C Appendix: Trading in Segmented Markets

C.1 General set-up

Our framework can provide insights about trade in segmented markets as well. Markets are segmented when investors, such as hedge funds and asset management firms, trade in some markets but not in others. Although segmented, markets can be connected, in the sense agents are able to trade in multiple venues at the same time. To study the implications in segmented markets, we extend our model in the following way.

We consider an economy in which there are N trading posts connected in a network g. At each trading post, I, there exist n^I risk-neutral dealers. The entire set of dealers is denoted $\mathcal{N} = \bigcup_{I=N}^{N} I$. Each dealer $i \in I$ can trade with other dealers in his own trading post and with dealers at any trading post J that is connected with the trading post I by a link IJ. Essentially, the link IJ represents a market in which dealers at trading posts I and J can trade with each other. However, they have access to trade in other markets at the same time. Let g^I denote the set of trading posts that are linked with I in the network g, and $m^I \equiv \left|g^I\right|$ represent the number of I's links.

As before, dealers trade a risky asset in zero net supply, and all trades take place at the same time**.** Each dealer is uncertain about the value of the asset. In particular, a dealer's value for the asset is given by θ^i, which is a random variable normally distributed with mean 0 and variance σ_θ^2. Moreover, we consider that values are interdependent across all dealers. In particular, $\mathcal{V}(\theta^i, \theta^j) = \rho\sigma_\theta^2$ for any two agents $i, j \in \mathcal{N}$. Each dealer receives a private signal, $s^i = \theta^i + \varepsilon^i$, where $\varepsilon^i \sim IID\, N(0, \sigma_\varepsilon^2)$ and $\mathcal{V}(\theta^j, \varepsilon^i) = 0$, for all i and j.

A dealer $i \in I$ seeks to maximize her final wealth

$$\sum_{J \in g^I} q_{IJ}^i \left(\theta^i - p_{IJ}\right),$$

where q_{IJ}^i is the quantity traded by dealer i in market IJ, at a price p_{IJ}. Similarly to the OTC model, the trading strategy of the dealer i with signal s^i is a generalized demand function $\mathbf{Q}^i : R^{m^i} \to R^{m^i}$ which maps the vector of prices, $\mathbf{p}_{g^I} = (p_{IJ})_{J \in g^I}$, that prevail in the markets in which dealer i participates in network g into a vector of quantities she wishes to trade

$$\mathbf{Q}^i(s^i; \mathbf{p}_{g^I}) = \left(Q_{IJ}^i(s^i; \mathbf{p}_{g^I})\right)_{J \in g^I},$$

where $Q_{IJ}^i(s^i; \mathbf{p}_{g^I})$ represents her demand function in market IJ.

Apart from trading with each other, dealers also serve a price-sensitive customer base. In particular, we assume that for each market IJ, the customer base generates a downward sloping demand

$$D_{IJ}(p_{IJ}) = \beta_{IJ} p_{IJ}, \tag{C.1}$$

with an arbitrary constant $\beta_{IJ} < 0$. The exogenous demand (C.1) ensures the existence of the equilibrium when agents are risk neutral, and facilitates comparisons with the OTC model.

The expected payoff for dealer $i \in I$ corresponding to the strategy profile $\left\{\mathbf{Q}^i\left(s^i; \mathbf{p}_{g^I}\right)\right\}_{i \in \mathcal{N}}$ is

$$E\left[\sum_{J \in g^I} Q_{IJ}^i(s^i; \mathbf{p}_{g^I}) \left(\theta^i - p_{IJ}\right) | s^i\right]$$

where p_{IJ} are the prices for which all markets clear. That is, prices satisfy

$$\sum_{i \in I} Q_{IJ}^i \left(s^i; \mathbf{p}_{g^I}\right) + \sum_{j \in J} Q_{IJ}^j \left(s^j; \mathbf{p}_{g^J}\right) + \beta_{IJ} p_{IJ} = 0, \forall \ IJ \in g. \tag{C.2}$$

C.2 Equilibrium concept

As in the OTC game, we use the concept of Bayesian Nash equilibrium. For completeness, we reproduce it below.

Definition 3 *A Linear Bayesian Nash equilibrium of the segmented market game is a vector of linear generalized demand functions* $\left\{\mathbf{Q}^i\left(s^i; \mathbf{p}_{g^I}\right)\right\}_{i \in \mathcal{N}}$ *such that* $\mathbf{Q}^i(s^i; \mathbf{p}_{g^I})$ *solves the problem*

$$\max_{(Q_{IJ}^i)_{J \in g^I}} E\left\{\left[\sum_{J \in g^I} Q_{IJ}^i(s^i; \mathbf{p}_{g^I})\left(\theta^i - p_{IJ}\right)\right] |s^i\right\}, \tag{C.3}$$

for each dealer i, where the prices p_{IJ} satisfy (C.2) .

A dealer i chooses a demand function in each market IJ, in order to maximize her expected profits, given her information, s^i, and given the demand functions chosen by the other dealers.

C.3 The Equilibrium

In this section, we outline the steps for deriving the equilibrium in the segmented market game for any network structure. First, we derive the equilibrium strategies as a function of posterior beliefs. Second, we construct posterior beliefs that are consistent with dealers' optimal choices. In the OTC game we used the conditional guessing game as an intermediate step in constructing beliefs. Here, we employ the same line of reasoning, although we do not explicitly introduce the conditional guessing game structure that would correspond to the segmented market game.

C.3.1 Derivation of demand functions

We conjecture an equilibrium in demand functions, where the demand function of dealer i in market IJ is given by

$$Q_{IJ}^i(s^i; \mathbf{p}_{g^I}) = t_{IJ}^I(y_{IJ}^I s^i + \sum_{K \in g^I} z_{IJ,IK}^I p_{IK} - p_{IJ}) \tag{C.4}$$

for any $i \in I$ and J. As evident in the notation, we consider that all dealers at trading post I are symmetric in their trading strategy, and weigh in same way the signal they receive and the prices they trade at. Nevertheless, they end up trading different quantities, as they have different realizations of the signal.

We solve the optimization problem (C.3) pointwise. That is, for each realization of the vector of signals, $\mathbf{s}$, we solve for the optimal quantity q_{IJ}^i that each dealer $i \in I$ demands in market IJ. Given the conjecture (C.4) and the market clearing conditions (C.2), the residual inverse demand function of dealer i in market IJ is

$$p_{IJ} = -\frac{t^I_{IJ} y^I_{IJ} \sum\limits_{k\in I, k\neq i} s^k + t^J_{IJ} y^J_{IJ} \sum\limits_{k\in J} s_k + (N_I - 1) \sum\limits_{L\in g^I, L\neq J} t^I_{IJ} z^I_{IJ,IL} p_{IL} + N_J \sum\limits_{L\in g^J, L\neq I} t^J_{IJ} z^J_{IJ,JL} p_{JL} + q^i_{IJ}}{(N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}}. \tag{C.5}$$

Denote

$$I^J_i \equiv -\frac{t^I_{IJ} y^I_{IJ} \sum\limits_{k\in I, k\neq i} s^k + t^J_{IJ} y^J_{IJ} \sum\limits_{k\in J} s_k + (N_I - 1) \sum\limits_{L\in g^I, L\neq J} t^I_{IJ} z^I_{IJ,IL} p_{IL} + N_J \sum\limits_{L\in g^J, L\neq I} t^J_{IJ} z^J_{IJ,JL} p_{JL}}{(N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}} \tag{C.6}$$

and rewrite (C.5) as

$$p_{IJ} = I^J_i - \frac{1}{(N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}} q^i_{IJ}. \tag{C.7}$$

The uncertainty that dealer i faces about the signals of others is reflected in the random intercept of the residual inverse demand, I^J_i, while her capacity to affect the price is reflected in the slope $-1/\left((N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}\right)$. In the segmented markets game, however, the random intercept I^J_i reflects not only the signals of the dealers at the trading post J, but also the signals of the other dealers at the trading post I.

Then, solving the optimization problem (C.3) is equivalent to finding the vector of quantities $\mathbf{q}^i = \mathbf{Q}^i(s^i; \mathbf{p}_{g^I})$ that solve

$$\max_{(q^i_{IJ})_{j\in g^I}} \sum_{J\in g^I} q^i_{IJ} \left(E\left(\theta^i | s^i, \mathbf{p}_{g^I}\right) - \left(I^J_i - \frac{q^i_{IJ}}{(N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}} \right) \right)$$

From the first order conditions we derive the quantities q^i_{IJ} that dealer $i \in I$ trades in each market IJ, for each realization of $\mathbf{s}$, as

$$2 \frac{1}{(N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}} q^i_{IJ} = I^J_i - E\left(\theta^i | s^i, \mathbf{p}_{g^I}\right),$$

This implies that the optimal demand function

$$Q^i_{IJ}(s^i; \mathbf{p}_{g^i}) = -\left((N_I - 1) t^I_{IJ} \left(z^I_{IJ,IJ} - 1\right) + N_J t^J_{IJ} \left(z^J_{IJ,IJ} - 1\right) + \beta_{IJ}\right) \left(E(\theta^i \left| s^i, \mathbf{p}_{g^I}\right.) - p_{IJ}\right) \tag{C.8}$$

for each dealer i in market IJ.

Further, given our conjecture (C.4), equating coefficients in equation (C.8) implies that

$$E(\theta^i \left| s^i, \mathbf{p}_{g^I}\right.) = y^I_{IJ} s^i + \sum_{K\in g^I} z^I_{IJ,IK} p_{IK}.$$

However, the projection theorem implies that the belief of each dealer i can be described as a unique linear combination of her signal and the prices she observes. Thus, it must be that $y^I_{IJ} = y^I$, and $z^I_{IJ,JK} = z^I_{IK}$ for all I, J, and K. In other words, the posterior belief of a dealer i is given by

$$E(\theta^i \left| s^i, \mathbf{p}_{g^I} \right.) = y^I s^i + \mathbf{z}_{g^I} \mathbf{p}_{g^I}, \tag{C.9}$$

where $\mathbf{z}_{g^I} = \left(z^I_{IJ}\right)_{J\in g^I}$ is a *row* vector of size m^i. Then, we obtain that the trading intensity of dealer at trading post I satisfies

$$t^I_{IJ} = (N_I - 1)\, t^I_{IJ}\left(1 - z^I_{IJ}\right) + N_J t^J_{IJ}\left(1 - z^J_{IJ}\right) - \beta_{IJ}. \tag{C.10}$$

If we further substitute this into the market clearing conditions (C.2) we obtain the price in market IJ as follows

$$p_{IJ} = \frac{t^I_{IJ}\left(\sum\limits_{i\in I} E\left(\theta^i | s^i, \mathbf{p}_{g^I}\right)\right) + t^J_{IJ}\left(\sum\limits_{j\in J} E\left(\theta^j | s^j, \mathbf{p}_{g^J}\right)\right)}{N_I t^I_{IJ} + N_J t^J_{IJ} - \beta_{IJ}}. \tag{C.11}$$

From (C.10) and the analogous equation for t^J_{IJ}, it is straightforward to derive the trading intensity that dealers at trading post I and J have. This implies that we can obtain the price in each market IJ as

$$p_{IJ} = w^I_{IJ}\left(\sum_{i\in I} E\left(\theta^i | s^i, \mathbf{p}_{g^I}\right)\right) + w^J_{IJ}\left(\sum_{j\in J} E\left(\theta^j | s^j, \mathbf{p}_{g^J}\right)\right), \tag{C.12}$$

where

$$w^I_{IJ} \equiv \frac{z^J_{IJ} - 2}{(N_J + N_I - 1)\, z^I_{IJ} z^J_{IJ} - 2\,(N_I - 1)\, z^I_{IJ} - 2\,(N_J - 1)\, z^J_{IJ} - 4}.$$

This expression is useful to relate the belief of a dealer $i \in I$ to the beliefs of other dealers at the same trading post, and at trading posts that are connected to I.

C.3.2 Derivation of beliefs

We follow the same solution method that we developed in Section 3.1. As before, the key idea is to reduce the dimensionality of the problem and use our conjecture about demand functions to derive a fixed point in beliefs, instead of the fixed point (C.8).

In the OTC game we constructed each dealer's equilibrium belief as a linear combination of the beliefs of her neighbors in the network. For this, we introduced the conditional guessing game. The conditional guessing game was a useful intermediate step in making the derivations more transparent, as well as an informative benchmark about the role of market power for the diffusion of information.

In the segmented market game it is less straightforward to formulate the corresponding conditional guessing game. Since there are multiple dealers at each trading post, it is not immediate how each dealer forms her guess. In particular, we would need to make additional assumptions about the linear combination of the guesses of dealers in the same trading post and dealers of the neighboring trading post, that each agent can condition her guess on.

Thus, in the segmented market game we construct beliefs directly as linear combinations of signals. We conjecture that for each dealer $i \in I$, her belief is an affine combination of the signals of all dealers in the economy

$$E\left(\theta^i|s^i, \mathbf{p}_{g^I}\right) = \bar{v}^I_{II} s^i + \sum_{K=1}^{N} v^I_{IK} S^K, \tag{C.13}$$

where $S^K = \sum_{k \in K} s^k$, $\forall K$. This further implies that

$$\sum_{i \in I} E\left(\theta^i|s^i, \mathbf{p}_{g^I}\right) = \bar{v}^I_{II} S^I + N_I \sum_{K=1}^{N} v^I_{IK} S^K.$$

Before we derive the fixed point equation for beliefs, it is useful to write (C.12) in matrix form, for each trading post I. For this we introduce some more notation. Unless specified otherwise, in the notation below we keep I fixed and vary $J \in \{1, ..., N\}$. Let $\mathbf{p}^I$ be a $N-$column vector with elements p_{IJ} if $IJ \in g$, and 0 otherwise. Let $\mathbf{z}^I$ be a $N-$column vector with elements z^I_{IJ} if $IJ \in g$, and 0 otherwise. Similarly, let $\mathbf{w}^I$ be the $N-$column vector with elements w^I_{IJ} if $IJ \in g$, and 0 otherwise, while W_I be a matrix with elements w^J_{IJ} on diagonal if IJ have a link, and 0 otherwise (all elements off-diagonal are 0, as well). Further, let $\mathbf{v}^I$ be the $N-$row vector with elements v^I_{IJ}, and $\bar{\mathbf{v}}^I$ be the $N-$row vector with elements $\bar{v}^I_{II}$ at position I and 0 otherwise. Let V be the square matrix with rows $\mathbf{v}^I$, and $\bar{V}$ be the matrix with rows $\bar{\mathbf{v}}^I$. Let $\mathbf{S}$ be the $N-$column vector with elements S^I. Let N be a square matrix with elements n^I on diagonal and 0 otherwise. Let $\mathbf{1}$ be the $N-$column vector of ones.

Substituting our conjecture for beliefs (C.13) in the equation for the price (C.12), we obtain the vector of prices which dealers at each trading post I are trading as

$$\mathbf{p}^I = \mathbf{w}^I \left(\bar{\mathbf{v}}^I + n^I \mathbf{v}^I\right) \mathbf{S} + W^I \left(\bar{V} + \mathsf{N} V\right) \mathbf{S}.$$

We are now ready to formalize the result.

Proposition C.1 *There exists an equilibrium in the segmented markets game if the following system of equations*

$$\mathbf{v}^I = \left(\mathbf{z}^I\right)^\top \left(\mathbf{w}^I \left(\bar{\mathbf{v}}^I + n^I \mathbf{v}^I\right) + W^I \left(\bar{V} + \mathsf{N} V\right)\right) \mathbf{1}, \forall I \tag{C.14}$$

and

$$\bar{v}^I_{II} = y^I, \forall I$$

admits a solution in $\mathbf{v}^I$*, for each* I*.*

Proof. As for the OTC game, the proof is constructive. Note that showing that equation (C.14) admits a solution is equivalent to showing that there exists a fixed point in $\mathbf{v}^I$. This is because, the projection theorem implies that $\mathbf{z}^I$, and inherently, $\mathbf{w}^I$ are a function of $\mathbf{v}^I$.

Let $\mathbf{v}^I$ be a fixed point of (C.14) and $\bar{v}^I_{II} = y^I$, for each I. We construct an equilibrium for the segmented-market game with beliefs given by (C.13), as follows. We choose conveniently $\mathbf{z}^I$ and $\mathbf{w}^I$ such that

$$E\left(\theta^i|s^i, \mathbf{p}_{g^I}\right) = y^I s^i + \left(\mathbf{z}^I\right)^\top \left(\mathbf{w}^I \left(\bar{\mathbf{v}}^I + n^I \mathbf{v}^I\right) + W^I \left(\bar{V} + \mathsf{N} V\right)\right) \mathbf{S}$$

is satisfied. Then, it follows that the prices given by (C.11) and demand functions given by (C.8) is an equilibrium of the OTC game. ■

The derivation we have outlined above also highlights the main technical difficulty of the segmented market game relative to the OTC game. That is, the signals of dealers in the same trading post obscure the (sum of) beliefs of the dealers in neighboring trading posts, such that a dealer can no longer invert the prices she observes and infer what his neighbors posteriors.

C.4 Learning and illiquidity in a star network

In this section, we illustrate the effects of market integration on learning from prices and market liquidity in an example.In particular, we restrict ourselves to considering a star network, in which there are n_P dealers at each periphery trading post, and n_C dealers at the central trading post. In particular, we conduct the following numerical exercise. We consider an economy with nine agents. Keeping their information set fixed, we compare the following four market structures:

1. 8 trading posts connected in a star network, with one agent in each trading post ($N = 8$, $n_P = 1$, $n_C = 1$), that is, 8 trading venues. This is our baseline model with a star network.

2. 4 trading posts connected in a star network, with two agents in each periphery node and one agent in the central node ($N = 4$, $n_P = 2$, $n_C = 1$), that is, 4 trading venues.

3. 2 trading posts connected in a star network, with four agents in each periphery node and one agent in the central node ($N = 2$, $n_P = 4$, $n_C = 1$), that is, 2 trading venues.

4. A centralized market ($N = 1$, $n_P = 9$, $n_C = 0$), that is, a single trading venue.

We consider two directions. First, we investigate what drives the illiquidity central and periphery agents face for changing degrees of market segmentation. We concentrate on (il)liquidity as this is a more commonly reported variable in the empirical literature, and we leave the analysis of welfare and expected profits to Appendix C. Second, to complement the analysis in Section 4 , we also analyze how much dealers can learn from prices under these market structures.

The left and center panels in Figure C.1 show the average illiquidity that a periphery, $\frac{1}{t_P}$, and a central dealer, $\frac{1}{t_C}$, face in each of the scenarios described above. We also plot the average illiquidity that any agent in a centralized market, $\frac{1}{t_V}$, faces. For easy comparison, all the parameters are the same as in Section 5.1.

To highlight the intuition, we start with the extreme cases of market segmentation comparing illiquidity under a star network and in a centralized market.

C.4.1 Extreme cases of market segmentation with a star network

In this part, we compare illiquidity of dealers in a centralized market and that of a periphery or central dealer in a star network.

The solid curve in Panels D and the curves in panel F in Figure 2 illustrate that compared to any agent in a centralized market, the central agent in the star faces higher trading price impact in general, but the periphery agents tend to face smaller price impact when the correlation across values is sufficiently high. We partially prove this result. The following proposition states that if ρ is sufficiently large, illiquidity for the central agent is larger, while illiquidity for the periphery agents is lower than that for an agent in a centralized market and, when ρ is sufficiently small, illiquidity for any agent in a star network is larger than the illiquidity for any agent in a centralized market.

Proposition C.2

1. *When ρ is sufficiently small, such that z_V is sufficiently close to $1-\frac{1}{n-1}$, then illiquidity for any agent in a star network is larger than for any agent in a centralized market*

2. *In the common value limit, when $\rho \to 1$,*

   (a) *illiquidity for a central agent is higher in a star network than for any agent in a centralized market, and*

   (b) *illiquidity for a periphery agent is lower in a star network than for any agent in a centralized market.*

Proof. The first part comes by the observation that as $z_V \to 1-\frac{1}{n-1}$, $t_V \to \infty$, while t_C and t_P are finite for these parameters. The second part comes from taking the limit $\rho \to 1$ of the ratio of the corresponding closed-form expressions we report in Appendices B.3 and B.2. In particular,

$$\begin{aligned}
\lim_{\rho\to1}\frac{t_V}{t_C} &= (n-1)\frac{z_C+z_P-z_Cz_P}{(2-z_P)\left((n-1)z_V-(n-2)\right)}=\infty \\
\lim_{\rho\to1}\frac{t_V}{t_P} &= (n-1)\frac{z_C+z_P-z_Cz_P}{(2-z_C)\left((n-1)z_V-(n-2)\right)}=\frac{n-1}{n}<1
\end{aligned}$$

■

Similarly to the comparison between the complete OTC network and the centralized market in Section 5.1.2, there are two main forces that drive the illiquidity ratios $\frac{t_V}{t_C}$ and $\frac{t_V}{t_P}$. First, the best response function **(31)** of a dealer in a centralized market is steeper and has a larger intercept than the best response function (26) of central and periphery dealers in the star OTC network. Simple algebra shows that if, counterfactually, the adverse selection parameters were equal, $z_P=z_C=z_V$ then $\frac{t_V}{t_C}|_{z_V=z_C=z_P}=\frac{t_V}{t_P}|_{z_V=z_C=z_P}>1$, that is, illiquidity for any agents in the OTC market would be higher than for any agent in the centralized market. This is the effect which dominates when ρ is small.

Second, parameters z_C, z_V and z_P differ. As we stated in Proposition 9 central agents face less liquid markets than periphery agents, $\frac{1}{t_P}<\frac{1}{t_C}$ because periphery agents are more concerned about adverse selection ($z_C<z_P$). This implies that $\frac{t_V}{t_C}>\frac{t_V}{t_P}$ and difference is increasing for higher ρ. In fact, in the common value the central agent faces an infinitely illiquid market in the sense that $t_C \to 0$, but consumers provide a relatively liquid trading environment for periphery agents. For periphery agents this is sufficiently strong to reduce their price impact below the centralized market level as stated in the second part of the proposition.

C.4.2 Intermediate cases of market segmentation with a star network

Interestingly, while the illiquidity a central agent faces is monotonic in segmentation, the illiquidity a periphery agents face is not. We see in left panel of Figure C.1 is how the relative

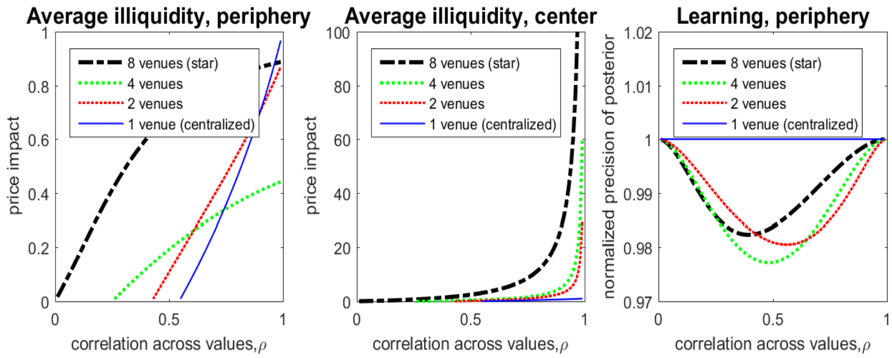

Figure C.1: Illiquidity on segmented markets. We show our measure of illiquidity for central agents , $\frac{1}{t_C}$, (left panel) and for periphery agents, $\frac{1}{t_P}$, (right panel) when there are 8 trading venues (dotted), 4 trading venues (dashed), 2 trading venues (dash-dotted), and in the centralized market (solid) as a function of the correlation across values, ρ. Other parameter values are $\sigma_\theta^2 = 1$, $\sigma_\varepsilon^2 = 0.1$, $B = 1$.

strength of the two forces identified in Section C.4.1 plays out in the four scenarios we consider. First, related to the effect of decentralization on best response functions, illiquidity for any agent decreases as the market structure approaches a centralized market. Second,the effect coming from the differing weights of z_C and z_P is weaker in more centralized markets. The reason is that as central dealers observe less prices in more centralized markets, they put a larger weight, z_C in each price, implying a smaller difference between z_P and z_C. This is the reason why the illiquidity a periphery agent faces under the 2 trading venues structure increases with ρ almost as fast as in centralized markets. With 4 venues the effect of ρ is weaker.

Turning to the effect of segmentation on learning, note that for the central dealer prices are fully revealing under any of the segmented market structures in this exercise. This is because each price she observes is a weighted sum of her own signal and the sum of signals of the periphery dealers trading in each venue. Hence, the prices the central dealer observes represent a sufficient statistic for all the useful information in the economy. This would not be the case if there were more than one dealer at the central trading post.

In contrast, as it is shown in the right panel of Figure C.1 a periphery agent in a segmented market always learns less than the central agent, or any agent in a centralized market. Interestingly, for small correlation across values, ρ, a periphery agent in a more segmented market learns more, while for a sufficiently large correlation across values the opposite is true. The intuition relies on the relative strength of opposing forces. The price a periphery agent learns from is a weighted average of the sum of posteriors of periphery agents in the same trading post and the posterior of the central agent. The posterior of the central agent is more informative than any of the posteriors that periphery agent at the same trading post have. The more segmented the market is, the easier is for a dealer at a periphery trading post to isolate the posterior of the central dealer (for example, in the baseline star network, any price reveals the posterior of the central dealer perfectly). At the same time, the sum of the posteriors of periphery dealers at a periphery trading post is more informative in a less segmented market, as the noise in the signal, as well as the private value components tend to cancel out. This latter effect helps learning more when the private value component is more important, that is, when ρ is small. This explains the pattern in the right panel of Figure C.1.

C.5 Welfare and expected profit in the star network

Finally, we illustrate with the following figure how expected profit and welfare changes with market segmentation. We leave the detailed analysis for future research and highlight only two interesting observations. First, as trading intensities were not monotonic for the periphery in the degree of segmentation, expected profit is not monotonic either. Also, total welfare is also not monotonic in segmentation.