Taking Orders and Taking Notes:
Dealer Information Sharing in Treasury Auctions[*]

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Abstract

The use of order flow information by financial firms has come to the forefront of the regulatory debate. A central question is: Should a dealer who acquires information by taking client orders be allowed to use or share that information? We explore how information sharing affects dealers, clients and issuer revenues in U.S. Treasury auctions. Because one cannot observe alternative information regimes, we build a model, calibrate it to auction results data, and use it to quantify counter-factuals. The model's key force is that sharing information reduces uncertainty about future value. With less uncertainty, risk-averse bidders bid more. We estimate that yearly auction revenues would be $2.4 billion higher with full-information sharing between clients and dealers. For investors, the welfare effects of information sharing depend on how information is shared and whether it increases or decreases asymmetry. The model shows that investors can benefit when dealers share information with each other, not when they share more with clients.

"[B]efore the Treasury holds an auction, salespeople at 22 primary dealers field billions of dollars in bids for government debt. Traders working at some of these financial institutions have the opportunity to learn specifics of those bids hours ahead of the auctions [and] also have talked with counterparts at other banks via online chatrooms [...]. Such conversations, both inside banks and among them, could give traders information useful for making bets on one of the most powerful drivers of global markets [...]." — Bloomberg (2015), "As U.S. Probes $12.7 Trillion Treasury Market, Trader Talk Is a Good Place to Start."

Recent financial market misconduct, involving misuse of information about clients' orders, cost the firms involved record fines and lost reputation. It also prompted investigations and calls for curbing dissemination of order flow information, between and within dealers. Recent investigations reportedly involve U.S. Treasury auctions (Bloomberg, 2015 above). But the use of order flow information has been central to our understanding of Treasury auctions (Hortaçsu and Kastl, 2012), to market making theory generally (Kyle, 1985) and to market practice for decades. In describing Treasury market pre-auction activities in the 1950s, Robert Roosa (1956) noted that "Dealers sometime talk to each other; and they all talk to their banks and customers; the banks talk to each other." Furthermore, sharing order-flow information–or, colloquially, "market color"–with issuers is even mandatory for primary dealers both in the U.S. and abroad. Of course, if information sharing leads to collusion, that has well-known welfare costs. But if collusion could be prevented with separate remedies, is information sharing in itself problematic? The strong conflicting views on a seemingly long-established practice raise the question of who gains or loses when order-flow information is shared.[1]

Measuring the revenue and welfare effects of information sharing directly would require data with and without sharing. In the absence of such data, we use a quantitative model. Our setting is an institutionally-detailed model of U.S. Treasury auctions, which we select because of the available data, the absence of other dealer functions, and their enormous economic importance. In the model, dealers observe client orders and may use that information to inform their own strategy, may share some of the information with clients, or may exchange information with other dealers. Then all agents submit continuous bid functions to a uniform-price auction with private values. To quantify the effects of information sharing and sign welfare results, we calibrate the model to auction results, including allotment data, as well as information about post-auction returns using market prices on the so-called on-the-run premium, or the differential value of a newly-auctioned versus an

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[1]Regulations on information sharing in sovereign auctions vary and are evolving. As of 2011, the UK Debt Management Office sanctioned that UK primary dealers, or Gilt-edged Market Makers, "whilst not permitted to charge a fee for this service, may use the information content of that bid to its own benefit" (GEMM Guidebook, 2011). The legality of U.S. primary dealers' use of client information, including sharing such information with other clients or dealers is currently being litigated. This paper does not take a view as to whether the described use of client information with respect to Treasury auction activity is legal or proper.

old Treasury security. In this setting, bids reflect risk premia associated with reselling Treasuries, at an unknown price, in the secondary market. This risk premia informs the model about how much uncertainty bidders face, and thus, how much information they have, on average. After estimating the model, we study the model-implied revenue and bidders' utilities with exogenously varying degrees and types of information sharing. We then extend the model to think about how information sharing affects bidders and dealers incentives to participate in the auction. Finally, we provide some empirical support for key model assumptions.

The model teaches us that the primary beneficiary of information sharing is the U.S. Treasury. By sharing information, bidders receive more information. More information allows them to better forecast secondary market prices, reducing their risk, if they need to liquidate in that secondary market. Risk-averse bidders faced with less risk bid more thus boosting auction revenues. Based on the model parameters, moving from the calibrated status-quo of a partial information sharing arrangements to full information sharing would raise Treasury auction revenues by $2.4 billion annually. If instead, all information sharing were prohibited, revenue would fall by $80 million. While the idea that better-informed investors bid more is not a new finding, the issue is rarely raised in policy debates, presumably because the magnitude of the effect is not known.

Our second finding is that dealer information sharing with other dealers and sharing with clients have opposite effects on investor utility. When all dealers share information with their clients, it typically makes the clients worse off. This is a form of the Hirshleifer (1971) effect, which arises here because better-informed clients have more heterogeneous beliefs and therefore share risk less efficiently. But surprisingly, when dealers share information with each other and then transmit the same amount of information to their clients, investor welfare improves. Our model shows that inter-dealer information sharing makes beliefs more common, and thereby improves risk-sharing and welfare. In essence, information sharing with clients is similar to providing more private information, while inter-dealer sharing effectively makes information more public.

More broadly, our findings contribute to our understanding of a symbiotic relationship between investors and intermediaries: it is the process of intermediating trades that reveals information to dealers. Information sharing is what induces clients to use intermediaries and induces large investors to intermediate.[2]

These findings are not meant to imply that dealers should have carte blanche in using information in any way they choose. The model assumes that clients know how dealers

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[2]Dealers in Treasury auctions do not diversify or transform risks, do not locate trading counterparties and cannot monitor issuers because they cannot influence fiscal policy.

use their information, and that communications are unbiased. Our setting does not clearly span the range of malpractices that may have been undertaken. In effect, we ask: If dealers disclose how information is used, what are the costs and benefits of limiting information sharing?

Treasury auctions are unique in their importance and their complexity. Our model balances a detailed description with a tractable and transparent model, which highlights insights that are broadly applicable. To Wang and Zender (2002), we add private values, which serve as the source of noise in prices, a resale market, which creates the cost and the benefit to information sharing, and a correlated information structure. Correlated information is the feature that captures information sharing. But it necessitates a state-space solution method. As in Wang and Zender (2002), our bidders are fully strategic. They correct for the winners' curse, exploit their price impact (bid shading) and bid in such a way as to optimally manipulate the beliefs of others (signal jamming). Market power is not what drives the results. If bidders were less strategic, the effects of information sharing would be qualitatively similar, but larger.

Information sharing occurs because dealers learn from observing bidders' order flow. The importance of this channel is supported by Hortaçsu and Kastl (2012). Using data from Canadian Treasury auctions, they find that order flow is informative about demand and asset values. They further show that information about order flow accounts for a significant fraction of dealers' surplus. In our setting, dealers not only collect this information but may also share some of it. Our structural equilibrium model allows us to go beyond just measuring the information, but also to analyze the effect of dealing information sharing, by using the model to do policy counter-factuals.

In order to match additional institutional features, we model the auction as a "mixed auction", meaning that investors can bid indirectly (through a dealer) or directly (without any intermediary). Finally, we account for minimum bidding requirements of primary dealers, who have historically been expected to bid "consistently" at all auctions for amounts, which today, are equal to the pro-rata share of the offered amount.

Contribution to the existing literature. Our contribution is to explore the revenue and utility effects of pre-auction information sharing, by risk-averse bidders. The main theoretical innovation, relative to Kyle (1989) and Wang and Zender (2002), is the information structure, which allows for a rich set of information sharing possibilities, but requires new tools to account for the associated covariance in signal noise.

Milgrom and Weber (1982) investigate the optimal auction mechanism in a affiliated-value auction model, where the seller can share information with the buyers. In contrast to our setting, any disclosure by the issuer (for example a Treasury announcement) is always

public information, which cannot widen information asymmetry. Also, their model has no risk aversion and thus no increase in price from a reduction in risk. Our main ideas are also connected to a microstructure literature that studies how pre-trade order flow information contributes to price formation (O'Hara, 1995, Chapter 9), raises bid-ask spreads (Bloomfield and O'Hara, 1999) and affects utility of informed and uninformed traders (Fishman and Longstaff, 1992; Röell, 1990). For example, dealers learn from sequential order flow in Easley, Kiefer, O'Hara, and Paperman (1996) and leverage asymmetric information and market power in Kyle (1985) and Medrano and Vives (2004).

We build on the auction design literature[3] by studying auction outcomes when dealers may send signals back to their clients and to other dealers. Also, we explore the incentive of a bidder to bid directly, or through a dealer. More broadly, our work offers a different framework for measurement. We use risk premia and the covariance of prices and payoffs to infer how much investors know. Our risk-based estimation approach predicts different revenue, market power and utility effects of information. Relative to Hortaçsu and Kastl (2012) and Hortaçsu, Kastl, and Zhang (2016), our model misses the realism of bids that are step functions. Instead, we assume demand is continuous and linear. This simplification allows for risk-averse utility, secondary markets and asymmetric information. Our model captures bidders speculating on post-auction appreciation, whereas private values models better describe buy-and-hold bidders, who receive a known payout at maturity. The costs and benefits of information sharing depend on this difference. For speculators with asymmetric information, observing others' information helps the speculator determine the future value of the asset more accurately. Speculators worry that sharing their information with others will induce others to bid more aggressively because information reduces their risk. Without risk aversion, this effect disappears. So, while our model compromises realism in bidding, it enables us to examine new effects of information sharing.[4]

The idea that intermediary behavior determines the equilibrium price of an asset arises in He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014). Their capital-

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[3]Hortaçsu and McAdams (2010) and others studies on how auction design affects revenues, or how it affects information acquisition (Cole, Neuhann, and Ordonez, 2017) complement our project. Theoretical work by Chari and Weber (1992), Bikhchandani and Huang (1989), Back and Zender (1993), and Wilson (1979) considers the merits of uniform-price auctions versus other alternatives. Empirical work by Nyborg and Sundaresan (1996), Malvey, Archibald, and Flynn (1995) and Malvey and Archibald (1998) compares revenues from 1992-1998 when the U.S. Treasury used both uniform and discriminatory price auctions. Armantier and Sbaï (2006) use French Treasury auction bids to structurally estimate the benefits of uniform price auctions. Similarly, He, Krishnamurthy, and Milbradt (2016) explore why US Treasuries are safe. We fix the auction format to a uniform-price multi-unit auction, fix the distribution of future Treasury values, and instead focus on how information sharing affects revenue and surplus.

[4]Outside of an auction setting, literature in industrial organization has studied incentives for information sharing among oligopolists (Raith, 1996, among others). This paper focuses on the benefits and costs of information sharing as opposed to incentives. Vives (1990) discusses the distinction by antitrust authorities between collusive behavior and sharing of aggregate and anonymous information such as the one considered in this paper.

constrained intermediaries provide households with access to risky asset markets and thus improve risk sharing. In Babus and Parlatore (2015), dealers fragment a market, which inhibits risk-sharing. In contrast, we explore how information-sharing induces some agents, who could access markets directly, to choose intermediation.

1 A Treasury auction Model with information sharing

As in Kyle (1989) or Wang and Zender (2002), strategic bidders submit continuous bid functions for a divisible asset. The novel feature of the model lies in its rich information structure. We vary the degree of information sharing exogenously, to explore the effect of policies that prohibit or allow sharing. We do not consider the choice of sharing arrangements because our main choice is a policy question: To what extent should information sharing be allowed? Pending litigations on this matter reveal a clear desire to share.
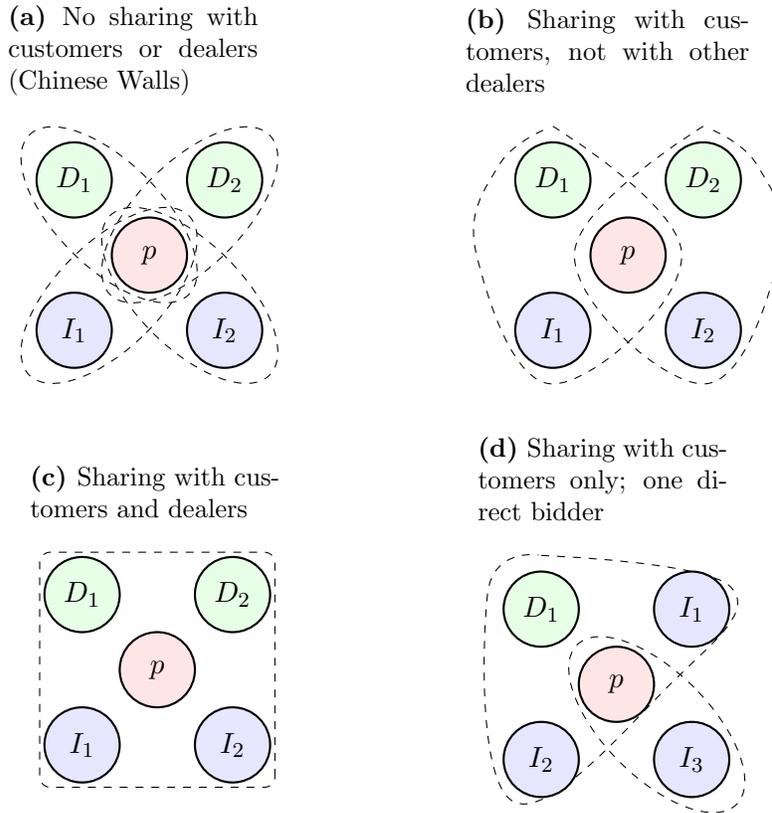
Figure 1 summarizes the alternative sharing arrangements that we consider, for a simplified setting with only a few market participants. Dealers are denoted with the letter "D," investors with the letter "I." Panel a) shows the case of no information sharing ("Chinese walls"), where each auction participant only observes his private information s_i.

When information is shared between dealers and customers (panel b), an investor's information set includes both her private signal and the dealer's; the dealer also observes this extended information set. With cross-dealer information sharing (panel c), each investor observes his dealer's and the other dealer's information. Investors who bid independently from the intermediary keep their signal private (panel d) resulting in a more dispersed information set both for the direct bidder and other bidders.

Of course, auction prices cannot possibly be observed while bids are still being formed. However, auction theory teaches us that each bidder should avoid the winner's curse by choosing a quantity for each price that would be optimal, if he observed that market-clearing price and included it in his information set. When they choose a quantity at each price, the bidder asks, "If this were the realized price, what would I infer about what others know?" Since bidders can set a different demand for every possible price, they can condition on the information contained in every possible price; the information set of investor i is effectively $\{s_i, p\}$.[5] Professional bond traders, who systematically fell victim to the winner's curse, which is taught to most first-year MBA students, would likely not be employed for long.

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[5]There is a long history of including market-clearing prices in information sets, including the literature building on Grossman and Stiglitz (1980), Kyle (1989) and Wang and Zender (2002). If traders fail to make rational inference from the realized price, Appendix C.8 shows that information sharing has an order of magnitude larger effect.

Figure 1: Information sets with alternative sharing assumptions. Letter D denotes dealers; I denotes an investor, either bidding through a dealer or directly; p is the equilibrium price. Dashed lines indicate sets in which information is shared.

(a) No sharing with customers or dealers (Chinese Walls)

(b) Sharing with customers, not with other dealers

(c) Sharing with customers and dealers

(d) Sharing with customers only; one direct bidder

While this simplified setting conveys the essence of information sharing, our model is richer along many dimensions. Most of the model features – heterogeneous preferences and information precision, private values, dealer bidding requirements, market power – improve the model quantitative performance. What is conceptually important is risk aversion, since most of our results work through risk premia, and the presence of a secondary market.

Evidence supporting the importance of the secondary market abounds. The largest auction bidders, primary dealers, sell almost all of their holdings in the secondary market, within a week after the auction (Fleming and Jones, 2015b). Primary dealer transaction data reveals that non-dealers also sell to dealers, shortly after auction. Hedge funds hold securities only briefly because of their limited capital (Wall Street Journal, 2015). This evidence is consistent with the well-known fact that newly issued Treasury notes are the world's most liquid fixed income securities.[6] In addition, we show that buying at auction and re-selling

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[6]See Krishnamurthy and Vissing-Jorgensen (2012); Vayanos and Weill (2008); Krishnamurthy (2002). U.S. primary dealers report their net positions weekly in the New York Fed's FR2004 reports Fleming and

in the secondary market is profitable. It is doubtful that financial actors ignore this fact when bidding. Finally, auction prices reveal strong evidence of such secondary market speculation (Section 6).

The model's secondary market is what makes one bidder's demand informative to others. If there were no secondary market, information sharing would be irrelevant. One's order would reveal a value that is uncorrelated with any other trader's value Therefore, information sharing would be neither harmful, nor beneficial. The fact that information sharing is being litigated suggests that some bidders have relevant information that they would prefer others not to know.

Assets and Secondary Market   The model economy lasts for two periods. Agents can bid for an asset (the newly issued Treasury security) and have a riskless storage technology with zero net return. The risky asset is auctioned by Treasury in a fixed number of shares (normalized to 1) using a uniform-price auction with a market-clearing price p.

After the auction closes, a secondary market opens, as in Hortaçsu (2002). Buyers in the secondary market are a measure-1 continuum of competitive agents who did not participate in the auction. They buy either zero or 1 unit per capita. Each secondary market buyer has private values $\tilde{f}_i \sim N(f, \tau_x^{-1})$. The mean of these private secondary market values is unknown and is distributed $f \sim N(\bar{f}, \tau_f^{-1})$.

Secondary market asset supply comes from auction participants who sell. In the spirit of Diamond and Dybvig (1983), all auction participants hit by a liquidity shock that requires them to sell a fraction α of their shares on the secondary market. Since their expected utility depends on secondary market outcomes, they speculate, or form beliefs about the secondary market price. The secondary-market-clearing price p_s equates demand and supply.

Bidders   To match key features of Treasury auctions, we consider four types of auction participants: dealers, as well as direct and indirect bidders and "non-competes," who submit non-price contingent market orders. Each bidder/dealer can submit a continuous function that specifies a quantity demanded, for every possible clearing price p. All dealers and direct bidders place bids directly in the auction. Indirect bidders are speculative bidders who bid through a dealer, instead of bidding directly. For now, the number of each type of bidders is fixed. Later, we examine the choice to bid (in)directly. There are

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Jones (2015a). Non U.S. sovereign securities, and especially short-dated zero-coupon bill markets such as those considered in Hortaçsu and Kastl (2012) are quite different along this dimension. Many bidders in those auctions hold those securities to maturity. Thus secondary market considerations are not as important for bills.

N_I indirect bidders, which we index by $i = \{1, \ldots, N_I\}$ and N_J direct investors, which we index by $j = \{1, \ldots, N_J\}$.

Every bidder has a private value for the Treasury security. For direct and indirect investors, $v_j \sim i.i.d. N(0, \tau_{vJ}^{-1})$ and $v_i \sim i.i.d. N(0, \tau_{vI}^{-1})$ per share. There are many reason why investors may value Treasury issues differently (see Hortaçsu and Kastl, 2012). For example, a depository institution might address a duration mismatch, a foreign official may be investing dollar-denominated reserves, or an investor might cover a short position in the forward Treasury market, known as the when-issued market.[7]

Each bidder has initial wealth W_{i0}, and chooses the quantity of the asset to hold, $q_i(p)$ at each price p per share, to maximize his expected utility,[8]

$$\mathbb{E}[-\exp(-\rho(W_i + (1-\alpha)q_i v_i))], \tag{1}$$

where ρ denotes absolute risk aversion. The budget constraint dictates that final wealth is initial wealth, minus amount paid at auction, $q_i p$, plus earnings from secondary market sales of αq_i shares and price p_s:

$$W_i = W_{i0} + q_i(\alpha p_s - p). \tag{2}$$

All bidders internalize the effect they have on market prices. Because they strategically consider their price impact, they are not perfectly competitive. They maximize their utility subject to the budget constraint as well as the market clearing condition.

While all other participants submit price-contingent (limit) orders, the non-competes submit market orders (which, in practice, are relatively small). When we talk about "bidders," these non-competes are not included. Non-competes have a private value for the asset, do not forecast future price, and do not condition their bids on price. Non-price contingent orders are exogenous and random. The aggregate non-price contingent demand is $\delta \sim N(0, \tau_\delta^{-1})$.

Dealers   There are N_D dealers, which we index by $d = \{1, \ldots, N_D\}$. Then $N = N_I + N_J + N_D$ is the total number of speculative auction participants. Like investors, dealers have heterogeneous values and resell a fraction α of their shares in the secondary market. For dealers, the value may arise, in part, from auctions rules known as "minimum bidding

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[7]Appendix C.9 explores the effect of the pre-auction market, known as the when-issued market and how its existence affects agents' information.

[8]Technically, the price of each Treasury is fixed at par and auction participants bid coupon payments. Here p is the present discounted value of coupons computed from other outstanding Treasury securities. CARA utility here serves to make demand linear. One can equivalently write a model with a more general utility specification and then do a first-order Taylor approximation of the first-order condition.

requirements." (See Appendix B for details.) If over time, a dealer is consistently allotted an insufficient share, his primary dealer status could be revoked. To capture the essence of this dynamic requirement in a static model, we give dealers values for each share that are typically positive, but decreasing in asset shares $v_d = \chi + \frac{\chi}{q_d}$, where q_d represents the number of shares awarded to dealer d at the market price. The decreasing value v_d represents the idea that when the dealer's bid q_d is too low, raising that bid reduces the risk of penalties for the dealer. When the bid is already high and the requirement is satisfied, additional shares might relax future bidding constraints, but provide diminishing value. This cost is a stand-in for the shadow cost of a dynamic constraint. Quantitatively, it allows us to match dealers' purchased share of the auction. Dealers choose asset demand functions $q_d(p)$ to maximize

$$\mathbb{E}[-\exp(-\rho(W_d + q_d v_d))] \qquad \text{where } W_d \text{ is given by } (2). \qquad (3)$$

Describing Information Sets and Updating Beliefs with Correlated Signals
Bidders can observe many possible pieces of information: their own private signal, signals from others who may share information with them, and their private value v_i. The dealers' value of the asset is common knowledge as it derives from a common and publicly known requirement while investors' values v_i are private information. Finally, since 2008, all non-price contingent bids have been publicly revealed before bidding closes. Therefore, we assume that δ is common knowledge. We explain each in turn. In addition, bidders can avoid the winners' curse by conditioning their bids on the information that would be revealed if each price were realized. This price information just keeps agents rational, but is not essential, or even favorable to our results. We find qualitatively similar, but quantitatively, stronger effects of information sharing when bidders don't condition on prices. (See Appendix C.)

Before trading, each bidder and dealer gets a signal about the average private value in the secondary market. This signal could represent a macroeconomic or financial forecast or some insight about future demand. Signals are unbiased, normally distributed and have private noise:

$$s_i = f + \varepsilon_i,$$

where $\varepsilon_i \sim N(0, \tau_\varepsilon^{-1})$.

By placing orders through dealers, customers reveal their order flow $q_i(p)$ to their dealer, which in the model is equivalent to sharing their expected value of the security $\mathbb{E}_i[f] + v_i$. Each dealer d receives orders from N_I/N_D clients.[9] The dealer constructs $\tilde{s}_d$, which is an

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[9]It is quite plausible that a dealer might also include his own private signal in the information he

average of his clients' expected valuations:

$$\tilde{s}_d = \frac{N_D}{N_I} \left(\sum_{i \in \mathcal{I}_d} \mathbb{E}_i[f] + v_i \right), \tag{4}$$

where $\mathcal{I}_d$ is the set of investors bidding through dealer d.

Dealers, in turn, can share some of this order flow information with their clients. Dealer-client information sharing takes the form of a noisy signal about $\tilde{s}_d$, which is the summary statistic for everything the dealer learned from client order flow. That noisy signal is $s_{\xi i} = \tilde{s}_d + \xi_i$ where $\xi_i \sim N(0, \tau_\xi^{-1})$ is the noise in the dealers' advice. The noise ξ_i varies by dealer and by client, but sums to zero for each dealer, in each state. Section 4.4 considers dealers who mislead clients, by not truthfully revealing their information sharing. Our model captures unbiased, noisy dealer advice, as well as two extreme cases: perfect information-sharing between dealers and clients ($\tau_\xi = \infty$) and no information-sharing ($\tau_\xi = 0$).

In addition, dealers may share information with other dealers. Let ψ be the size of the group of dealers who share their information with each other. In other words, each dealer reveals all of his or her signals to $\psi - 1$ other dealers. No sharing between dealers is the case where $\psi = 1$. All information sharing is mutual.

The final piece of information that all agents condition on is the auction-clearing price p. Let $s_i(p)$ denote the unbiased signal that agent i constructs from supposing that p is the auction-clearing price, when choosing each conditional demand $q(p)$. We guess and verify that $(s_i(p) - f) \sim N(0, \tau_{pi}^{-1})$, where τ_{pi} is a measure of the informativeness of the auction-clearing settlement price. Recall that direct and indirect bidders have private values that are private information. Adjusting their price inference for their own valuation, they infer $s(p|v_i)$ or $s(p|v_j)$ from a realized price p.

Signal vectors for the three types of agents are as follows: An investor who bids directly observes a vector of signals $S_j = [s_j, s(p|v_j)]$. Investors who bid through dealers observe the larger signal vector $S_i = [s_i, s_{\xi i}, s(p|v_i)]$. While these investors observe an extra signal, they also will end up having signals and thus making bids that covary more with price information. A dealer observes the same signals as an indirect investor, except that he sees the exact order flows, instead of a noisy signal of them. For dealer d, $S_d = [s_d, \tilde{s}_d, s(p)]$. Since non-price contingent bids δ and dealer valuations v_d are common knowledge, we don't

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transmits to clients. However, the policy debate focuses on the effect of dealers' sharing of client order flow information. We therefore exclude dealers' private information from $\tilde{s}$, to isolate effects from the sharing of order flow information. Note also that dealers' signals to clients covary with clients' private and public information. Our solution method accounts for this covariance.

include them in S. But every speculative bidder accounts for them.

For every agent, we use Bayes' law to update beliefs about f. Bayesian updating is complicated by the correlation in the signal errors. Therefore, we use a state-space filtering method that is not standard in this literature. The following are optimal linear projection formulas:

$$\mathbb{E}\left[f|S_j\right] = (1 - \beta' 1_m)\bar{f} + \beta' S_j \qquad \text{where} \tag{5}$$

$$\beta_j \equiv \mathbb{V}\left(S_j\right)^{-1}\mathbf{Cov}\left(f, S_j\right) \tag{6}$$

$$\mathbb{V}\left[f|S_j\right] = \mathbb{V}\left(f\right) - \mathbf{Cov}\left(f, S_j\right)' \mathbb{V}\left(S_j\right)^{-1}\mathbf{Cov}\left(f, S_j\right) \equiv \hat{\tau}_j^{-1}, \tag{7}$$

where m is the number of signals in the vector S_j, the covariance vector is $\mathbf{Cov}\left(f, S_j\right) = 1_m \tau_f^{-1}$ and the signal variance-covariance $\mathbb{V}\left(S_j\right)$, is worked out in Appendix A.2. The vector $\beta_j = [\beta_{sj}, \ \beta_{\xi j}, \ \beta_{pj}]$ dictates how much weight an agent puts on his signals $[s_j, \ s_{\xi d(j)}, \ s(p)]$ in his posterior expectation. In a Kalman filtering problem, β is like the Kalman gain.

Equilibrium A Bayesian Nash equilibrium, for a given information sharing arrangement $(\tau_\xi, \ \psi)$ is

1. A bid function by each direct or indirect bidder that maximizes

$$\max_{q_i(p)} \mathbb{E}[-\exp(-\rho(W_i + (1 - \alpha)q_i v_i))|S_i] \tag{8}$$

$$\text{s.t. } W_i = W_{0,i} + q_i(\alpha p_s - p) \qquad \text{and} \qquad (12) \tag{9}$$

The second constraint (12) is the auction clearing condition and reflects that the speculative bidders choose their quantity, taking into account the effect their demand has on the equilibrium price.

2. A bid function for each dealer that maximizes

$$\max_{q_d(p)} \mathbb{E}[-\exp(-\rho(W_d + q_d v_d))|S_d] \tag{10}$$

$$\text{s.t. } W_d = W_{0,d} + q_d(\alpha p_s - p) \qquad \text{and} \qquad (12) \tag{11}$$

3. An auction-clearing (settle) price that equates demand and supply:

$$\sum_{i=1}^{N_I} q_i + \sum_{j=1}^{N_J} q_j + \sum_{d=1}^{N_D} q_d + \delta = 1. \tag{12}$$

4. A secondary market price p_s that equates demand and supply.

2   Solving the Model

Equating demand and supply reveals that the secondary market price is $p_s = f + g$, where f is the normally-distributed mean of the secondary market private values and g depends on model parameters. Below, we substitute in this solution for p_s and derive optimal bid schedules of investors and dealers. Finally, we work out the auction equilibrium with different, exogenous information-sharing arrangements.

Since all investors' posterior beliefs about f turn out to be normally distributed, we will use the properties of a log-normal random variable to evaluate the expectation of each agent's objective function. We then substitute the budget constraint in the objective function, evaluate the expectation and take the log. The investor maximization problem simplifies to $\max_{q_j, p}$ $q_j(\alpha \mathbb{E}[f|S_j] + \alpha g + (1-\alpha)v_j - p) - \frac{1}{2}\rho\alpha^2 q_j^2 \mathbb{V}[f|S_j]$, subject to the market clearing condition (12), where the price is not taken as given. The first order condition with respect to q_j reveals that investors bid

$$q_j(p) = \frac{\alpha \mathbb{E}[f|S_j] + \alpha g + (1-\alpha)v_j - p}{\rho\alpha^2 \mathbb{V}[f|S_j] + dp/dq_j}. \tag{13}$$

For dealers, the expression is almost identical. The only difference arises from the gap in signal vector S that the dealer conditions on and the form of the private value v_d that is earned on all shares purchased. Since $v_d q_d = \chi q_d + \chi$, the constant χ drops out when taking the first order condition and the optimal dealer bid is

$$q_d(p) = \frac{\alpha \mathbb{E}[f|S_d] + \alpha g + \chi - p}{\rho\alpha^2 \mathbb{V}[f|S_d] + dp/dq_d}. \tag{14}$$

Equilibrium auction-clearing price   In order to understand the implications of different information sharing arrangements, we solve for auction outcomes in the three cases illustrated in Figure 1: 1) dealers and customers share information; 2) dealers also share information with other dealers; and 3) no information is shared either with customers or between dealers.

The no-information-sharing world is one with "Chinese walls," where dealers cannot use client information to inform their own or their clients' purchases. In recent years, a number of financial firms have reportedly implemented such a separation of brokerage activities and transactions for their own account. Regulators have also recommended that banks establish and enforce such internal controls to address potential conflicts of interest.[10] In our Chinese wall specification, each agent sees only their own private signal s_i and the price information $s_i(p)$ which they can condition their bid on, but not any signal from the

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[10]For example, the Financial Stability Board (FSB) 2014 report on "Foreign Exchange Benchmarks."

dealer: $S_i = [s_i, s_i(p)]$.

In the information sharing cases, investors observe the larger signal vector $S_i = [s_i, s_{\xi i}, s_i(p)]$. The signal $s_{\xi i}$ includes information from clients and/or information shared across dealers. In these cases, the investors' own information will also be shared with others.

The equilibrium auction price is obtained by adding up all investors' and dealers' asset demands as well as the volume of market orders x and equating them with total supply. As in most models with exponential utility, the price turns out to be a linear function of each signal. The innovation in this model is that information sharing changes the linear price weights, which affects utility. To the extent that signals are shared with more investors, that signal will influence the demand of more investors, and the weight on those signals in the price function will be greater.

Result 1. *Under each of the following three information-sharing regimes:*

1. *Dealers share information imperfectly with clients, but not with other dealers.*

2. *Dealers share information with clients and ψ other dealers.*

3. *There is no information sharing at all. Dealers cannot use client trades as information on which to condition their own bid (Chinese walls).*

auction revenues are always a linear function of signals s_i and investors' average private values $\bar{v}$:

$$p = A + B_I \bar{s}_I + B_J \bar{s}_J + B_D \bar{s}_D + C_I \bar{v}_I + C_J \bar{v}_J + D\delta \tag{15}$$

where $\bar{s}_I \equiv N_I^{-1} \sum_{i=1}^{N_I} s_i$, $\bar{s}_J \equiv N_J^{-1} \sum_{i=1}^{N_J} s_j$ and $\bar{s}_D \equiv N_D^{-1} \sum_{i=1}^{N_D} s_d$ are the average signals of indirect bidders (I), direct bidders (J) and dealers (D), and δ is the non-price contingent demand. The equilibrium pricing coefficients $A, B_I, B_J, B_D, C_I, C_J$ and D differ by model and are reported in Appendix A.

Models of competitive markets often have simple price coefficient solutions; this is not true in our setting. The complication is two-fold: 1) there are strategic agents whose demands are not linear in the coefficients of the price function and 2) shared signals are correlated with price information. Both sources of complexity are essential to understand how information sharing affects auction revenue. Appendix A proves that an equilibrium exists and is unique in four classes of models: low market power, little information sharing, widespread information sharing, and sufficiently symmetric bidders. Outside these classes, we establish existence numerically.

With Chinese walls, when dealers can no longer use the information in their clients' orders, the functional difference between indirect and direct bidders and dealers disappears. In other words, eliminating all information sharing effectively eliminates intermediation as

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well.[11]

Auction Revenues   Information sharing results in more information for the average investor. By its nature, information reduces uncertainty, or conditional variance. Assets with less uncertain payoffs are less risky. One of the most robust findings in finance and economics is that less risky assets consistently command higher prices. Because the supply of the Treasury asset is normalized to one, price and auction revenue are the same. Since private values and non-price contingent bids are both mean zero, from (15), an average auction's revenue is : $A + (B_I + B_J + B_D)(\bar{f} + g)$, where $(\bar{f} + g)$ is the average secondary market price. The term $A < 0$ incorporates both the risk premium needed to induce risk averse buyers to purchase the asset, as well as market power. The term $(B_I + B_J + B_D)$ is the sensitivity of the price to changes in secondary market demand. The next result shows that, in many cases, both A and B rise when information improves.

Result 2. *Information sharing raises revenue.* For a ball of parameters, $\{\tau_{vI}, \tau_{vJ}, \tau_f, \tau_s, \chi\} \in \Upsilon$, when bidders and dealers all have weakly more information from others (weakly lower $V[f|S]$ for all), then auction revenue p weakly rises, on average.

With normally distributed variables and signals, an additional signal always weakly decreases conditional variance. In fact, this concept is equivalent to Blackwell's definition of "informativeness." The modifier weakly is there simply because a signal might have no information content. But if at least one bidder has an informative signal and all others have no less information, the same proof shows that revenue is strictly higher. This effect arises because $V[f|S]$ shows up in the denominator of the first order condition (14), representing the idea that risk-averse bidders bid more for a less risky asset. The proof further shows that the other term in the denominator dp/dq, representing market power, also falls. There is less scope for price manipulation when other market participants are better informed because risk-averse bidders bid more aggressively on mispriced assets when they are better-informed.

When the model is sufficiently asymmetric (parameters outside Υ), the market power result can reverse. In these cases, information sharing among a subset of agents, such as dealers, can increase market power because it exacerbates information asymmetry. (Section 4.2 offers an example.)

While this type of information-price effect shows up in many imperfect information asset pricing models, it has largely been neglected in the policy discourse on information regulation. Our contribution is to quantify how much revenue it costs.

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[11]The finding that there is no longer any meaningful distinction between a dealer and a non-dealer large investor is reflected in the fact that in the price formula, if the number of dealers and large investors is equal and the dealers do not face a minimum bidding requirement, then the coefficients on the signals of dealers s_d and the signal of large investors s_j are equal as well.

Expected Utility   When all bidders share information, are they collectively better off? This is a distinct question from whether an individual is better off if they alone choose to share information. The individual's sharing decision is analyzed in Section 5. The following result establishes that information sharing can be like a prisoners' dilemma problem. To make this point clearly, we examine a situation where each bidder simply gets more information. This limiting case is instructive because when one investor gets such information, this cannot possibly be bad for that individual – there is free disposal of information. But when all bidders get this additional information, bidders are collectively made worse off. This prisoners' dilemma effect arises in cases where the information makes beliefs more heterogeneous, as in the case with additional private signals.

Result 3. *Better private information is collectively harmful to bidders.* *If N is sufficiently high and χ sufficiently low, and either*

(a) *there is no direct bidder; or*

(b) *there are direct bidders and $\tau_{vI} \in B_{\epsilon_v}(\tau_{vJ})$ and $\tau_\xi \in B_{\epsilon_v}(0)$ where $B_{\epsilon_v}(\tau_{vJ})$, $B_{\epsilon_\xi}(0)$ are open balls of parameter values; or*

(c) *there are direct bidders, but $\frac{N_J}{N}$ is sufficiently low,*

then indirect bidders have higher ex-ante expected utility when no bidders have a private signal s_i.

This result, similar to Hirshleifer (1971), arises because heterogeneous information undermines risk-sharing. The ex-ante identical bidders' socially optimal bids should result in symmetric allocations of the Treasury security. Heterogeneous information encourages bidders to take larger or smaller positions than their peers, resulting in less symmetric allocations and worse risk-sharing. The numerical results show examples where information sharing functions like better private information, reducing utility, as well as other instances where the sharing reduces belief heterogeneity, to improve bidder utility.

3   Mapping the Model to the Data

The model has thirteen parameters. We map the model to the data by fixing the number of agents (three parameters) and then calibrating the remaining nine parameters to twelve moments from Treasury auction allotments and market pricing data. The rest of this section provides detail on the calibration. Our sample starts in September 2004 and ends in June 2014. To study a comparable sample and estimate yield curves, we restrict attention to 2-, 3-, 5-, 7- and 10-year notes and exclude bills, bonds and TIPS. In 2013 alone, Treasury issued nearly $8 trillion direct obligations in the form of marketable debt as bills, notes,

bonds and inflation protected securities (TIPS), in about 270 separate auctions.[12]

In each auction, price-contingent (called "competitive") bids specify a quantity and a rate, or the nominal yield for note securities. "Non-competes" is Treasury-auction parlance for non-price contingent bidders; they specify a total amount to purchase at the market-clearing rate. Price-contingent bids can be direct or indirect. To place a direct bid, investors submit electronic bids to Treasury's Department of the Public Debt or the Federal Reserve Bank of New York. Indirect bids are placed on behalf of their clients by depository institutions or brokers and dealers.

All bids are received prior to the auction close. The auction clears at a uniform price, which is determined by first accepting all non-price contingent bids, and then price-contingent bids in ascending yield order. The rate at the auction (or stop-out rate) is then equal to the interest rate that produces the price closest to, but not above, par when evaluated at the highest yield, at which bids were accepted.

Using data published by the U.S. Treasury, for each maturity, we compute the mean share of securities allotted to primary dealers, non-competes, direct and indirect bidders. Primary dealers bidding for their own account, are the largest bidder category at auctions accounting for 53% on average of all price-contingent bids. Indirect bidders are the second largest at about 37%. Direct bids account for about 9% and non-competes about 1%.

The next set of calibration moments are the mean and variance of auction prices and secondary market values. Measuring prices and payoff risk (speculative risk) is central to our calibration strategy because risk and return help to pin down the precision of bidders' information.[13] When calculating auction prices p, note that, up to rounding, the auction price clears at par. The stop-out coupon rate is what is uncertain. It is a function of issue-specific value as well as future interest rates. In our calibration, we focus on issue-specific fundamentals, or the "on-the-run" value of the issue. Investors can and do hedge interest rate risk by shorting a portfolio of outstanding securities. To strip out the hedged interest-rate effects, we assume that the bidder enters the auction with an interest-rate-neutral portfolio, which holds one unit of the auctioned security and shorts a replicating portfolio of bonds trading in the secondary market. Thus, price p in our model corresponds to *the auction price, minus the present value of the security's cash-flows*, where future cash flows

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[12]Treasury bills are auctioned at a discount from par, do not carry a coupon and have terms of not more than one year. Bonds and notes, instead, pay interest in the form of semi-annual coupons. The maturity of notes range between 1 and 10 years, while the term of bonds is above 10 year.

[13]Risks faced by speculative Treasury bidders are different from those faced by investors underwriting corporate bonds. Because the U.S. sovereign secondary market is deep and liquid, Treasury investors can hedge issuer-specific risks by shorting already-issued securities. Newly issued government securities do, however, carry a liquidity premium relative to already-issued securities. Investors' demand for specific issues is the key determinant of these liquidity differences. As a result, key underwriting risks for bidders are issue-specific rather than issuer-specific.

are discounted using a yield curve. To compute this measure, we estimate a Svensson yield curve following the implementation details of Gürkaynak, Sack, and Wright (2007) but using intraday price data as of 1pm, which is when the auction closes (data from Thomson Reuters TickHistory).

To be consistent, the models' secondary market value $g + f$ corresponds to the secondary market *value of the interest-rate neutral portfolio on the date when the security is delivered to the winning bidders*, which is when secondary markets open. This delivery date lags the auction date by an average of 5.5 days with a standard deviation of 2.3 days. The average revenue from selling a new coupon-bearing security is about 40 basis points higher than the replicating portfolio formed using outstanding securities. This well-known "on-the-run" premium (Lou, Yan, and Zhang, 2013; Amihud and Mendelson, 1991; Krishnamurthy, 2002) is positive across all maturities. Appendix B documents the algorithm to calculate payoffs and explores other ways of hedging the interest rate risk.

Table 1: Calibrated parameters. The valuation-related parameters in the Table $(\tau_f^{-\frac{1}{2}}, \tau_\varepsilon^{-\frac{1}{2}}, \tau_{vI}^{-\frac{1}{2}}, \tau_{vJ}^{-\frac{1}{2}}, \tau_\xi^{-\frac{1}{2}}$ and χ) are expressed in basis points. The standard deviation of the non-price contingent parameter $\tau_\delta^{-\frac{1}{2}}$ is measured as a share.

α	$\bar{f}$	$\tau_f^{-\frac{1}{2}}$	$\tau_\varepsilon^{-\frac{1}{2}}$	$\tau_{vI}^{-\frac{1}{2}}$	$\tau_{vJ}^{-\frac{1}{2}}$	$\tau_\xi^{-\frac{1}{2}}$	$\tau_d^{-\frac{1}{2}}$	ρ	χ	N_I	N_J	N_D
0.40	54.81	181.92	5.60	7.45	0.96	1.00	1.00	488.09	42.57	200	50	20

Calibration Table 1 lists the 13 parameters in the model. Six of these parameters can be matched directly to data. The three parameters that govern the number of market participants (N_D, N_I and N_J) are chosen directly to approximate the observed number of dealers (about 20) and produce 10 clients per dealer. Since indirect bidders take down almost four times as much of the auction as direct bidders do, we set the number of direct bidders $N_J = N_I/4 = 50$. Next, the mean and standard deviation of the secondary market price ($\bar{f}$ and $\tau_f^{-1/2}$) correspond directly to the first and second moments of the secondary market buyers' average valuations, measured in basis points. Note that the mean of the secondary market value distribution $\bar{f}$ and the pricing constant g do not affect the auction solution separately. Therefore, we calibrate their sum, $\bar{f} + g$. The sixth directly-measured parameter is α, the probability of secondary market sale. We know that dealers take down half the auction and sell almost all of their inventory within one week of auction. From secondary market volumes, we also know that others must also sell holdings. This implies that at least half the auction changes hands in the first week. More turnover makes the effects of information sharing stronger. Therefore, we choose a conservative value of 40% and explore other values as robustness checks.

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Risk aversion closely governs the price of the Treasury and thus auction revenues. For a given set of other parameters, we can infer the value of risk aversion that matches expected revenue.[14] Thus, for each set of candidate parameters, risk aversion ρ is chosen such that the expected revenue (p) of the auction matches exactly observed data.

Table 2: Calibration targets and model-implied values. Prices and excess revenues are all expressed in basis points. N_I, N_J and N_d are set directly, resulting in three over-identifying moments.

	Data	Model
Expected resale value($\alpha \left(\bar{f} + g \right)$)	40.36	40.36
Stdev resale value ($\alpha \tau_f^{-1/2}$)	72.77	72.77
Expected revenue (p)	36.74	36.74
Stdev revenue	71.97	73.08
Price constant (A)	-1.56	-3.55
Price sensitivity to fundamental $(\tilde{B})$	0.97	1.00
Pricing Error Stdev. (σ_ϵ)	30.19	8.03
Indirect share (%)	36.89	34.83
Dealer share (%)	53.31	56.53
Volatility of dealer share	14.50	7.39
Direct share (%)	9.80	8.64
Volatility of direct share	8.56	18.41

We calibrate the remaining six parameters jointly to provide the best fit to the remaining nine aggregate moments in Table 2. Note that there are more moments than parameters. Since the model is not an exact representation of reality, it cannot match all the moments. The over-identifying moments provide extra information to guide parameter calibration and gauge the fit of the model to the data. The calibration objective function for these parameters includes the variance of the auction revenue (or the on-the-run premium at the auction), the mean allotted share to primary dealers ($\sum_{d=1}^{N_D} q_d$), indirect bidders ($\sum_{i=1}^{N_I} q_i$), and to direct bidders as well as the variance of the direct and dealer share. In addition, we estimate the empirical counterpart of the equilibrium pricing equation (15):

$$p_t = \gamma_0 + \tilde{B} f_t + \epsilon_t, \qquad \text{where } \tilde{B} = B_I + B_J + B_D \tag{16}$$

where, p_t and f_t are "on-the-run premiums" at the auction and issuance dates, respectively. From (15) and (16), we see that excess revenues are positively correlated to the fundamental value on issue date ($\tilde{B} > 0$). The estimated value $\hat{\gamma}_1 = .97$ (standard error = .034) reported in Table 2 suggests that the auction price reflects expectations for secondary market value, nearly one-for-one. The estimate of σ_ϵ is the variance of the residual from

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[14]Absolute risk aversion looks large. But that is only because we set the supply to one. When we instead set supply to 100 or 1000, estimated risk aversion is 2-3 orders of magnitude smaller. The higher demand, associated with this smaller risk aversion, clears the larger market supply.

that regression.

To reflect the spirit of the minimum bidding requirement, we can set the level of minimum bids χ to be equal to the pro-rata share of the issuance at the expected price. But we do not list this parameter because it does not affect the demand functions. As a constant, it drops out of the first order condition. The χ parameter does matter: If we set it to 0, but keep other parameters at the calibrated values, expected revenue is roughly 3 basis points lower and dealers take down only about 10 percent of the auction.

The model moments are computed by drawing 100,000 realizations of the fundamental f, all the signals S_i, and non-price contingent demands δ, and calculating the average equilibrium outcomes. We solve the model by solving for the equilibrium pricing coefficients in Result 1. This amounts to solving for a fixed point in a set of twelve non-linear equations (six for pricing coefficients, three for demand elasticities, and three for the belief vector of indirect bidders). We iterate to convergence, using the average violation of the market clearing condition (12) to ensure that we find the equilibrium pricing coefficients. At our solution, the average violation of the market clearing condition is about 10^{-12}. We use multiple starting points to ensure that the maximum is a global one.

4   Results: Effects of Information Sharing

We examine two forms of information sharing. We first study information sharing between dealers and clients by varying the precision of the dealer signal to their clients, without allowing dealers to communicate amongst each other. Then, we hold the precision of client communication fixed and vary the number of other dealers that each dealer shares information with. In both cases, we find that information sharing increases auction revenues as well as revenue volatility. The surprising finding is that investors dislike, as a group, when dealers share more precise information with them, but sometimes benefit when dealers share information with each other. The intuition for this puzzling finding is that client information sharing increases information asymmetry and inhibits risk sharing, as in Hirshleifer (1971), while inter-dealer talk can reduce information asymmetry and improve risk sharing.

Since the quantity of auctioned securities is fixed and normalized to 1, the auction price and auction revenues are the same. In the plots that follow, we study expected excess revenues varying one exogenous parameter at a time. In each exercise, all parameters other than the one being varied are held at their calibrated values from Table 1.

Figure 2: Dealer Information Sharing. Left: dealer information sharing with clients; right: dealer information sharing with other dealers. In the left panel, the horizontal axis shows the precision of the dealer signal τ_ξ from zero (no information sharing) to infinity (perfect information sharing).

(a) Sharing with clients: Expected Revenue   **(b) Sharing with dealers:** Expected Revenue
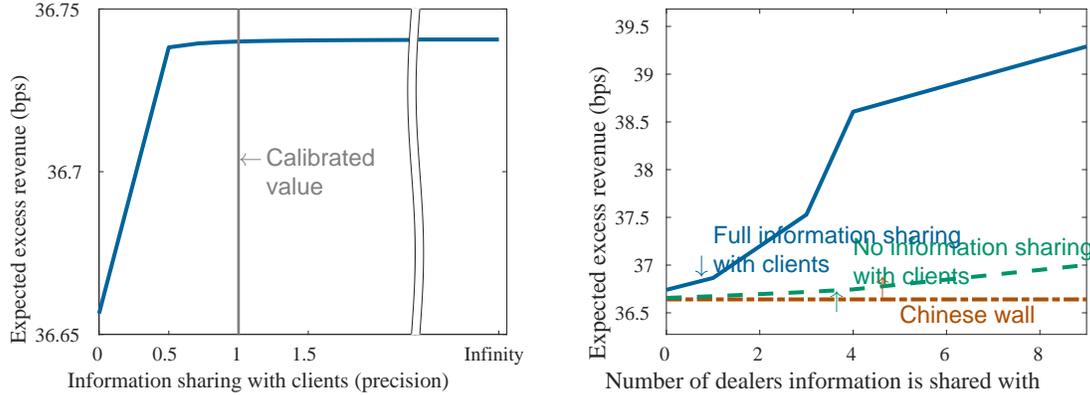
4.1 Information Sharing Raises Auction Revenue

Information sharing – of either kind – makes the average bidder better informed, which in turn makes Treasuries less risky to the average investor, eliciting stronger bids, resulting in higher auction revenues. However, the quantitative revenue effects of client-sharing and dealer-sharing are quite different. The left panel of Figure 2 plots expected auction revenues, as a function of different levels of dealer information sharing with clients. The horizontal axis shows the precision of the dealer signal τ_ξ from zero (no information sharing) to infinity (perfect information sharing). More information sharing means that dealers reveal their information $\bar{s}_d$ with less noise to their clients. In the absence of inter-dealer talk ($\psi = 1$ in left panel), moving from no sharing to perfect information sharing with clients results in a very small increase in expected revenue of a tenth of a basis point. The vertical line on the plot represents the amount of client information sharing implied by the model calibration. This calibrated status quo corresponds to revenues of 36.74 bps. How much can client information sharing raise revenue? Given an annual Treasury issuance of about \$8 trillion, the model implies that going from no sharing to perfect sharing with clients would increase total auction revenues by a modest \$80 million. Furthermore, the model suggests no revenue gain from encouraging further client information disclosure compared to the calibrated status-quo. Indeed the revenue curve to the right of the current level of information sharing is flat. Importantly this result assumes that dealers do not share information with each other. The model suggests that without dealer sharing, the benefits of client information sharing are limited.

The biggest revenue gains arise when both types of information sharing take place as shown in the right panel of Figure 2. As shown by the brown dashed line, if dealers do not share information with their clients, the revenue benefits of dealer talk are small, less than 0.5 basis points. In contrast, the combination of inter-dealer sharing and sharing information with clients is a powerful revenue generator. In the presence of full client information sharing (solid blue line), increasing the number of dealers with which each dealer shares information, auction revenues increase by almost 3 basis points.[15] Given the current level of client information sharing implied by our model, the additional revenue from allowing all dealers to share with four (or more) other dealers amounts to $ 2.4 billion.

In unreported results, we also find that both types of information sharing reduce the variance of auction revenue, but that this effect is quite small (order of less than a basis point).[16] We also find that when prior uncertainty about the future value of the asset is high (precision τ_f is low), or if the variance of non-price contingent bids grows, information sharing raises revenue by more. The reason is that both make bidders more uncertain ex-ante. When bidders are more uncertain, there is more scope for information sharing to reduce risk and raise revenue.

One proposed policy is an open order book. An open book allows all bids to be observed by all market participants. In our setting, the open order book corresponds to perfect order information sharing between clients and dealers ($\tau_\xi = \infty$) and perfect interdealer information sharing ($\psi = N_D$) but does not imply full sharing of all observed signals. Because of the strategic bidding, open order book yields slightly lower revenue than full information sharing. The difference is that when dealers share information, they convey signals directly. Orders on the order book are bids. Because of private values, bids convey signals, mixed up with private value information. So bids convey imperfectly what others know and are more open to manipulation. If instead of a strategic bidder market, this were a large, competitive market, the benefits of an open order book would rise further to 40.36 basis points. That's a 3.6 basis point increase over the status quo, corresponding to an additional $2.9 billions in Treasury revenue.

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[15]Since we assume dealers are symmetric, we need the number of dealers in an information-sharing collective to be a factor of 20, the calibrated number of dealers. Thus, we stop at 9, which implies that two groups of 10 dealers each are sharing information with each other. Any more information sharing beyond this level would be perfect inter-dealer sharing.

[16]The reason for the small change in variance is because two countervailing effects nearly offset each other. In a model with common values, an increase in information sharing would increase revenue volatility: As investors put more weight on their more informative signals, the auction clearing price becomes more sensitive to changes in the fundamental value f. With private values, when information sharing makes the auction price more responsive to the speculative return, it also becomes less responsive to private values. The result is small changes in revenue variance.

The role of minimum bidding requirements Primary dealers are required to be consistent, active participants in Treasury auctions. While rules have evolved over time, today, primary dealers are expected to bid at all auctions an amount equal to the pro-rata share of the offered amount, with bids that are "reasonable" compared to the market. The inclusion of minimum bidding penalties in dealers' private values is realistic but also helps to calibrate the model in a sensible way. Absent a reason for a high private value and given common risk aversion for all bidders, it would be hard for our model to explain why dealers bid for so much of the auction. One way to see this is by looking at the estimated level of $\chi = 55$ in Table 1, which is about as large as the standard deviation of the fundamental in the model ($\tau_f^{-\frac{1}{2}} = 73$). In words, the model needs a private value component for dealers which is of the same order as the secondary market price, to rationalize the observed shares. In unreported results we show that the main effect of minimum bidding requirements is that a higher penalty (χ) raises expected revenue by boosting demand by primary dealers, since dealers are incentivized to bid more aggressively. But bidding requirements leave the effect of client information-sharing on revenue and utility unchanged.

4.2 Bid Shading and Signal Jamming

Since our bidders have price impact and are strategic, they optimally use their bids to influence the auction-clearing price ("bid shading"), which is the central focus of Hortaçsu, Kastl, and Zhang (2016). Our bidders can also influence others' beliefs, so as to impact others' bids ("signal jamming"). In this section, we quantify how much bid shading and jamming reduce expected revenues. This strategic behavior does suppress revenue, but it does not interact much with information sharing. Market power has little effect on the cost and benefit of information sharing, except in the case where dealers share extensively.

Each speculator's and primary dealer's bid depends on her expected secondary market price and private value (numerator of (13)), and on the sensitivity to that expected value (denominator of (13)). The sensitivity (denominator) has two terms. The first is a risk aversion $\rho V[f|S_i]$ term. If investor i is more risk averse, then she bids for a smaller position in the asset. The second term is dp/dq_i. This is a strategic effect that captures her ability to influence the auction price. We break that strategic effect into two parts: bid shading (BS) and signal jamming (SJ).

If the bidder reduces their demand by one unit, and others' bidding best responses stayed fixed, auction-clearing price falls. Bid shading is the part of dp/dq_i that would remain, even if, when an investor reduces his bid, others do not make inference from the lower price: $BS = dp/dq_i|_{\beta_p=0}$, where $\beta_p = 0$ means that other bidders place zero weight on the price signal. The other strategic effect is the ability to influence others' be-

Figure 3: Bid Shading and Signal Jamming Revenue Effects. This Figure shows the effect of removing either bid shading $(dp/dq_i|_{\beta_p=0})$ or signal jamming $((dp/dq_i)^{-1} - BS^{-1})$ from bidders' demands, one at a time. Each line represents an average price (revenue). Left: dealer information sharing with clients; right: dealer information sharing with other dealers. Formulas for bids without jamming and shading are (131) and (133) in the Appendix.

(a) With Client Information Sharing

(b) With Dealer Talk

(c) Components of Demand Elasticity
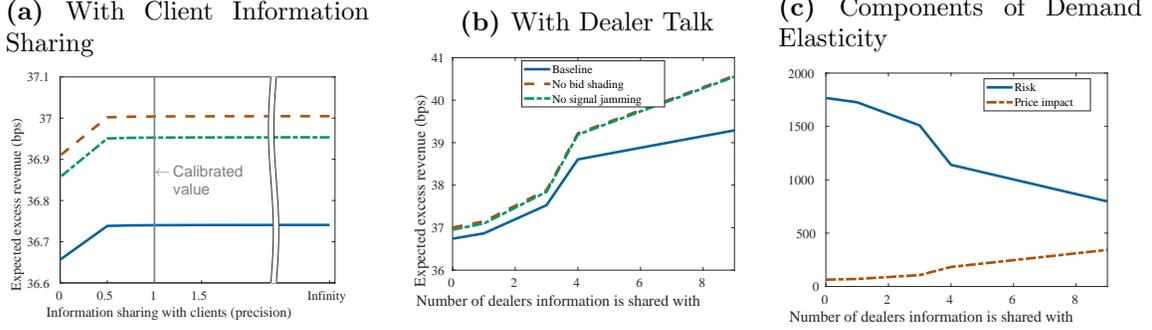
liefs through prices. This is signal jamming: $SJ = (dp/dq_i)^{-1} - BS^{-1}$.[17] If we let $M_l = (\rho\alpha^2 V[f|s_l] + dp/dq_l)^{-1}$, for each type of investor l, and let β_{lp} be the Bayesian updating weight bidder l puts on price information (from eq. (6)) and $\tilde{B}$ be the combined effect of all bidders' signals on price (from eq. (16)), then we can express signal jamming as $SJ = \frac{\alpha}{\tilde{B}}(M_I(N_I - 1)\beta_{Ip} + M_J N_J \beta_{Jp} + M_D N_D \beta_{Dp})$. The key piece of signal jamming is that it works through the β_p Bayesian weights. Manipulating the price to distort others' beliefs works to the extent that others make inference from the price they condition on, which is $\beta_p > 0$.

Figure 3 shows that, not surprisingly, removing bid shading and signal jamming causes bidders to bid more boosting expected revenues. But as shown in panel (a), the revenue curve shifts parallel. This means that information sharing with clients has the same effect on revenues regardless of market power. When information is shared between dealers (panel b), bid shading and signal jamming have a much larger effect on expected revenues. For modest dealer sharing, the shift is again parallel, meaning that market power still does not interact with information sharing. However, for extensive dealer sharing, the revenue curves diverge: The revenue benefits of extensive dealer information sharing are larger, without market power. As more dealers talk, we see that gap in revenue widens to about 2.5 bps, between auctions with and without strategic bids.

In most of our simulations, neither bid shading or signal jamming interacts with the cost/benefit of information sharing. There are two reasons for this irrelevance. One is that there are many market participants. The other is that risk swamps the effect of

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[17]Randomizing bids to jam signals is not a credible commitment because there is a unique utility-maximizing demand.

market power. Our estimation reveals that the volatile auction clearing price and the observed auction allocations are incompatible with high market power. Panel (c) reveals that market power is orders of magnitude smaller than risk. (The two terms are added in the denominator of demand (13)). However, both conditions are weakened when dealer information sharing is widespread. Widespread dealer sharing substantially reduces dealers' risk. Being relatively better informed, dealers bid for most of the auction shares. Because dealers get effectively larger, it is as if there are fewer other market participants. Also, when risk falls, market power is no longer relatively small (convergence of the two lines in panel (c)). Thus, extensive dealer sharing is a situation in which market power could significantly compromise auction revenue.

4.3   Client vs. Dealer Information Sharing: Utility Effects

So far, we studied effects of client and dealer information sharing on expected auction revenues. In this section, we study effects on bidders' welfare. A key insight of the model is that client and dealer information sharing are quite different for bidders' welfare. The reason for this opposite effect lies in how each type of information sharing affects information asymmetry and risk-sharing.

It would be logical to think that if dealers are passing along more of their information to their clients, that clients would be happy about that. That turns out not to be the case. Figure 4 plots investors' utility levels relative to the "Chinese walls" benchmark of no information sharing between dealers and customers. Panel (a) shows that bidders' utility declines when dealers share more information with them. Information acquisition is like a prisoners' dilemma in this setting. Each individual investor would like more of it. But when they all get more, all are worse off. One reason is that better-informed investors bid more for the asset; by raising prices, they transfer more surplus to the issuer (Treasury).

The other mechanism at work is that sharing information with clients increases information asymmetry. When dealers share little information with clients, clients' beliefs are not very different. They all average their priors with a heterogeneous, but imprecise, private signal. Because private information is imprecise, beliefs mostly reflect prior information, which is common to all investors. When different dealers transmit different signals, and investors get a more precise dealer's signal, they weigh it more heavily in their beliefs; this makes investors' beliefs differ. This increase in information asymmetry makes ex-ante similar investors hold different amounts of securities ex-post. Asymmetric information pushes the asset allocation further away from the efficient diversified benchmark. Because investor preferences are concave, investment asymmetry hurts average investor utility. In short, information reduces risk sharing, which reduces utility.

Figure 4: Clients Lose from Client Information Sharing but Can Gain from Dealer Talk. Both panels plot the change in clients' expected utility from information sharing, as a fraction of the utility each type gets in the Chinese wall (no sharing) equilibrium. Client information sharing makes allocations more heterogeneous. This reduces client expected utility. Dealer and client information sharing reduces this asymmetry and can improve utility.

(a) Sharing with clients

(b) Sharing with dealers
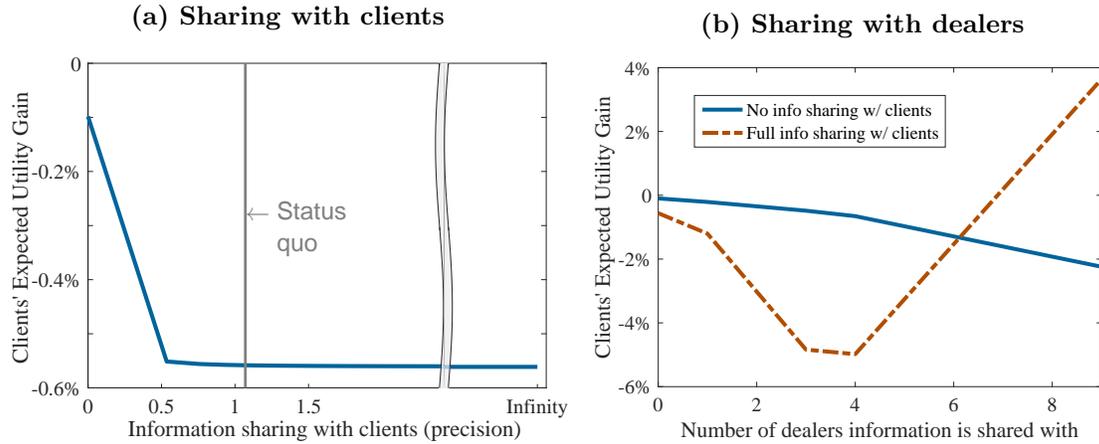
One might also expect that when dealers share information with each other, investors are harmed. When dealers share information with each other and do not pass this better information on to the clients, clients do suffer as shown by the blue line in panel (b) of Figure 4. However, if dealers share what they know with their clients, clients can benefit from inter-dealer talk as shown by the right side of the dashed line in panel (b). When only a few dealers talk, the limited dealer talk increases belief and investment dispersion, just like client information sharing. But when many dealers exchange information, their information sets become more similar. That is the essence of information sharing. Since dealers' beliefs are more similar, the signals that dealers share with their clients also become more similar. The similarity of these signals offset the dispersion increase arising from more precise information. When dealers share information with four other dealers, belief and investment dispersion stabilizes. When clients get more precise (shared) information from their dealers, but do not face the downside of more asymmetric auction outcomes, their utility rises.

When information is shared, two features of the information environment change simultaneously. First, the agents involved have more precise forecasts of post-auction appreciation. This creates the increase in auction revenues, which is common to both types of information sharing. Second, there may be more or less market-wide forecast disagreement, depending on how information is shared. Client (dealer) sharing is like observing a private (public) signal in a strategic game. Client information sharing is like more private information because it pushes beliefs further apart. The result that more informative private signals

can increase information asymmetry and thereby reduce utility is the same force that is at work in Hirshleifer (1971). In contrast, dealer sharing makes information sets more similar or more public. A large literature examines the different effects of public and private information in strategic environments. In some of those environments, coordinated actions are socially costly (Morris and Shin, 2002; Angeletos and Pavan, 2007); therefore, public signals are bad because they enable this costly coordination. In other environments, like Lucas (1972) island models, coordination is socially beneficial (Woodford, 2011). In the island models, like in this model, public information is good: In a way, dealer talk is equivalent to merging some of Lucas' islands together.

Profits of non-price contingent bidders Whenever information is shared, speculative bidders become better informed, surplus is transfered from bidders to the issuer and profits of non-price contingent bidders decline. Who are these bidders that lose out? Some non-price contingent bidders are small retail investors. Many are bids placed by the New York Fed on behalf of foreign and international monetary authorities (FIMA) that hold securities in custody at the Fed.[18]

4.4   What if Information Sharing Enabled Collusion?

One reason why some call for curbing information sharing is that dealers who share information may also bid collectively to maximize joint utility. We call this collusion. Many textbook analyses show economic losses associated with collusion. We do not repeat those arguments here. Instead, we look at how information sharing interacts with the costs of collusion.

Suppose that every time dealers shared information with each other, that group of dealers also colluded, meaning that they bid as one dealer, in order to amplify their price impact. How would this collusion and information sharing jointly affect auction revenue? Without collusion, dealer information sharing increases expected revenue because of the reduction in investors' risk (Figure 2, panel b). With collusion, the effect depends on client information sharing. When no information is shared with clients, investors don't perceive a risk reduction, and revenue declines as collusion increases. With client information sharing, there is a small region in which the joint effect of information sharing and collusion is to increase revenue slightly, before dropping below the "Chinese walls" benchmark (Figure 5).

When expected revenues decline, investors' utilities are higher, while taxpayers are worse off. In other words, if information enables collusion, the issuer is the main loser. From an

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[18]FIMA customers can place *non-competitive* bids for up to $100 million per account and $1 billion in total. Additional bids need to be placed competitively.

Figure 5: Collusion reduces revenue. Average equilibrium auction revenue, assuming that when ψ dealers share information, they also bid as one. These results differ from previous figures because here, varying information-sharing along the x-axis also varies the extent of collusion.
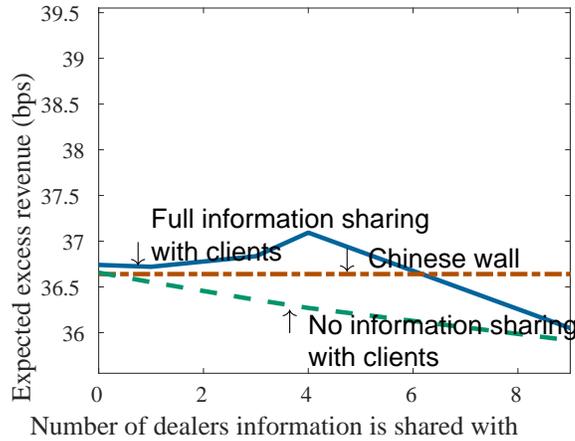
auction revenue perspective, this does not necessarily mean that prohibiting information-sharing would be optimal. If anti-collusion laws could be effectively enforced, without prohibiting the sharing of information, that would be the best possible outcome for Treasury revenue.

Lying about dealer talk Perhaps not all investors know that dealers swap order flow information with other dealers. Of course, one could enforce laws about disclosure of information practices, without prohibiting information sharing. But agents understanding of others' strategies do matter in the results that we have discussed so far. When a set of dealers share information and collude but others are not aware, auction revenue falls by more than in Figure 5.[19] When inter-dealer information sharing is undisclosed, even if information is subsequently shared with clients, revenue declines. This is because if clients are not aware that their information is very precise, they do not bid aggressively. Thus hidden information sharing fails to raise auction revenue.

5   Choosing Direct or Indirect Bidding

So far, the paper takes information sharing as given. A distinguishing feature of U.S. Treasury auctions is that they are mixed auctions: Any investor can choose to place an intermediated bid through a primary dealer, or to bid directly. When choosing how to bid, information sharing arrangements matter. In order to understand these effects of information sharing, we explore the choice of a single bidder deciding whether to bid

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[19]Details of this model variation and its results are reported in Appendix C.5.

directly or indirectly (through a dealer). Once clients have a direct/indirect bidding choice, it becomes clear why dealers may share some of their information with clients. Absent any information sharing, clients would have no incentive to bid with them. Similarly, a dealer's ability to use client information is what incentivizes them to be dealers.

Model: Choosing to Bid Directly or Indirectly Consider one investor choosing between bidding directly or indirectly through an intermediary (the dealer). The investor's choice of how to bid affects the information structure of that investor, its dealer, other investors bidding with that same dealer, and the information content of the price $s(p)$.[20] If investor i bids indirectly, through dealer d, the model and the signals are as discussed in the baseline specification. But when the investor chooses to bid directly on his own behalf, he observes only his own signal, private value and the price information: $S_i = [s_i, v_i, s_i(p)]$. The order flow signal of the dealer that investor j refused to bid through, now has a signal based on $N_I/N_D - 1$ clients' order flow signals. This dealer also knows one more piece of important information: that one investor, an investor who typically bids through him, decided to bid directly.

Solving the model with an endogenous direct versus indirect bidding decision introduces a technical challenge. The decision to bid directly or indirectly itself becomes a signal. We assume that the dealer who would intermediate this trade observes the investor's bidding decision and transmits this information to clients, with noise. If the investor bids through the dealer, the dealer observes his bid, as before. If the investor bids directly, the dealer learns that the investor's signal must lie in one of two disjoint regions of the distribution. This is problematic because doing Bayesian updating of beliefs with truncated normals would require involved simulation methods. Embedding that updating problem in our solution would render it intractable.

We circumvent this problem by constructing an approximating normal signal. Through simulation, we first estimate the mean and variance of the investor's signal, conditional on choosing direct bidding. Then, whenever the investor chooses to bid directly, the dealer, who would have intermediated that trade, makes inference from the direct bidding decision. That dealer observes a *normally distributed* signal, $s_q = f + e_q$ (q for quit) with the same mean and variance as the signals of the simulated direct bidders. This normal signal is included in the precision-weighted average signal of dealer d'. In Appendix B we show how this signal can be used to construct a precision-weighted average signal of dealer d' and derive the updated equilibrium pricing condition.

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[20]There may well be fixed costs associated with bidding directly for large investors, such as registering with the online direct bidding system known as TAAPSLink for large investors or setting up one's own trading desk. We abstract from such costs because they are difficult to quantify and do not change the main price asymmetry result.

Client Information Sharing and the Direct/Indirect Bidding Decision Examining expected utility in our model clarifies the incentives to bid directly and indirectly. Our results reveal how information sharing affects bidders' utility of bidding through dealers. This, in turn, helps to explain why information sharing with clients takes place.

When the investor chooses whether to invest through a dealer, he has seen his private signal s_i. In addition, the bidder knows his private value v_i. Thus the intermediation choice maximizes expected utility, with an additional expectation over the information that the investor has not yet observed. Computing the expectation over possible price realizations and dealer signals, but conditioning on an investor's private signal, we find that expected utility of any bidder i is[21]

$$EU_i = -\exp(\rho W_{0i})(1 + 2\theta_i \Delta \mathbb{V}_i)^{-\frac{1}{2}} \exp\left(-\frac{\mu_{ri}^2}{\theta_i^{-1} + 2\Delta \mathbb{V}_i}\right). \tag{17}$$

The intermediation decision affects utility in three ways: through the expected profit per unit allotted μ_{ri}, the sensitivity of demand to expected profit θ_i, and through the ex-ante variance of expected profit $\Delta \mathbb{V}_i$. These three terms are:

$$\mu_{ri} \equiv \mathbb{E}\{\alpha \mathbb{E}[f|S_i] + (1-\alpha)v_i - p|s_i\}, \tag{18}$$

$$\theta_i \equiv \rho[\rho\alpha^2 \mathbb{V}[f|S_i] + dp/dq_i]^{-1}\left(1 - \frac{1}{2}\rho[\rho\alpha^2 \mathbb{V}[f|S_i] + dp/dq_i]^{-1}\alpha^2 \mathbb{V}[f|S_i]\right), \tag{19}$$

$$\Delta \mathbb{V}_i \equiv \alpha^2 \mathbb{V}\{\mathbb{E}[f|S_i] + (1-\alpha)v_i - p|s_i\} = \mathbb{V}[\alpha f - p|s_i] - \alpha^2 \mathbb{V}[f|S_i]. \tag{20}$$

The first term μ_{ri} embodies the main cost of intermediation: It reveals some of one's private information s_i to others. This effect shows up as a reduction in μ_{ri}, the ex-ante expected profit per share, after all signals are observed. Information sharing reduces μ_{ri} because it raises price p (Result 1). Reducing the risk premium ($-A$ in the price equation (15)) raises the price, bringing it closer to expected value: $\alpha\mathbb{E}[f|S_i] + (1-\alpha)v_i$.

The second term θ_i captures the main advantage of intermediation: Dealers give their clients an additional signal, $s_{\xi i}$, which makes them better informed, lowering $V[f|S]$. Appendix A shows that θ_i is positive and strictly increasing in the posterior precision of the asset payoff $\mathbb{V}[f|S_i]^{-1}$. Thus, intermediation improves the investor's information, which decreases variance $\mathbb{V}[f|S_i]$, increases θ_i, and (holding all other terms equal) increases expected utility.

The third effect of intermediation operates through ex-ante variance $\Delta \mathbb{V}_i$. Theoretically, information sharing has an ambiguous effect. In our estimated model, this term turns out to be quantitatively unimportant.

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[21]See Appendix C.6 for derivation.

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Client information sharing and the existence of dealers   This utility expression reveals why information sharing is so integral to the primary dealer system. If dealers shared no information with clients, the cost of using a dealer, a reduction in μ_{ri}, would still be present because the dealer observes the client's order and may trade on this information. That is costly because it reduces the client's expected speculative profit. However, the benefit of using a dealer disappears. If clients get no information from dealers, the signal set S_i and thus the speculative risk $\mathbb{V}_i$ do not change. In such an environment with only costs and no benefits to indirect bidding, primary dealers would cease to exist.

Of course, one could prohibit primary dealers from trading on clients' information, which is the "Chinese wall" solution we examined before. But this would also not support a dealer system. First, investors would now be indifferent between bidding directly and indirectly in the sense that both μ_{ri} and θ_i would be unaffected. Second, there are costs to being a dealer, in the form of regulatory or minimum bidding constraints. In sum, while we do not explicitly model dealers' and bidders' participation decision, these results suggest that information sharing is what induces bidders to bid through dealers, and dealers to participate in the primary dealer system. In this sense, information sharing is at the core of the primary dealer system.

6   Supporting Evidence: Secondary Market Resale and Informed Bidders

This section presents evidence supporting three key features of the model: that bids incorporate information about secondary market prices, the private value assumption and that bids of investors with more precise signals are more informative about future market values. While we do not access confidential bidder-level data, our modeling strategy allows us to infer values and information from publicly available data on the volatility of awarded shares as well as the covariance of those shares and of auction prices with secondary market outcomes. The key idea is that those bidders that bid more when post-auction appreciation is positive must be better informed about future resale values. Importantly this is the case even if an omitted variable affects both auction and resale prices: under profit maximization, a bid of an investor that covaries more positively with the secondary market value must have observed a more precise signal. We use these ideas to form three model predictions.

Prediction 1. *If signals s_i are informative about the secondary market demand f, then the auction clearing price p is positively correlated with the secondary market price p_s.*

In the model, the liquidity shock ($\alpha > 0$) triggers secondary market resale. The expectation of this resale is what causes the auction clearing price to be correlated with the secondary

market price. In equilibrium, this correlation implies positive price coefficients on secondary market signals, or $B_I + B_J + SB_D$ in equation (15).

In reality, the prediction that bids reflect expected secondary market outcomes can be justified in three ways. First, it is profitable. Treasury securities appreciate post-auction (Lou, Yan, and Zhang, 2013), and it would be unusual for many investors not to attempt to exploit these profits. Second, data on inventory holdings of primary dealers, which are the largest participants in Treasury auctions, suggest that they typically resell all of their holdings within the first week of trading (Fleming and Jones, 2015b). Third, any investor who bids in the auction has the option to wait. When expectations about p_s are low even a buy-and-hold investor would be better off not bidding at the auction and purchase in the secondary market, lowering demand and therefore price at the auction.

The next result is that volatile private values lower the correlation of bidders' bids with the secondary market price p_s and secondary market demand f.

Prediction 2. *Consider an investor k for whom the private value is less variable than for other investors, or $\tau_{vk}^{-1} < \tau_{vJ}^{-1}, \tau_{vI}^{-1}$. Then the higher share q_k allotted to that investor, at any given price $\bar{p}$, the higher post-auction appreciation $p_s - p$.*

From the first order condition (13) the quantity $q_j(p)$ demanded by each bidder is proportional to the sum of the expected return $\mathbb{E}[f|S_j] - p$ and the private value v_j. If agent k has a less volatile private value v_k component, she is more of a speculator. Then k's first order condition implies a lower correlation (or regression loading) of post-auction returns $\mathbb{E}[f|S_k] - p$ and allotted shares q_k.

Prediction 3. *Consider an investor k that has a more precise signal S_k about secondary market demand f. Then the higher allotted share q_k, the higher post-auction appreciation $p_s - p$.*

When the signal s is informative about the secondary market demand f, the correlation between realized $f - p$ and the expected $E[f - p|S_i]$ rises. Information aligns beliefs with outcomes. The quantity q_i, demanded by any bidder is a linear function of $E[f - p|S_i]$. Thus, the covariance of q_i and $f - p$ is higher. Since the expected secondary market price p_s is linear in secondary market demand f, the covariance of q_i and $p_s - p$ is higher for a better informed investor.

Supporting evidence Evidence supporting Prediction 1 was provided in Table 2. Indeed to calibrate the B parameters in the price equation (Proposition 1), we estimated the regression (equation 16) of p on p_s. Consistent with speculation on post-auction appreciation, we find a highly statistically significant coefficient of 0.97. In words, the auction price p moves (on average) nearly one-for-one with the secondary market price p_s. This

Table 3: Speculative bidders and dealers bid more when profits $(p_s - p)$ will be high.. The dependent variable is the post-auction appreciation measured as the difference between the value of the interest-rate neutral portfolio on issue date (p_s) and on auction date (p) expressed in basis points units. The speculative bidders are bids by primary dealers and direct/indirect bids of domestic investors. Non-PD speculative shares is domestic bidders except primary dealers. All shares are measured in percent. Robust standard errors reported in square brackets. *** significant at 1%, ** significant at 5%, *significant at 10%.

	(1)	(2)	(3)	(4)
Spec Share		0.77***	0.92***	
		[0.21]	[0.26]	
PD Share				0.97***
				[0.26]
non-PD Spec Share				0.70**
				[0.30]
Const	2.71**	-57.63***	-73.59***	-2.01
	[1.36]	[16.05]	[21.56]	[13.38]
Adj. R2	0.00	0.05	0.24	0.24
Obs.	494	494	494	494
Month FEs?	No	No	Yes	Yes
Tenor FEs?	No	No	Yes	Yes

covariance would be impossible if most investors were not highly attuned to indicators of secondary market conditions.

Prediction 2 requires identifying bidders with less private value motives and more speculative motives for bidding. Dealers are one such group. Since we know they sell almost all their purchases within a week, secondary market prices feature prominently in their payoffs. The other, broader, group is what we call the speculative share: all bidders except the non-competes (non-price-contingent bidders). The non-competes are largely official investors, who hold Treasuries to manage their foreign exchange policies and their respective domestic economic conditions.[22]

We therefore estimate the relationship between this speculative share and $(f - p)$, the post-auction appreciation of the hedged portfolio from the time of the auction close to the issue date. As shown in the first column of Table 3, the value of the newly issued security appreciates on average 2.7 basis points between the auction date and the issue date (column 1).[23] As shown in the second column, this appreciation is higher when

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[22]Bernanke, Reinhart, and Sack (2004) and Warnock and Warnock (2009) claim that foreign official purchases of Treasuries are completely exogenous to U.S. economic and market conditions. Krishnamurthy and Vissing-Jorgensen (2012) provide supporting evidence for this hypothesis in the context of the convenience yield.

[23]This average post-auction appreciation estimate is consistent with the findings of Lou, Yan, and Zhang

the share of speculative bids is higher (column 2), with a highly statistically significant coefficient (t-stat = 3.5, column 2). The point estimate of 0.77 implies that a 10% increase in the speculative share (Std. Dev. = 9.1%) is associated with a sizable positive effect of 7.7% in $f - p$ (Std. Dev = 30%). This empirical result is stronger after including month and tenor fixed effects (column 3), which supports Prediction 2.

Prediction 3 pertains to dealers. Prior literature (for example Hortaçsu and Kastl, 2012, in the context of Canadian auctions) find that dealers are at an informational advantage. This is also true in our model in which dealers share a noisier signal with clients meaning that dealers are better informed about f. Consistent with Prediction 3, post-auction appreciation is increasing with the allotted share to primary dealers, which display a larger coefficient vis-a-vis other speculative bidders. The coefficient on the primary dealer share is 0.97 versus a coefficient of 0.70 on the speculative share excluding primary dealers (p-val=.11).

Importantly neither the speculative bidders nor the primary dealer results in Table 3 are the mechanical result from higher demand. When speculative demand is high, the price is lower on average, relative to the payoff. It is that low price relative to fundamental value that induces informed investors and speculators to buy more securities.

7   Conclusion

Recent news about dealers sharing clients' order flow information with other clients or dealers has prompted calls to restrict financial intermediaries' use of order flow information. The need to prohibit collusion and misleading clients about information sharing are quite clear. But when collusion does not occur and information sharing is common knowledge, the gains and losses of information sharing are not as apparent. Using data from U.S. Treasury auctions, we calibrate a structural auction model, with a secondary market, to quantify the costs and benefits of information sharing both between dealers as well as between dealers and customers.

To analyze the impact of information sharing, this paper brings a new feature to empirical auction models: information sharing. Instead of relying on bid-level dispersion, whose measurement relies on confidential data, we back out bidders' uncertainty and average bidders' information from measured risk premia. This new approach is essential to understanding information sharing. If valuations are private, then by observing order flow one only learns about other bidders' demand. When bidders care about resale value, order flow is informative about everyone's future valuation of the asset. With this perspective

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(2013). See Data Appendix for a full set of summary statistics on these variables.

in mind, one can understand our main results. We find that the way in which information is shared matters. Dealers sharing information with other dealers about future demand makes bidders' beliefs more correlated. On the opposite, dealer sharing information with clients makes beliefs about future demand more dispersed. Beliefs about the secondary market demand are the heart of our utility results. Without the uncertain future demand, this effect, as we describe it, would not be present.

The model also shows that information sharing raises auction revenues by making bidders better informed. Dealer talk benefits issuers by raising auction revenues, but also can improve risk sharing by lowering asymmetric information. These results assume full disclosure about how information is used and no collusion; model extensions show that these can overturn the welfare effect. While our model does not detect whether collusion and misrepresentation occurs, it suggests different remedies to enforce disclosure and anti-collusion laws, perhaps without prohibiting information sharing.

Against a backdrop of policy initiatives aimed at curbing information sharing, other novel features of our model – investors' choice to bid directly or through dealers and dealers' minimum bidding requirements – highlight that information sharing is an integral part of Treasury auctions and the primary dealer system. Without client information sharing, clients would not want to bid through dealers. At the same time, prohibiting dealer use of client order flow data, while imposing bidding requirements on dealers, arguably creates a dealer system with large costs but limited benefits. Information sharing may not be optimal, depending on feasible alternatives and social welfare criterion. But it has upsides, as well as downsides.

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Table of Contents

A Solution and Proofs

This section shows how to solve the model. The solution method involves backwards induction. We start with the last period, the secondary market, and then work backwards to belief formation, optimal bids at auction and auction revenue.

A.1 Secondary Market Price Solution

Each secondary market buyer buys one unit if their private value $\tilde{f}_i \geq p$. Thus, the demand is the mass of $\tilde{f}_i$'s, above p. If we let $\Phi(\cdot)$ denote a standard normal cumulative density function, and f and $\tau_x^{-1/2}$ are the mean and standard deviation of $\tilde{f}_i$, then demand is $1 - \Phi(\sqrt{\tau_x}(p - f))$.

Since the total amount auctioned is normalized to 1 and a fraction α of auctioned shares are sold in the secondary market, the secondary market supply is α. Equating demand with the supply yields

$$1 - \Phi(\sqrt{\tau_x}(p - f)) = \alpha \tag{21}$$

$$\Phi(\sqrt{\tau_x}(p - f)) = 1 - \alpha \tag{22}$$

$$\sqrt{\tau_x}(p - f) = \Phi^{-1}(1 - \alpha) \tag{23}$$

$$p = f + \tau_x^{-1/2}\Phi^{-1}(1 - \alpha). \tag{24}$$

Thus, the constant g in the secondary market price is $g = \tau_x^{-1/2}\Phi^{-1}(1 - \alpha)$, where Φ is the standard normal cdf.

A.2 Incorporating Information in Beliefs

In many ways, this is a standard auction, or noisy rational expectations model. But what distinguishes this model from others, and what complicates its solution, is that there are many sources of correlated information. Accounting for the correlation in beliefs is essential for correctly characterizing the costs and benefits of information sharing. Doing this requires recasting the problem in a state-space representation, where all signals and the auction price are linear combinations of orthogonal, underlying shocks. Given this representation, we can apply optimal linear projection theorems to form Bayesian posterior beliefs about the secondary market demand. The following subsection uses these beliefs to form asset demands and determine the auction-clearing price.

Define $\bar{v}_I$ and $\bar{v}_J$ to be the average private value of indirect and direct bidders:

$$\frac{1}{N_I}\sum_{i=1}^{N_I} v_i \equiv \bar{v}_I \tag{25}$$

$$\frac{1}{N_J}\sum_{j=1}^{N_J} v_j \equiv \bar{v}_J \tag{26}$$

If $v_i \sim iid\, N(0, \tau_{vI}^{-1})$ and $v_j \sim iid\, N(0, \tau_{vJ}^{-1})$, then $var(\bar{v}_I) = 1/N_D\tau_{vI}^{-1} \equiv \tau_{\bar{v}I}^{-1}$ and $var(\bar{v}_J) = 1/N_J\tau_{vJ}^{-1} \equiv \tau_{\bar{v}J}^{-1}$. These $\tau_{\bar{v}}$ terms are the noise in prices.

We conjecture a linear price function p:

$$p = A + B_I \bar{s}_I + B_J \bar{s}_J + B_D \bar{s}_D + C_I \bar{v}_I + C_J \bar{v}_J + D\delta \tag{27}$$

where $\bar{s}_I = \frac{1}{N_I} \sum_i s_i$, $\bar{s}_J = \frac{1}{N_J} \sum_j s_j$, and $\bar{s}_D = \frac{1}{N_D} \sum_{d=1}^{N_D} s_d$.[24]

The price signal for dealers is:

$$s(p) = \frac{p - A - D\delta}{B_I + B_J + B_D} \tag{28}$$

Note that since non-price contingent bids are common knowledge, the dealer and all other bidders simply subtract this from this price signal. It is not a source of price noise.

Investors have private information about price noise $\bar{v}$. Investors can subtract the effect of their own private value from $\bar{v}$ and obtain a slightly more precise estimate of the noise, and thus extract a slightly more precise signal from prices. Indirect investor i faces residual price noise from indirect investors of $\bar{v}_I - \mathbb{E}[\bar{v}_I | v_i]$. For a direct investor, the residual direct investor price noise is $\bar{v}_J - \mathbb{E}[\bar{v}_J | v_j]$. Note that dealers have no private value information. Their v_d values are known to all and get incorporated in the price constant term A. Thus, the price signals for indirect and direct investors are:

$$s(p|v_i) = \frac{p - A - C_I v_i / N_I - D\delta}{B_I + B_J + B_D} \tag{29}$$

$$s(p|v_j) = \frac{p - A - C_J v_j / N_J - D\delta}{B_I + B_J + B_D} \tag{30}$$

The next steps construct conditional expectations of f for indirect, direct investors, and dealers: $\mathbb{E}[f|s_i, s_{\xi i}, s(p|v_i)]$, $\mathbb{E}[f|s_j, s(p|v_j)]$, and $\mathbb{E}[f|\tilde{s}_d, s(p)]$.

Give all signals a state-space representation: The vector of orthogonal shocks Z is a column vector of size $N_Z = N + 2N_I + N_J + 1$, where

$$Z = [\epsilon_1, \ldots, \epsilon_N, v_1, \ldots, v_{NI+NJ}, \xi_1, \ldots, \xi_{NI}, \delta]' \tag{31}$$

and the variance matrix of Z is

$$var(Z) = diag([\tau_\epsilon^{-1} \mathbf{1_N}, \tau_{vI}^{-1} \mathbf{1}_{N_I}, \tau_{vJ}^{-1} \mathbf{1}_{N_J}, \tau_\xi^{-1} \mathbf{1}_{N_I}, \tau_\delta^{-1}]) \tag{32}$$

where $\mathbf{1_N}$ is a vector of 1s of size N. Let ϕ_i be a vector of size N_Z of zeros with one 1 in ith position. For example, $\phi_3 = [0, 0, 1, 0, \ldots, 0]$. Then $s_i = f + \phi_i Z$ and $\tilde{s}_d = f + \frac{N_D}{N_I + N_D} \sum_{i \in d(i)} \phi_i Z$. Here, $\frac{N_D}{N_I + N_D}$ means the number of clients per dealer.

Dealers' price signal. How do we represent price signals in state space? Recall that $\tilde{B} = B_I + B_J + B_D$, which is the sum of the price coefficients on signals. For a dealer, the

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[24] Why isn't dealer signal noise ξ_i in the price? Because each dealer is assumed to transmit unbiased signals with zero signal noise, on average, to his clients, it implies that dealer signal noise realizations ξ_d, have no effect on the market-clearing price. Note that each ξ is equally-weighted in demand by each client i. For the purpose of solving the price, we can drop the ξ_d in demand (but not it's precision τ_ξ).

price signal is

$$s(p) = \frac{p - A - D\delta}{\tilde{B}} = \frac{B_I \bar{s}_I + B_J \bar{s}_J + B_D \bar{s}_D}{\tilde{B}} + \frac{C_I}{\tilde{B}} \bar{v}_I + \frac{C_J}{\tilde{B}} \bar{v}_J. \tag{33}$$

To represent $\bar{v}$, we need a $1 \times N_Z$ vector ϕ_{vI} that is N zeros, followed by N_I ones, followed by $N_J + N_I$ zeros:

$$\phi_{vI} = [\mathbf{0_N}, \mathbf{1_{N_I}}, \mathbf{0_{N_J}}, \mathbf{0_{N_I+1}}] \tag{34}$$

$$\phi_{vJ} = [\mathbf{0_N}, \mathbf{0_{N_I}}, \mathbf{1_{N_J}}, \mathbf{0_{N_I+1}}] \tag{35}$$

These vectors select out the private values of I or J investors from Z. Then $\bar{v}_I = (1/N_I)\phi_{vI} \cdot Z$ and $\bar{v}_J = (1/N_J)\phi_{vJ} \cdot Z$.

Next, we define binary vectors that select from Z the signal noise of all indirect investors, all direct investors, or all dealers:

$$\phi_{\epsilon I} = [\mathbf{1_{N_I}}, \mathbf{0_{N_Z-N_I}}] \tag{36}$$

$$\phi_{\epsilon J} = [\mathbf{0_{N_I}}, \mathbf{1_{N_J}}, \mathbf{0_{N_Z-N_I-N_J}}] \tag{37}$$

$$\phi_{\epsilon D} = [\mathbf{0_{N_I+N_J}}, \mathbf{1_{N_D}}, \mathbf{0_{N_Z-N}}]. \tag{38}$$

Finally, we define binary vectors that select from Z the signal noise ϵ or the private value v_i of all clients of a given dealer d:

$$\tilde{\phi}_{\epsilon d'}(i) = 1 \quad \text{if} \quad d' = d(i) \text{ and } 0 \text{ otherwise.} \tag{39}$$

$$\tilde{\phi}_{v d'}(N + i) = 1 \quad \text{if} \quad d' = d(i) \text{ and } 0 \text{ otherwise.} \tag{40}$$

Then dealers' price signal is

$$s(p) = \frac{p - A - D\delta}{\tilde{B}} = f + \frac{B_I}{\tilde{B}N_I}\phi_{\epsilon I} \cdot Z + \frac{B_J}{\tilde{B}N_J}\phi_{\epsilon J} \cdot Z + \frac{B_D}{\tilde{B}N_D}\phi_{\epsilon D} \cdot Z + \frac{C_I}{N_I\tilde{B}}\phi_{vI} \cdot Z + \frac{C_J}{N_J\tilde{B}}\phi_{vJ} \cdot Z \equiv f + \pi_p Z \tag{41}$$

Dealers' information from indirect bids. The dealer observes the bid function (13) of each indirect investor i that bids through the dealer: $i : d(i) = d$. The dealer can multiply the bid by $\rho V[f|S_i] + dp/dq_i$, which all depend on known parameters, to infer $E[f|s_i] + v_i - p$, for each value p. The dealer can add p back in to infer $E[f|s_i] + v_i$. Recall from (5) that the conditional expectation is $(1 - \beta' 1_m)\bar{f} + \beta' S_i$. The dealer knows the prior belief $\bar{f}$ and can thus subtract that to infer $\beta' S_i + v_i$. Breaking out the signal vector in its component parts yields $\beta_{Is}s_i + \beta_{I\xi}s_{\xi i} + \beta_{Ip}(s(p) - C_I/(\tilde{B}N_I)v_i) + v_i$. Note that the indirect bidder's private value affects his bid in two ways, once directly affecting demand, and once by changing the way he interprets the price. The dealer can again take out the known terms $\beta_{Ip}s(p)$ and $\beta_{I\xi}s_{\xi i}$, which the dealer knows since he sent that signal to his client. Thus, the known component of beliefs that each dealer subtracts from average client valuations is $s_{public} = (1 - \beta' 1_m)\bar{f} + \beta_{Ip}s(p) + \beta_{I\xi}s_{\xi i}$. That leaves $\beta_{Is}s_i + (1 - \beta_{Ip}C_I/(\tilde{B}N_I))v_i$. Dividing by β_{Is}, we obtain the unbiased signal that a dealer can infer from each of his N_I/N_D clients indirect bids. Since each of these signals is equally precise, the dealer optimally averages

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them to yield:

$$\tilde{s}_d = f + \frac{N_D}{N_I} \sum_{i \in d(i)} \epsilon_i + \beta_{Is}^{-1} \left(1 - \frac{\beta_{Ip} C_I}{\tilde{B} N_I} \right) \frac{N_D}{N_I} \sum_{i \in d(i)} v_i \tag{42}$$

So a dealer's 3 signals can be represented as

$$\begin{bmatrix} s_d \\ \tilde{s}_d \\ s(p) \end{bmatrix} = \begin{bmatrix} f \\ f \\ f \end{bmatrix} + \begin{bmatrix} \phi_i \\ \pi_d \\ \pi_p \end{bmatrix} \cdot Z \tag{43}$$

where

$$\pi_d = \frac{N_D}{N_I} \tilde{\phi}_{\epsilon d} + \beta_{Is}^{-1} \left(1 - \frac{\beta_{Ip} C_I}{\tilde{B} N_I} \right) \frac{N_D}{N_I} \tilde{\phi}_{vd}.$$

Indirect and direct bidders' price signals: Indirect and direct investors remove the effect of their own private valuations from the price when they condition on it. Their signals are the same as the dealers' price signal $s(p)$, minus all the terms that load on v_i or v_j for that investor:

$$s(p|v_i) = s(p) - \frac{C_I}{N_I \tilde{B}} \phi_{N+i} \cdot Z \tag{44}$$

$$s(p|v_j) = s(p) - \frac{C_J}{N_J \tilde{B}} \phi_{N+N_I+j} \cdot Z \tag{45}$$

Note that ϕ_{N+i} has a 1 in the position that corresponds to v_i in Z and ϕ_{N+N_J+j} has a 1 in the position that corresponds to v_j for direct investor j.

Indirect bidders' information from dealers: The dealer takes all the information collected from all his clients $\tilde{s}_d$, adds noise ξ_i to it for each bidder i and transmits the resulting $s_{\xi i}$ signal to his client. This signal has the same state space representation as the dealer's signal $\tilde{s}_d$, with one additional term $\phi_{N_Z - N_D + i}$ that adds the signal noise ξ_i:

$$s_{\xi i} = f + (\pi_d + \phi_{N_Z - N_D + i}) Z. \tag{46}$$

Signals for indirect investors are:

$$\begin{bmatrix} s_i \\ s_{\xi i} \\ s(p|v_i) \end{bmatrix} = \begin{bmatrix} f \\ f \\ f \end{bmatrix} + \begin{bmatrix} \phi_i \\ \pi_d + \phi_{N_Z - N_D + i} \\ \pi_p - \frac{C_I}{N_I \tilde{B}} \phi_{N+i} \end{bmatrix} \cdot Z \tag{47}$$

Direct bidders' signals: The signal vector for direct investors is:

$$\begin{bmatrix} s_j \\ s(p|v_j) \end{bmatrix} = \begin{bmatrix} f \\ f \end{bmatrix} + \begin{bmatrix} \phi_i \\ \pi_p - \frac{C_J}{N_J \tilde{B}} \phi_{N+N_I+j} \end{bmatrix} \cdot Z \tag{48}$$

In sum the 3×1 signal loading matrix of a dealer's signals, an indirect bidder's signals and

a direct bidder's signals can be written as:

$$\Pi_{D,d} \equiv \begin{bmatrix} \phi_i & \pi_d & \pi_p \end{bmatrix}' \tag{49}$$

$$\Pi_{I,i} \equiv \begin{bmatrix} \phi_i & \pi_{d(i)} + \phi_{N_Z - N_D + i} & \pi_p - \frac{C_I}{N_I \tilde{B}} \phi_{N+i} \end{bmatrix}' \tag{50}$$

$$\Pi_{J,j} \equiv \begin{bmatrix} \phi_i & \pi_p - \frac{C_J}{N_J \tilde{B}} \phi_{N+N_I+j} \end{bmatrix}' \tag{51}$$

Given this state space representation, we just apply (5),(6), and (7) to form conditional expectations and variance. $v(S_j) = \tau_f^{-1} \mathbf{1}\mathbf{1}' + \Pi_j v(z) \Pi_j'$ delivers $\beta, \mathbb{E}[f|S]$, and $\mathbb{V}[f|S]$. Let $\beta_I, \beta_J, \beta_D$ be the weights on signals given by (6) for each type of market participant. Then we can express the conditional expectation of the payoff as $\mathbb{E}[f|S_i] = (1 - \beta'\mathbf{1})\bar{f} + \beta'S_i$. Let $\beta_I = [\beta_{Is}, \beta_{I\xi}, \beta_{Ip}]'$ and define β_J and β_D components analogously.

A.3   Auction Price Solution

Next, we use agents' beliefs about the secondary market to form their asset demands and solve for the uniform price that clears the auction.

Define M_I, M_J, and M_D as follows.

$$M_I = \left(\rho \alpha^2 \mathbb{V}[f|S_i] + \frac{dp}{dq_i} \right)^{-1} \quad \texttt{for indirect investors} \tag{52}$$

$$M_J = \left(\rho \alpha^2 \mathbb{V}[f|S_j] + \frac{dp}{dq_j} \right)^{-1} \quad \texttt{for direct investors} \tag{53}$$

$$M_D = \left(\rho \alpha^2 \mathbb{V}[f|S_d] + \frac{dp}{dq_d} \right)^{-1} \quad \texttt{for dealers} \tag{54}$$

Using the first-order conditions (13) and (14) and the definition of M from (52), (53) and (54), we rewrite the market clearing condition as:

$$\sum_{i=1}^{N_I} \left(\alpha \mathbb{E}(f|S_i) + \alpha g + (1-\alpha)v_i - p \right) M_I + \sum_{j=1}^{N_J} \left(\alpha \mathbb{E}(f|S_j) + \alpha g + (1-\alpha)v_j - p \right) M_J$$
$$+ \sum_{d=1}^{N_D} \left(\alpha \mathbb{E}(f|S_d) + \alpha g + \chi - p \right) M_D + \delta = 1 \tag{55}$$

Substituting in the state space representation of conditional expectations:

$$\begin{aligned}
1 &= \alpha M_I [\sum_{i=1}^{N_I} (1 - \beta_I'\mathbf{1}')\bar{f} + \beta_I'S_i] + (1-\alpha)N_I M_I \bar{v}_I \\
&+ \alpha M_J [\sum_{j=1}^{N_J} (1 - \beta_J'\mathbf{1}')\bar{f} + \beta_J'S_j] + (1-\alpha)N_J M_J \bar{v}_J \\
&+ \alpha M_D [\sum_{d=1}^{N_D} (1 - \beta_D'\mathbf{1}')\bar{f} + \beta_D'S_d] + N_D M_D \chi + \delta + \alpha \tilde{M}g - \tilde{M}p,
\end{aligned} \tag{56}$$

where $\tilde{M} = N_I M_I + N_J M_J + N_D M_D$. Next, we break out the signal vectors into their

constituent parts.

$$
\begin{aligned}
1 &= \tilde{A} + \alpha N_I M_I (\beta_{Is}\bar{s}_I + \beta_{I\xi}\bar{s}_\xi + \beta_{Ip}\bar{s}(p|v_i)) \\
&+ \alpha N_J M_J (\beta_{Js}\bar{s}_J + \beta_{Jp}\bar{s}(p|v_j)) + \alpha N_D M_D (\beta_{Ds}\bar{s}_D + \beta_{D\xi}\bar{s}_\xi + \beta_{Dp}s(p)) \\
&- \tilde{M}p + (1-\alpha)N_I M_I \bar{v}_I + (1-\alpha)N_J M_J \bar{v}_J + N_D M_D \chi + \delta
\end{aligned}
\tag{57}
$$

where $\tilde{A}$ is a collection of all $\bar{f} + g$ terms $\tilde{A} = \alpha M_I N_I (1 - \beta_I' \mathbf{1}')\bar{f} + \alpha M_J N_J (1 - \beta_J' \mathbf{1}')\bar{f} + \alpha M_D N_D (1 - \beta_D' \mathbf{1}')\bar{f} + \alpha \tilde{M} g$.

Define the average signal transmitted by a dealer to clients as: $\bar{s}_\xi = (1/N_I) \sum_{i=1}^{N_I} s_{\xi i}$. Note that this is the same as the average order flow information observed by dealers because we have assumed that dealer signal noise averages to zero. From the analysis of dealer's information from indirect bids, we showed that this order flow information is a weighted sum of indirect bidders' signals and their private values. Averaging this signal yields $\bar{s}_\xi = \bar{s}_I + \beta_{Is}^{-1}(1 - \beta_{Ip}C_I/(\tilde{B}N_I))\bar{v}_I$.

Substitute in the conditional price signals to get:

$$
1 = \tilde{A} + \alpha M_I N_I (\beta_{Is}\bar{s}_I + \beta_{I\xi}\bar{s}_\xi + \beta_{Ip}(s(p) - \frac{C_I}{N_I \tilde{B}}\bar{v}_I)) + \alpha M_J N_J (\beta_{Js}\bar{s}_J + \beta_{Jp}(s(p) - \frac{C_J}{N_J \tilde{B}}\bar{v}_J))
$$

$$
+ \alpha M_D N_D (\beta_{Ds}\bar{s}_D + \beta_{D\xi}\bar{s}_\xi + \beta_{Dp}s(p)) - \tilde{M}p + (1-\alpha)M_I N_I \bar{v}_I + (1-\alpha)M_J N_J \bar{v}_J + N_D M_D \chi + \delta
\tag{58}
$$

Using $s(p) = (p - A - D\delta)/\tilde{B}$, we can gather coefficients of p. Then let $\tilde{Q} \equiv \tilde{M} - (N_I M_I \beta_{Ip} + N_J M_J \beta_{Jp} + N_D M_D \beta_{Dp})\frac{\alpha}{\tilde{B}}$.

Gathering terms in p and then matching A to all constants:

$$
\begin{aligned}
A &= \frac{1}{\tilde{Q}}\left[\tilde{A} - 1 + A(\tilde{Q} - \tilde{M}) + N_D M_D \chi\right] \tag{59} \\
&= \frac{1}{\tilde{M}}\left[\tilde{A} - 1 + N_D M_D \chi\right] \tag{60}
\end{aligned}
$$

where the second line comes from collecting terms in A. Note that $\tilde{A}$ does not contain A terms.

Substituting in A, $s(p)$, and $\bar{s}_\xi$, and rearranging the market clearing equation yields,

$$
\begin{aligned}
\tilde{Q}p &= A\tilde{Q} + (1-\alpha)(M_I N_I \bar{v}_I + M_J N_J \bar{v}_J) + \alpha M_I N_I \beta_{Is}\bar{s}_I + \alpha M_J N_J \beta_{Js}\bar{s}_J \\
&+ \alpha(M_I N_I \beta_{I\xi} + M_D N_D \beta_{D\xi})(\bar{s}_I + \beta_{Is}^{-1}(1 - \beta_{Ip}\frac{C_I}{N_I \tilde{B}})\bar{v}_I) + \alpha M_D N_D \beta_{Ds}\bar{s}_D \\
&- \alpha M_I \beta_{Ip}\frac{C_I}{\tilde{B}}\bar{v}_I - \alpha M_J \beta_{Jp}\frac{C_J}{\tilde{B}}\bar{v}_J - (\tilde{Q} - \tilde{M})D\delta + \delta \tag{61}
\end{aligned}
$$

Matching coefficients, gives us the solution for equilibrium prices, in terms of pricing impact

M:

$$B_I = \tfrac{\alpha}{Q}[M_I N_I \beta_{Is} + (M_I N_I \beta_{I\xi} + M_D N_D \beta_{D\xi})] \tag{62}$$

$$B_J = \tfrac{\alpha}{Q} M_J N_J \beta_{Js} \tag{63}$$

$$B_D = \tfrac{\alpha}{Q} M_D N_D \beta_{Ds} \tag{64}$$

$$C_I = \tfrac{1}{Q} M_I N_I \left(1 - \alpha - \alpha \beta_{Ip} \tfrac{C_I}{N_I \tilde{B}}\right) + \tfrac{\alpha}{Q}(M_I N_I \beta_{I\xi} + M_D N_D \beta_{D\xi}) \beta_{Is}^{-1} \left(1 - \beta_{Ip} \tfrac{C_I}{N_I \tilde{B}}\right) \tag{65}$$

$$C_J = \tfrac{1}{Q} M_J N_J \left(1 - \alpha - \alpha \beta_{Jp} \tfrac{C_J}{N_J \tilde{B}}\right). \tag{66}$$

$$D = \tfrac{1}{2\tilde{Q} - \tilde{M}} \tag{67}$$

A.4 Price Impact and Market Power

One last piece of the solution is needed to determine bidders' bid functions. That missing piece is price impact, also called market power. To solve for dp/dq_j, start with market-clearing in (58) but write one indirect investor's demand as an exogenous amount q_1:

$$
\begin{aligned}
1 \;=\;& \tilde{A} + \alpha M_I (N_I - 1)(\beta_{Is} \bar{s}_I + \beta_{I\xi} \bar{s}_{DI} + \beta_{Ip}(s(p) - \tfrac{C_I}{(N_I - 1)\tilde{B}} \bar{v}_I)) \\
+\;& \alpha M_J N_J (\beta_{Js} \bar{s}_J + \beta_{Jp}(s(p) - \tfrac{C_J}{N_J \tilde{B}} \bar{v}_J)) + \alpha M_D N_D (\beta_{Ds} \bar{s}_{DI} + \beta_{Dp} s(p)) \\
-\;& (\tilde{M} - M_I)p + (1 - \alpha) M_I (N_I - 1)\bar{v}_I + (1 - \alpha) M_J N_J \bar{v}_J + \delta + q_1 + N_D M_D \chi \tag{68}
\end{aligned}
$$

Recall that $ds(p)/dp = 1/\tilde{B}$. Then use the implicit function theorem to solve for

$$\frac{dp}{dq_I} = \left[\tilde{M} - M_I - \frac{\alpha}{\tilde{B}}\left(M_I(N_I - 1)\beta_{Ip} + M_J N_J \beta_{Jp} + M_D N_D \beta_{Dp}\right)\right]^{-1} \tag{69}$$

Similarly, for direct bidders,

$$\frac{dp}{dq_J} = \left[\tilde{M} - M_J - \frac{\alpha}{\tilde{B}}\left(M_I N_I \beta_{Ip} + M_J(N_J - 1)\beta_{Jp} + M_D N_D \beta_{Dp}\right)\right]^{-1} \tag{70}$$

and for dealers,

$$\frac{dp}{dq_D} = \left[\tilde{M} - M_D - \frac{\alpha}{\tilde{B}}\left(M_I N_I \beta_{Ip} + M_J N_J \beta_{Jp} + M_D(N_D - 1)\beta_{Dp}\right)\right]^{-1} \tag{71}$$

Then the model solution is characterized jointly by the M's, the price coefficients and the updating formulas.

A.5 Result 1: Linear Auction Revenue

This result has three cases. We consider each separately.

Case 1: Only Dealer-Client Information Sharing The set of equations (62)-(66), along with (69)-(71) substituted into M_D, M_I and M_J constitute a set of 8 equations

in 8 unknowns. The fact that we could impose optimality, budget and market clearing conditions and then write price as a linear function of $\bar{s}_I$, $\bar{s}_J$, $\bar{s}_D$, $\bar{v}_I$ and $\bar{v}_J$, proves the linear price conjecture.

Case 2: Dealer-Dealer information sharing   In this setup, dealers share information with clients using the same noisy signal as before, but they also share information with $\psi - 1$ other dealers. Then ψ is the size of the dealer chat room. Dealer-dealer sharing is symmetric, which requires that the number of dealers in an information-sharing collective be a factor of 20. We also require that $\psi \neq 20$, as that would imply perfect inter-dealer sharing. Thus, we only consider $\psi \in \{1, 2, 4, 5, 10\}$.

It would be repetitive to re-derive each part of the preceding analysis when most of it can be preserved. So, rather than do that, we simply point out the piece of the solution that is different.

First, define a set of dealers who share information with any given dealer d. Let $chat(d) = \{d', d'', \ldots\}$ such that dealers d', d'' and d share information. Information sharing means observing the order flow of the clients of all the dealers in $chat(d)$. Since all investor order flow signals are equally informative, all dealers in a chat group average all the order flow signals they see in the same way. Each dealer now sees a new, more precise composite order flow signal which is:

$$\tilde{s}_d = f + \frac{N_D}{\psi N_I} \sum_{d' \in chat(d(i))} \sum_{i \in d'} s_i + \beta_{Is}^{-1} \left(1 - \frac{\beta_{Ip} C_I}{\tilde{B} N_I} \right) \frac{N_D}{\psi N_I} \sum_{d' \in chat(d(i))} \sum_{i \in d'} v_i \quad (72)$$

Thus the dealer's signals have the same state space representation as in (43), except that we redefine π_d, the weight the order flow information puts on the underlying shocks, as

$$\pi_d = \frac{N_D}{\psi N_I} \sum_{d' \in chat(d(i))} \tilde{\phi}_{\epsilon d'} + \beta_{Is}^{-1} \left(1 - \frac{\beta_{Ip} C_I}{\tilde{B} N_I} \right) \frac{N_D}{\psi N_I} \sum_{d' \in chat(d(i))} \tilde{\phi}_{vd'}.$$

For indirect bidders, the signals are the same, except that π_d is redefined, as above. For direct bidders, there is no change in the signal vector. Of course, information sharing will change bids and thus change the variance and covariance of auction-clearing price. But all these effects will show up through the change in the signal vector, represented by the change in π_d.

This change in the model does not change the linearity of the price in $\bar{s}_I$, $\bar{s}_J$, $\bar{s}_D$, $\bar{v}_I$ and $\bar{v}_J$. The equations (62)-(66), along with (69)-(71) substituted into M_D, M_I and M_J still characterize the solution to the model.

Case 3: No Information Sharing ("Chinese walls")   In this model, dealers do not use or share any information derived from client order flow. Practically speaking, it is as if each type of investor submits bids on their own behalf, rather than through an intermediary. Each investor's information set is therefore a 2×1 vector $S_i = [s_i, s_i(p)]$, comprised of their private signal s_i and the counterfactual price signal $s_i(p)$. In this regime, the only difference between dealers and non-dealer large investors is that dealers are subject to a minimum bidding penalty, while investors have private values that are private information.

We can solve this model by simply changing the signal vector weights on each of the underlying shocks. In sum the 2×1 signal loading matrix of a dealer's signals, an indirect bidder's signals and a direct bidder's signals now becomes:

$$\Pi_{D,d} \equiv \begin{bmatrix} \phi_i & \pi_p \end{bmatrix}' \tag{73}$$

$$\Pi_{I,i} \equiv \begin{bmatrix} \phi_i & \pi_p - \frac{CM_I}{\tilde{B}}\phi_{N+i} \end{bmatrix}' \tag{74}$$

$$\Pi_{J,j} \equiv \begin{bmatrix} \phi_i & \pi_p - \frac{CM_J}{\tilde{B}}\phi_{N+j} \end{bmatrix}' \tag{75}$$

Once we adjust the signal structure, the rest of the solution method goes through unchanged. In the price coefficient solutions (62)-(66), this change implies that the weight put on dealers' order flow signals (now no longer existent) $\beta_{I\xi}$ and $\beta_{D\xi}$ are both 0. Pricing simplifies to:

$$B_I = \frac{1}{\tilde{Q}} M_I N_I \beta_{Is} \tag{76}$$

$$B_J = \frac{1}{\tilde{Q}} M_J N_J \beta_{Js} \tag{77}$$

$$B_D = \frac{1}{\tilde{Q}} M_D N_D \beta_{Ds} \tag{78}$$

$$C_I = \frac{1}{\tilde{Q}} M_I N_I \left(1 - \beta_{Ip} \frac{C_I}{N_I \tilde{B}} \right) \tag{79}$$

$$C_J = \frac{1}{\tilde{Q}} M_J N_J \left(1 - \beta_{Jp} \frac{C_J}{N_J \tilde{B}} \right). \tag{80}$$

The existence of a set of coefficients verifies the price conjecture. Since the supply of the asset is one, auction revenue is the price of the asset. The solution to this model is a joint solution to (69)-(71) substituted into M_D, M_I and M_J and the price coefficient equations above.

B   Measuring Treasury Payoffs

This appendix provides additional detail about how payoffs are calculated. Because of lags between trade and settlement dates, the appendix also provides detail on funding costs. We begin by reporting summary statistics of post-auction appreciation and the speculative (competitive) share (Table 4). Then, we go into detail about how these variables are constructed and what alternative methods yield. The first subsection describes what those terms are and argues that they are small and stable. The second subsection discusses an alternative hedging strategy, known as a coupon roll. The third explains why information from the when-issued-market (or WIs) is not relevant in our setting.

Note that we exclude amounts allotted to the Fed's own portfolio through roll-overs of maturing securities, which are an add-on to the auction.

Funding position. In the model, winning bids pay p and the common fundamental value is f. In Treasury auctions bidders bid a coupon rate rather than a price. The price is always set to \$100 up to rounding, which we rescale to \$1 for the purposes of this discussion. To assess auction results from the issuer perspective we discount future interest payments using a yield curve estimated on outstanding Treasury securities. Economically this means

Table 4: Summary statistics for Table 3. Shares are in percent; post-auction appreciation $(f - p)$ is measured in basis points.

	Post-auction appreciation $(f - p)$	Spec. share	PD share	non-PD Spec. share
Mean	2.7	78.8	53.3	25.5
P25	-8.6	74.1	42.2	14.2
P50	-1.0	79.9	51.2	25.8
P75	10.8	84.5	63.7	34.8
Stdev	30.2	9.1	14.4	13.4
Obs	494	494	494	494

that we measure issuance cost relative to other debt outstanding at the time of the auction. Newly issued Treasury securities are typically valued more than older securities because of their better liquidity, a phenomenon known as the on-the-run premium (see e.g., Vayanos and Weill 2008). As a result of the on-the-run premium, the discounted value of Treasury's future interest and principal payments is smaller than the price at which the security sells ($1), and we define net auction revenue as the gap between the two:

$$\hat{R}_a = 1 - \left(\sum_{t=0}^{T} Z_a(t) \, C + Z_a(T) \right), \tag{81}$$

where C is the coupon determined at the auction, T is the maturity, $Z_a(j) = exp(-i \times y_a(j))$ is the price at the time of the auction of a zero-coupon bond maturing at i, $y(j)$ is the jth maturity yield from the yield curve estimated on outstanding securities at the time of the auction.

Trades in the secondary Treasury market settle on the business day following a trade, meaning that securities are delivered and cash is paid a day after a transaction is agreed upon. In Treasury auctions, instead, investors pay bids to Treasury and receive securities on the issuance date, which occurs one to 14 days following the date of the auction. This different settlement rule is the source of extra funding cost/income in our setting.

We measure f as the market price of the security on the issuance date, which is when the security is first available to investors. The value of f depends on the general level of interest rates and the on-the-run premium. While fluctuations in interest rates between auction and issuance date create risk for investors, this risk can be hedged with other outstanding Treasuries. We assume that investors hedge interest rate risk optimally by selling a replicating portfolio of other Treasury securities. On the auction date, the investor buys the new security and shorts the replicating portfolio of off-the-run issues. On the issuance date, the investor reverses by selling the new security and covering the short in older securities. The per-unit value of the hedged portfolio at auction is equal to $-\hat{R}_a$, and to:

$$\hat{f}_i = \left(\sum_{t=0}^{T} Z_i(t) \, C + Z_i(T) \right) - P_i, \tag{82}$$

on the issuance date, where P_i is the market price of the new security on that date. Detailed

steps in the investment strategy are:

1. Auction date:

   (a) Place bid

   (b) For each unit of successful bid alloted, sell T zero coupon bond each priced at $Z_a(t)$ and in amounts equal to C for $t < T$ and $1+C$ for $t = T$. The zero coupon bonds could either be stripped Treasuries (as in Fleckenstein, Longstaff, and Lustig, 2014) or proxied with a combination of coupon securities.

2. Post-auction date:

   (a) Borrow (to post-issuance date) the amount $\mathcal{Z}_a = \sum_{t=0}^{T} Z_a(t)\,C + Z_a(T)$ paying the per-diem unsecured rate r_b.

   (b) Borrow zero-coupon bonds with reverse repos (to post-issuance date) and receive the per-diem repo rate r_r. Deliver the T zero coupons to the auction-date buyer.

3. Issuance date:

   (a) Borrow \$1 at rate r_b. Receive new issue from, and pay \$1, to Treasury; sell issue in the secondary market

   (b) Buy portfolio of T zero-coupon bonds at $\mathcal{Z}_{issuance}$

4. Post-issuance date:

   (a) Receive payment of p_i and repay the issuance-date loan

   (b) Receive T zero-coupon bonds and deliver into the reverse repo;

   (c) Receive payment of $\mathcal{Z}_a$ from reverse-repo and pay $\mathcal{Z}_i$ to settle the issue-date purchase; Repay post-auction date loan

The cash flows from this position at the post-issue date are:

$$(P_i - 1) + (\mathcal{Z}_a - \mathcal{Z}_i) + \frac{(\text{date}_i - \text{date}_a)}{360} \times (r_r - r_b) \times \mathcal{Z}_a - \frac{r_b}{360} \times 1 \qquad (83)$$

In our calculations we disregard the two funding terms because they are small and don't vary much when $r_r \approx r_b$. The repo rate for old issues, which are being funded between the post-auction and post-issue date, typically trades within a few basis points to the unsecured rate r_b, so the funding terms are small. For example (see e.g. Duffie, 1996), reports that first off-the-runs repo rates around about 25 basis points below the (general collateral) repo rate. This difference has only a minimal impact on the payoff as the position is only held between the auction and issue dates. Furthermore, off-the-run securities rarely go "on special" as indirectly observed in the Federal Reserve's securities loan auctions (Fleming and Garbade, 2007a). Instead, repo rates for new (or first-off-the-run) securities can trade far off from uncollateralized rates and be volatile because funding rates balance the supply and demand of new securities, which can be in high demand to take short position in interest rates (see e.g. Duffie, 1996; Jordan and Jordan, 1997). As per the detailed steps above the new issue is never shorted or funded, as it is sold as soon as it is received by

the investor. Thus fluctuations in the special-repo rate do not affect the returns in our position.

Coupon roll An investor could achieve approximately the same hedged position by shorting only the previously on-the-run (same maturity) security. This strategy is fairly common around Treasury auctions as discussed by Fleming and Garbade (2007b). While this would be a preferred approach in practice, the paper focuses on a OTR strategy for two reasons. First, interest hedging with the former on-the-run is imperfect because maturities are not matched and additional accrued interest calculations would need to be accounted for. Second, the repo rate for recently issued securities can trade "special," that is at a significant gap to the r_b so that the funding terms would become more important. At the same time historical special repo rates are not readily available, so we focus on OTR for which these terms are not important.

Minimum Bidding Requirement Details In the current design of the primary dealer system, dealers are expected to bid for a pro-rata share of the auction at "reasonably competitive" prices Federal Reserve Bank of New York (2016). Prior to 1992, an active primary dealer had to be a "consistent and meaningful participant" in Treasury auctions by submitting bids roughly commensurate with the dealer's capacity. See appendix E in Brady, Breeden, and Greenspan (1992). In 1997, the New York Fed instituted an explicit counterparty performance scorecard and dealers were evaluated based on the volume of allotted securities (FOMC, November 2007). In 2010 the NY Fed clarified their primary dealer operating policies and strengthened the requirements (Federal Reserve Bank of New York, 2016).

C   Existence, Extensions and Robustness

This section contains additional theoretical and numerical analysis that is not needed to understand the results in the main text. It provides additional proof, context and robustness.

C.1   Equilibrium Existence and Uniqueness

We prove equilibrium existence and uniqueness for various classes of models. One class of models are ones with little market power, because any one or more of the following is true: the number of bidders N_J, N_I, or N_D is sufficiently high, risk aversion (ρ) is low, because resale is infrequent (low α), or because secondary market prices are sufficiently predictable (τ_f sufficiently high). A second class of models is one with sufficiently symmetric bidders and little information sharing. A third class of models is one with sufficiently symmetric bidders and abundant sharing between dealers and their clients. A fourth class of models is one where bidders are sufficiently symmetric and the probability of secondary market resale is high. In any one of these classes, the equilibrium exists and is unique.

The role of these assumptions is to preserve as much tractability as possible. Without them, the number of terms in the pricing equation multiplies and it becomes impossible to characterize the model's solution with one equation.

Existence and uniqueness in class 1: Low market power. We start by proving that low ρ, α or high τ_f makes dp/dq arbitrarily close to zero. Market power goes away in these settings. Recall that we defined the demand sensitivity to price to be M_j, where $1/M_j = \rho\alpha^2 V[f|S_j] + dp/dq_j$ for any type of bidder j. From (70)-(72), we see that $(dp/dq)^{-1}$ is a weighted sum of these M_j terms for all investors.

If $\alpha \to 0$ or $\rho \to 0$, the first term of $1/M_j$ goes to zero. Similarly, if $\tau_f \to \infty$, then f has no variance, so $V[f|S] \to 0$. If $\rho\alpha^2 V[f|S_j] \to 0$, then $1/M_j \to dp/dq_j$. We can rewrite (70)-(72) in the form $(dp/dq_j)^{-1} = z_I M_I + z_J M_J + z_D M_D$, where z_I, z_J, z_D are combinations of parameters. Substituting $1/M_j \approx dp/dq_j$, we get $(dp/dq_j)^{-1} = z_I(dp/dq_I)^{-1} + z_J(dp/dq_J)^{-1} + z_D(dp/dq_D)^{-1}$. The solution is that $M_j = (dp/dq_j)^{-1} = 0$ for all bidders j.

If market power is sufficiently low, then the existence and uniqueness of equilibrium, for arbitrary information structures has been proven by Lou, Parsa, Ray, Li, and Wang (2019). Ozsoylev and Walden (2011) prove that this existence extends to settings with finite agents, with small amounts of market power as well.

Existence and uniqueness in class 2: Little information sharing. Consider the following reference model. (At the end, we consider a broader set of nearby models.) Assume that $N_I = l\,N_D = lN/(l+1)$ and $N_J = 0$. We further assume that the minimum bidding requirement cost χ is heterogeneous, private information, and has the same distribution as v_i. We call it v_d.

In this reference model, all investors get the same information content, but different signal realizations. Thus, they all put the same weight on each signal when they form their beliefs. Identical signal precision implies that $M_J = M_D = M$. Therefore, the price conjecture and price signal can be written as:

$$p = A + B\bar{s} + C\bar{v} \tag{84}$$

$$s_i(p) = \frac{p - A - Cv_i}{B} = f + \bar{\epsilon} + \frac{N-1}{N}\frac{C}{B}\bar{v}$$

Under no information sharing, we have that $S_i = S_d = [s_i, s_i(p)]$ and the market clearing condition is:

$$\sum_{i=1}^{lN/(l+1)} (\alpha E[f|S_i] + \alpha g + (1-\alpha)v_i - p)M + \sum_{d=1}^{N/(l+1)} (\alpha E[f|S_d] + \alpha g + \chi - p)M = 1 \tag{85}$$

where l is the number of clients per dealer. Replacing $E[f|S]$ with (5), summing and dividing by MN yields: $\alpha\left[\bar{f}(1-\beta_s-\beta_p)+\beta_s\bar{s}+\beta_p\bar{s}(p)\right]+\alpha g+\frac{l}{l+1}(1-\alpha)\bar{v}+\frac{1}{l+1}\chi-p = \frac{1}{MN}$ where $\bar{s}(p) = \frac{p-A}{B} - \frac{C}{BN}\bar{v}$. Solving out for p:

$$p(1-\alpha\beta_p B^{-1}) = \alpha\left[\bar{f}(1-\beta_s-\beta_p)-A\beta_p B^{-1}\right]-(MN)^{-1}+\alpha\beta_s\bar{s}+\left(\frac{l(1-\alpha)}{l+1}-\frac{\alpha\beta_p C}{BN}\right)\bar{v}+\frac{\chi}{l+1}+\alpha g$$

Matching coefficients we get:

$$A = \frac{\alpha[\bar{f}(1 - \beta_s - \beta_p) - A\beta_p B^{-1}] + \alpha g + \frac{1}{l+1}\chi - (MN)^{-1}}{1 - \alpha\beta_p B^{-1}} \tag{86}$$

$$B = \frac{\alpha\beta_s}{1 - \alpha\beta_p B^{-1}} \tag{87}$$

$$C = \frac{l(1 - \alpha)/(l + 1) - \alpha\beta_p B^{-1}C/N}{1 - \alpha\beta_p B^{-1}} \tag{88}$$

The signals' weight in the optimal linear predictor are $\beta = V[S]^{-1}1_m\tau_f^{-1}$. In this case, $V[S]$ from the Bayesian updating equation has diagonal elements $\tau_f^{-1} + \tau_s^{-1}$ and $\tau_f^{-1} + \tau_p^{-1}$ and off-diagonal covariance $\tau_f^{-1} + \tau_s^{-1}/N$.

$$V[S]^{-1} = \frac{1}{(\tau_f^{-1} + \tau_s^{-1})(\tau_f^{-1} + \tau_p^{-1}) - (\tau_f^{-1} + \tau_s^{-1}/N)^2} \begin{bmatrix} \tau_f^{-1} + \tau_p^{-1} & -(\tau_f^{-1} + \tau_s^{-1}/N) \\ -(\tau_f^{-1} + \tau_s^{-1}/N) & \tau_f^{-1} + \tau_s^{-1} \end{bmatrix}$$

The denominator of the fraction above can be rearranged as $\tau_f^{-1}[\tau_p^{-1} - \tau_s^{-1}/N] + \tau_f^{-1}[\tau_s^{-1} - \tau_s^{-1}/N] + \tau_s^{-1}[\tau_p^{-1} - \tau_s^{-1}/N^2]$. Following (6), we obtain the Bayesian updating weight β by multiplying the precision matrix $V[S]^{-1}$ by the covariance vector $1_m\tau_f^{-1}$: Multiplying the numerator and denominator by $\tau_s N/(N-1)\tau_f[\tau_p^{-1} - \tau_s^{-1}/N]^{-1}$ yields:

$$\beta_s = \frac{\tau_s N/(N-1)}{\tau_s N/(N-1) + [\tau_p^{-1} - \tau_s^{-1}/N]^{-1} + \tau_f^{-1}N/(N-1)[\tau_p^{-1} - \tau_s^{-1}/N^2][\tau_p^{-1} - \tau_s^{-1}/N]^{-1}}$$

Finally, we replace $\tau_p^{-1} = \frac{\tau_s^{-1}}{N} + \left(\frac{C}{B}\right)^2 \frac{N-1}{N} \frac{\tau_v^{-1}}{N}$ to get β_s and follow exactly the same procedure for the second row of β, to get β_p:

$$\beta_s = \frac{\tau_s}{\tau_s + (B/C)^2 N\tau_v + \tau_f[1 + (B/C)^2\tau_v/\tau_s]} \tag{89}$$

$$\beta_p = \frac{(B/C)^2 N\tau_v}{\tau_s + (B/C)^2 N\tau_v + \tau_f[1 + (B/C)^2\tau_v/\tau_s]} \tag{90}$$

With the vector β solved, we can solve for the posterior variance, $\hat{\tau}^{-1} = \tau_f^{-1} - 1_m'\tau_f^{-1}\beta$:

$$\hat{\tau}^{-1} = \frac{1 + (B/C)^2\tau_v/\tau_s}{\tau_s + (B/C)^2 N\tau_v + \tau_f[1 + (B/C)^2\tau_v/\tau_s]} \tag{91}$$

In order to complete the characterization of the equilibrium, we need to compute the price impact to obtain M. To compute the price impact of a single bid, we need to pull out one bidder's demand, as q. The market clearing condition becomes $\sum_{i=1}^{lN/(l+1)-1}(\alpha E[f|S_i] + ag + (1-\alpha)v_i - p)M + \sum_{d=1}^{N/(l+1)}(\alpha E[f|S_d] + \alpha g + \chi - p)M + q = 1$. Replacing $E[f|S]$ and

dividing by $M(N-1)$, with one exogenous demand q yields:

$$p(1 - \alpha\beta_p B^{-1}) = \alpha[\bar{f}(1 - \beta_s - \beta_p) - A\beta_p B^{-1}] - (M(N-1))^{-1} + \alpha\beta_s\bar{s}$$
$$+ \left(\frac{lN/(l+1) - 1}{N-1}(1 - \alpha) - \alpha\beta_p \frac{C}{BN}\right)\bar{v} + \mathbf{q}(M(N-1))^{-1} + \alpha g + \frac{N/(l+1)}{N-1}\chi.$$
$$(92)$$

Thus, $dp(1 - \alpha\beta_p B^{-1}) = dq(M(N-1))^{-1}$, and we obtain $dp/dq = (M(N-1))^{-1}(1 - \alpha\beta_p B^{-1})^{-1}$. Using the definition of M, we have that $M^{-1} = \rho\alpha^2\hat{\tau}^{-1} + M^{-1}(N-1)^{-1}(1 - \alpha\beta_p B^{-1})^{-1}$.

Thus, the full characterization of the equilibrium is: (86) - (91) and

$$M = \frac{1 - (N-1)^{-1}(1 - \alpha\beta_p B^{-1})^{-1}}{\rho\alpha^2\hat{\tau}^{-1}} \qquad (93)$$

Note that β_s and β_p only depend on C/B, so C and B do not depend on A or M. Also, since β_s and β_p are positive, it is easy to see that B and C are positive as well.

We need to prove that the closed system given by the equations for B and C plus the definitions of β_s and β_p has a solution. First, we divide the expressions for B and C: $B/C = \alpha(\beta_s + \beta_p)\left[1 - \alpha\frac{N-1}{N}\frac{\beta_p}{\beta_s + \beta_p}\right]$, which simplifies to $B/C = \alpha[\beta_s + (1 - \alpha(N-1)/N)\beta_p]$. Substituting in the definitions of β_s and β_p yields

$$\frac{B}{C} = \frac{\alpha[\tau_s + ((1-\alpha)N + \alpha)(B/C)^2\tau_v]}{\tau_s + (B/C)^2 N\tau_v + \tau_f[1 + (B/C)^2\tau_v/\tau_s]}$$

The idea of the proof is that while the left hand side is increasing in (B/C), the right hand side (RHS) is decreasing (since B and C are positive, we can use the derivative with respect to $(B/C)^2$). To see this, let $x = (B/C)^2$, then:

$$\frac{\partial \text{RHS}}{\partial x} = \frac{\alpha}{(\tau_s + xN\tau_v + \tau_f[1 + x\tau_v/\tau_s])^2} \times$$
$$\left[[(1-\alpha)N + \alpha]\tau_v[\tau_s + xN\tau_v + \tau_f + x\tau_f\tau_v/\tau_s] - [x\tau_v[(1-\alpha)N + \alpha] + \tau_s][N\tau_v + \tau_f\tau_v/\tau_s]\right]$$
$$= \frac{\alpha}{(\tau_s + xN\tau_v + \tau_f[1 + x\tau_v/\tau_s])^2}\left[\alpha(1 - N)\tau_s\tau_v + (1-\alpha)(N-1)\tau_v\tau_f\right].$$

To show existence, we use the intermediate value theorem. To do this, we need to show that there exists a value for (B/C) such that $(B/C) < \text{RHS}$ and another value such that $(B/C) > \text{RHS}$. For $(B/C) = 0$, we have that $RHS = \alpha\tau_s/(\tau_s + \tau_f) > 0$. For $(B/C) = 1$, we have that RHS $= \alpha(\tau_s + [(1-\alpha)N + \alpha]\tau_v)/(\tau_s + N\tau_v + \tau_f[1 + \tau_v/\tau_s]) < 1$. Then, since the function is continuous, there exists an equilibrium value for (B/C) between 0 and 1.

Furthermore, since the RHS is montonically, strictly decreasing, and the left side B/C

is monotonically strictly increasing in B/C, there is a single crossing and thus a unique solution.

Given the equilibrium value for (B/C), equations (89),(90) give us the values for β_s and β_p. Substitution yields the equilibrium values for the rest of the variables.

Finally, note that the derivative is a strict inequality and a continuous function of all the (positive) parameters, including the number of agents and their information precisions. Therefore, by continuity there exists a ball of models with parameters near the reference model, for which the inequality still holds. For this collection of models, the equilibrium exists and is unique.

Class 3: Widespread information sharing. Under the same bidder symmetry assumptions as above and perfect information sharing, a dealer observes the signal of each client and shares that information with the other clients. With $N_I = lN_D$, every agent observe $l + 1$ signals and every signal is observed by $l + 1$ agents. Let $\bar{s}_{l+1} = \sum_{i \in d(i)} s_i$, then we have that all agents have the same information set $S_i = \{\bar{s}_{l+1}, s(p)\}$.

Since agents give the same weight to each of the three private signals they observe, the market clearing condition is the same as before. Thus, the equilibrium conditions we found for the Chinese wall still holds, but for different β's. In particular, the unconditional variance now is:

$$V[S] = \begin{bmatrix} \tau_f^{-1} + \tau_s^{-1}/(l+1) & \tau_f^{-1} + \tau_s^{-1}/N \\ \tau_f^{-1} + \tau_s^{-1}/N & \tau_f^{-1} + \tau_p^{-1} \end{bmatrix}.$$

Then, using the same steps as in the Chinese wall case, we get:

$$\beta_s = \frac{\tau_s}{\tau_s + \frac{N-1}{N-l-1}(B/C)^2 N \tau_v + \tau_f[1 + (B/C)^2 \tau_v/\tau_s]} \tag{94}$$

$$\beta_p = \frac{\frac{N-1}{N-l-1}(B/C)^2 N \tau_v}{\tau_s + \frac{N-1}{N-l-1}(B/C)^2 N \tau_v + \tau_f[1 + (B/C)^2 \tau_v/\tau_s]} \tag{95}$$

These modifications do not affect any part of the proof. Now, the equation for (B/C) is:

$$\frac{B}{C} = \alpha \underbrace{\frac{\tau_s + \frac{N-1}{N-l-1}[(1-\alpha)N + \alpha](B/C)^2 \tau_v}{\tau_s + \frac{N-1}{N-l-1}(B/C)^2 N \tau_v + \tau_f[1 + (B/C)^2 \tau_v/\tau_s]}}_{\text{RHS}}$$

$$\text{where} \quad \frac{\partial \text{RHS}}{\partial x} = \alpha \frac{\frac{N-1}{N-l-1}\tau_v \tau_s(1-N)\alpha + \tau_v \tau_f(\frac{N-1}{N-l-1}[(1-\alpha)N + \alpha] - 1)}{(\tau_s + x\frac{N-1}{N-l-1}N\tau_v + \tau_f[1 + x\tau_v/\tau_s])^2}.$$

By the intermediate value theorem, for all $B/C > 0$, a solution exists. By strict monotonicity, it is unique, just as in the previous case. For the special case, $(B/C) = 0$, we have that $RHS = \alpha \tau_s/(\tau_s + \tau_f) > 0$. For $(B/C) = 1$, we have that $\text{RHS} = \alpha(\tau_s + \frac{N-1}{N-l-1}[(1-\alpha)N + \alpha]\tau_v)/(\tau_s + \frac{N-1}{N-l-1}N\tau_v + \tau_f[1 + \tau_v/\tau_s]) < 1$. Then, there exists a unique

equilibrium with perfect information sharing. Since both the left and right hand sides are continuous functions of the amount of information sharing by dealers, there exists a range of sufficiently-symmetric, high-sharing models where the inequality still holds and thus the equilibrium still exists and is unique.

Class 4: Sufficiently symmetric   Let Υ be the set of parameters $\upsilon = \{\tau_{vI}, \tau_{vJ}, \tau_f, \tau_s, \chi\}$ such that

(a) $\exists$ an open ball $B_\epsilon(\mathbb{V}(f \mid S_J))$ such that $\mathbb{V}(f \mid S_I), \mathbb{V}(f \mid S_D) \in B_\epsilon(\mathbb{V}(f \mid S_J))$;

(b) $\exists$ open balls $B_{\epsilon_{\beta p}}(\beta_{Jp})$ and $B_{\epsilon_{\beta s}}(\beta_{Js})$ such that $\beta_{Ip}, \beta_{Dp} \in B_{\epsilon_{\beta p}}(\beta_{Jp})$ and $\beta_{Is}, \beta_{Ds} \in B_{\epsilon_{\beta s}}(\beta_{Js})$;

(c) $\beta_{I\xi}, \beta_{D\xi} \ll \min\{\beta_{Is}, \beta_{Js}, \beta_{Ds}\}$.

If (a), (b) and (c) hold, then we say that bidders are "sufficiently symmetric."

If the probability of resale α is high, then the private value drops out for all agents. The resale price acts as a common value. If, in addition, there are fully symmetric bidders, the model becomes isomorphic to Kyle (1989) and Wang and Zender (2002). Since the equilibrium exists and is a unique linear equilibrium in that setting, the same is true here for full symmetry. Since the inequality that establishes symmetry is continuous in the mean and variance of beliefs, there must exist a ball of parameters $\upsilon \in \Upsilon$ such that the inequality still holds and existence and uniqueness are established.

C.2   Information Sharing, Risk and Revenue

Theorem C.2.1. *If $\{\tau_{vI}, \tau_{vJ}, \tau_f, \tau_s, \chi\} \in \Upsilon$ (defined in previous result, class 4), and information sharing reduces $\mathbb{V}[f|S_i]$, $i \in \{I, J, D\}$ weakly for all agents, then market power dp/dq_i falls and revenue p rises.*

Proof. **Step 1:** Prove that $\beta_p \leq 1$ and $\beta_s \leq 1$ element by element. Start with (6) which defines β's.

$$\mathbf{Cov}(f, S_j) = 1_m \tau_f^{-1}, \tag{96}$$

$$\mathbb{V}(S_j) = \tau_f^{-1} 1_m 1_m' + \text{positive term}, \tag{97}$$

where the positive term is strictly positive if all shocks have positive variance. Therefore, we have

$$\beta_j = \mathbb{V}(S)^{-1} \mathbf{Cov}(f, S_j) \leq 1 \tag{98}$$

element by element.

Step 2: Suppose that there are N_J direct bidders, and no dealers or indirect bidders, i.e. $N_I = N_D = 0$. For this simple case, we show that if $\mathbb{V}[f \mid S_j]$ decreases, then market power dp/dq_J falls and revenue p rises.

To show p rises, it suffices to show that $q_J(p)$ rises for a given p, because $q_J(p)$ decreases in p, so p must then rise to clear the market.

By the expectations martingale theorem (Doob, 1953), more precise information does not change $\mathbb{E}[f \mid S_j]$ on average. Therefore, it cannot change any term in the numerator of $q_J(p)$. For the denominator, recall that $M_J^{-1} = \rho\alpha^2 \mathbb{V}[f \mid S_j] + dp/dq_J$. By the definition of more precise information, $\mathbb{V}[f \mid S_j]$ falls. Then the key question becomes how does a change in $\mathbb{V}[f \mid S_j]$ affect dp/dq_J.

With $N_I = N_D = 0$, we can simplify $\tilde{M} = N_I M_J$, and (71) collapses to

$$\frac{dp}{dq_J} = \left[(N_J - 1)M_J - \frac{\alpha}{B_J}M_J(N_J - 1)\beta_{Jp}\right]^{-1}$$

$$= \frac{1}{M_J(N_J - 1)}\left[1 - \frac{\alpha\beta_{Jp}}{B_J}\right]^{-1}. \tag{99}$$

Similarly, the formula for $\tilde{Q}$ just after (59) simplifies to

$$\tilde{Q} = \tilde{M} - \frac{\alpha}{\tilde{B}}N_J M_J \beta_{Jp} = N_J M_J (1 - \frac{\alpha\beta_{Jp}}{B_J}), \tag{100}$$

Substituting this $\tilde{Q}$ expression into (64) yields $B_J = \alpha(1 - \frac{\alpha\beta_{Jp}}{B_J})^{-1}\beta_{Js} = \alpha(\frac{B_J - \alpha\beta_{Jp}}{B_J})^{-1}\beta_{Js}$. Multiplying $B_J - \alpha\beta_{Jp}$ on both sides and rearranging, we have

$$B_J = \alpha(\beta_{Jp} + \beta_{Js}). \tag{101}$$

Then plug (101) into (99),

$$\frac{dp}{dq_J} = \frac{1}{M_J(N_J - 1)}\left[1 - \frac{\alpha}{B_J}\beta_{Jp}\right]^{-1} \tag{102}$$

$$= \frac{1}{M_J(N_J - 1)}\frac{\beta_{Jp} + \beta_{Js}}{\beta_{Js}}. \tag{103}$$

By assumption, we know that $\alpha < 1$. From Step 1, we know that $\beta_{Jp} < 1$. Thus, $\bar{C}_J \equiv \frac{\beta_{Jp} + \beta_{Js}}{(N_J - 1)\beta_{Js}} > 0$ Then,

$$\frac{dp}{dq_J} = \frac{\bar{C}_J}{M_J} = \bar{C}_J(\rho\alpha^2 \mathbb{V}[f \mid S_j] + \frac{dp}{dq_J}) \tag{104}$$

$$\implies \frac{dp}{dq_J} = \frac{\bar{C}_J}{1 - \bar{C}_J}\rho\alpha^2 \mathbb{V}[f \mid S_j] \tag{105}$$

To determine if market power falls when information sharing reduces uncertainty, we need to determine if $\frac{\bar{C}_J}{1 - \bar{C}_J} > 0$. That is true if and only if $0 < \bar{C}_J < 1$. Since we know that $\bar{C}_J > 0$, this requires $(\beta_{Jp} + \beta_{Js})/((N_J - 1)\beta_{Js}) < 1$. The necessary and sufficient condition for that is

$$N_J > 2 + \frac{\beta_{Jp}}{\beta_{Js}}. \tag{106}$$

If N_J is big enough, this holds and thus $\frac{dp}{dq_J} > 0$. If information decreases variance $\mathbb{V}[f \mid S_j]$,

then market power $\frac{dp}{dq_J}$ falls, M_J, demand, and price rise.

Step 3: When bidders are sufficiently symmetric, it means we are close to a reference model where $\beta_{Ip} = \beta_{Jp} = \beta_{Dp} \equiv \beta_p$, $\beta_{Is} = \beta_{Js} = \beta_{Ds} \equiv \beta_s$, $\mathbb{V}(f \mid S_i) = \mathbb{V}(f \mid S_j) = \mathbb{V}(f \mid S_d) \equiv \mathbb{V}(f \mid S)$, and $\beta_{I\xi}, \beta_{D\xi} \ll \beta_s$. The next step proves that, in such a reference model, market power dp/dq falls and revenue p rises when $\mathbb{V}[f \mid S]$ decreases. We show this in a similar way to the previous step and then broaden the result to a nearby class of models.

Recall that $\tilde{Q} = \tilde{M} - \frac{\alpha}{\tilde{B}}(N_I M_I \beta_{Ip} + N_J M_J \beta_{Jp} + N_D M_D \beta_{Dp})$. With $\beta_{Ip} = \beta_{Jp} = \beta_{Dp} \equiv \beta_p$, $\tilde{Q}$ simplifies to

$$\tilde{Q} = \tilde{M}\left(1 - \frac{\alpha \beta_p}{\tilde{B}}\right). \tag{107}$$

Recall also that $\tilde{B} = B_I + B_J + B_D$. With $\beta_{Is} = \beta_{Js} = \beta_{Ds} \equiv \beta_s$, $\tilde{B}$ simplifies to

$$\tilde{B} = \frac{\alpha}{\tilde{Q}}\left[\tilde{M}\beta_s + M_I N_I \beta_{I\xi} + M_D N_D \beta_{D\xi}\right] \approx \frac{\alpha}{\tilde{Q}}\tilde{M}\beta_s. \tag{108}$$

Plug (107) into (108), we have

$$\tilde{B} = \alpha\beta_s\left(1 - \frac{\alpha\beta_p}{\tilde{B}}\right)^{-1}. \tag{109}$$

Multiplying $\left(1 - \frac{\alpha\beta_p}{\tilde{B}}\right)$ on both sides and rearranging, we have

$$\tilde{B} \approx \alpha(\beta_p + \beta_s). \tag{110}$$

Plug (110) into dp/dq_J, we have

$$
\begin{aligned}
\frac{dp}{dq_J} &= \left[\tilde{M} - M_J - \frac{\alpha\beta_p}{\tilde{B}}\left(\tilde{M} - M_J\right)\right]^{-1} \\
&= \frac{1}{\tilde{M} - M_J}\left[1 - \frac{\alpha\beta_p}{\tilde{B}}\right]^{-1} \\
&\approx \frac{1}{\tilde{M} - M_J}\frac{\beta_p + \beta_s}{\beta_s}.
\end{aligned}
$$

With $\mathbb{V}(f \mid S_i) = \mathbb{V}(f \mid S_j) = \mathbb{V}(f \mid S_d)$, we can further write out dp/dq_I, dp/dq_J and dp/dq_D as

$$\frac{dp}{dq_I} \approx \left[\frac{N_I - 1}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_I} + \frac{N_J}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_J} + \frac{N_D}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_D}\right]^{-1}\frac{\beta_p + \beta_s}{\beta_s},$$

$$\frac{dp}{dq_J} \approx \left[\frac{N_I}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_I} + \frac{N_J - 1}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_J} + \frac{N_D}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_D}\right]^{-1}\frac{\beta_p + \beta_s}{\beta_s},$$

$$\frac{dp}{dq_D} \approx \left[\frac{N_I}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_I} + \frac{N_J}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_J} + \frac{N_D - 1}{\rho\alpha^2\mathbb{V}(f \mid S) + dp/dq_D}\right]^{-1}\frac{\beta_p + \beta_s}{\beta_s}.$$

These expressions reveal that dp/dq_I, dp/dq_J and dp/dq_D are approximately equal. There-

fore, we drop the subscript for q. Then

$$\frac{dp}{dq} = \frac{\beta_p + \beta_s}{(N-1)\beta_s}\left[\rho\alpha^2\mathbb{V}(f \mid S) + \frac{dp}{dq}\right] \tag{111}$$

Define $\bar{C} = \frac{\beta_p + \beta_s}{(N-1)\beta_s}$, we have

$$\frac{dp}{dq} = \bar{C}(\rho\alpha^2\mathbb{V}[f \mid S] + \frac{dp}{dq}) \tag{112}$$

$$\implies \frac{dp}{dq} = \frac{\bar{C}}{1-\bar{C}}\rho\alpha^2\mathbb{V}[f \mid S]. \tag{113}$$

To determine if market power falls with information sharing, we need to determine the sign of $\frac{\bar{C}}{1-\bar{C}}$. By the same argument as in step 2, we find that $\bar{C}/(1-\bar{C}) > 0 \iff N > 2 + \beta_p/\beta_s$. When there are many market participants (high N), this condition N is satisfied. Therefore, dp/dq falls with $\mathbb{V}(f \mid S)$, meaning that information sharing reduces market power.

Step 4:

Since market power dp/dq_i, $i \in \{I, J, D\}$ and revenue p are continuous functions, then the same strict inequality holds for open balls of nearby parameters. Thus, if bidders are sufficiently symmetric ((a), (b) and (c) hold), then $N > 2 + \beta_p/\beta_s$ still ensures that $\bar{C}/(1-\bar{C}) > 0$. So, market power dp/dq_i falls and revenue p rises when $\mathbb{V}[f \mid S_i]$, $\mathbb{V}[f \mid S_j]$ and $\mathbb{V}[f \mid S_d]$ decrease symmetrically for all bidders.

This result holds for different sets of parameters, for any N_I, N_J, N_D, a set of parameters $\{\tau_{vI}, \tau_{vJ}, \chi, \tau_f, \tau_s\}$, as long as they make bidders sufficiently symmetric, satisfying conditions (a)-(c).

C.3 Welfare and the Information Prisoners' Dilemma

Theorem C.3.1. *(Bidders prefer no private information)*

(1) *If there is no direct bidder, then for sufficiently high N and low χ, indirect bidders have higher ex-ante expected utility when no private signal s_i is available.*

(2) *If there are direct bidders, then for sufficiently high N and low χ, there $\exists$ open balls $B_{\epsilon_v}(\tau_{vJ})$, $B_{\epsilon_\xi}(0)$ and $B_{\epsilon_N}(0)$, such that if*

   (a) *$\tau_{vI} \in B_{\epsilon_v}(\tau_{vJ})$ and $\tau_\xi \in B_{\epsilon_v}(0)$; or*

   (b) *$\frac{N_J}{N} \in B_{\epsilon_N}(0)$,*

   then indirect bidders have higher ex-ante expected utility when no private signal s_i is available.

Proof.
Step 1: calculating the general formula of ex-ante utility with signals.

Let EU_j be the expected utility conditional on S_j for the direct bidders (same algebra applies to indirect bidders, and for dealers only small modification is needed). Then

$$EU_j = \mathbb{E}\left[-e^{-\rho(W_{0,j}+q_j(\alpha p_s - p)+(1-\alpha)q_j v_j)}\right]$$
$$= -e^{-\rho W_{0,j}}\mathbb{E}\left[e^{-\rho q_j(\alpha \mathbb{E}[f|S_j]+\alpha g - p + (1-\alpha)v_j)+\frac{1}{2}\rho^2\alpha^2 q_j^2 \mathbb{V}[f|S_j]}\right]. \tag{114}$$

Let $\bar{C}_J \equiv \frac{\beta_{Jp}+\beta_{Js}}{(N_J-1)\beta_{Js}} > 0$, then

$$\frac{dp}{dq_j} = \frac{\bar{C}_J}{1-\bar{C}_J}\rho\alpha^2 \mathbb{V}[f \mid S_j]. \tag{115}$$

Plugging dp/dq into the optimal bid schedule (13), we have

$$q_j(p) = \left(1-\bar{C}_J\right)\frac{\alpha\mathbb{E}[f \mid S_j]+\alpha g + (1-\alpha)v_j - p}{\rho\alpha^2\mathbb{V}[f \mid S_j]}.$$

Plug it back into (114):

$$EU_j = -e^{-\rho W_{0,j}}e^{-\frac{1-\bar{C}_J^2}{2\alpha^2}\frac{1}{\mathbb{V}[f|S_j]}(\alpha\mathbb{E}[f|S_j]+\alpha g+(1-\alpha)v_j-p)^2}. \tag{116}$$

$$\text{Let} \quad F_J \equiv \mathbb{E}\left[\alpha\mathbb{E}[f \mid S_j]+\alpha g + (1-\alpha)v_j - p\right], \tag{117}$$
$$\Sigma_J \equiv \mathbb{V}\left[\alpha\mathbb{E}[f \mid S_j]+\alpha g + (1-\alpha)v_j - p\right], \tag{118}$$
$$z_j \equiv \frac{\alpha\mathbb{E}[f \mid S_j]+\alpha g + (1-\alpha)v_j - p}{\sqrt{\Sigma_J}}.$$

For dealers, the analogous expressions are: $F_D \equiv \mathbb{E}\left[\alpha\mathbb{E}[f \mid S_d]+\alpha g + \chi - p\right]$, $\Sigma_D \equiv \mathbb{V}\left[\alpha\mathbb{E}[f \mid S_d]+\alpha g + \chi - p\right]$, and $z_d \equiv (\alpha\mathbb{E}[f \mid S_d]+\alpha g + \chi - p)/\sqrt{\Sigma_D}$.

Ex-ante, $z_j \sim N(\frac{F_J}{\sqrt{\Sigma_J}}, 1)$. We can rewrite the conditional expected utility as

$$EU_j = -e^{-\rho W_{0,j}}e^{-\frac{1-\bar{C}_J^2}{2\alpha^2}\frac{1}{\mathbb{V}[f|S_j]}\Sigma_J z_j^2}.$$

Notice that z_j^2 has a non-central chi-square distribution. Using its moment-generating function, we have

$$EU = \mathbb{E}[EU_j] = -e^{-\rho W_{0,j}}\frac{\exp\left\{\frac{-\frac{1-\bar{C}_J^2}{2\alpha^2}\frac{F_J^2}{\mathbb{V}[f|S_j]}}{1+\frac{\Sigma_J}{\mathbb{V}[f|S_j]}}\right\}}{\sqrt{1+\frac{\Sigma_J}{\mathbb{V}[f|S_j]}}},$$

or re-normalizing by dividing by $-e^{\rho W_0}$ and taking log:

$$V_J \equiv -2\ln\left[\frac{-EU}{e^{-\rho W_0}}\right] = \frac{1 - \bar{C}_J^2}{\alpha^2}\frac{F_J^2}{\mathbb{V}[f \mid S_j] + \Sigma_J} + \ln\left[\frac{\mathbb{V}[f \mid S_j] + \Sigma_J}{\mathbb{V}[f \mid S_j]}\right]. \qquad (119)$$

Step 2: Assume that $N_I = lN_D = lN/(l+1)$, $N_J = 0$ and $\delta = 0$. We then compare EU under no information sharing with and without private signals.

With no information sharing, our signal vector is $S_i = S_d = [s_i, s_i(p)]$. For simplicity, we drop subscript i, d, I or D whenever no ambiguity is created. We denote the case with private signal with superscript I and the case without private signal U.

Case 1: Bidders have a private signal s_i. Using the formula for ex-ante expected payoff (117), we get

$$
\begin{aligned}
F^I &= \mathbb{E}\left[\alpha\mathbb{E}\left[f \mid S_i\right] + \alpha g + (1 - \alpha)v_i - p\right] \\
&= \mathbb{E}\left[\alpha\left(1 - \beta_s - \beta_p\right)\bar{f} + \alpha\beta_s s_i + \alpha\beta_p\left(\frac{p - A}{B} - \frac{C}{BN}\bar{v}_I\right) + \alpha g - p\right] \\
&= \alpha\left(1 - \beta_s - \beta_p\right)\bar{f} + \alpha\beta_s\bar{f} - \alpha\beta_p\frac{A}{B} + \alpha g - (A + B\bar{f})\left(1 - \frac{\alpha\beta_p}{B}\right) \\
&= \alpha\left(1 - \beta_s - \beta_p\right)\bar{f} + [\alpha\left(\beta_s + \beta_p\right) - B]\bar{f} + \alpha g - A.
\end{aligned}
$$

From (86) and (101), recall that in this case the pricing coefficients are $A = \alpha\bar{f}(1 - \beta_s - \beta_p) - (M^I N)^{-1} + \alpha g + \frac{1}{l+1}\chi$ and $B = \alpha(\beta_s + \beta_p)$. Plugging them into F^I, we can further simplify it to

$$F^I = \left(M^I N\right)^{-1} - \frac{1}{l+1}\chi.$$

Using (118), the conditional payoff variance with private signals is

$$
\begin{aligned}
\Sigma^I &= \mathbb{V}\left[\alpha\mathbb{E}\left[f \mid S_i\right] + \alpha g + (1 - \alpha)v_i - p\right] \\
&= \mathbb{V}\left[\alpha\left(1 - \beta_s - \beta_p\right)\bar{f} + \alpha\beta_s s_i + \alpha\beta_p\left(\frac{p - A}{B} - \frac{C}{BN}\bar{v}_I\right) + \alpha g + (1 - \alpha)v_i - p\right] \\
&= \mathbb{V}\left[\alpha\beta_s s_i - \alpha\beta_p\frac{C}{BN}\bar{v}_I + (1 - \alpha)v_i - (B\bar{s} + C\bar{v})\left(1 - \frac{\alpha\beta_p}{B}\right)\right] \\
&= \mathbb{V}\left[\left(\alpha\beta_s - \left(\frac{B}{N} - \frac{\alpha\beta_p}{N}\right)\right)s_i\right] + \mathbb{V}\left[\left(1 - \alpha - \left(\frac{C}{N_I} - \frac{\alpha\beta_p C}{BN_I} + \frac{\alpha\beta_p C}{BNN_I}\right)\right)v_i\right] \\
&\quad + \mathbb{V}\left[-\sum_{i' \neq i}s_{i'}\left(\frac{B}{N} - \frac{\alpha\beta_p}{N}\right) - \sum_{i' \neq i}v_{i'}\left(\frac{C}{N_I} - \frac{\alpha\beta_p C}{BN_I} + \frac{\alpha\beta_p C}{BNN_I}\right)\right] \\
&= \mathbb{V}\left[\frac{N - 1}{N}\alpha\beta_s\epsilon_i\right] + \mathbb{V}\left[\left(1 - \alpha - \frac{l + 1}{lN}\right)v_i\right] + \mathbb{V}\left[-\frac{l + 1}{lN}\sum_{i' \neq i}v_{i'}\right] \\
&= \left(\frac{N - 1}{N}\right)^2\alpha^2\beta_s^2\tau_\epsilon^{-1} + \left[(1 - \alpha)^2 - \frac{(l + 1)(1 - 2\alpha)}{lN}\right]\tau_v^{-1}
\end{aligned}
$$

Case 2: Bidders have no private signals. Therefore, the price does not contain any information. The market clearing condition is

$$\sum_{i=1}^{lN/(l+1)} (\alpha E[f] + \alpha g + (1-\alpha)v_i - p)M^U + \sum_{d=1}^{N/(l+1)} (\alpha E[f] + \alpha g + \chi - p)M^U = 1 \quad (120)$$

Replacing $E[f]$ and dividing by $M^U N$ we have:

$$\alpha \bar{f} + \alpha g + \frac{l}{l+1}(1-\alpha)\bar{v} + \frac{1}{l+1}\chi - p = \frac{1}{M^U N}$$

$$\implies p = \alpha \bar{f} - (M^U N)^{-1} + \frac{l(1-\alpha)}{l+1}\bar{v} + \frac{1}{l+1}\chi + \alpha g$$

Matching coefficients we get:

$$A = \alpha \bar{f} - (M^U N)^{-1} + \alpha g + \frac{1}{l+1}\chi \quad (121)$$

$$C = \frac{l(1-\alpha)}{l+1}. \quad (122)$$

To determine price impact, we replace one bidder's demand with q, impose market clearing and then apply the implicit function theorem.

$$1 = \alpha \tilde{M} g + \alpha \left(\tilde{M} - M_I \right) \bar{f} - \left(\tilde{M} - M_I \right) p + (1-\alpha)M_I(N_I - 1)\bar{v}_I + M_D N_D \chi + q_1$$

$$\implies \frac{dp}{dq_I} = \left(\tilde{M} - M_I \right)^{-1} = \frac{1}{M^U(N-1)} = \frac{\bar{C}^U}{M^U},.$$

where $\bar{C}^U = \frac{1}{N-1}$. Recall that

$$\left(M^U \right)^{-1} = \rho \alpha^2 \mathbb{V}[f] + \frac{dp}{dq_I} = \rho \alpha^2 \tau_f^{-1} + \left(M^U \right)^{-1} \bar{C}^U$$

$$\implies M^U = \frac{1 - \bar{C}^U}{\rho \alpha^2 \tau_f^{-1}}.$$

We adapt (117) and (118) for the no-signal case to get

$$F^U = \mathbb{E}\left[\alpha \mathbb{E}\left[f \right] + \alpha g + (1-\alpha)v_i - p \right]$$
$$= \mathbb{E}\left[\alpha \bar{f} + \alpha g - A - C\bar{v} \right]$$
$$= \alpha \bar{f} + \alpha g - A$$
$$= (M^U N)^{-1} - \frac{1}{l+1}\chi,$$

and

$$\begin{aligned}
\Sigma^U &= \mathbb{V}\left[\alpha\bar{f} + \alpha g + (1-\alpha)v_i - p\right] \\
&= \mathbb{V}\left[(1-\alpha)v_i - A - C\bar{v}\right] \\
&= \mathbb{V}\left[\left(1-\alpha-\frac{C}{N_I}\right)v_i - \frac{C}{N_I}\sum_{i'\neq i}v_{i'}\right] \\
&= \mathbb{V}\left[\left(1-\alpha-\frac{1-\alpha}{N}\right)v_i - \frac{1-\alpha}{N}\sum_{i'\neq i}v_{i'}\right] \\
&= \frac{N-\frac{l+2}{l+1}}{N}(1-\alpha)^2\tau_v^{-1}.
\end{aligned}$$

Now, we are ready to compare ex-ante utilities with and without private signals. We take their difference and compute it in two parts.

First term   Define

$$\Delta_1 \equiv \frac{1-\left(\bar{C}_I^I\right)^2}{\alpha^2}\frac{\left(F^I\right)^2}{\hat{\tau}^{-1}+\Sigma^I} - \frac{1-\left(\bar{C}_I^U\right)^2}{\alpha^2}\frac{\left(F^U\right)^2}{\tau_f^{-1}+\Sigma^U}$$

to be the diffence in the first term of (119) for markets with and without signals. Then

$$\Delta_1 < 0 \iff \left[1-\left(\bar{C}_I^I\right)^2\right]\frac{\left(F^I\right)^2}{\hat{\tau}^{-1}+\Sigma^I} < \left[1-\left(\bar{C}_I^U\right)^2\right]\frac{\left(F^U\right)^2}{\tau_f^{-1}+\Sigma^U}.$$

Recall that $M^I = \frac{1-\bar{C}^I}{\rho\alpha^2\hat{\tau}^{-1}}$, then if χ is sufficiently small, we have

$$\begin{aligned}
F^I &\approx \left(M^I N\right)^{-1} = \frac{\rho\alpha^2\hat{\tau}^{-1}}{\left(1-\bar{C}^I\right)N}, \\
F^U &\approx \left(M^U N\right)^{-1} = \frac{\rho\alpha^2\hat{\tau}^{-1}}{\left(1-\bar{C}^U\right)N}.
\end{aligned}$$

Then

$$\begin{aligned}
\Delta_1 < 0 &\iff \frac{1+\bar{C}^I}{1-\bar{C}^I}\frac{\rho^2\alpha^4\hat{\tau}^{-2}}{N^2\left(\hat{\tau}^{-1}+\Sigma^I\right)} < \frac{1+\bar{C}^U}{1-\bar{C}^U}\frac{\rho^2\alpha^4\tau_f^{-2}}{N^2\left(\tau_f^{-1}+\Sigma^I\right)} \\
&\iff \frac{1+\bar{C}^I}{1-\bar{C}^I}\frac{\hat{\tau}^{-2}}{1+\Sigma^I\hat{\tau}} < \frac{1+\bar{C}^U}{1-\bar{C}^U}\frac{\tau_f^{-2}}{1+\Sigma^U\tau_f}
\end{aligned}$$

Notice that $\bar{C}^I = \frac{1}{N-1}\left(1 + \frac{\beta_p}{\beta_s}\right)$ and $\bar{C}^U = \frac{1}{N-1}$. Thus

$$\frac{1 + \bar{C}^U}{1 - \bar{C}^U} = \frac{N}{N-2},$$

$$\frac{1 + \bar{C}^I}{1 - \bar{C}^I} = \frac{N + \frac{\beta_p}{\beta_s}}{N - 2 - \frac{\beta_p}{\beta_s}}.$$

If additionally N is sufficiently large, we have $\frac{1 + \bar{C}^I}{1 - \bar{C}^I} \approx \frac{N}{N-2}$. Therefore it boils down to find parameter regions where $\frac{\hat{\tau}^{-2}}{\tau_f^{-2}} < \frac{1 + \Sigma^I \hat{\tau}}{1 + \Sigma^U \tau_f}$ holds. Notice that $\frac{\hat{\tau}^{-2}}{\tau_f^{-2}} < 1$, so a sufficient condition would be

$$\Sigma^I \hat{\tau} > \Sigma^U \tau_f$$

$$\iff \left[\left(\frac{N-1}{N}\right)^2 \alpha^2 \beta_s^2 \tau_\epsilon^{-1} + \left[(1-\alpha)^2 - \frac{(l+1)(1-2\alpha)}{lN}\right]\tau_v^{-1}\right]\left[\tau_f + \frac{1 + xN\tau_v/\tau_\epsilon}{1 + x\tau_v/\tau_\epsilon}\tau_\epsilon\right]$$

$$> \frac{N - \frac{l+2}{l+1}}{N}(1-\alpha)^2 \tau_v^{-1}\tau_f$$

$$(123)$$

When N is sufficiently large, $\frac{1 + xN\tau_v/\tau_\epsilon}{1 + x\tau_v/\tau_\epsilon} \approx N$. Then (123) simplifies to

$$\left[\alpha^2\beta_s^2\tau_\epsilon^{-1} + (1-\alpha)^2\tau_v^{-1}\right][\tau_f + N\tau_\epsilon] > (1-\alpha)^2\tau_v^{-1}\tau_f$$

$$\iff \alpha^2\beta_s^2\tau_\epsilon^{-1}\tau_f + \alpha^2\beta_s^2\tau_\epsilon^{-1}N\tau_\epsilon + (1-\alpha)^2\tau_v^{-1}N\tau_\epsilon > 0,$$

$$(124)$$

which is always true. Therefore, when N is sufficiently large and χ sufficiently small, $\Delta_1 < 0$ holds.

Second term Define

$$\Delta_2 \equiv \ln\left[\frac{\hat{\tau}^{-1} + \Sigma^I}{\hat{\tau}^{-1}}\right] - \ln\left[\frac{\tau_f^{-1} + \Sigma^U}{\tau_f^{-1}}\right]$$

to be the difference in the second term of (119) for markets with and without signals. Then

$$\Delta_2 < 0 \iff \frac{\Sigma^I}{\hat{\tau}^{-1}} < \frac{\Sigma^U}{\tau_f^{-1}}$$

$$\iff \left(\frac{N-1}{N}\right)^2 \alpha^2\beta_s^2\tau_\epsilon^{-1}\tau_f + \left[(1-\alpha)^2 - \frac{(l+1)(1-2\alpha)}{lN}\right]\tau_v^{-1}\tau_f$$

$$< \frac{N - \frac{l+2}{l+1}}{N}(1-\alpha)^2\tau_v^{-1}\left[\tau_f + \frac{\tau_\epsilon + xN\tau_v}{1 + x\tau_v/\tau_\epsilon}\right].$$

Again, when N is sufficiently large, the above condition simplifies to

$$\alpha^2\beta_s^2\tau_\epsilon^{-1}\tau_f < (1-\alpha)^2\tau_v^{-1}N\tau_\epsilon,$$

$$(125)$$

which is satisfied when $N > \frac{\alpha^2\tau_f\tau_v}{(1-\alpha)^2\tau_\epsilon^2}$ since $0 < \beta_s \leq 1$.

Therefore, when N is sufficiently large and χ sufficiently small and there is no information sharing, $EU^I - EU^U = \Delta_1 + \Delta_2 < 0$, that is with private signal about f, the ex-ante utility of indirect bidders is lower.

Step 3: Assume that $N_I = lN_D = lN/(l+1)$, $N_I = 0$ and $\delta = 0$. We then compare $\overline{EU}$ under perfect information sharing with and without private signals. Under perfect information sharing, all agents have the same information $S_i = [\bar{s}_{l+1}, s(p)]$.

Price coefficients and M are the same as in Step 2. We have different expressions for $\beta_s, \beta_p, \frac{B}{C}$ and $\hat{\tau}^{-1}$. Now,

$$\hat{\tau} = \tau_f + \frac{1 + \frac{N-1}{N-l-1}xN\tau_v/\tau_\epsilon}{1 + x\tau_v/\tau_\epsilon}\tau_\epsilon.$$

When N is large enough, we still have $\hat{\tau} \approx \tau_f + N\tau_\epsilon$. We also have $0 < \beta_s \leq 1$. Thus we can replicate the previous step with little change. Therefore, when N is sufficiently large and χ sufficiently small and there is perfect information sharing, $EU^I - EU^U = \Delta_1 + \Delta_2 < 0$, that is with private signal about f, the ex-ante utility of indirect bidders is lower.

Step 4: Generalizing to imperfect information sharing and three types of agents.
When τ_ξ^{-1} is arbitrarily close to 0, that is the information shared by dealers to the indirect bidders is very precise, then indirect bidders will have information sets that are arbitrarily close to those of the dealers. Then the results from the perfect information case apply. If there is sufficiently small proportion of direct bidders, that is $\frac{N_J}{N}$ sufficiently small, or if indirect and direct bidders are sufficiently symmetric, that is τ_{vI} and τ_{vJ} are sufficiently close, and τ_ξ sufficiently small, then by continuity, inequalities (124) and (125) still hold, and the results can be extended to include direct bidders. □

C.4   Bid Shading and Signal Jamming

The term M for each investor type measures the bid sensitivity to changes in expected returns. Since expected returns are typically positive (this is a compensation for the risk of the uncertain common value), a larger value of M denotes a smaller average bid and a lower average equilibrium price.

From (52), (53) and (54), we know that the sensitivity M for each of the three types of bidders is the inverse of a sum of $\rho\alpha^2 V[f|S]$ term that measures risk aversion and risk, plus a dp/dq term that arises because strategic bidders internalize the impact they have on price. Bid shading and signal jamming are about this strategic dp/dq term.

The inverse of this price impact term is the sum of a direct effect, which is bid shading, and an indirect effect, which works through its effect on the beliefs of others:

$$\left(\frac{dp}{dq_I}\right)^{-1} = \tilde{M} - M_I - \frac{\alpha}{\tilde{B}}\left(M_I(N_I - 1)\beta_{Ip} + M_J N_J \beta_{Jp} + M_D N_D \beta_{Dp}\right)$$

$$\left(\frac{dp}{dq_J}\right)^{-1} = \tilde{M} - M_J - \frac{\alpha}{\tilde{B}}\left(M_I N_I \beta_{Ip} + M_J(N_J - 1)\beta_{Jp} + M_D N_D \beta_{Dp}\right)$$

$$\left(\frac{dp}{dq_D}\right)^{-1} = \tilde{M} - M_D - \frac{\alpha}{\tilde{B}}\left(M_I N_I \beta_{Ip} + M_J N_J \beta_{Jp} + M_D(N_D - 1)\beta_{Dp}\right)$$

The first two terms of each expression capture the direct effect of one bidder's demand on the price. $\tilde{M}$ is the sum of every bidder's demand sensitivity to return. The more sensitive demand is to return, the less the return needs to change to clear the market. This sum represents the inverse price elasticity to a change in demand. The higher it is, the larger the price impact of a change in bids. But if one bidder changes their demand, they do not absorb their own change in demand. Thus, bid shading is the price impact when all bidders, except one bidder of type I (or J or D), adjust their bids to the new equilibrium price:

$$S_I = \tilde{M} - M_I; \qquad S_J = \tilde{M} - M_J; \qquad S_D = \tilde{M} - M_D \qquad (126)$$

The large term on the right describes how the price change affects others' demands through their beliefs. β_{Ip} is the sensitivity of bidder type I's beliefs to a one-unit change in the price p. The sum in the parentheses is the sum of all the effects on beliefs of every bidder, except the one changing their demand (they do not fool themself). The final term $\tilde{B}$ maps these changes in beliefs to a change in price. Thus, signal jamming is defined as

$$SJ_I = \frac{dp}{dq_I} - S_I; \qquad SJ_J = \frac{dp}{dq_J} - S_J; \qquad SJ_D = \frac{dp}{dq_D} - S_D \qquad (127)$$

HKZ measure of bid shading Hortacsu, Kastl and Zhang (2017) define bid shading as the quantity-weighted expected difference between the bidder's marginal valuation for the last unit awarded and the price paid. In our notation:

$$B(v_i, S_i) = \frac{\mathbb{E}[q_i \left(\frac{\partial EU}{\partial q_i} - p \right)]}{\mathbb{E}[q_i]} \qquad (128)$$

Our model has two key differences. First, in HKZ, the uncertainty is about the realized price. Valuations are known. In our setting, bidders' uncertainty is about the payoff. So, we use marginal *expected* utility, in place of HKZ's marginal utility.

The second key difference is that our utility is not quasi-linear in bid payments. Instead, there is a risk-averse utility function over the value of the asset (itself a financial value) net of the payment. There are two possible ways to deal with this

1. Instead of taking marginal utility of the payment, then subtracting the price ($MU(f) - p$), a natural adaption would be to compute the expected marginal value of the asset, net of payment($MEU(f - p)$). In other words, we bring the price paid inside the utility function because that's internally consistent with our model. Log expected utility (from text just before eqn (14)) is $q_j(\alpha\mathbb{E}[f|S_j] + \alpha g + (1-\alpha)v_j - p) - \frac{1}{2}\rho\alpha^2 q_j^2 \mathbb{V}[f|S_j]$. The associated marginal utility is:

$$\frac{\partial EU}{\partial q_i} = \alpha\mathbb{E}[f|S_j] + \alpha g + (1-\alpha)v_j - p - q_j \frac{dp}{dq_j} - \rho\alpha^2 q_j \mathbb{V}[f|S_j]. \qquad (129)$$

   Marginal utility (without the log) is just a rescaling: $\frac{\partial EU}{\partial q_i} \times E[U]$. The problem is that this quantity is always zero. Why? Because it's our first order condition. Bid for more q_i until the marginal additional unit yields zero marginal utility.

2. However, we could instead be more true to the HKZ definition by keeping the price

Figure 6: A Price Impact Measure of Bid Shading.   This plots bid shading, as defined in (131).
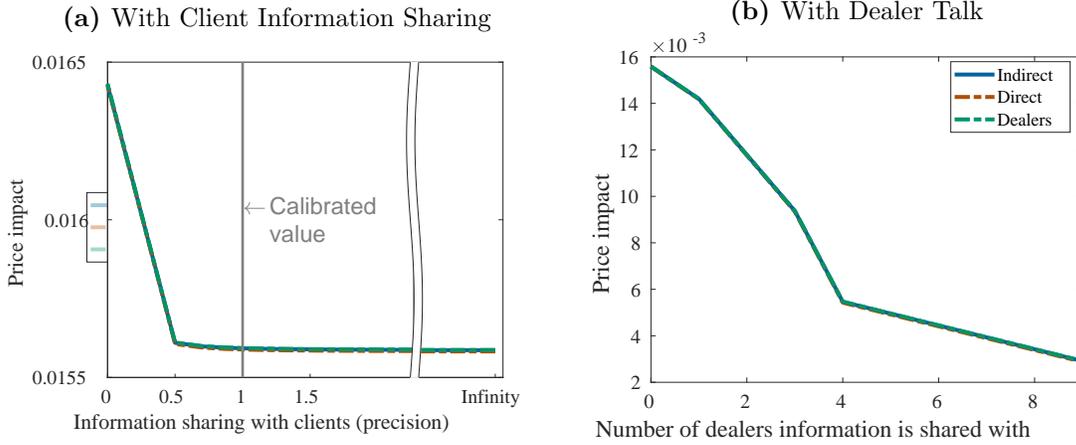
out of the marginal utility. We compute marginal utility, as if price were zero, and then subtract the price. We get

$$\left.\frac{\partial EU}{\partial q_i}\right|_{p=0} - p = q_i \frac{\partial p}{\partial q_i} \tag{130}$$

In our model, the price impact term $\frac{\partial p}{\partial q_i}$ is a function of parameters, not of random variables. So, we can pull it out of the expectation. When we substitute this into (128), the $E[q_i]$ terms cancel and we get

$$B(v_i, S_i) = \frac{\partial p}{\partial q_i}. \tag{131}$$

This measure is plotted below in Figure 6. It shows that information sharing, of either kind, reduces bid shading. The fact that only one line is visible indicates that, in this model, the price impact of a dealer trade, a client trade or a direct bidder trade are indistinguishable.

Since the main question of the paper is about how information sharing affects auction revenue, our primary measure of bid sharing is how much revenue is lost to bid shading (and signal jamming), and how that interacts with information sharing. To compute this revenue loss, we simply turn off some or all of the dp/dq term in the first-order condition. This term is the only piece of demand that differs from the demand of a fully competitive, measure-zero bidder. When we set $dp/dq = 0$ and re-solve the model (agents are aware that others are not strategic and correctly infer different information from the auction-clearing price), we capture all lost revenue due to strategic bidding. Then, we break up that lost revenue into two pieces: bid shading and signal jamming as follows.

Signal jamming Signal jamming is the revenue lost because bidders try to influence each others' beliefs. We compute optimal signal jamming now, both analytically and quantitatively. We compare its magnitude to price impact more generally and to the

magnitude of bid shading. Equation (67) shows that the price impact of an indirect investor (for example, other classes of agents have analogous expressions) is:

$$\frac{dp}{dq_I} = \left[\tilde{M} - M_I - \frac{\alpha}{\tilde{B}} \left(M_I(N_I - 1)\beta_{Ip} + M_J N_J \beta_{Jp} + M_D N_D \beta_{Dp} \right) \right]^{-1} \tag{132}$$

where $\tilde{M} - M_I$ represents the price elasticity of all other market participants collectively. This is the direct effect of one unit of additional demand from one I investor on the market price. The long last term is signal jamming:

$$\text{Signal Jamming} = \frac{\alpha}{\tilde{B}} \left(M_I(N_I - 1)\beta_{Ip} + M_J N_J \beta_{Jp} + M_D N_D \beta_{Dp} \right) \tag{133}$$

The β_{Ip}, β_{Jp}, and β_{Dp} terms measure how much a change in the price affects other indirect, direct investor' and dealers' beliefs. Investors in our model consider how their bids affect the information transmitted by the price and they are optimally adjusting their bid to distort that price signal.

C.5 Auction price with dealer collusion

When dealers collude, they share information and then bid in order to maximize their joint utility. From an information point of view, if collusion takes place in pairs (each dealer shares information and bids jointly with 1 other dealer), it is as if there are $N_D/2$ dealers, each with twice as many orders as before. If collusion takes place in groups of size ψ, the information structure is as if there are N_D/ψ dealers. The only difference between the collusion model and the reduced-number of dealers model is that the demand of each collusive group is larger than it would be if there were only 1 dealer. Two colluding bidders bid have a larger appetite for risk. One can think of collusion as a contractual arrangement whereby each dealer commits to give half his profits to the other dealer and thereby internalizes his effect on the other dealer.

The portfolio optimization problem of colluding dealers is

$$\max_{q_d, q_{d'}, p} \mathbb{E} \left[-\exp\left(-\rho\frac{1}{2}((W_d + q_d v_d) + (W_{d'} + q_{d'} v_{d'})) \right) | S_d \right] \tag{134}$$

$$\text{s.t. } W_d = W_{0,d} + q_d(\alpha p_s - p), \text{ and } W_{d'} = W_{0,d'} + q_{d'}(\alpha p_s - p) \tag{135}$$

$$\sum_{i=1}^{N_I} q_i + \sum_{j=1}^{N_J} q_j + \sum_{d=1}^{N_D} q_d = 1. \tag{136}$$

Taking the expected value of the lognormal yields

$$-\exp\left(\text{const} - \rho\frac{1}{2}((q_d + q_{d'})(\alpha\mathbb{E}[f|S_d] - p + \alpha g + \chi)) + \frac{\rho^2\alpha^2}{8}(q_d^2 + q_{d'}^2 + 2q_d q_{d'})\mathbb{V}[f|S_d] \right)$$

where const is the constant that depends on initial wealth. Then computing the first order condition with respect to q_d reveals that

$$q_d(p) + q_{d'}(p) = 2 \cdot \frac{\alpha\mathbb{E}[f|S_d] + \alpha g + \chi - p}{\rho\alpha^2\mathbb{V}[f|S_d] + 2dp/dq_d}. \tag{137}$$

So, the two colluding dealers jointly bid for twice as much of the asset, but adjusted for twice the price impact. This is the same formula as that which would hold for one dealer who has $1/2$ the risk aversion. Therefore, we numerically solve the collusion model by reducing the number of dealers from N_D to N_D/ψ and reducing each dealer's risk aversion from ρ to ρ/ψ for $\psi \geq 1$.

Figure 7: Lying about Dealer Talk Reduces Revenue. Figure plots average equilibrium auction revenue, against the number of other dealers that share information. We assume here that when dealers share information, no one else knows.
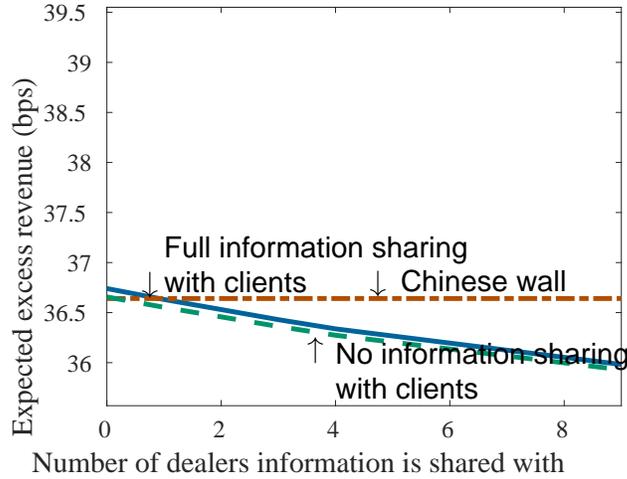
Lying about Dealer Talk A related issue is that in practice, not all market participants may know that dealers are swapping order flow information. Of course, this also has a separate legal remedy. One can enforce laws about disclosure of information practices, without prohibiting the information sharing. But our results on what happens when others are not aware highlights the importance of the assumption that agents understand others' strategies.

When a set of dealers share information and others are not aware, auction revenue falls. This is true even if the information is shared with clients. If the clients are not aware that their information is very precise, they do not bid as if they are better informed. By not bidding aggressively, these clients fail to push up auction revenue as they do in the baseline case. Just as with collusion, when revenue declines, bidder utilities rise. All bidders are better off because prices are lower. But taxpayers are left to foot the bill.

To compute the revenue in Figure 7, we simulated a version of our model where a set of ψ dealers share information and bid collusively on that more precise information. We vary the size of the set of dealers. But every other bidder and dealer bids using the no-dealer-sharing bid functions. The idea is that if they are unaware of the information sharing, then their strategy should be unchanged by it. For each ψ, we resolved for the equilibrium pricing coefficients and then computed the average auction revenue.

C.6 Intermediation Choice: Solution with one bidder who switches

Our objective is to illustrate the properties of the intermediation decision of a client. To do that, we simplify the model by assuming that all participants in the auction (including dealers) have private values drawn from $v_i \sim N\left(0, \tau_v^{-1}\right)$ and focusing on the model without demand shocks. We focus on the case where dealers share information perferctly with their clients and study, instead, how the intermediation decision changes when dealers share information with each other. Without loss of generality, we assume that client 1 of dealer 1 is the agent making the intermediation decision.

If one bidder switches from being an indirect bidder through a dealer to a direct bidder through Treasury Direct, how does the signal structure for bidders and dealers change? If the dealer did not make any inference from the direct bidding choice of the client, then the solution would be the same as before, only adjusting the number of indirect and direct bidders. But a rational dealer who observes a regular client not showing up infers that the client's signal must be in a particular range. We propose a solution method that includes that inferred information.

Define a conglomerate to be the set of dealers that share information with each other, as well as all their clients. Without loss, let conglomerate 1 be the conglomerate that the marginal bidder would be bid through, if he decided to bid through a dealer. This is the group of agents that learn from seeing bidder 1 bid directly or indirectly. The intermediation decision of the client depends on both the client's signal and private value. The key to our solution method is that we approximate the truncated normal signal that can be extracted from the intermediation choice with a normal signal $s_q = f + m_q + e_q$, with the same mean m_q and variance τ_q^{-1} as the true signal. Denote also by p_q the probability of the client choosing to bid directly.

If bidder 1 chooses to bid through the dealer, the dealer sees the intermediation decision, which reveals that bidder 1's order flow must be in a range. But the intermediating dealer also sees exactly what bidder 1's order flow is. The additional information from seeing the choice to bid indirectly is redundant. Thus, in this case, we do not need to construct an approximated dealer signal from the intermediation decision. Just seeing the order flow contains all the relevant information.

In cases where the bidder bids indirectly, we solve the model using an approximating normal signal. The normal signal is included in the precision-weighted average signal of dealer d'.

$$\tilde{s}_{d'} = \iota \left(\frac{1}{N_I/N_D - 1} \left(\sum_{i \in \mathcal{I}_d} \mathbb{E}_i[f] + v_i \right) - s_{public} \right) + (1 - \iota)s_q, \qquad (138)$$

where $\mathcal{I}_d$ is the reduced set of investors bidding through dealer d – excluding the direct bidder – and s_{public} is solved for in Appendix B. The dealer is constructing $\tilde{s}_d$ from an average of his clients' expected valuations plus private values, minus a term s_{public} that includes all public information in $E_i[f]$, and from the information s_q inferred from the direct bidding decision. If investor j bids through the dealer, the problem and the solution are the same as in the baseline model.

The equilibrium price if bidder 1 chooses to bid indirectly (through the dealer) can be

expressed as

$$p = A + B_I \frac{\nu_I - 1}{N_I + N_D}\bar{s}_{I1} + B_I \frac{N_D + N_I - \nu_I}{N_D + N_I}\bar{s}_{I2} + \frac{B_I}{N_D + N_I}s_1 + \frac{B_J}{N_J}\bar{s}_J \qquad (139)$$
$$+ C_I \frac{\nu_I - 1}{N_I + N_D}\bar{v}_{I1} + C_I \frac{N_D + N_I - \nu_I}{N_D + N_I}\bar{v}_{I2} + \frac{C_I}{N_I + N_D}v_1 + C_J\bar{v}_J,$$

where

$$\bar{s}_{I1} = \frac{1}{\nu_I - 1}\left(\sum_{i=2}^{\psi N_I/N_D} s_i + \sum_{d=1}^{\psi} s_d\right); \qquad \bar{v}_{I1} = \frac{1}{\nu_I - 1}\left(\sum_{i=2}^{\psi N_I/N_D} v_i + \frac{1}{1-\alpha}\sum_{d=1}^{\psi} v_d\right);$$

$$\bar{s}_{I2} = \frac{1}{N_D + N_I - \nu_I}\left(\sum_{i=\psi N_I/N_D+1}^{N_I} s_i + \sum_{d=\psi+1}^{N_D} s_d\right); \quad \bar{v}_{I2} = \frac{1}{N_D + N_I - \nu_I}\left(\sum_{i=\psi N_I/N_D+1}^{N_I} v_i + \frac{1}{1-\alpha}\sum_{d=\psi+1}^{N_D} v_d\right)$$

$$\bar{s}_J = \frac{1}{N_J + 1}\sum_{j=1}^{N_J+1} s_j; \qquad \bar{v}_J = \frac{1}{N_J + 1}\sum_{j=1}^{N_J+1} v_j,$$

and $\nu_I = (\psi(N_I + N_D))/N_D$.

If bidder 1 chooses to bid directly, conglomerate 1 learns from that decisions, and all the other agents observe that decision but do not learn from the truncated normal signal, we can express the equilibrium price as

$$p = A_d + B_{I1}\bar{s}_{I1} + B_{I2}\bar{s}_{I2} + \frac{B_{J,d}}{N_J + 1}s_1 + \frac{B_{J,d}N_J}{N_J + 1}\bar{s}_J \qquad (140)$$
$$+ C_{I1}\bar{v}_{I1} + C_{I2}\bar{v}_{I2} + \frac{C_{J,d}}{N_J + 1}v_1 + \frac{C_{J,d}N_J}{N_J + 1}\bar{v}_J + Fs_q. \qquad (141)$$

Notice that, in this case, we have one more direct bidder, and dealer conglomerate 1 has one less client than all the other conglomerates.

In this model, the price signal for dealers and their clients in conglomerate 1 is now

$$s\left(p|\, v_i\right) = \frac{p - A_d - C_{I1}v_i/(\nu_I - 1) - Fm_q}{\tilde{B}},$$

for dealers and their clients in all other conglomerates is

$$s\left(p|\, v_i\right) = \frac{p - A_d - C_{I2}v_i/(N_D + N_I - \nu_I)}{\tilde{B}},$$

and for direct bidders

$$s\left(p|\, v_j\right) = \frac{p - A_d - C_J v_j/(N_J + 1)}{\tilde{B}},$$

where $\tilde{B} = B_{I1} + B_{I2} + B_J + F$.

The vector of orthogonal shocks Z is a column vector of size $N_Z = 2 * N + 1$, where

$$Z = [\epsilon_1, \ldots, \epsilon_N, v_1, \ldots, v_N, e_q],$$

and the variance matrix of Z is

$$var\left(Z\right) = diag\left(\left[\tau_\epsilon^{-1}\mathbf{1}_N, \tau_v^{-1}\mathbf{1}_N, \tau_q^{-1}\right]\right).$$

Consider now representing the price signals. Let

$$\phi_{vI,1} = \left[\mathbf{0}_N, 0, \mathbf{1}_{\psi N_I/N_D - 1}, \mathbf{0}_{N_I - \psi N_I/N_D}, \mathbf{0}_{N_J}, \mathbf{1}_\psi, \mathbf{0}_{N_D - \psi}, 0\right]$$
$$\phi_{vI,2} = \left[\mathbf{0}_N, 0, \mathbf{0}_{\psi N_I/N_D - 1}, \mathbf{1}_{N_I - \psi N_I/N_D}, \mathbf{0}_{N_J}, \mathbf{0}_\psi, \mathbf{1}_{N_D - \psi}, 0\right]$$
$$\phi_{vJ} = \left[\mathbf{0}_N, 1, \mathbf{0}_{N_I - 1}, \mathbf{1}_{N_J}, \mathbf{0}_{N_D}, 0\right]$$

be the vectors that select the private values of dealers and their clients and of direct bidders, respectively. Then, $\bar{v}_{I1} = \left(1/\left(\nu_I - 1\right)\right)\phi_{vI,1} \cdot Z$, $\bar{v}_{I2} = \left(1/\left(N_I + N_D - \nu_I\right)\right)\phi_{vI,2} \cdot Z$ and $\bar{v}_I = \left(1/(N_J + 1)\right)\phi_{vJ} \cdot Z$. Similarly, the vectors that select the signal noise are given by

$$\phi_{\epsilon I,1} = \left[0, \mathbf{1}_{\psi N_I/N_D - 1}, \mathbf{0}_{N_I - \psi N_I/N_D}, \mathbf{0}_{N_J}, \mathbf{1}_\psi, \mathbf{0}_{N_D - \psi}, \mathbf{0}_N, 0\right]$$
$$\phi_{\epsilon I,2} = \left[0, \mathbf{0}_{\psi N_I/N_D - 1}, \mathbf{1}_{N_I - \psi N_I/N_D}, \mathbf{0}_{N_J}, \mathbf{0}_\psi, \mathbf{1}_{N_D - \psi}, \mathbf{0}_N, 0\right]$$
$$\phi_{\epsilon J} = \left[1, \mathbf{0}_{N_I - 1}, \mathbf{1}_{N_J}, \mathbf{0}_{N_D}, \mathbf{0}_N, 0\right].$$

Thus, the price can be represented as

$$p = A_d + \tilde{B}f + \frac{B_{I1}}{\nu_I - 1}\phi_{\epsilon I,1} \cdot Z + \frac{B_{I2}}{N_D + N_I - \nu_I}\phi_{\epsilon I,2} \cdot Z + \frac{B_J}{N_J + 1}\phi_{\epsilon J} \cdot Z$$
$$+ \frac{C_{I1}}{\nu_I - 1}\phi_{vI,1} \cdot Z + \frac{C_{I2}}{N_D + N_I - \nu_I}\phi_{vI,2} \cdot Z + \frac{C_J}{N_J + 1}\phi_{vJ} \cdot Z + F\phi_q \cdot Z$$
$$\equiv A_d + \tilde{B}f + \tilde{B}\pi_p Z.$$

With this representation of the equilibrium price, the information that a dealer or one of its clients in conglomerate 1 extracts from the price is

$$s\left(p|\, v_i\right) = \frac{p - A_d - Fm_q}{\tilde{B}} - \frac{C_{I1}}{\left(\nu_I - 1\right)\tilde{B}}\phi_{N+i} \cdot Z \equiv s\left(p\right) - \frac{F}{\tilde{B}}m_q - \frac{C_{I1}}{\left(\nu_I - 1\right)\tilde{B}}\phi_{N+i} \cdot Z,$$

in any other conglomerate, a dealer or one of its clients extracts

$$s\left(p|\, v_i\right) = s\left(p\right) - \frac{C_{I2}}{\left(N_I + N_D - \nu_I\right)\tilde{B}}\phi_{N+i} \cdot Z,$$

and the signal that a direct investor extracts from the price is

$$s\left(p|\, v_j\right) = s\left(p\right) - \frac{C_J}{\left(N_J + 1\right)\tilde{B}}\phi_{N+N_I+j} \cdot Z.$$

It now remains to determine how dealers aggregate their own signals together with the signals they get from their clients (and other dealers). Similarly to the belief weighting in

the no intermediation choice model, a dealer in conglomerate 1 optimally averages all the signals to yeild

$$\tilde{s}_{d1} = f + \frac{1}{\nu_I - 1} \sum_{i \in d_\psi(i)} \epsilon_i + \beta_{Is,1}^{-1} \left(1 - \frac{\beta_{Ip,1} C_{I1}}{\tilde{B} (\nu_I - 1)}\right) \frac{1}{\nu_I - 1} \sum_{i \in d_\psi(i)} v_i,$$

and a dealer belonging to any other conglomerate optimally averages all the signals to yeild

$$\tilde{s}_{d2} = f + \frac{1}{\nu_I} \sum_{i \in d_\psi(i)} \epsilon_i + \beta_{Is}^{-1} \left(1 - \frac{\beta_{Ip} C_{I2}}{\tilde{B} (N_I + N_D - \nu_I)}\right) \frac{1}{\nu_I} \sum_{i \in d_\psi(i)} v_i.$$

Thus, the signals for the indirect investors and dealers in conglomerate 1 are given by

$$\begin{bmatrix} s_i \\ s_{\xi i} \\ s(p|v_i) \\ s_q \end{bmatrix} = \begin{bmatrix} f \\ f \\ f \\ f \end{bmatrix} + \begin{bmatrix} \phi_i \\ \pi_{d1} \\ \pi_p - \frac{C_{I1}}{(\nu_I - 1)\tilde{B}} \phi_{N+i} \\ \phi_q \end{bmatrix} \cdot Z,$$

where

$$\pi_{d1} = \frac{1}{\nu_I - 1} \tilde{\phi}_{\epsilon d,1} + \beta_{Is,1}^{-1} \left(1 - \frac{\beta_{Ip,1} C_{I1}}{\tilde{B} (\nu_I - 1)}\right) \frac{1}{\nu_I} \tilde{\phi}_{vd,1}.$$

Thus, the signals for the indirect investors and dealers in any other conglomerate are given by

$$\begin{bmatrix} s_i \\ s_{\xi i} \\ s(p|v_i) \end{bmatrix} = \begin{bmatrix} f \\ f \\ f \end{bmatrix} + \begin{bmatrix} \phi_i \\ \pi_{d2} \\ \pi_p - \frac{C_{I2}}{(N_I + N_D - \nu_I)\tilde{B}} \phi_{N+i} \end{bmatrix} \cdot Z,$$

where

$$\pi_{d2} = \frac{1}{\nu_I} \tilde{\phi}_{\epsilon d,2} + \beta_{Is,2}^{-1} \left(1 - \frac{\beta_{Ip,2} C_{I2}}{\tilde{B} (N_I + N_D - \nu_I)}\right) \frac{1}{\nu_I} \tilde{\phi}_{vd,2}.$$

The signals for the direct dealers are given by

$$\begin{bmatrix} s_j \\ s(p|v_j) \end{bmatrix} = \begin{bmatrix} f \\ f \end{bmatrix} + \begin{bmatrix} \phi_j \\ \pi_p - \frac{C_J}{(N_J + 1)\tilde{B}} \phi_{N+N_I+j} \end{bmatrix} \cdot Z.$$

Using the first-order conditions and this belief representation, we can now rewrite the

market clearing condition as:

$$1 = M_{I,1} \sum_{i=2}^{\psi N_I/N_D} (\alpha \mathbb{E}[f|S_i] + \alpha g + (1-\alpha)v_i - p) + M_{I,2} \sum_{i=\psi N_I/N_D+1}^{N_I} (\alpha \mathbb{E}[f|S_i] + \alpha g + (1-\alpha)v_i - p)$$

$$+ M_J \sum_{j=1}^{N_J+1} (\alpha \mathbb{E}[f|S_j] + \alpha g + (1-\alpha)v_j - p)$$

$$+ M_{I,1} \sum_{d=1}^{\psi} (\alpha \mathbb{E}[f|S_d] + \alpha g + \chi - p) + M_{I,2} \sum_{d=\psi+1}^{N_D} (\alpha \mathbb{E}[f|S_d] + \alpha g + \chi - p)$$

$$= M_{I,1} \sum_{i=2}^{\psi N_I/N_D} \left[\alpha((1-\beta'_{I1}\mathbf{1}')\bar{f} + \beta'_{I1}S_i) - p\right] + M_{I,2} \sum_{i=\psi N_I/N_D+1}^{N_I} \left[\alpha\left((1-\beta'_{I2}\mathbf{1}')\bar{f} + \beta'_{I2}S_i\right) - p\right]$$

$$+ M_J \sum_{j=1}^{N_J+1} \left[\alpha\left((1-\beta'_J\mathbf{1}')\bar{f} + \beta'_J S_i\right) - p\right] + (1-\alpha)M_J (N_J+1)\bar{v}_J$$

$$+ M_{I,1} \sum_{d=1}^{\psi} \left[\alpha\left((1-\beta'_{I1}\mathbf{1}')\bar{f} + \beta'_{I1}S_d\right) - p\right] + M_{I,2} \sum_{d=\psi+1}^{N_D} \left[\alpha\left((1-\beta'_{I2}\mathbf{1}')\bar{f} + \beta'_{I2}S_d\right) - p\right]$$

$$+ (1-\alpha)(\nu_I - 1)M_{I,1}\bar{v}_{I1} + (1-\alpha)(N_D + N_I - \nu_I)M_{I,2}\bar{v}_{I2} + \alpha\tilde{M}g.$$

Define $\tilde{M} = (\nu_I - 1)M_{I1} + (N_I + N_D - \nu_I)M_{I2} + (N_J + 1)M_J$. Breaking out the signal vectors into the individual components, we obtain

$$1 = \tilde{A} + \alpha(\nu_I - 1)M_{I1}\left(\beta_{Is,1}\bar{s}_{I1} + \beta_{I\xi,1}(\nu_I - 1)\tilde{s}_{d1} + \beta_{Ip,1}\left(s(p) - \frac{C_{I1}}{(\nu_I - 1)\tilde{B}}\bar{v}_{I1} - \frac{F}{\tilde{B}}m_q\right) + \beta_q s_q\right)$$

$$+ \alpha(N_I + N_D - \nu_I)M_{I2}\left(\beta_{Is,2}\bar{s}_{I2} + \beta_{I\xi,2}(N_I + N_D - \nu_I)\tilde{s}_{d2} + \beta_{Ip,2}\left(s(p) - \frac{C_{I2}}{(N_I + N_D - \nu_I)\tilde{B}}\bar{v}_{I2}\right)\right)$$

$$+ \alpha(N_J + 1)M_J\left(\beta_{Js}\bar{s}_J + \beta_{Jp}\left(s(p) - \frac{C_J}{(N_J + 1)\tilde{B}}\bar{v}_J\right)\right) - \tilde{M}p$$

$$+ (1-\alpha)\left[M_J(N_J + 1)\bar{v}_J + (\nu_I - 1)M_{I,1}\bar{v}_{I1} + (N_D + N_I - \nu_I)M_{I,2}\bar{v}_{I2}\right],$$

where

$$\tilde{A} = \alpha\left[(\nu_I - 1)M_{I1}(1 - \beta'_{I1}\mathbf{1}')\bar{f} + (N_I + N_D - \nu_I)M_{I2}(1 - \beta'_{I2}\mathbf{1}')\bar{f} + M_J(N_J + 1)(1 - \beta'_J\mathbf{1}')\bar{f} + \tilde{M}g\right].$$

Using $s(p) = (p - A)/\tilde{B}$, we can collect terms in p to obtain

$$\tilde{Q}p = \tilde{A} - 1 + A_d\left(\tilde{Q} - \tilde{M}\right) - \alpha M_{I1}\left(\nu_I - 1\right)\beta_{Ip,1}\frac{F}{\tilde{B}}m_q + \alpha M_{I1}\left(\nu_I - 1\right)\left(\beta_{Is,1} + \beta_{I\xi,1}\right)\bar{s}_{I1}$$

$$+ \alpha M_{I2}\left(N_I + N_D - \nu_I\right)\left(\beta_{Is,2} + \beta_{I\xi,2}\right)\bar{s}_{I2} + \alpha M_J\left(N_J + 1\right)\beta_{Js}\bar{s}_J$$

$$+ M_{I1}\left(\nu_I - 1\right)\left(1 - \alpha + \alpha\frac{\beta_{I\xi,1}}{\beta_{Is,1}} - \alpha\left(1 + \frac{\beta_{I\xi,1}}{\beta_{Is,1}}\right)\frac{C_{I1}\beta_{Ip,1}}{\tilde{B}\left(\nu_I - 1\right)}\right)\bar{v}_{I1}$$

$$+ M_{I2}\left(N_I + N_D - \nu_I\right)\left(1 - \alpha + \alpha\frac{\beta_{I\xi,2}}{\beta_{Is,2}} - \alpha\left(1 + \frac{\beta_{I\xi,2}}{\beta_{Is,2}}\right)\frac{C_{I2}\beta_{Ip,2}}{\tilde{B}\left(N_I + N_D - \nu_I\right)}\right)\bar{v}_{I2}$$

$$+ M_J\left(N_J + 1\right)\left(1 - \alpha - \alpha\frac{C_J\beta_{Jp}}{\tilde{B}\left(N_J + 1\right)}\right)\bar{v}_J + \left(\nu_1 - 1\right)M_{I1}\beta_q s_q$$

where $\tilde{Q} = \tilde{B}^{-1}\left(M_{I1}\left(\nu_I - 1\right)\left(\tilde{B} - \beta_{Ip,1}\right) + M_{I2}\left(N_I + N_D - \nu_I\right)\left(\tilde{B} - \beta_{Ip,2}\right) + M_J\left(N_J + 1\right)\left(\tilde{B} - \beta_{Jp}\right)\right)$.
Matching coefficients to the price equation, we obtain

$$A_d = \frac{1}{\tilde{M}}\left(\tilde{A} - 1 - \alpha M_{I1}\left(\nu_I - 1\right)\beta_{Ip,1}\frac{F}{\tilde{B}}m_q\right)$$

$$B_{I1} = \frac{\alpha}{\tilde{Q}}M_{I1}\left(\nu_I - 1\right)\left(\beta_{Is,1} + \beta_{I\xi,1}\right)$$

$$B_{I2} = \frac{\alpha}{\tilde{Q}}M_{I2}\left(N_I + N_D - \nu_I\right)\left(\beta_{Is,2} + \beta_{I\xi,2}\right)$$

$$B_J = \frac{\alpha}{\tilde{Q}}M_J\left(N_J + 1\right)\beta_{Js}$$

$$C_{I1} = \frac{1}{\tilde{Q}}M_{I1}\left(\nu_I - 1\right)\left(1 - \alpha + \alpha\frac{\beta_{I\xi,1}}{\beta_{Is,1}} - \alpha\left(1 + \frac{\beta_{I\xi,1}}{\beta_{Is,1}}\right)\frac{C_{I1}\beta_{Ip,1}}{\tilde{B}\left(\nu_I - 1\right)}\right)$$

$$C_{I2} = \frac{1}{\tilde{Q}}M_{I2}\left(N_I + N_D - \nu_I\right)\left(1 - \alpha + \alpha\frac{\beta_{I\xi,2}}{\beta_{Is,2}} - \alpha\left(1 + \frac{\beta_{I\xi,2}}{\beta_{Is,2}}\right)\frac{C_{I2}\beta_{Ip,2}}{\tilde{B}\left(N_I + N_D - \nu_I\right)}\right)$$

$$C_J = \frac{1}{\tilde{Q}}M_J\left(N_J + 1\right)\left(1 - \alpha - \alpha\frac{C_J\beta_{Jp}}{\tilde{B}\left(N_J + 1\right)}\right)$$

$$F = \frac{\alpha}{\tilde{Q}}M_{I1}\left(\nu_1 - 1\right)\beta_q.$$

Finally, analogously to the no intermediation choice model, the price impact of indirect bidders and dealers in conglomerate 1 is given by

$$\frac{dp}{dq_{I1}} = \left[\tilde{M} - M_{I1} - \frac{\alpha}{\tilde{B}}\left(M_{I1}\left(\nu_I - 2\right)\beta_{Ip,1} + M_{I2}\left(N_D + N_I - \nu_I\right)\beta_{Ip,2} + M_J\left(N_J + 1\right)\beta_{Jp}\right)\right]^{-1},$$

the price impact of indirect bidders and dealers in any other conglomerate by

$$\frac{dp}{dq_{I2}} = \left[\tilde{M} - M_{I2} - \frac{\alpha}{\tilde{B}}\left(M_{I1}\left(\nu_I - 1\right)\beta_{Ip,1} + M_{I2}\left(N_D + N_I - \nu_I - 1\right)\beta_{Ip,2} + M_J\left(N_J + 1\right)\beta_{Jp}\right)\right]^{-1},$$

and the price impact of direct bidders by

$$\frac{dp}{dq_J} = \left[\tilde{M} - M_J - \frac{\alpha}{\tilde{B}} \left(M_{I1} \left(\nu_I - 1 \right) \beta_{Ip,1} + M_{I2} \left(N_D + N_I - \nu_I \right) \beta_{Ip,2} + M_J N_J \beta_{Jp} \right) \right]^{-1}.$$

Agents outside of conglomerate 1 do not observe the intermediation decision. That is, they perceive the price to be a probability-weighted average of the pricing coefficients in (139) and (140):

$$p = \bar{A} + \bar{B}_{I1} \bar{s}_{I1} + \bar{B}_{I2} \bar{s}_{I2} + \bar{B}_{J1} s_1 + \bar{B}_{J2} \bar{s}_J + \bar{C}_{I1} \bar{v}_{I1} + \bar{C}_{I2} \bar{v}_{I2} + \bar{C}_{J1} v_1 + \bar{C}_{J2} \bar{v}_J + \bar{F} s_q, \tag{142}$$

where

$$\bar{A} = \left(1 - p_q \right) A + p_q A_d; \qquad \bar{B}_{I1} = \left(1 - p_q \right) B_I \frac{\nu_I - 1}{N_I + N_D} + p_q B_{I1};$$

$$\bar{B}_{I2} = \left(1 - p_q \right) B_I \frac{N_D + N_I - \nu_I}{N_D + N_I} + p_q B_{I2}; \qquad \bar{B}_{J1} = \left(1 - p_q \right) \frac{B_I}{N_D + N_I} + p_q \frac{B_{J,d}}{N_J + 1};$$

$$\bar{B}_{J2} = \left(1 - p_q \right) B_J + p_q \frac{B_{J,d} N_J}{N_J + 1}; \qquad \bar{C}_{I1} = \left(1 - p_q \right) C_I \frac{\nu_I - 1}{N_I + N_D} + p_q C_{I1};$$

$$\bar{C}_{I2} = \left(1 - p_q \right) C_I \frac{N_D + N_I - \nu_I}{N_D + N_I} + p_q C_{I2}; \qquad \bar{C}_{J1} = \left(1 - p_q \right) \frac{C_I}{N_D + N_I} + p_q \frac{C_{J,d}}{N_J + 1};$$

$$\bar{C}_{J2} = \left(1 - p_q \right) C_J + p_q \frac{C_{J,d} N_J}{N_J + 1}; \qquad \bar{F} = p_q F.$$

Dealers and clients of conglomerate 1, on the other hand, know the intermediation choice made by client 1, and perceive the price to be different conditional on the intermediation choice.

C.7 The Role of Risk Aversion

Since risk aversion is always a difficult parameter to identify with aggregate data, we show results with risk aversion that is 50% higher and 50% lower than our baseline value of 448. Table 5 shows that while the exact revenue and utility numbers change, the ordering and magnitudes are quite stable.

C.8 Bidders who do not condition on price information

This section presents results for a model that is identical to the model in the main paper, except that bidders do not adjust for the winner's curse. When forming their bids, they do not ask themselves: "If this price were realized, what would I learn about what others know?" We implement this model by simply forcing agents, when the update beliefs, to put zero weight on the information in price ($\beta_p = 0$).

What Figures 8 and 9 reveal is that the predictions of the main model are qualitatively similar. Information sharing still increases revenue. Dealer information sharing still has a non-monotonic effect on bidder utility. The main difference is the magnitudes. Information sharing has much larger effects on revenue and utility when price information is not used. This is simply because, when information is more scarce, additional information is more
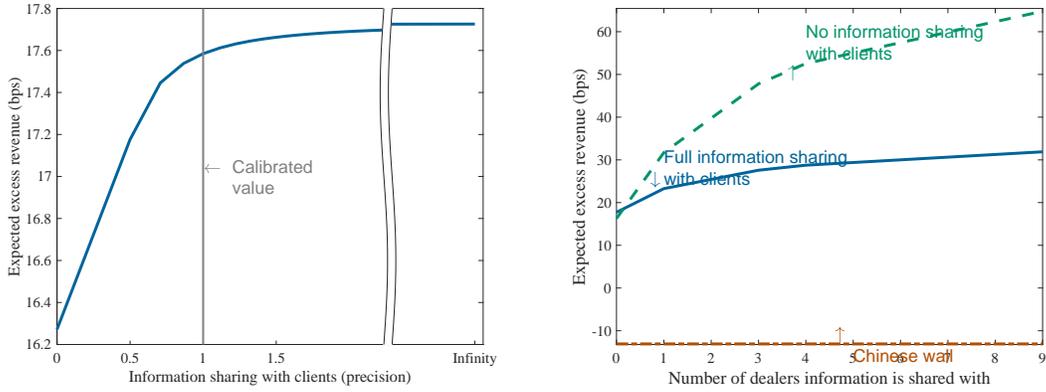
Figure 8: Revenue with bidders who do not condition on price information.
Parameter values listed in Table 2. On the left graph, we assume dealers are not sharing order data.
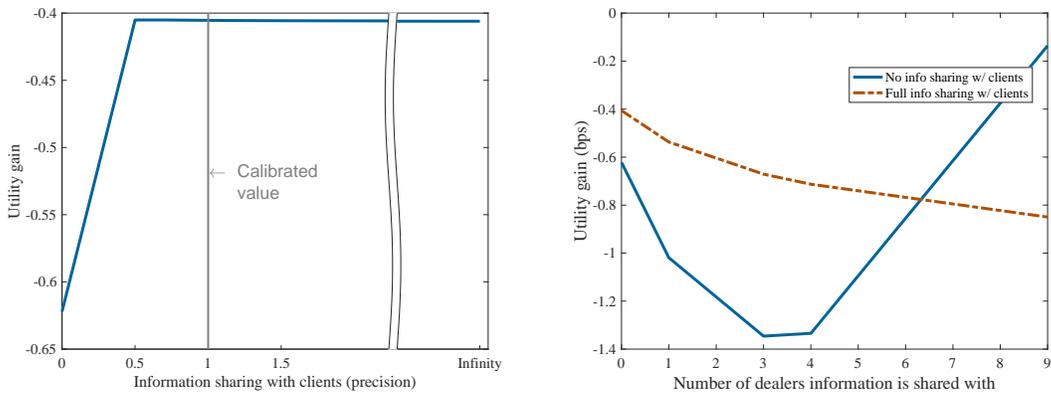

Figure 9: Bidder utility with bidders who do not condition on price information.
Parameter values listed in Table 2.

Table 5: The Role of Risk Aversion.

	Baseline τ_ξ	Chinese wall	Open order book
	Auction Revenue		
Baseline	36.740	32.884	39.311
1.5ρ	38.831	36.014	40.708
$\rho/1.5$	36.616	32.699	39.227
	Bidder Utility		
Baseline	0.810	1.915	0.975
1.5ρ	1.457	1.709	0.923
$\rho/1.5$	1.436	1.925	0.983

valuable. So if one believes that auction participants often fall victim to the winner's curse, then the arguments about information sharing remain the same, but the consequences become an order of magnitude larger.

C.9 The Role of the When-Issued Market

Before each Treasury auction, investors can bet on the auction-clearing price by transacting in the when-issued (often called "WI") market. WI is an over-the-counter forward market. In a way, purchasing WI contracts is like direct bidding: An investor who bids in the WI market does not learn from a dealer's signal, implying a lower θ_i. At the same time, the investor does not reveal her order flow to a dealer who shares that information with others (implying a higher μ_{ri}). Of course, the person with whom the investor transacts will know the order and the market price will reflect it.

The decision of an investor to bid in the WI market, as opposed to the actual auction, depends on risk preferences and on information sharing. Investors who purchase securities in the WI market limit auction uncertainty by purchasing newly-issued securities at a predetermined price. But this price will reflect in equilibrium risk compensation on the part of the sellers. Indeed, securities outstanding in the WI market are in zero net supply, meaning that whenever an investor is long in a WI, another will be short. The other feature that differentiates WI from auction bidding is that the opportunity to bid through a dealer allows an investor to benefit from information sharing.

WI activity may also affect the benefits of information sharing. WI market commitments affect investors' private values. When private values are more important, shared information about secondary market prices is less important. One might think that, because the WI market is often an accurate forecast of the auction-clearing price, this would matter as well. However, since our model allows bidders to condition on every possible price, they have no use for a price forecast. They simply form bids by asking the question, if p were the auction clearing price, what would I learn and how would I want to bid? Continuous price-contingent bids make price forecasts redundant.

Figure 10: Expected revenue without aggregate uncertainty. This figure plots expected revenue as a function of information sharing under the assumption that average secondary market private value is known.

(a) Sharing with clients

(b) Sharing with other dealers
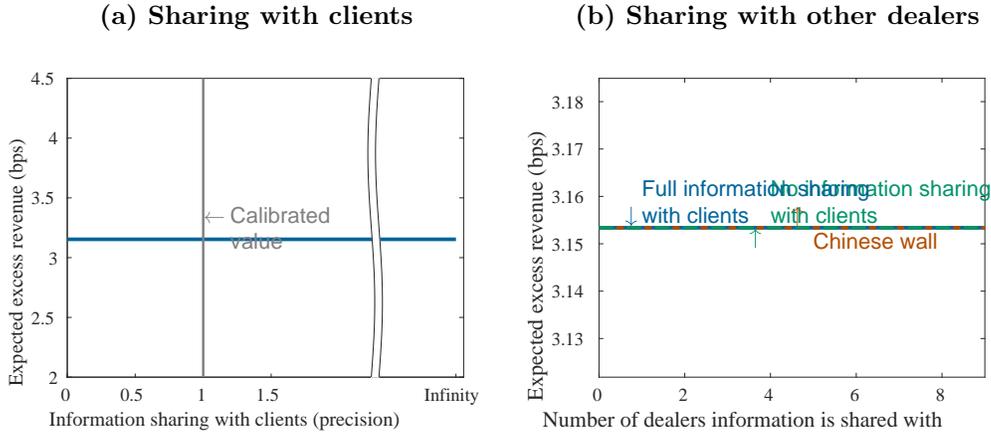
C.10 The Role of the Secondary Bond Market

The secondary bond market risk is essential to our results. Without the secondary market, or without its results being uncertain, information sharing will have zero effect on revenue or utility. Figure 10 illustrates this point. The reason secondary markets are so essential is that they make one agent's information relevant to others. Information about private values, without any uncertain resale possibility or common value, does not affect any bidder's optimal bidding strategy. The auction will still function. But information sharing will have neither harm nor benefit to any bidder. The ongoing lawsuits where plaintiffs allege great harm from the sharing of their information suggest that this indifference is not a relevant case.

To compute these results, we set the average (only) secondary market price to be $\bar{f} = 0$. But fixing it at any other level also results in flat lines. Changing the secondary market value just shifts auction revenue up or down by a fixed amount. Without the risk in secondary market, the answer to our main question would be trivial.