ_V is decreasing if and only if

$$\frac{(2\alpha-1)(1-F(s))}{f(s)(2\alpha-1-s)^2} - \frac{s}{2\alpha-1-s} \quad \textit{is increasing in } s \in (0, 2\alpha-1). \tag{6}$$

Any beta distribution Beta(a, b) with parameters $a \leq 1, b \leq 1$ satisfies condition (6).

Using Taylor expansion around $2\alpha - 1$, one can verify that the uniform distribution $\mathbb{U}([0, 1])$ and beta distributions—for all parameters—satisfy condition (5) and thus have n-shaped marginal welfare Δ_W.[13] To interpret condition (5), we note that it holds at the extremes under *any* distribution F: the equation goes to infinity as s approaches 0 or $2\alpha-1$. Condition (5) only rules out the distributions for F whose marginal welfare Δ_W oscillates over moderate values of the informed ratio β: any distribution F whose pdf f does not oscillate too much admits an n-shaped marginal welfare Δ_W.

We can verify that (6) is satisfied for any uniform distribution and for beta distributions Beta(a, b) with parameters $a \leq 1, b \leq 1$. Such distributions starkly demonstrate the effect

[13]The beta distribution Beta(a, b) (pdf $f(s) = \frac{s^{a-1}(1-s)^{b-1}}{B(a,b)}$) is a highly general class of bounded distributions that embeds the uniform distribution when $a = b = 1$. One can also numerically verify that common unbounded distributions—Normal, Chi-squared, and Gamma—satisfy condition (5) when truncated on $[0, 1]$.

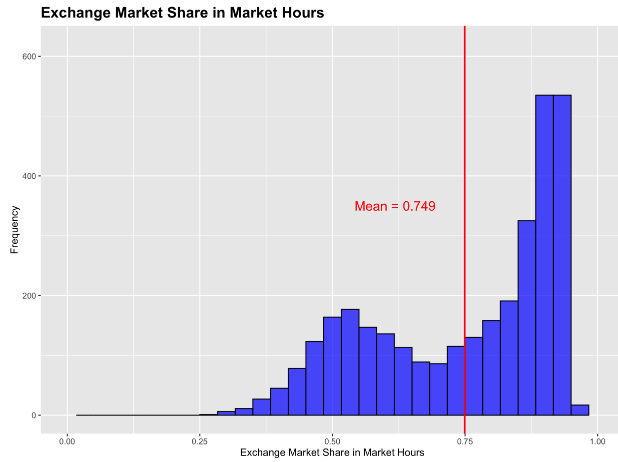

Figure 6: Exchange Market Share of Dollar Value of Trades in US-listed Equities

of cheap substitution. Because the entrants' hedging benefits are uniformly larger than the exiters' benefits, closing the OTC market can raise welfare—even as it reduces aggregate volume—for the assets that attract relatively few informed traders.

4 Empirical Evidence

We use US equities data to document (1) substantial OTC market share even in US-listed equites and (2) a positive correlation between the exchange market share and the exchange quoted spread predicted by Proposition 1. We then summarize the evidence related to our mechanism. The evidence is broadly consistent with our theory.

4.1 Exchange Market Share for US-listed Equities

Does OTC trading dominate only for historically OTC traded assets such as bonds? Figure 6 plots the average weekly exchange market share of US-listed equities from January 2, 2017 to March 5, 2021. It shows that even among US-listed equities, many are OTC dominated while much of the remainder exhibit large OTC market shares. We compute each ticker's weekly share of volume traded on exchanges ("exchange market share") by subtracting the (weekly) OTC trade volume reported by the Financial Industry Regulatory

Agency (FINRA) from the aggregate trade volume by Trade-and-Quote (TAQ). We exclude exchange-traded funds and tickers that do not exist in both the first and the last weeks of the sample period. Only the trades during market hours are included to avoid an upward bias for OTC market share. (Results are nearly identical if all trades are included). The final data consists of 3,210 tickers observed over 218 weeks. Appendix B details the data and our variables, and presents the summary statistics.

4.2 Correlation between Exchange Market Share and Spread

Proposition 1 Part (c) predicts a positive correlation between exchange market share and the exchange quoted spread *if* the observations vary substantively in the mass of informed traders μ but not in label precision (θ, γ). We estimate the correlation within a narrow asset class, controlling for time fixed effects. Precisely, we partition US exchange-listed equities into quintiles by average weekly dollar volume and estimate the correlation within each quintile. Our empirical assumption is that across stocks within each dollar volume quintile in a given week, (i) the amount of available information about their individual traders (for example, the type of firm, reputation, past disclosures) is similar, so their label accuracies are also similar, and (ii) there is idiosyncratic variation in adverse selection risk (from, say, ticker-specific news).

We compute the percent quoted spread on exchanges ("quoted spread" or "percent quoted spread") as the time-weighted best bid-ask spread normalized by the contemporaneous mid-price for each ticker i in each week w from millisecond TAQ quotes. Table 1 presents the regression estimates for log exchange market share on log quoted spreads.[14] All regressions control for week fixed effects, thus our estimates capture cross-sectional variation. Standard

[14] In work that (SSRN-)postdates ours, Bogousslavsky and Collin-Dufresne (2021) report a positive correlation between aggregate turnover and the bid-ask spread. Our empirical findings differ from theirs in three ways. First, the results are qualitatively distinct. We examine the intensive margin of *where* trades occur and necessarily distinguish between the trades on exchanges versus over-the-counter. They examine the extensive margin of *how much* trading occurs in the aggregate. Second, our finding is independent of theirs because we control for dollar volume—we find a positive correlation between exchange market share and the quoted spread *conditional on* aggregate volume. Third, our finding holds in the entire sample of all stocks. Their positive correlation finding only seems to hold for a subsample of the top 20% market cap stocks.

Table 1: Dependent Variable: log(Exchange Market Share)

Observations are weekly and include 3,210 non-ETF US-listed tickers that exist in both the first and the last weeks of the 218 weeks in the sample, from January 2, 2017 to March 5, 2021. Trades outside of market hours are excluded. Standard errors are clustered at the ticker level. Corresponding t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

Independent Variables	Quintile 1			Quintile 2			Quintile 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(percent quoted spread)	0.074***	0.076***	0.072***	0.046***	0.144***	0.069***	0.061***	0.143***	0.077***
	(11.61)	(11.05)	(11.66)	(4.32)	(15.57)	(7.52)	(3.62)	(10.10)	(5.71)
log(dollar volume)		0.005			0.129***			0.125***	
		(0.89)			(24.39)			(18.90)	
log(number of trades)			0.029***			0.123***			0.150***
			(5.74)			(19.27)			(14.49)
Week FE	Yes								
R^2	0.059	0.059	0.068	0.027	0.168	0.182	0.029	0.140	0.208
N	137,453			139,184			139,010		

Independent Variables	Quintile 4			Quintile 5		
	(10)	(11)	(12)	(13)	(14)	(15)
log(percent quoted spread)	0.087***	0.131***	0.095***	0.028***	0.038***	0.044***
	(5.74)	(9.65)	(8.16)	(2.61)	(2.98)	(3.20)
log(dollar volume)		0.095***			0.014	
		(10.30)			(1.57)	
log(number of trades)			0.146***			0.034***
			(13.08)			(2.83)
Week FE	Yes					
R^2	0.074	0.146	0.273	0.051	0.056	0.078
N	139,273			139,383		

errors are clustered at the ticker level. Under each quintile, the left-most regression has no controls. Consistent with Proposition 1 (c), for every quintile, the correlation between log exchange market share and log quoted spread is positive. Our results do not depend on covid or other time-varying shocks common across tickers, due to the week fixed effects.

We examine if our results are genuinely separate from the illiquidity explanation described in the introduction and, if so, whether the effect of our mechanism on exchange market share is in the same magnitude as the liquidity effect. To this end, the other regressions in Table 1 each controls for one of two proxies for liquidity, namely, log weekly total dollar volume ("dollar volume") or log weekly total number of trades. It shows that the quoted spread is positively correlated with the exchange market share independently of liquidity—if anything, the coefficient estimates for quoted spread become larger once we control for liquidity. That is, our findings are not explained by more liquid tickers being easier to trade on exchanges. Furthermore, the coefficient estimates for the quoted spread and the liquidity proxies are in the same magnitude. These findings suggest that our mechanism (of venue choice driven by adverse selection risk) is not second order to the typical illiquidity explanation.

4.3 Further Evidence

Table 2: Asset Types by Primary Trading Venue

Primarily OTC Traded	**Primarily Exchange Traded**
Corporate bonds	Listed equities (Tuttle, 2014)
Municipal bonds	Equity options
Government bonds	(Nybo, Sears and Wade, 2014)
Credit default swaps	Government bond futures
(Riggs, Onur, Reiffen and Zhu, 2018)	Exchange-traded funds
Interest rate swaps (Nagel, 2016)	(Stafford, 2016)
Repos (Han and Nikolaou, 2016)	
Foreign exchange	

Asset types are categorized as in Duffie (2012, Chp. 1) unless followed by a citation. The latter are categorized as in the cited paper.

Informed trading and OTC dominance

The key intuition behind Proposition 1 is that a higher share of volume is traded over the counter if a lower fraction of traders pose adverse selection risk. We present here three bits of anecdotal evidence that broadly support our mechanism. First, a pattern emerges in which the more OTC-traded assets have less informative prices. Table 2 lists mostly OTC-traded assets on the left and mostly exchange-traded assets on the right. Evidence points to the right-side assets having more informative prices than the left-side assets. Trades are rarely informative in corporate bonds (Oehmke and Zawadowski, 2017) and repurchase agreements (Han and Nikolaou, 2016). Stock prices predict corporate bond prices more often than vice versa (Gebhardt, Hvidkjaer and Swaminathan, 2005, Downing, Underwood and Xing, 2009, Hong, Lin and Wu, 2012), and the bulk of price discovery in government bonds occur in

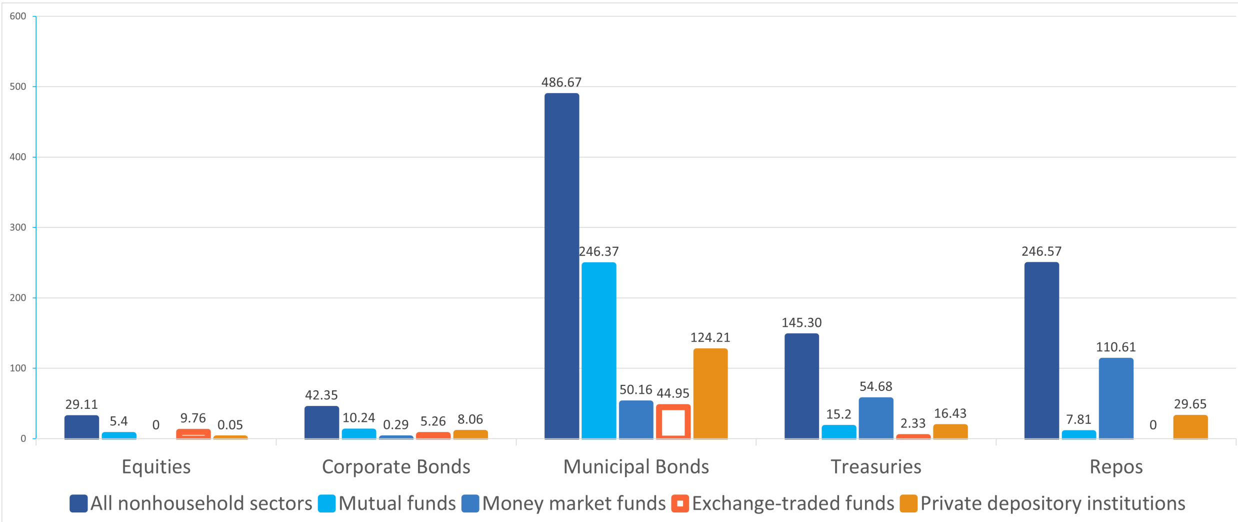

Figure 7: Ratio of Dollar Volume of given Type to Dollar Volume of Hedge Funds

the futures rather than the spot market (Upper and Werner, 2002, Campbell and Hendry, 2007, Mizrach and Neely, 2008). Further, equity options are more OTC-traded than equities (42% vs 17%; Tuttle, 2014, Nybo et al., 2014); and indeed, equity prices predict option prices and not the reverse, despite the larger trade volume of options (Chakravarty, Gulen and Mayhew, 2004, Muravyev, Pearson and Broussard, 2013). A caveat is that not all price discovery occurs through informed trading (Brogaard, Hendershott and Riordan, 2018). We complement the indirect evidence from price discovery with cross-asset observations on the amount of informed trading.

Figure 7 contains suggestive evidence that informed traders are less active in the more OTC-dominated assets. The US National Income Accounts report quarterly dollar value of trades by various types of institutions for US equities, corporate and municipal bonds, Treasuries, and repos. In Figure 7, each bar represents the ratio of the dollar volume by a given type of institution to the dollar volume by hedge funds in an asset class during the year from 2020Q4 to 2021Q3, the latest available quarter at the time of this analysis. We show all institutions ("All nonhousehold sectors") and the four largest institution types, and exclude households, who typically cannot access any asset beyond equities. Solid bars mark the institution types whose ratio to hedge funds is lower in equities than in each of the four

OTC-dominated assets; the outlined bar marks otherwise.

Using hedge funds as a proxy for informed traders, taller bars indicate less informed trading. The dark blue bars (All nonhousehold sectors in Figure 7) suggest informed traders are proportionally far less active in OTC-dominated assets than in equities.[15] The other bars show mutual funds, money market funds, and deposit-taking banks driving this aggregate pattern. The latter two consist of uninformed traders, because money market funds and deposit-taking banks are tightly restricted from speculative trading by fiduciary duty and the Volcker Rule. The mutual funds' ratios to hedge funds in equities is not-so-decisively lower than the ratios in the OTC-dominated assets, especially for Treasuries and repos, perhaps since mutual funds include (likely informed) active funds and (likely uninformed) passive funds. Exchange-traded funds similarly include active and passive funds, and its ratio to hedge funds has a mixed pattern, where its ratio is lower in equities than in municipal bonds but higher than in other OTC-dominated assets. These patterns are broadly consistent with the OTC-dominated assets attracting relatively fewer informed traders than equities.

Third, the migration of most corporate bond trades from exchanges to the OTC market coincides with a sudden, exogenous halt to speculative trading. Biais and Green (2007) show that the proportion of corporate bond trading on NYSE falls sharply in the 1930s and 40s. Meanwhile, the proportion of corporate bonds held by institutions greatly increased, especially by insurance companies and pension funds. Homer (1975), a brokerage president in the 1930s, delivers a first-hand account of this transition. Pre-1930s, the corporate bond traders were primarily, "small, country investors or big-city investors," (Homer, 1975, p. 379) trading on the NYSE. Particularly active were sophisticated traders who often "grabbed up" new issues that, "if well priced they sold at quick premiums" (Homer, 1975, p. 379). The Great Depression pushed out such traders from the corporate bond market en-masse. It became instead, "almost wholly an institutional business," in which dealers bought at fire-sale prices from distressed investors then resold them to life insurance companies (Homer, 1975, p. 381). Unlike the previously dominant types of traders, these insurers preferred

[15] Caution is in order: for each type of institution, within quarter and asset class, the National Income Accounts net out buys and sells. One concern is that the hedge funds' volume is especially underestimated, as they often keep little inventory. But this underestimation would merely scale down the bars in Figure 7 and leave our analysis intact. We believe it is unlikely that the netting introduces major systematic bias.

to trade over the counter although, "[t]he exchange tried hard to retain its bond business" (Homer, 1975, p. 381). On the whole, this history of corporate bond trading mirrors our mechanism that more uninformed trading (lower μ) leads to higher OTC market share.

Price discrimination by dealers

The driving mechanism in our model is that the dealer price discriminates in favor of those less likely to be informed. A testable implication is that OTC trades are less informative and less costly. Are they true? We find support in the large "upstairs" trading literature. (Upstairs trades are the OTC trades of stocks.) Rose (2014) compares limit order book (LOB) and upstairs trades on the Australian Stock Exchange, and finds that the LOB trades earn a profit on average while the upstairs trades make a loss. Moreover, loss-making traders are more likely than others to trade upstairs and pay a lower trading cost upstairs than on the LOB. The opposite holds for profitable traders. Others in the literature also find that upstairs trades are less informative and less costly (Madhavan and Cheng, 1997, Booth, Lin, Martikainen and Tse, 2002, Bessembinder and Venkataraman, 2004, Bernhardt, Dvoracek, Hughson and Werner, 2005), and more often come from uninformed traders (Smith, Turnbull and White, 2001, Westerholm, 2009). These results are not driven by larger traders, who may obtain better prices, concentrating in the upstairs market. In fact, the upstairs discount is decreasing in trade size (Westerholm, 2009) or is smaller for large orders than medium-sized ones (Bernhardt et al., 2005). As a direct evidence for our mechanism, Collin-Dufresne, Junge and Trolle (2020) finds substantial variation in dealers' index credit default swap pricing which is explained by the dealers charging higher spreads to traders who seem to be informed. The findings echo our mechanism that dealers price discriminate according to a trader's likelihood of being informed.

Liquid and standardized swaps

Collin-Dufresne et al. (2020) also documents the existence of informed trading in index CDS, an OTC-dominated asset class. This finding is consistent with our assumption of imperfectly informative labels. Without a comparison to another asset class, they cannot establish whether the level of informed trading is high or low in index CDS. Few studies do compare the information content of index CDS to other assets, and are divided on if index CDS prices lag behind (underlying) equity indices (Byström, 2006, Fung, Sierra, Yau and Zhang, 2008) or if the relationship is mixed (Procasky, 2020). Likewise, the evidence is split on whether interest rate swap (IRS) spreads lag interest rate future prices (Poskitt, 2007) or can lead during overnight trading (Frino and Garcia, 2018). Looking at (generally illiquid) single-name CDS, a large empirical literature remains divided on if CDS spreads lag equity prices (Hilscher, Pollet and Wilson, 2015, Zimmermann, 2021) or lead (Marsh and Wagner, 2016, Lee, Naranjo and Velioglu, 2018). Theory predicts index CDS trades to contain substantially less information than single-name CDS trades, due to the "information destruction effect" of pooling (DeMarzo, 2005). Broadly, it is an open question whether liquid, standardized, and OTC-dominated swaps (say, index CDS and IRS) attract mostly hedging-motivated traders as our theory predicts.

5 Policy Implications

This section applies our results to recent policy debates.

5.1 Regulatory efforts to close OTC markets

Recent regulations in the US, EU, and Japan seek to push OTC trades onto exchanges. One might be tempted to exempt mostly OTC-traded assets, as the large OTC market share reflects preference for OTC trading. However, for precisely those OTC-dominated assets, we find that private preference leads to exactly the *opposite* of the socially efficient outcome. Closing the OTC markets of OTC-dominated assets would actually improve utilitarian welfare (Propositions 2 and 3).

The US Dodd-Frank Act seeks to encourage the exchange trading of swaps by ensuring *access* to swaps exchanges. Under Dodd-Frank, most swaps trades must be initiated on Swap Execution Facilities (SEFs), platforms which are required to offer a limit order book. To prevent bias against order book trading, OTC dealers cannot own more than 40% of any SEF. In addition, Dodd-Frank mandates "fair access" to the order book, which restricts the conditions or fees that the SEFs can impose on order book trading. Typically, the

SEFs impose more restrictive requirements to trade over the counter than on the order book. For example, MarketAxess charges a fee only on (OTC) request-for-quote trades (MarketAxess, 2015), and Refinitiv charges the same fee on all trades but subjects the access to certain OTC trades to a $5,000 monthly fee (Refinitiv, 2019).[16] The Security and Exchange Commission has further proposed, in 2022, to extend the fair access rule to trading platforms for Treasuries. Japan has adopted rules similar to Dodd-Frank (Duffie, 2017).

Our model suggests that merely ensuring access to exchanges is likely insufficient to undermine OTC markets. With access to exchanges, it is nonetheless privately optimal for the traders who pose low adverse selection risk to trade over the counter. Thus, the access-based approach does not mitigate the externality of OTC trading, namely that the adverse selection risk on the exchange intensifies as the low-risk traders are cream-skimmed. If the low-risk traders were forced to trade on exchanges, the adverse selection risk there would be diluted which lowers the costs of other traders—exchange trading is a public good. In contrast, the dealers offer trader-specific prices, and so prevent cross subsidization among traders. Hence with mere access to exchanges, there may be inefficiently little exchange trading. Indeed, 95% of swaps trades are over the counter several years after Dodd-Frank (Nagel, 2016).

Unlike Dodd-Frank, the EU's Markets in Financial Instruments Directive II (MiFID II) aims to *force* nearly all trades onto exchanges. It for instance requires every dealer to maintain a public and binding quote for all assets that pass certain minimum liquidity requirement, such as corporate bonds that trade at least twice a day. Moreover, the dealers cannot trade at other (not publicly quoted) prices if the trade size is below certain thresholds (Surowiecki, 2018). Among bonds, the thresholds are €1.5M for corporate bonds and €5.5M for government bonds (European Securities and Markets Authority, 2021). Such thresholds effectively ban price discrimination by the dealers on smaller trades.

The mandate-based approach of MiFID II is more likely to succeed in undermining the OTC market and undo the harm it may do to welfare. The US regulators took such a mandate-based approach when they banned "name give-up" in 2020, as we now discuss.

[16]The biggest SEFs are operated by Bloomberg and TradeWeb, whose fee schedules are not publicly available.

5.2 Post-trade Name Give-Up

The recent ban on "post-trade name give-up" demonstrates how venue choice crucially affects the impact of policy. Most swaps trades—from over 80% for index credit default swaps to 45% for single-name CDS (Nagel, 2016) are executed on SEFs, which offer two ways to trade: request-for-quote (RFQ) or all-to-all (A2A). The RFQ replaces bilateral OTC trading with a form of first-price auction in which a trader submits a (non-anonymous) trade request for a stated amount to multiple dealers simultaneously. Because of its non-anonymity pre-trade, an RFQ trade is thereby an OTC trade in our model. The A2A trading instead involves either trading on a limit order book or via open auctions, both of which are pre-trade anonymous and thus represent exchange trading in our model.

Most SEFs traditionally practice post-trade name give-up (NGU) wherein parties to an A2A trade or auction learn each other's identities after the trade. Many traders, especially buyside firms, intensely oppose NGU, which was the target of at least two class-action lawsuits (Managed Funds Association, 2015). The buyside firms oppose NGU since, "information leakage associated with sharing its trading activity" undermines A2A trading (Citadel LLC, 2020). The dealers support NGU because it helps them "tailor their pricing on requests-for-quote" and increase the liquidity they provide (JPMorgan Chase & Co., 2018). Such comments are consistent with NGU leading to more accurate labels (higher θ), aiding the dealers cream-skim the uninformed traders from the A2A market. Moreover, the dealers argue that traders are "free to choose for themselves" whether to trade on a SEF with NGU (Securities Industry and Financial Markets Association, 2018). They even cite research that RFQs provide lower spreads and generate more volume than A2A (for example, Riggs et al., 2018). The Commodity Futures Trading Commission (CFTC) initially supported the dealers' position, with a previous commissioner asserting, "SEFs should be free to operate either on a name give-up or anonymous basis," so that traders may "individually elect whether or not to permit limited identifying information to be provided to trade counterparties" (Giancarlo, 2015, p. 67). In 2020, the CFTC approved a rule banning NGU (fully in force since July 2021).

Did the CFTC make the right call by banning NGU? The ban on NGU is akin to reducing the label accuracy θ. As swaps trades are OTC dominated (Nagel, 2016, Augustin, Subrahmanyam, Tang and Wang, 2016), Proposition 2 Part (b) predicts the ban on NGU to improve welfare. (Our theory has no predictions for illiquid swaps, including single-name CDS, which may be impractical to trade all to all.) More importantly, it is having the *choice* of name give-up SEFs that impose an externality on the traders on the SEFs without NGU, and those pushed out by this externality have larger gains from trade than those who would only trade under NGU. Therefore, neither the claim that offering more choices is always better nor that higher volume indicates a superior outcome are well-founded.

Our model views the NGU ban as a step in the right direction. However, the migration of trading from RFQ to A2A after the NGU ban is predicted to be limited, because the RFQ would still be preferred by buyside firms that are more likely to trade for liquidity, such as insurers and passive funds. A more resolute approach may be necessary to fundamentally transform swaps trading.

Name give-up highlights our connection to the studies of how dealers compete for orders (for example, Lester, Rocheteau and Weill, 2015).[17] A recent literature (Hendershott and Madhavan, 2015, Lester et al., 2015, Riggs et al., 2018, Liu, Vogel and Zhang, 2018) examines fast-growing multi-dealer platforms for OTC trading and how these platforms affect competition among dealers. We abstract away from the microstructure of OTC trading and assume competitive dealers. We show that closing the OTC market can still raise welfare under this ideal setting.

5.3 Permissioned Blockchain

We predict that the current plans to apply blockchain to financial markets would undermine exchanges in favor of OTC markets. Blockchain is an electronic recordkeeping procedure that broadcasts every transaction throughout a network. Each member of the network, called a "node", maintains a ledger of all transactions. These ledgers are period-

[17]We are related to the literature that study the cream-skimming effect of payment-for-order flow. Neither theoretical (Lin, Sanger and Booth, 1995, Chordia and Subrahmanyam, 1995, Battalio and Holden, 2001) nor empirical work considers the implication on welfare, and the empirical evidence (Easley, Kiefer and O'Hara, 1996, Battalio, 1997) is mixed on whether payment-for-order flow causes cream-skimming in practice.

ically reconciled with one another by an algorithm. Non-anonymity is crucial to generate trust in the reconciled record. As all trades are broadcast non-anonymously, a node can deduce what another trader owns from her trade history. This way, the nodes can detect and exclude fraudulent trades. On Bitcoin and Ethereum, users split trades across many pseudonymous accounts to maintain some privacy. However, pseudonymity and the ability to create accounts at will violate anti-money-laundering rules (Elwell, Murphy and Seitzinger, 2013); most proposals for the blockchain in financial markets do not have them.

The Depository Trust & Clearing Corporation (DTCC) plans to move the ownership records of most of its 11-trillion-dollar credit derivatives onto a blockchain (Irrera, 2017).[18] To that end, the DTCC began a pilot of a "permissioned" blockchain in which 15 major dealers are the nodes—and no one else (DTCC, 2018). ICAP, the dominant interdealer broker, initiated a similar project in foreign exchange markets around the same time. In 2020, the DTCC proposed a permissioned blockchain for equities records (DTCC, 2020).

All the proposals by DTCC or ICAP would reveal all trading histories to a selected number of dealers, allowing the dealers to better separate traders by their trading motives. In our model, this represents an increase in the label accuracy (higher θ). More accurate labels let the dealer better identify the uninformed traders and cream-skim them. Thus, Proposition 0 predicts the permissioned blockchains to worsen adverse selection on the exchanges and raise their bid-ask spreads. Proposition 2 Part (b) in turn implies that the DTCC's permissioned blockchain for credit derivatives is likely to harm welfare, because credit derivatives are mostly traded over the counter.

6 Conclusion

We show that closing the OTC market can improve utilitarian welfare, under the conservative setup of competitive pricing in the OTC market. In practice, search frictions and the dealers' market power hamper price competition in OTC markets. As OTC trading moves onto electronic platforms, such frictions are dissipating (Hendershott and Madhavan, 2015, O'Hara and Zhou, 2021, Hau, Hoffmann, Langfield and Timmer, 2021). Price discrimination

[18]DTCC is the dominant clearhouse for most securities.

by the dealers remains a fundamental feature of OTC trading. We show this price discrimination leads to the OTC dominance of liquid and standardized assets that largely attract traders who pose a low adverse selection risk. However, for precisely those assets, closing the OTC markets would *raise* welfare due to cheap substitution.

While the competitive pricing assumption in the OTC market underlines the strength of our results, that our price on the exchange is competitive takes away from it. Our model misses out on some important sources of inefficiency on exchanges. For example, we do not consider how price impact (Vives, 2011) or sniping by fast traders (Budish, Cramton and Shim, 2015) might interact with the choice between trading over the counter or on the exchange. We view fixing the inefficiencies of exchanges as a separate question from whether the OTC market should be closed. Those inefficiencies can be addressed by improving the design of exchanges as several studies propose.[19] Moreover, these inefficiencies of exchanges dissipate when more low-(adverse selection)-risk traders participate. Our theory predicts most traders of OTC-dominated assets to be low-risk, and hence suggests that the exchanges for these assets would face minimal inefficiencies once their OTC markets are closed.

Previous work show that price discovery in secondary markets affect corporate investment decisions (for example, Goldstein and Guembel, 2008). We leave for future research the analysis of price discovery in the presence of an exchange and an OTC market for two reasons. In our model, a focus on price discovery *within* each market is an uninteresting one—higher the informed ratio β in the market, better is its price discovery. On the other hand, analyzing *aggregate* price discovery would require a stance on exactly how the quotes and transaction prices in the two markets are incorporated into the aggregate price discovery measure. For instance, specific price disclosure rules would determine the relative availability and importance of the trade prices over the counter versus those on the exchange.

Lastly, cheap substitution is adjacent to the "misallocation effect" found in the third-

[19] Malamud and Rostek (2017), Chen and Duffie (forthcoming) show that optimal market fragmentation can address price impact, and Budish et al. (2015) proposes frequent batch auctions to resolve sniping by fast traders.

degree price discrimination literature.[20] Starting from Pigou (1920), many papers study monopolistic pricing under private value uncertainty. Their key insight is that price discrimination can benefit or harm welfare depending on the curvature of the customers' demand (Aguirre, Cowan and Vickers, 2010, Cowan, 2016). By changing this curvature, any individually rational combination of consumer and producer surplus can be achieved (Bergemann, Brooks and Morris, 2015). Whereas adverse selection is absent in this literature, it is the driving friction in ours. Our focus on adverse selection allows us to provide a simple and practical guidance on welfare: price discrimination reduces welfare if aggregate adverse selection risk is low and it raises welfare if the risk is high. This guidance is particularly applicable to financial markets, where adverse selection risk is a first order concern.

[20] Certain search models can generate endogenous random prices (Burdett and Judd, 1983, Stahl, 1989). These models do not feature heterogenous private valuations, so cannot have cheap substitution. If one were to combine search friction and heterogenous private valuations and endogenize random prices, we anticipate an effect similar to cheap substitution. This effect is likely to amplify the social cost of search friction.

Appendix

A Proofs

A.1 Proofs for Section 2.3

Proof of Proposition 0. Part (a): It suffices to show that there exists at least one solution to the zero profit condition (2) so that $S(\beta)$ is well defined. We use Figure A.8, which plots the market maker's payoff $s[1-F(s)]-(2\alpha-1-s)^{+}\beta$ over the spread s. The payoff curve is continuous. Her payoff is negative at $s=0$, as she is adversely selected yet has no revenue. It is positive at $s=2\alpha-1$, as she breaks-even on the trades against the informed and profits on the uninformed. The Intermediate Value Theorem implies that there exists at least one solution to the zero profit condition. The smallest solution $S(\beta)$ is thus well defined.

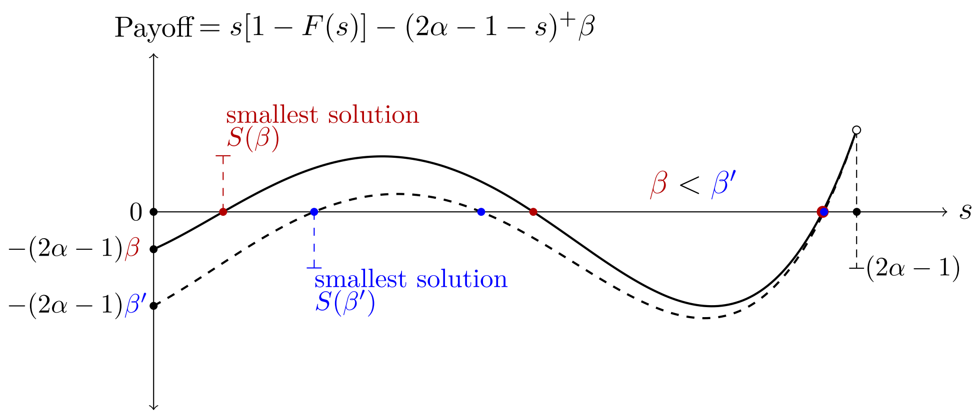

Figure A.8: Finding the equilibrium spread

Part (b): We proceed in three steps. First, we show that the spread function $S(\beta)$ is increasing in the informed ratio $\beta \in [0,\infty)$. We see this easily in Figure A.8: increasing β (to β') shifts the entire payoff curve downwards and the crossing point $S(\beta)$ to the right. Intuitively, as the informed traders impose losses on the market maker,more informed traders requires a higher spread for the market maker to break-even.

Second, we solve for the spreads in the OTC market. All traders with the same label share the same OTC spread, because they are indistinguishable to the dealer. For an LU-trader, the equilibrium OTC spread is $S(\beta_{\mathrm{LU}})$, where β_{LU} is the informed ratio of the LU-traders. As LU-traders consist of $(1-\theta)\mu$ informed and γ uninformed traders, their OTC spread is $S\left(\frac{1-\theta}{\gamma}\,\mu\right)$. Similarly, the LI-traders' OTC spread is $S\left(\frac{\theta}{1-\gamma}\,\mu\right)$.

Third, we turn to the exchange spread S_{E}. If the market maker sets $S_{\mathrm{E}} \in (S(\beta_{\mathrm{LU}}), S(\beta_{\mathrm{LI}})]$, all LU-traders choose the OTC market, whereas all LI-traders choose the exchange. Then the informed ratio on the exchange $\beta_{\mathrm{E}} = \beta_{\mathrm{LI}}$. The market maker thus earns zero profit if and only if she sets $S_{\mathrm{E}} = S(\beta_{\mathrm{LI}})$ in this case. If the market maker sets $S_{\mathrm{E}} \leq S(\beta_{\mathrm{LU}})$, then every trader chooses the exchange, implying $\beta_{\mathrm{E}} = \mu > \beta_{\mathrm{LU}}$, and thus the market maker earns a non-zero profit. Therefore in equilibrium, *(i)* the exchange spread is $S_{\mathrm{E}} = S(\beta_{\mathrm{LI}}) = S\left(\frac{\theta}{1-\gamma}\,\mu\right)$, the lowest spread that earns the market maker a zero profit, and *(ii)* all LU-traders choose the OTC market, whereas all LI-traders choose the exchange. $\square$

Proof of Proposition 1. We prove Parts (b) and (c), and use Part (c) to prove Part (a).

Part (b): The proof of Proposition 0 Part (b) showed that the spread function $S(\beta)$ is strictly increasing in the informed ratio β. Since $\beta_{\mathrm{O}} < \beta_{\mathrm{E}}$, then $S_{\mathrm{O}} < S_{\mathrm{E}}$.

Part (c): The ratio $V_{\mathrm{E}}/V_{\mathrm{O}}$ equals

$$\frac{V_{\mathrm{E}}}{V_{\mathrm{O}}} := \frac{(1-\gamma)(1-S_{\mathrm{E}}) + \theta\mu}{\gamma(1-S_{\mathrm{O}}) + (1-\theta)\mu}$$

The derivative of $V_{\mathrm{E}}/V_{\mathrm{O}}$ with respect to μ is positive if and only if

$$\frac{-\frac{\gamma}{1-\theta}\frac{\partial S_{\mathrm{O}}}{\partial \mu} + 1}{\frac{\gamma}{1-\theta}(1-S_{\mathrm{O}}) + \mu} < \frac{-\frac{1-\gamma}{\theta}\frac{\partial S_{\mathrm{E}}}{\partial \mu} + 1}{\frac{1-\gamma}{\theta}(1-S_{\mathrm{E}}) + \mu}. \tag{A.1}$$

It suffices to show that

$$\frac{\gamma}{1-\theta}(1-S_{\mathrm{O}}) > \frac{1-\gamma}{\theta}(1-S_{\mathrm{E}}) > 0, \tag{A.2}$$

$$\text{and} \quad \frac{1-\gamma}{\theta}\frac{\partial S_{\mathrm{E}}}{\partial \mu} < \frac{\gamma}{1-\theta}\frac{\partial S_{\mathrm{O}}}{\partial \mu} < 1. \tag{A.3}$$

Inequality (A.2) follows from $\gamma/(1-\theta) > (1-\gamma)/\theta > 0$ and $S_{\mathrm{O}} < S_{\mathrm{E}} < 2\alpha - 1 < 1$. One can show that $S(\beta)$ is strictly concave. Then (A.3) follows as

$$\frac{1-\gamma}{\theta}\frac{\partial S_{\mathrm{E}}}{\partial \mu} = S'\left(\frac{\theta}{1-\gamma}\mu\right) < S'\left(\frac{1-\theta}{\gamma}\mu\right) = \frac{\gamma}{1-\theta}\frac{\partial S_{\mathrm{O}}}{\partial \mu}$$
$$< S'(0) = 2\alpha - 1 < 1.$$

Part (a): We fix some $\underline{O} \in (0,1)$ and for any $\mu > 0$, we let

$$A(\mu) = \{(\theta,\gamma) : V_{\mathrm{O}}/V > \underline{O}\}.$$

There exists some (θ,γ) such that $\theta+\gamma > 1$, $\theta > 0$, $\gamma > 0$, and V_{O}/V is arbitrarily close to 0 or 1. For example, one can let $(\theta,\gamma) \approx (1,0)$, which results in $V_{\mathrm{O}}/V \approx 0$. Similarly, letting $(\theta,\gamma) \approx (0,1)$ would lead to $V_{\mathrm{O}}/V \approx 1$. By the Intermediate Value Theorem, there exists (θ,γ) such that the OTC market share V_{O}/V is equal to any arbitrary value in $(0,1)$. Thus, the set $A(\mu) \neq \varnothing$. Since the OTC market share V_{O}/V is strictly increasing as μ decreases for given (θ,γ), then the set $A(\mu)$ is strictly expanding as μ decreases. $\square$

A.2 Proofs for Section 3

We proceed with the proofs in reverse order. We prove Propositions 5 and 6, then applying Proposition 6 to $F = \mathbb{U}[0,1]$ proves Propositions 2 to 4.

The proof of Proposition 0 showed that the spread function $S(\beta)$ is increasing. As $S(\beta)$ is also left-continuous in β, then $S(\beta)$ is left differentiable. We let $S'(\beta)$ be the left derivative. Marginal volume Δ_V and marginal welfare Δ_W as in (3) and (4) are thus well defined.

Proof of Proposition 5. To prove Proposition 5 Parts (a) to (c), we first prove Part (d) which varies the label accuracy θ while the OTC market is open. Then we show that Proposition 5 (a)-(c) are a special case of Part (d).

Part (d): The change in aggregate trade volume V as the label accuracy θ falls from θ_1 to

θ_0 is

$$\underbrace{(1-\gamma)\int_{S\left(\frac{\theta_0}{1-\gamma}\mu\right)}^{S\left(\frac{\theta_1}{1-\gamma}\mu\right)} f(s)\,\mathrm{d}s}_{\substack{\text{Entry by uninformed}\\ \text{LI-traders}}} - \underbrace{\gamma\int_{S\left(\frac{1-\theta_1}{\gamma}\mu\right)}^{S\left(\frac{1-\theta_0}{\gamma}\mu\right)} f(s)\,\mathrm{d}s}_{\substack{\text{Exit by uninformed}\\ \text{LU-traders}}}$$

equal to

$$(1-\gamma)\int_{\frac{\theta_0}{1-\gamma}\mu}^{\frac{\theta_1}{1-\gamma}\mu} \Delta_V(\beta)\,\mathrm{d}\beta - \gamma\int_{\frac{1-\theta_1}{\gamma}\mu}^{\frac{1-\theta_0}{\gamma}\mu} \Delta_V(\beta)\,\mathrm{d}\beta. \tag{A.4}$$

Weighting (A.4) by the hedging benefit, we find the change in welfare

$$(1-\gamma)\int_{\frac{\theta_0}{1-\gamma}\mu}^{\frac{\theta_1}{1-\gamma}\mu} \Delta_W(\beta)\,\mathrm{d}\beta - \gamma\int_{\frac{1-\theta_1}{\gamma}\mu}^{\frac{1-\theta_0}{\gamma}\mu} \Delta_W(\beta)\,\mathrm{d}\beta. \tag{A.5}$$

The proofs are intuitive with the aid of graphs. Figure A.9 plots a generic Δ_W. We first show that Δ_W begins at $\Delta_W(0) = 0$ from which Δ_W strictly increases before eventually strictly decreasing to zero. When $\beta = 0$, $S(0) = 0$ and so $\Delta_W(0) = 0$. As β becomes large, $S(\beta)$ approaches $2\alpha - 1$, then

$$S'(\beta) = \frac{1}{\beta'(S(\beta))} = \frac{2\alpha - 1 - S(\beta)}{\frac{(2\alpha-1)[1-F(S(\beta))]}{2\alpha-1-S(\beta)} - S(\beta)f(S(\beta))} \xrightarrow{\beta\to\infty} 0$$

and thus $\Delta_W(\beta) \to 0$ as $\beta \to \infty$. One can verify that $\ln(\Delta_W)$ is differentiable in a neighborhood of $\beta = 0$ and

$$(\ln\Delta_W)'(\beta) = \left(\ln(S')\right)'(\beta) + S'(\beta)\left(\frac{1}{S(\beta)} + \frac{f'(S(\beta))}{f(S(\beta))}\right) \xrightarrow{\beta\downarrow 0} \infty.$$

Thus, $\ln(\Delta_W)$ is strictly increasing in a neighborhood of $\beta = 0$. That is, there exists some $\underline{\beta} > 0$ below which Δ_W is strictly increasing. By a similar argument, there exists some $\bar{\beta} > \underline{\beta}$, above which $\Delta_W(\beta)$ is strictly decreasing. Altogether, Δ_W begins at $\Delta_W(0) = 0$ from which Δ_W strictly increases before eventually strictly decreasing towards the lower limit of zero.

We define $\underline{\mu}$ such that $\frac{\theta_1\mu}{1-\gamma} = \underline{\beta}$ (see Figure A.9). If $\mu = \underline{\mu}$, the second term in (A.5)

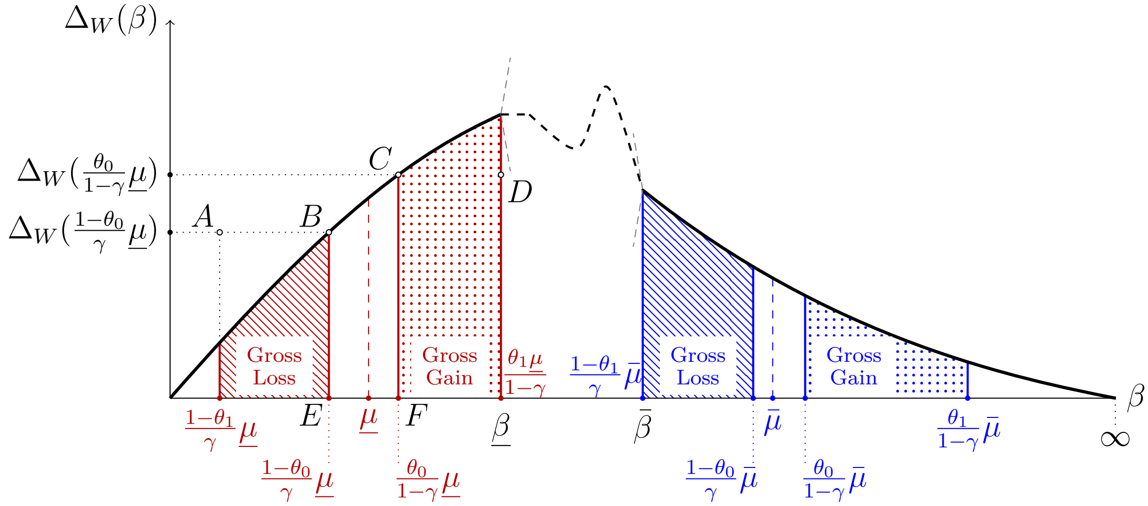

Figure A.9: Generic Δ_W

(marked "Gross Loss" in red) has a strict upper bound

$$\gamma \cdot \left(\frac{1-\theta_0}{\gamma}\underline{\mu} - \frac{1-\theta_1}{\gamma}\underline{\mu}\right) \cdot \Delta_W\left(\frac{1-\theta_0}{\gamma}\right) = (\theta_1 - \theta_0) \cdot \underline{\mu} \cdot ||\overline{BE}|| > 0,$$

which corresponds to the area ABE in Figure A.9 scaled by the mass γ of uninformed LU-traders. The first term in (A.5) (marked "Gross Gain" in red) has a strict lower bound

$$(\theta_1 - \theta_0) \cdot \underline{\mu} \cdot ||\overline{CF}||$$

marked by the area CDF. Since the segment $\overline{CF}$ is longer than $\overline{BE}$ (because Δ_W is strictly increasing in $\beta \in [0, \underline{\beta}]$), the Gross Gain in welfare is strictly larger than the Gross Loss. The same argument applies to any $\mu < \underline{\mu}$, so that closing the OTC market raises welfare if the informed mass μ is small. Likewise, we choose $\bar{\mu}$ such that $\frac{(1-\theta_1)\bar{\mu}}{\gamma} = \bar{\beta}$ and follow analogous steps to show that the Gross Loss in welfare (in blue) is larger than the Gross Gain if the informed mass μ is large $\mu \geq \bar{\mu}$.

We next show that if Δ_W is n-shaped, there is a single cutoff on μ denoted μ^* above which a decrease in θ strictly reduces welfare and below which it strictly raises welfare. To prove this, we choose two constants $\mu_R > \mu_L > 0$ as shown in Figure A.10. We set μ_L to be the highest μ such that $\Delta_W\left(\left(\frac{(1-\theta_0)\mu}{\gamma}\right)^-\right) \leq \Delta_W\left(\left(\frac{\theta_1\mu}{1-\gamma}\right)^-\right)$ and μ_R to be the highest μ such that $\Delta_W\left(\left(\frac{(1-\theta_1)\mu}{\gamma}\right)^-\right) \leq \Delta_W\left(\left(\frac{\theta_0\mu}{1-\gamma}\right)^-\right)$, where $\Delta_W(\beta^-)$ is the left limit of Δ_W at β. For the ease of exposition only, Figure A.10 illustrates the case where Δ_W is continuous in which case $\Delta_W\left(\frac{1-\theta_0}{\gamma}\,\mu_L\right) = \Delta_W\left(\frac{\theta_1}{1-\gamma}\,\mu_L\right)$ (line $\overline{BD}$) and $\Delta_W\left(\frac{1-\theta_1}{\gamma}\,\mu_R\right) = \Delta_W\left(\frac{\theta_0}{1-\gamma}\,\mu_R\right)$ (not shown). The same proof works if Δ_W is not continuous. As Δ_W is n-shaped, we know that such μ_L and μ_R exist, and that $\mu_L < \mu_R$. We proceed in two steps: *(i)* we show that the change in welfare (A.5) is strictly positive for all $\mu < \mu_L$ and strictly negative for all $\mu > \mu_R$; and *(ii)* that (A.5) is strictly decreasing between μ_L and μ_R. Together, *(i)* and *(ii)* establish the existence of the single cutoff μ^*. For *(i)*, we only show the case where $\mu \leq \mu_L$ since the argument is symmetric in the case where $\mu \geq \mu_R$. Setting $\mu = \mu_L$, an upper bound of the second term in (A.5) ("Gross Loss" in Figure A.10) is

$$(\theta_1 - \theta_0) \cdot \mu_L \cdot \Delta_W\left(\left(\frac{(1-\theta_0)\mu_L}{\gamma}\right)^-\right) = (\theta_1 - \theta_0) \cdot \mu_L \cdot ||\overline{BE}||$$

marked $ABEJ$ in Figure A.10. This upper bound is equal to the strict lower bound—marked $CDFH$—on the first term of (A.5) ("Gross Gain"). Hence (A.5) is strictly positive. To prove *(ii)* that (A.5) is strictly decreasing over $\mu \in (\mu_L, \mu_R)$, the derivative of (A.5) with respect to μ is, written geometrically,

$$\underbrace{\left(\theta_1 \cdot ||\overline{DF}|| - \theta_0 \cdot ||\overline{GH}||\right)}_{\text{Derivate of the gross welfare gain}} - \underbrace{\left((1-\theta_0) \cdot ||\overline{BE}|| - (1-\theta_1) \cdot ||\overline{IJ}||\right)}_{\text{Derivate of the gross welfare loss}}. \tag{A.6}$$

Due to Δ_W being n-shaped and how μ_L and μ_R are chosen, both $||\overline{BE}||$ and $||\overline{GH}||$ are strictly greater than $||\overline{DF}||$ and $||\overline{IJ}||$. Then (A.6) is strictly negative. In sum, as θ decreases from θ_1 to θ_0, the change in welfare is strictly positive if $\mu \leq \mu_L$, strictly negative if $\mu \geq \mu_R$, and strictly decreasing across $\mu \in (\mu_L, \mu_R)$, which together imply that a single cutoff μ^* exists.

Lastly, we show that if Δ_V is strictly decreasing, the change in volume (A.4) is strictly negative. Figure A.11 plots a decreasing Δ_V. The second term of (A.4) ("Exiters" in

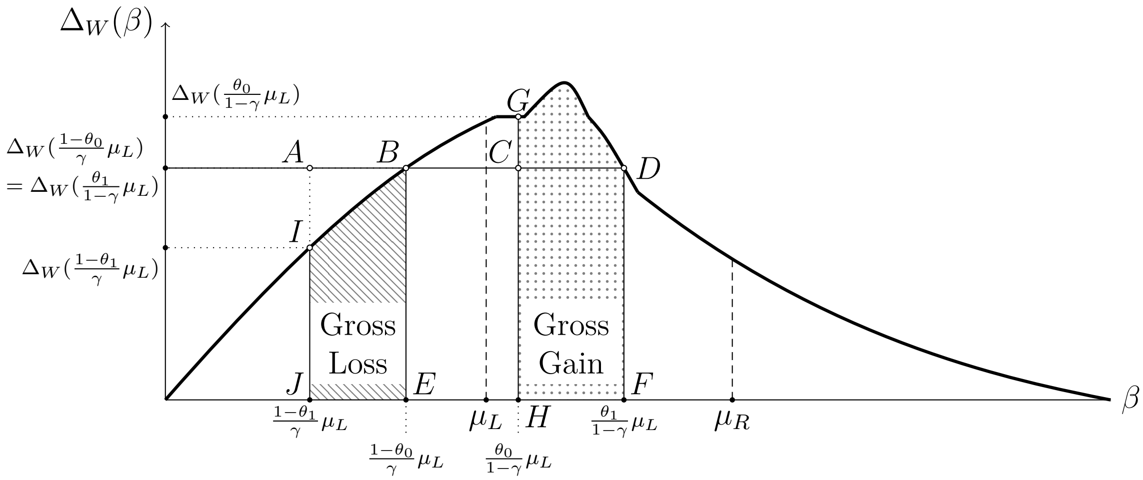

Figure A.10: "n-shaped" Δ_W

Figure A.11) has a strict lower bound

$$(\theta_1 - \theta_0)\,\mu \cdot ||\overline{BE}||$$

marked ABE, which is larger than the first term's strict upper bound ("Entrants")

$$(\theta_1 - \theta_0)\,\mu \cdot ||\overline{DF}||$$

marked CDF, and thus (A.4) is strictly negative.

Parts (a)-(c): We show that Parts (a)-(c) are a special case of Part (d). This is because Parts (a)-(c) compare the effects on welfare and on volume of closing the OTC market, which is equivalent to reducing the label accuracy θ from some level $\theta_1 > 1-\gamma$ to the uninformative level $\theta_0 = 1-\gamma$. □

Proof of Proposition 6. The marginal welfare Δ_W can be written as

$$\Delta_W(\beta) = S'(\beta)S(\beta)f(S(\beta)) = \frac{S(\beta)f(S(\beta))}{\beta'(S(\beta))}.$$

Since the spread function $S(\beta)$ is strictly increasing in β, then $\Delta_W(\beta)$ is n-shaped if and only

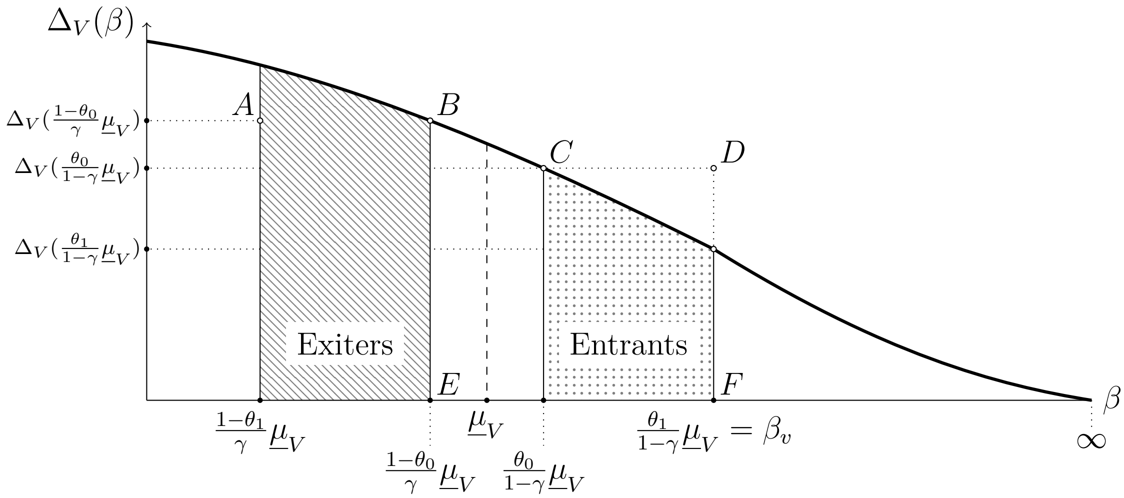

Figure A.11: Decreasing Δ_V

if $\beta'(s)/(sf(s))$ is U-shaped in $s \in (0, 2\alpha - 1)$. Differentiating (2) with respect to s yields

$$1 - F(s) + \beta - sf(s) = (2\alpha - 1 - s)\beta'(s),$$

which can be rearranged to

$$\beta'(s) = \frac{1 - F(s) + \beta - sf(s)}{2\alpha - 1 - s}.$$

From (2), we can express $\beta(s)$ as function of s:

$$\beta(s) = \frac{(1 - F(s))s}{2\alpha - 1 - s}.$$

Then marginal welfare $\Delta_W(\beta)$ is n-shaped if and only if condition (5) holds. Likewise, marginal volume $\Delta_V(\beta)$ is decreasing if and only if (6) is true. $\square$

B Data, Variables, and Summary Statistics

We combine milisecond Trade-and-Quote (TAQ) quote and trade data sets with weekly OTC trade volumes from the Financial Industry Regulatory Agency (FINRA).[21] In the FINRA data, OTC volumes are separated into Alternative Trading Systems (ATS) versus Non-ATS OTC volumes. The ATS consists of dark pools, batch auctions, and limit order books that are not designated as "national securities exchanges" by the US Securities and Exchange Commissions. Since trading on the ATS is anonymous, and thus do not allow trader-specific price discrimination, the ATS correspond to the exchange in our model. The Non-ATS OTC refers to traditional bilateral and request-for-quote trades. Therefore, only the Non-ATS trades are counted as over the counter in our analysis.

The sample period is January 2, 2017–March 5, 2021, the available range of FINRA OTC data at the time of this analysis. We exclude all trades outside of market hours. Our sample consists of 3,210 US-listed non-ETF tickers that exist in both TAQ and FINRA data on both the first and the last weeks of the 218 weeks in the sample period.

Exchange market share for ticker i and week w is 1 minus the ratio of week w OTC dollar volume of trades from FINRA to the week w aggregate dollar volume from TAQ. To compute *percent quoted spread* for ticker i and week w, we use the millisecond TAQ quotes to calculate the time-weighted percent best quoted spread, *(best offer - best bid) /midpoint*, for each day then we take the simple average across the number of days observed for ticker i in week w. The total *number of trades* and total *dollar volume* of trades are computed for each ticker i and week w from millisecond TAQ trade data. Table B.1 provides the summary statistics.

[21] FINRA data used here is available publicly at http://www.finra.org/industry/otc-transparency.

Table B.1: Summary Statistics

Each observation is one ticker for one week.

	Obs	Mean	SD	Min	25%	50%	75%	Max
	All Observations							
Exchange Market Share	694,305	0.750	0.198	0.000	0.597	0.828	0.914	1.000
Percent Quoted Spread	694,305	0.027	0.053	0.000	0.004	0.010	0.026	6.995
Dollar Volume of Trades	694,305	384.4M	2,752.6M	0.0M	3.3M	27.5M	187.2M	376,000.0M
Number of Trades	694,305	38,401	107,820	2	1,714	9,434	36,594	13,458,361
	Quintile 1 (by average weekly dollar volume of trades) Observations							
	Obs	Mean	SD	Min	25%	50%	75%	Max
Exchange Market Share	137,455	0.615	0.185	0.000	0.484	0.609	0.758	1.000
Percent Quoted Spread	137,455	0.067	0.086	0.001	0.016	0.042	0.089	6.995
Dollar Volume of Trades	137,455	1.6M	3.7M	0.0M	0.4M	0.9M	1.9M	543.8M
Number of Trades	137,455	997	3,495	2	189	474	1,027	491,416
	Quintile 2 Observations							
	Obs	Mean	SD	Min	25%	50%	75%	Max
Exchange Market Share	139,184	0.659	0.193	0.001	0.506	0.652	0.839	1.000
Percent Quoted Spread	139,184	0.037	0.055	0.001	0.011	0.022	0.044	4.943
Dollar Volume of Trades	139,184	8.3M	18.8M	0.0M	2.7M	5.4M	9.8M	1,570.1M
Number of Trades	139,184	5,240	14,348	7	1,345	2,815	5,745	950,784
	Quintile 3 Observations							
	Obs	Mean	SD	Min	25%	50%	75%	Max
Exchange Market Share	139,010	0.775	0.194	0.005	0.667	0.859	0.922	1.000
Percent Quoted Spread	139,010	0.018	0.033	0.000	0.007	0.012	0.019	3.687
Dollar Volume of Trades	139,010	37.6M	50.9M	0.0M	16.2M	27.8M	46.3M	4,236.7M
Number of Trades	139,010	14,577	25,721	5	5,120	9,755	17,342	1,986,649
	Quintile 4 Observations							
	Obs	Mean	SD	Min	25%	50%	75%	Max
Exchange Market Share	139,273	0.830	0.164	0.008	0.800	0.896	0.935	1.000
Percent Quoted Spread	139,273	0.008	0.012	0.000	0.003	0.005	0.009	0.487
Dollar Volume of Trades	139,273	153.5M	153.4M	0.0M	72.2M	119.7M	194.3M	14,100.0M
Number of Trades	139,273	32,783	36,820	59	14,249	25,524	41,738	3,485,211
	Quintile 5 Observations							
	Obs	Mean	SD	Min	25%	50%	75%	Max
Exchange Market Share	139,383	0.867	0.108	0.013	0.851	0.902	0.931	1.000
Percent Quoted Spread	139,383	0.003	0.005	0.000	0.001	0.002	0.004	0.226
Dollar Volume of Trades	139,383	1,714.1M	5,957.4M	0.3M	427.1M	726.2M	1,409.3M	376,000.0M
Number of Trades	139,383	137,773	206,702	1,161	51,324	86,649	153,925	13,458,361

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