Information Linkages and Correlated Trading*

Paolo Colla 
*Università Bocconi

Antonio Mele 
London School of Economics

First draft: September 13, 2004
This version: November 20, 2005

Abstract

In a market with informationally connected traders, the dynamics of volume, price informativeness, price-volatility, and price-impacts are severely affected by the number of information linkages every trader experiences with his neighbors. We show that in the presence of information linkages amongst traders, volume and price informativeness increase, asymmetric information costs decrease, and traders’ welfare is damaged. Our model also predicts patterns of trades correlation consistent with patterns identified in the empirical literature: ‘neighbor’ trades are positively correlated and ‘distant’ trades are negatively correlated.

*We wish to thank Marco Pagano, Andrea Prat, Hyun Shin, Dimitri Vayanos, Paolo Vitale and seminar participants at the 2005 CORE Summer School, Ente Luigi Einaudi (Rome), the LSE, the 2005 Society for Advancement in Economic Theory meeting in Vigo, and the 2005 CEPR/ Studienzentrum Gerzensee ESSFM for very useful comments. The first author acknowledges the financial support provided through the European Community’s Human Potential Programme under contract HPRN-CT-2002-00232. The second author thanks the EPSRC for financial support via grant EP/C522958/1. The usual disclaimer applies. Address correspondence to Antonio Mele, The London School of Economics and Political Science, Houghton Street, London WC2A 2AE, United Kingdom, or email: a.mele@lse.ac.uk.
Introduction

One pervasive feature in financial markets is the existence of information linkages amongst market participants. Traders and investors are socially connected and have access to comparable sources of information. Many writers describe the financial community as one of overlapping groups of people who share similar opinions, either because they are endowed with comparable signals about fundamentals and/or communicate regularly with one another [e.g., Shiller (1984, 2005), Hertz (1998)], or simply because they are exposed to similar cultural biases [e.g., Guiso, Sapienza and Zingales (2005)]. Many information-based explanations of asset price movements hinge upon the assumption that individuals do not experience information linkages at all. In this paper, we relax this assumption and explore the resulting implications along traditional dimensions - asset price volatility, trading volume, market efficiency, and welfare.

Our notion of information linkages is tightly related to the recent empirical literature on the value of local information and social interactions in financial markets. For example, Coval and Moskowitz (1999) provide strong evidence that proximity influences investors’ portfolio choices. Hong, Kubik and Stein (2005) document that US fund managers quartered in the same city exhibit similar portfolio choices; they argue that these correlated portfolio choices arise a) through peer-to-peer communication; and b) simply because fund managers in a given area commit themselves to investment decisions based upon common sources of information - such as a local newspaper or TV station. Similarly, Feng and Seasholes (2004) find that in the Chinese stock-market, trades are positively correlated for geographically close investors, but negatively correlated for geographically distant investors.

A rational explanation of these findings must necessarily rely on some pronounced heterogeneity in investors’ signals and beliefs. Thus, at the heart of our analysis is the idea that in asset markets, there are groups of traders whose signals and beliefs are more correlated with some and less correlated with other groups of traders. A general measure of (informational) distance between two traders is the amount of information these two traders share. To elevate this notion of local information sharing to a market-wide level, we consider a dynamic model in which all traders are differentially informed about the long-term value of an asset, but also experience information sharing through local connections. These local connections give rise to overlapping reference groups which may include only one’s closest neighbors or even the entire market. Indeed, there are no obvious arguments suggesting whether information linkages should be best thought of as being local or global. Our framework is kept as general as possible to allow us to think about a wide spectrum of possibilities.
We claim that all available models do not allow for a sufficient heterogeneity in the informational distance amongst traders. For example, Foster and Viswanathan (1996) and Back, Cao and Willard (2000) developed a multi-traders generalization of the Kyle’s (1985) model. In these two papers, every trader is endowed with one signal about the long-term value of an asset, but the correlation between any two signals is the same for all traders. Our model is built upon the same economic construct underlying these two papers. But the existence of information linkages destroys the homogeneity in signals’ correlation, and induces patterns of signals correlation varying with traders’ geographical (informational) proximity. As a result, some traders may thus agree more with some and less with other peers. For example our model predicts that in some cases, two traders may not be directly connected to the same information linkages, but still exhibit highly correlated information endowments. This phenomenon occurs when two traders share some information with a third trader who is sharing information with each of the initial two traders.

Why do we need a model to explain that traders with comparable information trade similarly? First, we wish to examine the implications of our model on traditional market variables such as volume and liquidity. For example, do information linkages amongst traders boost stock-market volatility? What is the economic link between this volatility, volume and the existence of information linkages in the market? Second, we are interested in the equilibrium patterns of trade correlations amongst traders. In equilibrium, every trader makes use of the information available at the information link he has with his peers; but he also knows that by trading aggressively, he would reveal part of this information to distant peers. What is the ultimate effect on the correlation between ‘close’ and ‘distant’ trades? We will explain that our model generates predictions about these patterns that are quite distinct from the predictions of existing models - including models in which ‘close’ traders ‘herd’ on each other. Third, we wish to understand the welfare implications of these information linkages amongst traders: Do asset markets with many information linkages lead to an increase in traders’ welfare? This question has important practical scopes. Suppose for example that traders’ welfare deteriorates as the number of information linkages increases. (Below, we will explain that this is indeed the prediction of our model.) In this case, we would expect to see a small number of traders in markets with many information linkages, and vice-versa - a testable prediction.

More in detail, the predictions of our model are unambiguous and can be streamlined quite clearly:

1. The equilibrium price process, trading activity, returns volatility, and traders’ welfare are
severely affected by the number of information linkages amongst traders.

2. Compared to an economy without information linkages, an economy with information linkages is characterized by much higher liquidity, lower returns volatility, and higher volume.

3. The correlation among trades is heterogeneous, both temporally and spatially. Precisely, the correlation among trades is very high at the beginning of the trading period. The same correlation decreases with the unfolding of the trading period, but it does so differently - according to the informational distance among traders. This additional heterogeneity features the following patterns:

3.1 For traders who are sufficiently close (close neighbors, say), the correlation among opinions and trades is persistently high over the entire trading period.

3.2 Traders opinions and trades diverge with their relative informational distance. Eventually, the correlation between trades is negative for relatively distant traders. Deep divergences in trade occur even when the number of information linkages is so high to make any two traders’ opinions very close at the beginning of the trading period.

4. Finally, the existence of information linkages considerably and consistently damages traders welfare.

The severity of the first property makes our model economically meaningful and easy to interpret. Consider for example the prediction about high volume (second prediction). Its economic intuition is simple. Heterogeneity in private information is a source of monopolistic power for traders. And information linkages destroy part of this monopolistic power. As a result, every trader trades to preempt the actions of his peers, and market-wide volume increases widely. (Our predictions about liquidity and volatility can be understood in a similar vein.) As we explain in section 3.1, an economy without information linkages might lead to a similar conclusion only when the traders initial beliefs are extremely and implausibly high.

Next, consider the third property about the pattern of correlation amongst trades. This pattern is exactly the one we would like to see in light of the empirical evidence. The economic interpretation for the positive correlation for close trades is intuitive, for in economies without information linkages, the correlation among trades can only become negative eventually [see Foster and Viswanathan (1996)]. Perhaps more intriguingly, our model also matches the empirical evidence on the negative correlation between distant trades [see our previous discussion of Feng
and Seasholes (2004) findings]. In our model, this property emerges because of the very market clearing mechanism. Note that such a negative correlation does not necessarily emerge in models with rational herding. And at the same time, our model predicts a positive correlation amongst close trades - a property matching the empirical evidence and also shared by herding models. Naturally, the point of these remarks is not to exclude that herding behavior actually takes place in financial markets. Rather, our point here is that a herding-based explanation of positively correlated trades should not be taken as a self-evident truth.

The final prediction of our model is that the mere existence of information linkages damages traders welfare. This welfare result occurs under a wide range of conditions on initial beliefs heterogeneity and the market structure - as summarized by the number of traders and batch auctions, and the initial correlation amongst the traders’ information endowments. The explanation for our findings is indeed simple. In our model, traders face a crucial trade-off. On the one hand, the existence of information linkages entails a loss in the traders’ monopolistic power. On the other hand, these information linkages improve the quality of traders’ inference about the fundamental asset value. As it turns out, the losses generated by the first effect are always smaller than the gains associated with the second effect.\(^1\)

Our paper is also related to recent theoretical literature. In independent work, Ozsoylev (2005) has developed a model in which every investor is able to observe the expectations of his neighbors. In this sense, his model is very similar in spirit to our local information linkages mechanism. But there are two important differences between these two models. First, Ozsoylev considers a rational expectations model in which investors do not have market power. The assumption of no-market power allows the author to investigate asymmetric networks. In our model, traders do enjoy some monopolistic information power. But to avoid dimensionality issues related to forecasting the forecasts of others, we consider a symmetric network in which every trader regards the other traders in the same manner - and still has patterns of signal correlation varying with the proximity of his peers. The second difference between Ozsoylev’s model and our is that our model is dynamic. For all these reasons, Ozsoylev’s model and our have to be considered to be absolutely complementary.

The paper is organized as follows. In the next section, we develop the basic information

---

\(^{1}\)In the credit-markets literature, Pagano and Jappelli (1993) identified conditions under which banks find it profitable to exchange information about their customers’ quality. Under uncertainty about the borrower’s quality, credit bureaus allow lenders to improve their knowledge about new customers, at the cost of giving up to competitors one’s informational rent about existing customers. While similar trade-offs enter into our welfare calculations, in our model information sharing is not the result of any information exchange activity.
structure of our trading game. In section 2, we derive a dynamic equilibrium and in section 3, we analyze its properties. Section 4 concludes. The appendix contains all technical details omitted in the main text.

1 Information structure

1.1 Asset market and traders’ location

We consider a market for one risky asset organized in $N \geq 1$ batch auctions. This asset pays a random payoff $f \sim N(0, \sigma_f^2)$ at the end of the trading period. As in Kyle (1985) and in his subsequent extensions, $M$ traders are endowed with some pieces of information about the fundamental value $f$. The key feature of our model is that traders have information linkages, that is they have access to (or are endowed with) comparable though not identical signals (or beliefs) about the fundamental value of the asset. To model these information linkages, we assume that traders are physically located around a circle. By convention, we assume that traders are ordered clockwise, as to say that trader $i$ has trader $i + 1$ to his left and trader $i - 1$ to his right (see Figure 1). For reasons developed below, we assume that $M$ is an odd number.

A number of signals are observed at each trader’s location. Precisely, we assume that the signal $s_{i,0}$ available at the $i$-th trader’s location is also observed (or shared) by his neighbors. We consider “double-sided” information linkages. That is, the signal available at the $i$-th trader location is observed by $G$ traders to his right and by $G$ traders to his left. For example trader $i$ may share the signal at his location with traders $i - 1$ and $i + 1$ (see Figure 1). In this case both traders observe $s_{i,0}$ and trader $i$ observes $s_{i-1,0}$ and $s_{i+1,0}$. This mode of information sharing tilts the initial geographical information structure in a way that the $i$-th trader information set is $s_{i,0} = (s_{i-G,0}, \ldots, s_{i,0}, \ldots, s_{i+G,0})^\top$, $G \in [0, (M - 1)/2]$.

To easy notation, we let $\hat{G} = 2G + 1$ be the reference group size, or the number of signals resulting from information linkages and the signal available at the trader’s own location. Thus if information linkages are absent, $\hat{G} = 1$, and $s_{i,0} = s_{i,0}$ for all $i$. Theoretically, the maximum level of information linkages is $\hat{G} = M$, in which case $s_{i,0} = s_0$ for all $i$. However, such a complete information sharing economy may not have an equilibrium. Therefore, we shall limit ourselves to cases in which $\hat{G} < M$.

Our information structure can be interpreted in a variety of ways. As an example, every signal

\footnote{In this paper, we shall make an abuse in notation and write $G \in A$ for $G \in A \cap \mathbb{N}$, where $A$ is some set and $\mathbb{N}$ denotes the set of integers. A similar abuse in notation will occur for other objects related to $G$ - such as the number of traders located on some specific arcs of the circle.}
$s_{i,0}$ can be thought of as being broadcasted to trader’s $i$ location through a local newspaper or TV station. Reference groups among traders then arise because neighbors have access to the same source of information. If $\hat{G} = 1$, every trader gathers information from a unique local source of financial news, and there are no information linkages amongst agents. At the other extreme, all pieces of information are provided at a market-wide level whenever $\hat{G}$ is very close to $M$. In general, the group size $\hat{G} \in [1, M)$, and thus represents the media coverage of information providers. Another interpretation of our information structure is one in which geographical distance amongst traders stands for cultural, demographic or linguistic distance, or simply for some initial difference in beliefs. In all cases, we take the previous heterogeneity in traders’ signals and beliefs as given, and examine its market dynamics implications.

Next, we describe the distribution of the initial signals available at the traders’ location. To keep the presentation as general and tractable as possible, we follow Foster and Viswanathan (1996) and assume that individual signals are jointly normal with mean zero and

$$\Psi_0 \equiv E(h(s_{1,0}, s_{2,0}, \cdots, s_{M,0}))$$

a variance-covariance matrix. The signal unconditional distribution is symmetric in that: 1) each signal has variance $\Lambda_0$; 2) the covariance between any two signals is $\Omega_0$; and 3) the covariance between each signal and the fundamental value is $c_0$. Let $s_0$ be the $M \times 1$ vector of individual signals and $1$ be the $M \times 1$ vector of ones. The joint distribution of the vector $(f, s_{1,0}, \cdots, s_{M,0})^T$ is given by:

$$\begin{pmatrix} f \\ s_0 \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_f^2 & c_0 \Sigma_0 \\ c_0 \Sigma_0 & \Psi_0 \end{pmatrix} \right), \quad \Psi_0 \equiv \begin{bmatrix} \Lambda_0 & \Omega_0 & \cdots & \Omega_0 \\ \Omega_0 & \Lambda_0 & \Omega_0 & \cdots \\ \vdots & \vdots & \ddots & \vdots \\ \Omega_0 & \cdots & \cdots & \Lambda_0 \end{bmatrix}. \tag{1}$$

Let $(x_{i,n})_{n=1}^{N}$ be the orders submitted by the $i$-th trader over the trading period. These orders are submitted so as to,

$$\max_{(x_{i,n})} E \left[ \sum_{n=1}^{N} (f_n - p_n) x_{i,n} \bigg| F_{i,n} \right] = W_{i,n}, \tag{2}$$

where $F_{i,n}$ is the information set available for trader $i$ at the batch auction number $n$. (We will provide a precise description of such an information set in Section 2.1.) On top of these orders, a sector of noise traders submit liquidity motivated orders $(u_n)_{n=1}^{N}$, where $u_n \sim NID(0, \sigma_u^2)$ for all $n$. The aggregate order flow is therefore given by:

$$y_n = \sum_{i=1}^{M} x_{i,n} + u_n, \quad n = 1, \cdots, N. \tag{3}$$
Finally, the \((M + 1)\)-th market participant is a market maker who commits himself to offset
the order flow according to the Semi-Strong efficiency rule:

\[ p_n = E(f|y_1, \cdots, y_n), \quad n = 1, \cdots, N. \]

As we shall explain in the next section, our information structure simplifies each trader’s
dynamic inference about other traders’ signals, and allows to avoid infinite regress problems
related to forecasting the forecasts of others. Intuitively, this simplification arises because of the
symmetric distribution in eq. (1) - as explained by Foster and Viswanathan (1996). Moreover,
our trick to place traders around the circle allows us to study economies with heterogeneous
patterns of signals correlation. At a basic level, our model may be made exempt from infinite
regress issues because the circle makes these patterns of signals correlation the same for each
trader.

1.2 Average signals

Let \(\bar{s}_{i,0}\) denote trader \(i\)’s average signal:

\[ \bar{s}_{i,0} = \hat{G}^{-1} \sum_{k=-G}^{G} s_{i+k,0}. \] (4)

We refer to the full information liquidation value as the expectation of the final value conditional
on the information disseminated among traders, i.e. \(E(f|s_0)\). Let \(\kappa = c_0 (\Lambda_0 + (M - 1) \Omega_0)^{-1}\),
\(\theta = \kappa M\) and \(\bar{s} = M^{-1} \sum_{i=1}^{M} \bar{s}_{i,0}\). By eq. (1),

\[ E(f|s_0) = \theta \bar{s}. \] (5)

Therefore \(\bar{s}\), the average of the individual average signals, is a sufficient statistic for the full
information liquidation value. Note that \(\theta\) is well defined whenever matrix \(\Psi_0\) is invertible. Such
an invertibility condition requires the following restriction on the model parameters:

\[ \Lambda_0 > - (M - 1) \Omega_0. \] (6)

The unconditional variance-covariance matrix of the average signals \((\bar{s}_{i,0})_{i=1}^{M}\) is denoted as
\(\bar{\Psi}_0 \equiv E\left[(\bar{s}_{1,0}, \cdots, \bar{s}_{M,0})^T (\bar{s}_{1,0}, \cdots, \bar{s}_{M,0})\right]\). The elements of this matrix depend on the number of
information linkages in the market $\hat{G}$. Accordingly, we set $\Psi_0 \equiv \Psi_0 (G)$, where

$$\Psi_0 (G) \equiv \begin{bmatrix} \bar{\Lambda}_0 (G) & \bar{\Omega}_0 (1, G) & \cdots & \bar{\Omega}_0 \left( \frac{M-1}{2}, G \right) & \cdots & \bar{\Omega}_0 (-1, G) \\ \bar{\Lambda}_0 (G) & \bar{\Omega}_0 (G) & \cdots & \bar{\Omega}_0 (-2, G) & \cdots & \bar{\Lambda}_0 (G) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{\Lambda}_0 (G) & \bar{\Omega}_0 (G) & \cdots & \bar{\Omega}_0 (-2, G) & \cdots & \bar{\Lambda}_0 (G) \end{bmatrix},$$

and the elements

$$\begin{cases} \bar{\Lambda}_0 (G) & = \text{var} (\bar{s}_i, 0) \\ \bar{\Omega}_0 (k, G) & = \text{cov} (\bar{s}_{i+k, 0}, \bar{s}_i, 0), \quad k = \mp 1, \mp 2, \cdots, \mp \frac{M-1}{2} \end{cases}$$

denote, respectively, the unconditional variance of average signals and the unconditional covariance between the average signals of any two traders who are $k$-positions apart ($k \neq 0$). $\bar{\Lambda}_0 (G)$ is constant across traders due to the symmetric unconditional distribution (1) and the fact that $G$ is the same for all traders in equilibrium. Furthermore, due to the symmetric nature of our information sharing protocol, one has $\bar{\Omega}_0 (k, G) = \bar{\Omega}_0 (-k, G)$. Finally, we define the unconditional covariance between the sum of other traders’ average signals with $\bar{s}_i, 0$ as:

$$\bar{\Gamma}_0 (G) = \text{cov} \left( \sum_{j \neq i} \bar{s}_{j, 0}, \bar{s}_i, 0 \right).$$

Due to the geographical location of agents, $\bar{\Gamma}_0 (G)$ is independent of $i$. Finally, the covariance between the average signal $\bar{s}_i, 0$ and the fundamental value is simply

$$\bar{c}_0 = \text{cov} (f, \bar{s}_i, 0) = c_0,$$

and does not depend on $G$.

### 1.3 Correlations

By the distributional assumption in (1), and the definition of the average signal $\bar{s}_i, 0$ in (4),

$$\bar{\Lambda}_0 (G) = \frac{\Lambda_0 + 2G \Omega_0}{\hat{G}}. \quad (7)$$

Consider any two traders $i$ and $j = i + k$ with $k \neq 0$, and consider the unconditional covariance between average signals $\bar{\Omega}_0 (k, G)$. If $\hat{G} < M$, the covariance between average signals depends on $G$ and also on $k$ - i.e. the distance between trader $i$ and $i+k$. This dependence arises because the presence of information linkages makes the $i$-th trader have access to $2G$ additional signals from
his neighbors. However the number of individual signals each trader shares with other market participants depends on their relative position along the circle. As an example, assume that $2G < (M - 1)/2$. In this case trader $i$ shares $2G$ signals with trader $i + 1$, $2G - 1$ signals with trader $i + 2$ and in general $2G + 1 - k$ signals with trader $i + k$. Eventually, trader $i$ shares no signals with trader $i + 2G + 1$ and beyond (see Figure 2). As the simple example in Figure 2 demonstrates, the covariance between average signals does in general depend on $k$ in our model.

To compute the correlation amongst the traders’ information endowments, we distinguish between two cases according to whether $2G$ is less or greater than $(M - 1)/2$. If $2G \leq (M - 1)/2$, one has $s_{i+k,0} \cap s_{i,0} = \{\emptyset\}$ whenever $|k| > 2G$ (as in Figure 2), which implies $\Omega_0 (k, G) = \Omega_0$. On the other hand, $s_{i+k,0} \in s_{i,0}$ for all $|k| \leq 2G$. It is possible to show that (see appendix A for technical details),

$$\Omega_0 (k, G) = \begin{cases} \bar{A}_0 (G) - \hat{G}^{-2} k (\Lambda_0 - \Omega_0), & \text{for } k \in [1, 2G + 1] \\ \Omega_0, & \text{for } k \in [2G + 1, \frac{M-1}{2}] \end{cases} \quad (8a)$$

If (and only if) $2G \geq (M - 1)/2$, agents may share additional signals due to a “double overlap” of traders. Such a double overlap occurs when traders on the right semicircle within trader $i$’s reach share signals with traders on the left semicircle. For example, in Figure 3 trader $i$ shares his signal with trader $i - \ell$, but he shares no signals with trader $i + k_2$. On the other hand, traders $i + k_2$ and $i - \ell$ directly share their signals. This implies that trader $i$ knows $s_{i-\ell,0} \in s_{i+k_2,0}$, and $s_{i+k_2,0} \cap s_{i,0} \neq \{\emptyset\}$. In the appendix, we demonstrate that the occurrence of double overlap modifies the correlation structure in (8a) as follows:

$$\Omega_0 (k, G) = \begin{cases} \bar{A}_0 (G) - \hat{G}^{-2} k (\Lambda_0 - \Omega_0), & \text{for } k \in [1, \frac{M-1}{2}] - G] \\ 2\bar{A}_0 (G) - \hat{G}^{-2} M (\Lambda_0 - \Omega_0) - \Omega_0, & \text{for } k \in [2\left(\frac{M-1}{2} - G\right), \frac{M-1}{2}] \end{cases} \quad (8b)$$

By eqs. (7), (8a) and (8b), the variance-covariance matrix between average signals depends on the information sharing parameter $G$, as previously mentioned in this section. While the elements on the main diagonal in $\Psi_0 (G)$ are identical [see eq. (7)], the off-diagonal elements decrease with the distance from the main diagonal according to the pattern dictated by eqs. (8a)-(8b). It is worth noting that the sum of the off-diagonal elements is constant across different rows in $\Psi_0 (G)$. This sum is precisely what we previously defined as $\Gamma_0 (G)$, and is therefore identical across traders. This fact will allow us to avoid the infinite regress problem. In particular, in the appendix we
show that eqs. (8a)-(8b) imply that

\[ \bar{\Gamma}_0(G) = (M - 1)\Omega_0 + \frac{2G}{G} (\Lambda_0 - \Omega_0), \text{ for all } G \in [0, \frac{M-1}{2}] . \] (9)

1.4 Forecasts

We now turn to consider how trader \( i \) forecasts the final liquidation value as well as the sum of other traders’ average signals conditionally on his information set \( s_{i,0} \). By eq. (1),

\[ E(f|s_{i,0}) = \hat{G}\eta_1 \bar{s}_{i,0}, \] (10)

where \( \eta_1 \equiv c_0 (\Lambda_0 + 2G\Omega_0)^{-1} \). By eqs. (8a)-(8b), the correlation between average signals changes with any two agents’ relative location. Hence, by the Projection Theorem, each trader’s expectation of other traders’ average signals depends on the relative distance \( k \). However, the expectation of the sum of all other traders’ average signals is independent on \( k \) and linear in \( \bar{s}_{i,0} \):

\[ E\left( \sum_{j \neq i} \bar{s}_{j,0}|s_{i,0} \right) = E\left( \sum_{j \neq i} \bar{s}_{j,0}|\bar{s}_{i,0} \right) = (M - 1) \phi_1 \bar{s}_{i,0}, \] (11)

where the regression coefficient is

\[ \phi_1 \equiv \frac{\bar{\Gamma}_0(G)}{(M - 1)\bar{\Lambda}_0(G)}, \]

and \( \bar{\Lambda}_0(G) \) and \( \bar{\Gamma}_0(G) \) are given by eqs. (7) and (9).

2 Equilibrium characterization

2.1 Market maker’s inference

Let \( z_{i,t} = y_t - x_{i,t} \) be the residual order flow as of trader \( i \). We let \( F_{i,n} = \{s_{i,0}, (z_{i,t})_{t=1}^{n-1}, (x_{i,t})_{t=1}^{n-1}\} \) and \( F_{M+1,n} = \{(y_t)_{t=1}^{n}\} \) denote trader \( i \) and market maker information sets at the \( n \)-th batch auction. The market maker sets prices according to the Semi-Strong efficiency condition

\[ p_n = E(f|F_{M+1,n}), \]

and updates his estimate of individual signals as follows

\[ t_{i,n} = E(s_{i,0}|F_{M+1,n}). \]
Given our symmetric information structure for individual signals, the previous expectation does not depend on trader \(i\), and we set \(t_{i,n} = t_n\). A simple but important point is that \(t_n\) is also the updated estimate of each individual average signal

\[
E(\bar{s}_i,0| F_{M+1,n}) = \hat{G}^{-1}E \left[ \sum_{k=-G}^G s_{i+k,0} \right. F_{M+1,n} \left. \right] = \hat{G}^{-1} \sum_{k=-G}^G t_{i+k,n} = t_n. \tag{12}
\]

The relationship between \(p_n\) (market maker’s updated estimate of the asset value) and \(t_n\) (market maker’s updated estimate of the individual average signal) is given by:

\[
p_n = \theta t_n. \tag{13}
\]

Let \(s_{i,n}\) denote the \(i\)-th trader residual informational advantage on his own signal (relative to the market maker) after \(n\) rounds of trading,

\[
s_{i,n} \equiv s_{i,0} - E (s_{i,n}| F_{M+1,n}) = s_{i,0} - t_n.
\]

Trader \(i\) informational advantage on his average signal, \(\bar{s}_{i,n}\), has a similar interpretation, and due to eq. (12) is given by:

\[
\bar{s}_{i,n} = \bar{s}_{i,0} - E (\bar{s}_{i,n}| F_{M+1,n}) = \bar{s}_{i,0} - t_n. \tag{14}
\]

The market maker’s update results in the following residual variances:

\[
\begin{align*}
\sigma^2_{f,n} &= \text{var} \left[ E (f|s_0) \right] F_{M+1,n} = \text{var} \left( \theta \bar{s} - p_n \right| F_{M+1,n} ); \\
\Lambda_n &= \text{var} \left( s_{i,0} \right| F_{M+1,n} ) = \text{var} \left( s_{i,n} \right| F_{M+1,n} ) ; \\
\Omega_n &= \text{cov} \left( s_{i,0}, s_{j,0} \right| F_{M+1,n} ) = \text{cov} \left( s_{i,n}, s_{j,n} \right| F_{M+1,n} ) ; \\
\bar{\Lambda}_n (G) &= \text{var} \left( \bar{s}_{i,n} \left| F_{M+1,n} \right) ; \\
\bar{\Omega}_n (k,G) &= \text{cov} \left( \bar{s}_{i,n}, \bar{s}_{i+k,n} \right| F_{M+1,n} ).
\end{align*} \tag{15}
\]

\(\sigma^2_{f,n}\) is the residual variance of the full information fundamental value after \(n\) rounds of trading; \(\Lambda_n\) and \(\Omega_n\) are the individual signal residual variance and covariance respectively; finally, \(\bar{\Lambda}_n (G)\) and \(\bar{\Omega}_n (k,G)\) are the average signal counterparts. Then we have:

\[
\sigma^2_{f,n} = \frac{\theta^2}{M} \left[ \Lambda_n + (M-1) \Omega_n \right]. \tag{16}
\]
Furthermore the following recursions hold:

\[ \Omega_{n-1} - \Omega_n = \Lambda_{n-1} - \Lambda_n; \quad (17a) \]

\[ \sigma_{f,n-1}^2 - \sigma_{f,n}^2 = \theta^2 (\Lambda_{n-1} - \Lambda_n); \quad (17b) \]

\[ \bar{\Lambda}_{n-1} (G) - \bar{\Lambda}_n (G) = \Lambda_{n-1} - \Lambda_n, \quad \text{all } G; \quad (17c) \]

\[ \bar{\Omega}_{n-1} (k, G) - \bar{\Omega}_n (k, G) = \Lambda_{n-1} - \Lambda_n, \quad \text{all } k, G; \quad (17d) \]

\[ \bar{\Gamma}_{n-1} (G) - \bar{\Gamma}_n (G) = (M - 1)(\Lambda_{n-1} - \Lambda_n), \quad \text{all } G. \quad (17e) \]

Therefore, the off-diagonal elements in \( \bar{\Psi}_n (G) \equiv E \left[ (\bar{s}_{1,0}, \cdots, \bar{s}_{M,0})^\top (\bar{s}_{1,0}, \cdots, \bar{s}_{M,0}) \middle| F_{M+1,n} \right] \) depend on \( G \), while the difference \( \bar{\Psi}_{n-1} (G) - \bar{\Psi}_n (G) \) does not:

\[ \bar{\Psi}_{n-1} (G) - \bar{\Psi}_n (G) = (\Lambda_{n-1} - \Lambda_n) 11^\top. \]

To easy notation, we now supress the dependence of the various coefficients on \( G \).

### 2.2 Dimensionality issues

We focus on equilibria in which each trader’s forecasts of the asset value and the forecasts of others are linear in the trader’s average signal. In these equilibria, all higher order forecasts of other traders’ forecasts are also linear in the same average signals. Consequently, average signals constitute sufficient statistics for both the asset value and the forecasts of others. Furthermore, we focus on equilibria independent from forecasts’ history. As it turns out, our information structure makes the strategic gaming in our model comparable to the one introduced by Foster and Viswanathan (1996). Specifically, we assume that in equilibrium, traders’ demand and the market maker’s learning about the asset value take the following form:

\[ x_{i,n} = \hat{G}_n \beta_n \bar{s}_{i,n-1}; \quad (18) \]

\[ p_n = p_{n-1} + \lambda_n y_n. \quad (19) \]

Moreover, the market maker learning about individual (and average) signals evolves according to,

\[ t_n = t_{n-1} + \zeta_n y_n. \quad (20) \]

The relationship between the updating parameters \( \zeta_n \) and \( \lambda_n \) is given by:

\[ \lambda_n = \theta \zeta_n. \quad (21) \]
At the $n$-th trading round, trader $i$ forecasts the fundamental value that is not predicted by the market maker after $n - 1$ rounds, using his information $F_{i,n}$. By the assumption that trading strategies are linear [see eq. (18)], and the market maker’s recursive update in eqs. (14) and (20),

$$x_{i,n} = \hat{G}\beta_n \bar{s}_{i,n-1} = \hat{G}\beta_n (\bar{s}_{i,0} - t_{n-1}) = \hat{G}\beta_n \left(\bar{s}_{i,0} - \sum_{r=1}^{n-1} \zeta_r y_r\right).$$

Therefore, the residual order flow $(z_{i,t})_{t=1}^{n-1}$ is redundant, and we set $F_{i,n} = \{s_{i,0}, (y_t)_{t=1}^{n-1}\}$. As in Foster and Viswanathan (1996), trader $i$ can manipulate other traders’ beliefs about the asset value only through the aggregate order flow. As a result, every trader forecasts the asset value as follows:

$$E(f - p_{n-1}|F_{i,n}) = \hat{G}\eta_n \bar{s}_{i,n-1}. \tag{22}$$

That is, $\bar{s}_{i,n-1}$ is sufficient for trader $i$ to forecast the fundamental value before submitting his order at time $n$. Note that eq. (22) is the dynamic analog to the projection in eq. (10). Similarly, trader $i$ forecasts (the sum of) other traders’ forecasts of the fundamental value according to [and analogously to the static case in eq. (11)]

$$E \left(\sum_{j\neq i} s_{j,n-1}|F_{i,n}\right) = (M - 1) \phi_n \bar{s}_{i,n-1}. \tag{23}$$

As is clear, linear strategies as in eq. (18) play a key role in resolving the dimensionality issue, since they allow to conclude that the forecasts of the forecasts of others are linear in each trader’s average signal.

### 2.3 Equilibrium and deviation

Our linearity assumptions rule out the problem of increasing state history over time. The argument hinges on the fact that linear strategies in eq. (18) are played in equilibrium. When moving to consider deviations from the optimal play by trader $i$, one has to keep into account that $\bar{s}_{i,n-1}$ is no longer a sufficient statistic for predicting the fundamental value as well as other traders’ forecast as in eqs. (22)-(23). In fact $\bar{s}_{i,n-1}$ is sufficient only if trader $i$ played the strategy (18) in the first $n - 1$ trading rounds. Let us denote deviation from the equilibrium path with a prime ('). Trader $i$ deviation from the equilibrium play (18) to $(x'_{i,k})_{k=1}^{n-1}$ during the first $n - 1$ auctions would generate the aggregate order flow $(y'_{k} = y_{k} - (x_{i,k} - x'_{i,k}))_{k=1}^{n-1}$. Since the market maker’s update on the fundamental value and the average signals are linear in the order flow due to equations (19)-(20), trader $i$ deviation modifies the market maker’s learning process as well, resulting in $(p'_k)_{k=1}^{n-1}$ and $(t'_k)_{k=1}^{n-1}$. Given past suboptimal play, it turns out that the residual
average signal along the equilibrium path \( \bar{s}_{i,n-1} \) and the price deviation \((p_{n-1} - p'_{n-1})\) are jointly sufficient to forecast the fundamental value as well as the forecasts of other traders. This result allows to conjecture that trader \( i \)'s value function after \( n \) auctions takes the form:

\[
W_{i,n} = \alpha_n \bar{s}_{i,n}^2 + \psi_n \bar{s}_{i,n} (p_n - p'_n) + \mu_n (p_n - p'_n)^2 + \delta_n,
\]

where \( W_{i,n} \) is as in eq. (2). Past suboptimal play is captured by the second and third term in the value function in eq. (24). Moreover, trader \( i \)'s deviation coincides with the equilibrium strategy in eq. (18) plus an additional term reflecting the price deviation induced by suboptimal play in the previous \( n - 1 \) rounds:

\[
x'_{i,n} = \hat{G} \beta_n \bar{s}_{i,n-1} + \gamma_n (p_{n-1} - p'_{n-1}).
\]

The necessary and sufficient conditions for an equilibrium in our trading game hinge upon the mutual consistency between the conjectured value function in eq. (24) and the deviation in eq. (25). We have:

**Proposition 1.** There exists a symmetric linear recursive Bayesian equilibrium in which trading strategies and prices are as in eqs. (18)-(19); \( \lambda_n \) is the unique real, positive solution to:

\[
0 = \theta \left(M - \hat{G}\right) (\Lambda_n - \Omega_n) \sigma_u^4 \lambda_n^4 + \sigma_f^2 \psi_n \bar{\Lambda}_n \lambda_n^3 - \frac{\sigma_f^2}{\sigma_u^4} \left[2\Lambda_n + (M-1) \Omega_n - \frac{2\hat{G}}{\hat{G}} (\Lambda_n - \Omega_n)\right] \lambda_n^2
\]

\[
-\psi_n \bar{\Lambda}_n \lambda_n + \frac{\theta}{M} [\Lambda_n + (M-1) \Omega_n];
\]

and the trading strategy coefficients \( \beta_n \) and \( \gamma_n \) are given by:

\[
\beta_n = \frac{\theta \lambda_n \sigma_u^2}{GM \sigma_f^2};
\]

\[
\gamma_n = \frac{(1 - 2\lambda_n \mu_n) \left[1 - \theta^{-1} \hat{G} (M-1) \beta_n \lambda_n\right]}{2\lambda_n (1 - \lambda_n \mu_n)}.
\]
The value function coefficients satisfy the recursions:

\[
\alpha_{n-1} = \alpha_n \left[1 - \theta^{-1} \hat{G} (1 + (M - 1) \phi_n) \beta_n \lambda_n\right]^2 + \hat{G}^2 \beta_n \eta_n - \beta_n \lambda_n (1 + (M - 1) \phi_n) ;
\]

\[
\psi_{n-1} = \psi_n \left[1 - \lambda_n \gamma_n - \theta^{-1} \hat{G} (M - 1) \beta_n \lambda_n\right] \left[1 - \theta^{-1} \hat{G} (1 + (M - 1) \phi_n) \beta_n \lambda_n\right] 
+ \hat{G} \{\gamma_n \eta_n - \beta_n \lambda_n (1 + (M - 1) \phi_n)\} - \beta_n \gamma_n \lambda_n + \beta_n [1 - \theta^{-1} \hat{G} (M - 1) \beta_n \lambda_n] ; \tag{29}
\]

\[
\mu_{n-1} = \mu_n \left[1 - \lambda_n \gamma_n - \theta^{-1} \hat{G} (M - 1) \beta_n \lambda_n\right]^2 + \gamma_n [1 - \lambda_n \gamma_n - \theta^{-1} \hat{G} (M - 1) \beta_n \lambda_n] ;
\]

\[
\delta_{n-1} = \delta_n + \theta^{-2} \alpha_n \lambda_n^2 \sigma_u^2 + \theta^{-2} \hat{G}^2 \alpha_n \lambda_n^2 \beta_n^2 \text{var} \left(\sum_{j \neq i} \bar{s}_{j,n-1} \right| F_{i,n} \right) ;
\]

where \(\alpha_N = \psi_N = \mu_N = \delta_N = 0\) and

\[
\phi_n = \frac{\hat{\Gamma}_{n-1}}{(M - 1) \Lambda_{n-1}} ; \tag{30}
\]

\[
\eta_n = \frac{\theta (\hat{\Gamma}_{n-1} + \hat{\Lambda}_{n-1})}{G \hat{\Gamma}_{n-1}} ; \tag{31}
\]

\[
\text{var} \left(\sum_{j \neq i} \bar{s}_{j,n-1} \right| F_{i,n} \right) = M \left[\Lambda_{n-1} + (M - 1) \Omega_{n-1}\right] - \left[1 + \phi_n^2 (M - 1)^2\right] \hat{\Lambda}_{n-1} - 2 \hat{\Gamma}_{n-1}.
\]

Furthermore the following inequality must hold:

\[
\lambda_n (1 - \lambda_n \mu_n) > 0,
\]

and the following recursion on the full information residual variance must hold:

\[
\sigma_{f,n}^2 = \left(1 - \theta^{-1} \hat{G} M \beta_n \lambda_n\right) \sigma_{f,n-1}^2.
\]

In our model, not only are traders concerned with learning from the information that other traders possess. This learning process is also complicated by every trader's geographical location and the number of information linkages every trader has with his neighbors. As Proposition 1 reveals, trading strategies and value functions are heavily affected by the heterogeneous correlation structure arising from all these information linkages - a fact that we will examine in great detail in the next section.

### 3 Market dynamics implications

This section analyzes properties of the equilibrium price formation predicted by our model. To make the model produce concrete predictions, we need to impose some more structure on the
information disseminated in the economy. We assume that the signal available at the \(i\)-th trader location has the standard additive form,

\[
s_{i,0} = f + \epsilon_i,
\]

where \(\epsilon_i \sim N(0, \sigma^2_i)\), and is orthogonal to \(f\) as well as to all remaining sources of noise \(\{\epsilon_j\}_{j \neq i}\). We set \(\sigma^2_f = 1\) and \(\sigma^2_u = N^{-1}\); that is, we analyze a situation in which uncertainty about fundamentals equals uncertainty about non-fundamentals across all batch auctions.

The additive structure in eq. (32) implies that the covariance between any signal and the fundamentals equals \(c_0 = 1\); the covariance between any two individual signals equals \(\Omega_0 = 1\); and the correlation between any two individual signals equals,

\[
\rho = \frac{1}{1 + \sigma^2_{\epsilon_i}}.
\]

Finally, the variance of each individual signal equals \(\Lambda_0 = 1 + \sigma^2_{\epsilon_i} = \rho^{-1}\); and the parameter \(\theta\) in the full information liquidation value [see eq. (5)] equals \(\theta = \frac{\rho^M}{1 + (M - 1)\rho}\).

As is clear, the correlation \(\rho\), the number \(2G\) of information linkages for each trader, the number \(M\) of informed traders, and the length of the trading period \(N\) are the only free parameters in the model. In this paper, we set \(M = 7\) and consider \(N = 10\) batch auctions. (We have also experimented with different numbers of traders and auctions, but obtained qualitatively very similar results.) The resulting equilibrium is now parametrized by 1) the initial correlation between the signals at any two locations (\(\rho\); and 2) the number of information linkages for each trader \((2G)\). We use backward induction to solve for the equilibrium (please see Appendix D for details). In the next section, we describe the properties of the equilibrium arising for \(\rho = 10\%\) (low correlation) and \(\rho = 90\%\) (high correlation); and for \(G = 0\) (no information linkages), \(G = 1\) (information linkages) and \(G = 2\) (many information linkages).

3.1 Volume, liquidity, and volatility

We study how the existence of information linkages affects additional variables such as trading volume, liquidity and asset return volatility. As in Admati and Pfleiderer (1988), we decompose the (expected) volume at the \(n\)-th auction in terms of the contribution of the market maker, the \(M\) traders, and the liquidity traders. Precisely, we identify each component with its conditional standard deviation, and set \(Vol_n = Vol_{M,n} + Vol_{I,n} + Vol_{L,n}\), where

\[
Vol_{M,n} = \sqrt{G^2\beta^2_n M [\Lambda_n - 1 + (M - 1)\Omega_n - 1] + \sigma^2_u};
\]

\[
Vol_{I,n} = G\beta_n \sqrt{M [\Lambda_n - 1 + (M - 1)\Omega_n - 1]};
\]

17
and $Vol_{U,n} = \sigma_u$, for all $n$. Furthermore, we compute the asset return volatility by also conditioning on the market maker’s information set. By eqs. (18)-(19),

$$\text{var} (p_n - p_{n-1}|F_{M+1,n-1}) = \lambda_n^2 \cdot Vol_{M,n}^2.$$ 

The central prediction of the model is its ability to predict a high volume in the presence of information linkages. This result holds even with a moderate value of the initial correlation $\rho$. We developed economic intuition for this result in the introduction and so in the interest of space we do not repeat it here.

Can high volume be consistent with models without information linkages? Figure 4 illustrates that models without information linkages can be consistent with high volume. At the same time, these models can only do so if the signal correlation amongst traders is extremely high in the first place. Arguably, there is no evidence that this has occurred. Our model proposes an alternative simple mechanism based on information linkages between traders.

The trading activity due to informed traders, $Vol_{M,n}$, is depicted in Figure 5. As is clear, information linkages increase the incentives to preempt other traders thus resulting in higher volume. Not surprisingly, Figure 5 shows that these incentives are larger -and thus the effect of information linkages on volume is more pronounced- the lower is the initial correlation among individual signals, or equivalently, the larger is each trader’s monopolistic power.

Figure 6 plots the evolution of the fundamental residual variance, $\sigma_{\text{f},n}^2$, over time. Information linkages make the variance of the liquidation value decrease more rapidly. Moreover, the improvement in market efficiency -as measured by the ratio $1/\sigma_{\text{f},n}^2$- is more pronounced with low initial correlation. These findings are directly related to the volume dynamics previously documented. In fact, information linkages make competition among informed traders more intense. As a consequence, traders impound more information into their orders thus reducing the residual variance.

The price responsiveness to the order flow, $\lambda_n$, is displayed in Figure 7. Overall, the effect of information linkages is to increase market liquidity, i.e. the ratio $1/\lambda_n$. Again, the higher trade aggressiveness in the presence of information linkages (see Figure 5) decrease the adverse selection faced by the market maker since the order flow is more informative (see Figure 6). Thus the market maker reduces the price impact of the order flow, and the market is more liquid.

---

3 For reasons of space we do not plot the other components of total volume, most notably the volume traded by the market maker which exhibit a similar pattern.

4 Figure 6 reveals that $\sigma^2_{\text{f},0} < \sigma^2_{\text{f}}$ (in our case, $\sigma^2_{\text{f}} \equiv 1$). When signals are as in eq. (32), this inequality has to be expected for $\sigma^2_{\text{f},0} = \frac{\sigma^2_{\text{f}}}{\rho^2} [\Lambda_0 + (M - 1) \Omega_0] = \frac{M}{\rho^2 + M - 1}$. 

---
The dynamics of asset return volatility are shown in Figure 8. For a given number of information linkages, both the evolution of the price impact and the expected (informed) order flow affect the volatility dynamics. Since both components are shown to decrease over time, so does volatility. Moreover, information linkages increase both volume and liquidity. From Figure 8 it emerges that the overall effect is to increase volatility during the first trading rounds, and to decrease it afterwards.

3.2 Correlated trading

Figure 9 shows the time variation in the average signal correlation every trader has with his neighbors, or \( \bar{\rho}_n (k,G) \equiv \bar{\Omega}_n (k,G) / \bar{\Lambda}_n (G) \) (\( k = 1,2,3 \)). Clearly, this correlation is inversely related to monopolistic power deriving from the information shared by every trader with neighbors. Interestingly, \( \text{corr} (x_{i,n}, x_{i+k,n} | F_{M+1,n-1}) = \bar{\rho}_{n-1} (k,G) \).

Therefore, \( \bar{\rho} (\cdot) \) also measures how information linkages make neighbors’ trades “resemble” one another. In general, traders are worse off as \( \bar{\rho} (\cdot) \) increases. For a given \( G \), \( \bar{\rho}_n (k,G) \) is increasing in \( \rho \) for all \( n \) and \( k \) as one might have expected. Moreover, for given \( k \) and \( G \), \( \bar{\rho}_n (\cdot) \) decreases over time. As noted in Foster and Viswanathan (1996) this is related to the market maker’s learning about the (average of the) traders’ signals over time. Furthermore, for all \( k \), \( \bar{\rho}_n (k) \) increases with \( G \) for the first trading rounds. In other terms, information linkages generally entail a loss in traders’ monopolistic power. Intuitively, this is so because information sharing induces an increase in the initial correlation \( \bar{\rho}_0 (\cdot) \) between all traders’ average signals. Noteworthy, in the presence of information linkages, 1) it takes fewer batch auctions for the correlation between distant traders to become negative with respect to the case \( G = 0 \) and 2) correlation between close neighbors remains positive throughout the trading game. As mentioned in the Introduction, this behavior is completely consistent with findings in Feng and Seasholes (2004).

3.3 Welfare

Information linkages do damage traders’ welfare. Such a result holds in an unambiguously huge number of parametrizations of the model - in terms of the number of batch auctions \( N \), the number of traders \( M \), the number of information linkages \( 2G \) available for each trader, and the initial correlation \( \rho \) between individual signals. Figure 10 illustrates this point in an exemplary manner. Figure 10 also reveals another striking result. Namely, for any fixed \( G \), traders’ welfare
is nonmonotonic in the initial correlation $\rho$. More generally, our numerical results suggest that for any fixed tuple $(M, N, G)$, there exists a value of the initial correlation $\rho$ which maximizes the traders’ welfare.

What are the origins of these results? Consider the relationship in eq. (33). This relationship reveals that the initial correlation $\rho$ is related to two distinct effects. First, as $\rho$ increases, every trader loses more and more bits of information endowments available only to him. At the same time, an increase in $\rho$ is obviously associated with a decrease in $\sigma_\varepsilon^2$, and thus helps imperfectly informed traders to improve their estimates about the fundamental asset value. When $\rho$ is low, the losses in monopolistic power associated with the first effect dominate over the precision gains deriving from the second effect. When $\rho$ is high, the losses in monopolistic power are dominated by the precision gains.

In our model an increase in the number of information linkages $2G$ measures similar effects. On the one hand, a trader with many information linkages has a better estimate of the fundamental value of the asset. On the other hand, these information linkages also make our trader lose part of his monopolistic informational power. But in contrast with the simple situation in which there exists a level of correlation maximizing traders welfare, here there are not optimal information linkages maximizing the traders’ power.

To develop some intuition about this result, consider again the average signal $\bar{s}_{i,0}$ trader $i$ has about the fundamental [see eq. (4)]. By replacing eq. (32) into the average signal in eq. (4), we find that

$$\bar{s}_{i,0} = f + \frac{1}{2G+1} \sum_{k=-G}^{G} \epsilon_{i+k}.$$  

(34)

By the Law of Large Numbers, the probability limit $\operatorname{plim}_{G \to \infty} \bar{s}_{i,0} = f$, for every trader $i = 1, \cdots, M$. Yet this result implies that the monopolistic power of the traders eventually shrinks to nil. Alternatively, it may be the case that the number of traders required for such a reduction does not exist in the first place.

Finally, the convergence of the average signal $\bar{s}_{i,0}$ to the truth $f$ takes place at the usual $G$ rate. In contrast, the boost in precision obtained with an increase in $\rho$ takes a place at a much faster rate. For example, suppose that $\rho = 0.1$. By eqs. (32)-(33), $\operatorname{var}(\bar{s}_{i,0}) = 1 + \frac{1-\rho}{\rho} = 10$. And by eq. (34), $\operatorname{var}(\bar{s}_{i,0}) = 1 + \frac{1}{2G+1} \frac{1-\rho}{\rho}$. So an increase in the initial correlation from $\rho = 0.1$ to $\rho = 0.5$ makes the variance $\operatorname{var}(\bar{s}_{i,0})$ decrease from 10 to 2. This is indeed a noticeable boost in precision associated with some market power deteration. In contrast, a five-fold reduction in the variance $\operatorname{var}(\bar{s}_{i,0})$ through activation of new information linkages necessitates $2G = 8$ such linkages! This is a much more noticeable reduction in market power.
4 Conclusion

This paper develops a dynamic model of trading with differentially informed traders experiencing information linkages related to the long-term value of an asset. We show that in the presence of information linkages, volume and price informativeness increase, asymmetric information costs decrease, and traders’ welfare is damaged. Finally, the model predicts a clear relationship between patterns of trades correlation and traders’ geographical location: ‘neighbor’ trades are positively correlated and ‘distant’ trades are negatively correlated. All of these predictions appear in line with robust phenomena documented in the empirical literature, and cannot be simultaneously accommodated within traditional models dealing with differentially informed traders experiencing symmetric signal distributions.
Appendix

A.

Derivation of eqs. (7)-(9). To derive eq. (7), we use the definition of the average signal in eq. (4). A simple computation leaves:

\[ \text{var} (\bar{s}_{i,0}) = \frac{\hat{G} \Lambda_0 + 2 \hat{G} \hat{G} \Omega_0}{G^2}, \]

or equivalently (7). Next, we derive eqs. (8a) and (8b). These equations correspond to two cases: 
a) \( 2G \leq (M - 1)/2 \) and 
b) \( 2G \geq (M - 1)/2 \), which we now study separately.

Case a) \( 2G \leq (M - 1)/2 \). Consider traders \( i \) and \( j = i + k, \ k \neq 0 \). We have: \( s_{i+k,0} \notin s_{i,0} \) for all \( |k| > G \). Therefore

\[ \bar{\Omega}_0(k,G) \equiv \text{cov} (\bar{s}_{i,0}, \bar{s}_{i+k,0}) = \hat{G}^{-2} \sum_{l=-G}^{G} \sum_{m=-G}^{G} \text{cov} (s_{i+l,0}, s_{i+k+m,0}) = \Omega_0, \]

for all \( |k| > 2G \), which is the second line in (8a). If instead \( |k| \leq 2G \), \( s_{i+k,0} \in s_{i,0} \) for all \( |k| \leq G \) and \( s_{i+k,0} \cap s_{i,0} \neq \{\emptyset\} \). In particular, trader \( i \) shares \((2G + 1 - k)\) signals with trader \( i + k \). Each of these signals contributes for \( (\Lambda_0 + 2G \Omega_0)/(2G + 1)^2 \) to \( \bar{\Omega}_0(k,G) \). Shared signals thus contribute for

\[ \frac{\Lambda_0 + 2G \Omega_0}{(2G + 1)^2} \cdot (2G + 1 - k) \]

to \( \bar{\Omega}_0(k,G) \). The remaining (not shared) \( k \) signals contribute for

\[ \frac{(2G + 1) \Omega_0}{(2G + 1)^2} \cdot k \]

to \( \bar{\Omega}_0(k,G) \). Therefore,

\[ \bar{\Omega}_0(k,G) = \frac{(\Lambda_0 + 2G \Omega_0) (\hat{G} - k) + \hat{G} \Omega_0 k}{G^2}. \]

Grouping terms in the previous expression yields the first line in (8a).

Case b) \( 2G \geq (M - 1)/2 \). Due to the double overlap phenomenon discussed in the main text, the number of signals shared by traders \( i \) and \( i + k \) is:

\[ L(k,G) \equiv 2G + 1 - k + n(k,G), \quad k = 1, \cdots, \frac{M-1}{2}. \]
The term \( n(k, G) \) arises because traders on trader \( i \)'s r.h.s. semicircle might be sharing signals with traders lying between \( i + 1 \) and \( i + (M - 1)/2 \) on the l.h.s. semicircle (see Figure 3); and obviously the \( i \)-th trader shares signals with traders lying between \( i - 1 \) and \( i - G \) as well. Double overlap occurs if and only if trader \( i + k \) on the l.h.s. semicircle and trader \( i - c \) with \( c \in \left[ 1, \frac{M - 1}{2} \right] \) on the r.h.s. semicircle are such that \( \ell \) and \( k \) satisfy:

\[
\begin{cases}
\frac{M - 1}{2} - (\ell - 1) + \frac{M - 1}{2} - k \leq G \\
G \geq \ell \geq 1 \\
\frac{M - 1}{2} \geq k \geq 1
\end{cases}
\]

The first inequality in the previous restrictions requires trader \( i - \ell \) to share his signal with trader \( i + k \). The second and third constraints restrict trader \( i - \ell \) to be on the r.h.s. semicircle and trader \( i + k \) to be on the l.h.s. semicircle relative to trader \( i \). Thus, for fixed \( k (1 \leq k \leq (M - 1)/2) \), double overlap occurs if and only if

\[
G \geq \ell \geq M - G - k, \quad k = 1, \ldots, \frac{M - 1}{2},
\]

and \( \ell \geq 1 \). Clearly, \( \min_k (M - G - k) = \frac{M - 1}{2} - G + 1 \geq 1 \). Hence, the constraint that \( \ell \geq 1 \) is redundant. By the previous inequalities, it immediately follows that:

\[
n(k, G) = \max \left[ G - (M - G - k) + 1, 0 \right].
\]

By replacing this result into eq. (A1) leaves:

\[
L(k, G) = \begin{cases}
4G + 1 - (M - 1), & \frac{M - 1}{2} \geq k \geq 2 \left( \frac{M - 1}{2} - G \right) \\
2G + 1 - k, & 1 \leq k \leq 2 \left( \frac{M - 1}{2} - G \right)
\end{cases}
\]

For all \( k \in \left[ 1, 2 \left( \frac{M - 1}{2} - G \right) \right] \), \( \bar{\Omega}_0(k, G) \) is thus exactly as in case a) for \( k \in [1, 2G] \), and the first line of eqs. (8b) follows. For all \( k \in \left[ 2 \left( \frac{M - 1}{2} - G \right), \frac{M - 1}{2} \right] \), tedious but straightforward computations lead to the second line of eqs. (8b).

Finally, we demonstrate that eq. (9) holds true. As usual, we consider the two cases in which \( 2G \geq (M - 1)/2 \). If \( 0 \leq 2G \leq (M - 1)/2 \), there are \( [M - (4G + 1)] \) traders \( i + k \) such that \( s_{i+k,0} \cap s_{i,0} = \emptyset \). In correspondence of these indexes, \( \text{cov} (\bar{s}_{i+k,0}, \bar{s}_{i,0}) = \Omega_0 \). Therefore,

\[
\bar{\Gamma}_0(G) = 2 \sum_{k=1}^{2G} \bar{\Omega}_0(k, G) + [M - (4G + 1)] \Omega_0.
\]

The \( 2G \) covariances in the summation can be computed through the first line in (8a). Eq. (9) follows by the expression of \( \bar{\Lambda}_0(G) \) in eq. (7). Next, consider the case \( (M - 1)/2 \leq 2G \leq M - 1 \).
We have:
\[
\bar{\Gamma}_0 (G) = 2 \left\{ \sum_{k=1}^{M-1-2G} \bar{\Omega}_0 (k, G) + \left( 2G - \frac{M-1}{2} \right) \left[ 2\bar{\Lambda}_0 (G) - \frac{M(\Lambda_0 - \Omega_0)}{G^2} - \Omega_0 \right] \right\}.
\]

By plugging eqs. (8b) and (7) into the previous equation, we find that the expression of \(\bar{\Gamma}_0 (G)\) is the same as the one obtained in the case \(0 \leq 2G \leq (M-1)/2\), and eq. (9) follows. 

**Derivation of eq. (11).** Consider the projection of \(s_{i+k,0}\) onto \(s_{i,0}\) for \(|k| \leq G\). We have \(s_{i+k,0} \in s_{i,0}\) for \(k = 0, \mp 1, \cdots, \mp G\). Hence,
\[
E (s_{i+k,0} | s_{i,0}) = s_{i+k,0}, \quad k = 0, \mp 1, \cdots, \mp G.
\]

Next, consider a signal outside the \(i\)-th individual reach, i.e. take \(s_{i+k,0}\) for \(k = \mp (G + 1), \cdots, \mp \frac{M-1}{2}\). Let \(\Psi_{0,G} = E (s_{i,0}s_{i,0}^\top)\) be the \(\hat{G} \times \hat{G}\) variance-covariance matrix of the vector \(s_{i,0}\). \(\Psi_{0,G}\) is a \(\hat{G} \times \hat{G}\) submatrix extracted from \(\Psi_0\), and its inverse can be obtained with the same strategy of proof as in Foster and Viswanathan (1996) (p. 1479). Let \(K \equiv \left[ (\Lambda_0 - \Omega_0)(\Lambda_0 + 2G\Omega_0) \right]^{-1}\).

We have:
\[
\left( \Psi_{0,G} \right)^{-1} = K \cdot \begin{bmatrix}
\Lambda_0 + (2G - 1)\Omega_0 & -\Omega_0 & \cdots & -\Omega_0 \\
-\Omega_0 & \Lambda_0 + (2G - 1)\Omega_0 & -\Omega_0 & \cdots \\
\cdots & \cdots & \cdots & \cdots \\
-\Omega_0 & -\Omega_0 & \cdots & \Lambda_0 + (2G - 1)\Omega_0
\end{bmatrix}.
\]

Since \(cov (s_{i+k,0}, s_{i,0}) = \Omega_0 1\) for \(|k| > G\), the Projection Theorem then leaves:
\[
E (s_{i+k,0} | s_{i,0}) = \Omega_0 1^\top (\Psi_{0,G})^{-1} s_{i,0}
\]
\[
= \Omega_0 \frac{\Lambda_0 + (2G - 1)\Omega_0 - 2G\Omega_0}{(\Lambda_0 - \Omega_0)(\Lambda_0 + 2G\Omega_0)} 1^\top s_{i,0}
\]
\[
= \frac{\hat{G}\Omega_0}{\Lambda_0 + 2G\Omega_0} s_{i,0}, \quad k = 0, \mp 1, \cdots, \mp G.
\]

Thus individual signals are projected according to:
\[
E (s_{i+k,0} | s_{i,0}) = \begin{cases} 
  s_{i+k,0} & \text{for } k = 0, \mp 1, \cdots, \mp G \\
  \frac{\hat{G}\Omega_0}{\Lambda_0 + 2G\Omega_0} s_{i,0} & \text{for } k = \mp (G + 1), \cdots, \mp \frac{M-1}{2}
\end{cases}
\]
We now compute the projection of the trader $i$ projection of the sum of other traders’ average signals onto $s_{i,0}$. Since $\bar{s}_{i,0} \in s_{i,0}$, and obviously $\sum_{j=1}^{M} \bar{s}_{j,0} = \sum_{j=1}^{M} s_{j,0}$,

\[
E \left( \sum_{j \neq i} \bar{s}_{j,0} \mid s_{i,0} \right) = \sum_{j=1}^{M} E \left( s_{j,0} \mid s_{i,0} \right) - \bar{s}_{i,0} = 1_{G}s_{i,0} + \sum_{|k| > G} E \left( s_{i+k,0} \mid s_{i,0} \right) - \bar{s}_{i,0} = (2G + 1) \bar{s}_{i,0} + \frac{(M - (2G + 1)) \Omega_0}{\Lambda_0 + 2G\Omega_0} (2G + 1) \bar{s}_{i,0} - \bar{s}_{i,0} = \frac{(M - 1)(2G + 1) \Omega_0 + 2G (\Lambda_0 - \Omega_0)}{\Lambda_0 + 2G\Omega_0} \bar{s}_{i,0}.
\]

Grouping terms in the last equality yields eq. (11), where $\phi_1$ is as in the main text. ■

B.

**Derivation of eq. (13).** By Semi-Strong market efficiency, $p_n = E \left( f \mid F_{M+1,n} \right)$. By eq. (5), $\bar{s}$ is a sufficient statistic for $E \left( f \mid s_0 \right)$. Therefore,

\[
p_n = E \left( f \mid F_{M+1,n} \right) = E \left\{ E \left[ E \left( f \mid s_0 \right) \mid \bar{s}, F_{M+1,n} \right] \mid F_{M+1,n} \right\} = E \left[ E \left( \theta \bar{s} \mid \bar{s}, F_{M+1,n} \right) \mid F_{M+1,n} \right] = \frac{\theta}{M} E \left( \sum_{i=1}^{M} \bar{s}_{i,0} \mid F_{M+1,n} \right) = \theta t_n,
\]

where the last line follows by eq. (12). ■

**Derivation of eq. (16).** By the Law of Iterated Expectations:

\[
E \left( \theta \bar{s} \mid F_{M+1,n} \right) = E \left[ E \left( f \mid s_0 \right) \mid F_{M+1,n} \right] = E \left( f \mid F_{M+1,n} \right) = p_n.
\]
Hence,

\[
\sigma_{f,n}^2 = E \left[ \left( \frac{\theta}{M} \sum_{i=1}^{M} \bar{s}_{i,0} - \frac{\theta}{M} \sum_{i=1}^{M} t_{i,n} \right)^2 \right] F_{M+1,n}
\]

\[
= \frac{\theta^2}{M^2} E \left[ \left( \sum_{i=1}^{M} \bar{s}_{i,n} \right)^2 \right] F_{M+1,n}
\]

\[
= \frac{\theta^2}{M^2} E \left[ \left( \sum_{i=1}^{M} s_{i,n} \right)^2 \right] F_{M+1,n}
\]

\[
= \frac{\theta^2}{M} [\Lambda_n + (M - 1) \Omega_n].
\]

**Derivation of eqs. (17a)-(17e).** Let \( c_n \equiv \text{cov}(s_{i,n-1}, y_n | F_{M+1,n-1}) \), which is clearly independent of \( i \), and \( \Psi_n \equiv E \left[ (s_{1,0} - t_n, \ldots, s_{M,0} - t_n)^T (s_{1,0} - t_n, \ldots, s_{M,0} - t_n) | F_{M+1,n} \right] \). By the Projection Theorem,

\[
\Psi_n = \Psi_{n-1} - \frac{c_n^2}{\text{var}(y_n | F_{M+1,n-1})} \mathbf{1}^T
\]

which gives the recursions:

\[
\Lambda_n = \Lambda_{n-1} - \frac{c_n^2}{\text{var}(y_n | F_{M+1,n-1})} ; \tag{B1}
\]

\[
\Omega_n = \Omega_{n-1} - \frac{c_n^2}{\text{var}(y_n | F_{M+1,n-1})} ;
\]

or equivalently (17a). Taking one lag in equation (16) yields:

\[
\sigma_{f,n-1}^2 = \frac{\theta^2}{M} [\Lambda_{n-1} + (M - 1) \Omega_{n-1}]
\]

giving the recursion:

\[
\sigma_{f,n-1}^2 - \sigma_{f,n}^2 = \frac{\theta^2}{M} [\Lambda_{n-1} - \Lambda_n + (M - 1) (\Omega_{n-1} - \Omega_n)] = \theta^2 (\Lambda_{n-1} - \Lambda_n),
\]

where the last equality follows by eq. (17a). Now consider the variance of average signals \( \bar{\Lambda}_n (G) \). By eq. (7), \( \bar{\Lambda}_n (G) \) can be expressed in terms of the elements in the individual signals variance-covariance matrix \( \Psi_n \) as:

\[
\bar{\Lambda}_n (G) = \frac{(\Lambda_n + 2G\Omega_n)}{G}
\]

26
and eq. (17c) follows by eq. (17a), and by simple computations. We now provide the update for \( \Omega_n (k, G) \), thus completing the specification of the variance-covariance matrix \( \Psi_n (G) \equiv E \left[ (\bar{s}_{1,0} - t_n, \ldots, \bar{s}_{M,0} - t_n)^\top (\bar{s}_{1,0} - t_n, \ldots, \bar{s}_{M,0} - t_n) \right] F_{M+1,n} \]. By eq. (17a) and the expression of the off-diagonal elements in \( \Psi_n (G) \) [see eqs. (8a) and (8b) evaluated at \( n \)],

\[
\Omega_{n-1} (k, G) - \Omega_n (k, G) = \Lambda_{n-1} - \Lambda_n, \quad \text{all } k, G.
\]

Finally, from eq. (9) one has the recursion:

\[
\bar{\Gamma}_{n-1} (G) - \bar{\Gamma}_n (G) = (M - 1) (\Lambda_{n-1} - \Lambda_n). \quad \blacktriangleleft
\]

**Derivation of eq. (20).** By the definition of \( t_n \) and \( s_n \),

\[
t_n - t_{n-1} = E (s_{i,0} - t_{n-1} | F_{M+1,n}) = E (s_{i,n-1} | F_{M+1,n}) = \zeta_n y_n,
\]

where \( \zeta_n \) is the regression coefficient of \( s_{i,n-1} \) (or equivalently of \( \bar{s}_{i,n-1} \)) on \( y_n \), viz

\[
\zeta_n = \frac{cov (s_{i,n-1}, y_n | F_{M+1,n-1})}{var (y_n | F_{M+1,n-1})} = \frac{c_n}{\text{var} (y_n | F_{M+1,n-1})}. \quad \blacktriangleleft \ (B2)
\]

**Derivation of eq. (21).** We have:

\[
E \left( \frac{1}{M} \sum_{i=1}^{M} s_{i,n-1} | F_{M+1,n} \right) = \frac{1}{M} E \left( \sum_{i=1}^{M} s_{i,n-1} | F_{M+1,n} \right) = \zeta_n y_n.
\]

By eq. (13), \( p_{n-1} = \theta t_{n-1} \). Hence,

\[
\bar{s} - 1 \theta p_{n-1} = \bar{s} - t_{n-1} = \frac{1}{M} \sum_{i=1}^{M} (\bar{s}_{i,0} - t_{n-1}) = \frac{1}{M} \sum_{i=1}^{M} \bar{s}_{i,n-1}.
\]

Therefore,

\[
E (\theta \bar{s} - p_{n-1} | F_{M+1,n}) = \theta E \left( \frac{1}{M} \sum_{i=1}^{M} \bar{s}_{i,n-1} | F_{M+1,n} \right) = \theta \zeta_n y_n.
\]

But by eq. (5), \( E [E (f | s_0)] F_{M+1,n} = E (\theta \bar{s}) F_{M+1,n} \). Hence, by the Law of Iterated Expectations,

\[
E (\bar{s} - p_{n-1} | F_{M+1,n}) = E [E (f | s_0) - p_{n-1} | F_{M+1,n}] = E (\theta \bar{s} - p_{n-1} | F_{M+1,n}) = \theta \zeta_n y_n,
\]

and eq. (21) follows by eq. (19) and \( E (\theta \bar{s} | F_{M+1,n}) = p_n \). \quad \blacktriangleleft

27
The following lemma is needed to derive eqs. (22)-(23).

**Lemma 1.** For all \( i, j = 1, \cdots, M \) and \( n = 2, \cdots, N \),

\[
E(s_{j,n-1}|F_{i,n}) = E(s_{j,n-1}|s_{i,n-1}).
\]

**Proof.** By eqs. (18), (20) and (21), the aggregate order flow can be recursively written as

\[
y_n = \left( \frac{\beta_n a_{n-1}}{\beta_{n-1}} \right) y_{n-1} + \varepsilon_n,
\]

where \( a_{n-1} \equiv 1 - \theta^{-1} \hat{G} M \beta_{n-1} \lambda_{n-1} \) and \( \varepsilon_n \equiv u_n - \beta_n \beta_{n-1}^{-1} u_{n-1} \). Solving backward yields,

\[
y_n = b_{n-1} y_1 + \sum_{j=1}^{n-2} b_j \varepsilon_{n-j} + \varepsilon_n,
\]

where \( b_j \equiv \beta_n \beta_{n-j}^{-1} \prod_{h=1}^{j} a_{n-h} \). Hence, \( \{y_n\}_{n \geq 1} \) is a Gaussian process. Therefore, it is sufficient to show that \( \text{cov}[s_{j,n-1}, (y_1, \cdots, y_{n-1})^\top] = 0_{(n-1) \times 1} \). For all \( k \leq n-1 \),

\[
\text{cov}(y_k, s_{j,n-1}) = E( y_k \cdot s_{j,n-1} ) = E[ E( y_k \cdot s_{j,n-1} | y_1, \cdots, y_{n-1} ) ] = E[ E( y_k \cdot ( s_{j,n-1} | y_1, \cdots, y_{n-1} ) ) ] = 0,
\]

where the first line follows because \( E( y_1, \cdots, y_{n-1})^\top = 0_{(n-1) \times 1} \), the second line holds by the Law of Iterated Expectations, and the last line follows by the definition of \( s_{j,n-1} \). 

**Derivation of eqs. (22)-(23).** We have:

\[
E(f - p_{n-1}|F_{i,n}) = E[E(f - p_{n-1}|s_0)|s_{i,0}, F_{M+1,n-1}]
= E(\theta \bar{s} - p_{n-1}|s_{i,0}, F_{M+1,n-1})
= \theta E\left( \frac{1}{M} \sum_{i=1}^{M} \bar{s}_{i,n-1} \bigg| s_{i,n-1}, F_{M+1,n-1} \right)
= \theta E\left( \frac{1}{M} \sum_{i=1}^{M} \bar{s}_{i,n-1} \bigg| s_{i,n-1}, F_{M+1,n-1} \right)
= \frac{\theta}{M} E\left( s_{i,n-1} + \sum_{j \neq i} s_{j,n-1} \bigg| \bar{s}_{i,n-1} \right)
= \frac{\theta}{M} \left( 1 + \frac{\bar{\Gamma}_{n-1}}{\bar{\Lambda}_{n-1}} \right) \bar{s}_{i,n-1},
\]

28
by the Law of Iterated Expectations, the fact that \( \theta s - p_{n-1} = \frac{\theta}{M} \sum_{i=1}^{M} \bar{s}_{i,n-1} \) [see the derivation of eq. (21)], and lemma 1. This is eq. (22) with \( \eta_n = \theta (GM)^{-1} (1 + \Lambda_n^{-1} \Gamma_n^{-1}) \). By the same arguments,

\[
E \left( \sum_{j \neq i} \bar{s}_{j,n-1} \bigg| F_{i,n} \right) = \frac{\Gamma_{n-1}}{\Lambda_n^{-1}} \bar{s}_{i,n-1},
\]

which is eq. (23) with \( \phi_n = (M - 1)^{-1} \Lambda_n^{-1} \Gamma_n^{-1} \).

C. Proof of Proposition 1

We proceed in three steps. In the first step, we derive a recursive expression for the price deviation induced by traders’ suboptimal play. In the second step, we derive the traders’ optimality conditions. In the third step, we compute market maker updates.

**Step 1: Price deviation**

We show that the price deviation induced by suboptimal play of a given trader \( i \) has the following recursive structure:

\[
p_n - p'_n = (p_{n-1} - p'_{n-1}) \left[ 1 - \theta^{-1} \hat{G}(M - 1) \beta_n \lambda_n \right] + \hat{G} \lambda_n \beta_n \bar{s}_{i,n-1} - \lambda_n x'_{i,n}. \tag{C1}
\]

Indeed, let \( y'_n = \sum_{j \neq i} x_{j,n} + x'_{i,n} + u_n \) and \( t'_n \) be the aggregate order flow and the market maker’s update when trader \( i \) deviates to \( x'_{i,n} \). By eq. (20),

\[
t_n = \sum_{k=1}^{n} \zeta_k y_k.
\]

Similarly \( t'_n = \sum_{k=1}^{n} \zeta_k y'_k \). Therefore, by eq. (14),

\[
\bar{s}_{j,n-1} - \bar{s}'_{j,n-1} = (\bar{s}_{j,0} - t_{n-1}) - (\bar{s}_{j,0} - t'_{n-1})
\]

\[
= \sum_{k=1}^{n-1} \zeta_k y'_k - \sum_{k=1}^{n-1} \zeta_k y_k
\]

\[
= \frac{1}{\theta} \left( \sum_{k=1}^{n-1} \lambda_k y'_k - \sum_{k=1}^{n-1} \lambda_k y_k \right)
\]

\[
= \frac{1}{\theta} \left( p'_n - p_n - 1 \right), \tag{C2}
\]

where the third line follows by eq. (21), and the fourth line follows because eq. (19) implies that \( p_n = \sum_{k=1}^{n} \lambda_k y_k \). Thus, by eq. (14) and eq. (20),

\[
\bar{s}_{i,n} = \bar{s}_{i,0} - t_n = \bar{s}_{i,n-1} - (t_n - t_{n-1}) = \bar{s}_{i,n-1} - \zeta_n y_n.
\]

29
Substituting for the equilibrium order flow and taking expectations yields:

\[
E(\bar{s}_{i,n} | F_i,n) = \bar{s}_{i,n-1} - \frac{\hat{G}\beta_n \lambda_n}{\theta} \left[ \bar{s}_{i,n-1} + E\left( \sum_{j \neq i} \bar{s}_{i,n-1} | F_i,n \right) \right] \\
= \left[ 1 - \frac{\hat{G}\beta_n \lambda_n}{\theta} (1 + (M - 1) \phi_n) \right] \bar{s}_{i,n-1},
\]

(C3)

where the last line follows by eq. (30). Using the equilibrium strategy in eq. (18) and the price recursion in eq. (19), we find that the price deviation has the following expression:

\[
p_n - p_n' = p_{n-1} - p_{n-1}' + \lambda_n (y_n - y_n') \\
= p_{n-1} - p_{n-1}' + \lambda_n \left[ \sum_{j \neq i} \hat{G}\beta_n (\bar{s}_{j,n-1} - \bar{s}_{j,n-1}') + \hat{G}\beta_n \bar{s}_{i,n-1} - \bar{x}_{i,n}' \right].
\]

Substituting for \((\bar{s}_{j,n-1} - \bar{s}_{j,n-1}')\) from eq. (C2) in the previous equation gives eq. (C1).

**Step 2: Traders’ strategies**

First, we show that the value function in eq. (24) and the strategy in eq. (25) are mutually consistent. Trader \(i\) faces the following recursive problem:

\[
W_{i,n-1} = \max_{x_{i,n}'} E\left[ (f - p_n) x_{i,n}' + W_{i,n} | F_i,n \right] \\
= \max_{x_{i,n}'} E\left[ (f - p_{n-1} - \lambda_n x_{i,n}' - \lambda_n \sum_{j \neq i} x_{j,n}) x_{i,n}' + W_{i,n} | F_i,n \right].
\]

Given the trading strategy conjectured in eq. (24), the optimality conditions of the previous problem lead to:

\[
0 = E\left( f - p_{n-1}' | F_i,n \right) - \hat{G}\beta_n \lambda_n E\left( \sum_{j \neq i} \bar{s}_{j,n-1}' | F_i,n \right) \\
- 2\lambda_n x_{i,n}' - \lambda_n \psi_n E(\bar{s}_{i,n} | F_i,n) - 2\lambda_n \mu_n E\left( p_n - p_{n}' | F_i,n \right) \quad \text{(first order conditions)};
\]

and

\[-\lambda_n + \lambda_n^2 \mu_n < 0 \quad \text{(second order conditions)}.
\]

Because \((\bar{s}_{j,n-1}, (p_{n-1} - p_{n-1}')) \in F_i,n\), the first order conditions can be reorganized as follows:

\[
0 = E\left( f - p_{n-1} | F_i,n \right) + (p_{n-1} - p_{n-1}') - \hat{G}\beta_n \lambda_n \sum_{j \neq i} (\bar{s}_{j,n-1} - \bar{s}_{j,n-1}') \\
- \hat{G}\beta_n \lambda_n E\left( \sum_{j \neq i} \bar{s}_{j,n-1} | F_i,n \right) - 2\lambda_n x_{i,n}' - \lambda_n \psi_n E(\bar{s}_{i,n} | F_i,n) - 2\lambda_n \mu_n E\left( p_n - p_{n}' | F_i,n \right).
\]

By replacing eqs. (C1), (C2) and (C3) in the previous equation, and by rearranging terms, we obtain eq. (25), where \(\gamma_n\) is as in eq. (28) and

\[
\beta_n = \frac{\eta_n - \hat{G}\lambda_n \psi_n}{\lambda_n \left[ 1 + (1 - \theta^{-1} \lambda_n \psi_n) (1 + (M - 1) \phi_n) \right]}.
\]

(C4)
Next, we use eq. (25), and find that the expected profit of a single auction is:

\[
E \left[ (f_p - p_n) x'_{i,n} \mid F_{i,n} \right] = \hat{G}^2 \beta_n \left[ \eta_n - \beta_n \lambda_n \left( 1 + (M - 1) \phi_n \right) \right] \bar{s}^2_{i,n-1} \\
+ \gamma_n \left[ 1 - \lambda_n \left( \gamma_n + \theta^{-1} \hat{G} (M - 1) \beta_n \right) \right] (p_{n-1} - p'_{n-1})^2 \\
+ \left\{ \gamma_n (\eta_n - 2 \beta_n \lambda_n) + \beta_n \left[ 1 - (M - 1) \lambda_n \left( \gamma_n \phi_n + \theta^{-1} \hat{G} \beta_n \right) \right] \right\} \\
\times \hat{G} \bar{s}_{i,n-1} (p_{n-1} - p'_{n-1}).
\]

By taking the conditional expectation of the value function in eq. (24) leaves:

\[
E (W_{i,n} \mid F_{i,n}) = \alpha_n E (\bar{s}^2_{i,n} \mid F_{i,n}) + \psi_n (p_n - p'_n) E (\bar{s}_{i,n} \mid F_{i,n}) + \mu_n (p_n - p'_n)^2 + \delta_n.
\]

By eqs. (C1) and (C3), both \(E (\bar{s}_{i,n} \mid F_{i,n})\) and \((p_n - p'_n)\) are linear in \((p_{n-1} - p'_{n-1})\) and \(\bar{s}_{i,n-1}\). To identify all coefficients of the value function, we are therefore left with finding the conditional expectation \(E (\bar{s}^2_{i,n} \mid F_{i,n})\). By eqs. (14) and (20),

\[
E (\bar{s}^2_{i,n} \mid F_{i,n}) = \bar{s}^2_{i,n-1} + \zeta_n^2 E (y_{i,n}^2 \mid F_{i,n}) - 2 \zeta_n \bar{s}_{i,n-1} E (y_{i,n} \mid F_{i,n}) \\
= \left[ 1 - \theta^{-1} \hat{G} \beta_n \lambda_n (1 + (M - 1) \phi_n) \right]^2 \bar{s}^2_{i,n-1} \\
+ \theta^{-1} \lambda_n^2 \sigma_n^2 + \theta^{-1} \hat{G}^2 \beta_n^2 \lambda_n^2 \text{var} \left( \sum_{j \neq i} \bar{s}_{j,n-1} \mid F_{i,n} \right),
\]

where

\[
\text{var} \left( \sum_{j \neq i} \bar{s}_{j,n-1} \mid F_{i,n} \right) = \text{var} \left( \sum_{j \neq i} \bar{s}_{j,n-1} \mid \bar{s}_{i,n-1} \right) \\
= E \left[ \left( \sum_{j \neq i} \bar{s}_{j,n-1} - (M - 1) \phi_n \bar{s}_{i,n-1} \right)^2 \right] \\
= \text{var} \left( \sum_{j \neq i} \bar{s}_{j,0} \mid F_{M+1,n-1} \right) - (M - 1)^2 \phi_n^2 \text{var} (\bar{s}_{i,0} \mid F_{M+1,n-1}) \\
= M \left[ \Lambda_{n-1} + (M - 1) \Omega_{n-1} \right] - \left[ 1 + (M - 1)^2 \phi_n^2 \right] \bar{\Lambda}_{n-1} - 2 \bar{\Gamma}_{n-1}.
\]

and the first equality follows by the arguments utilized to show lemma 1 in appendix B. Finally, by plugging eq. (C6) into eq. (C5), and using the expression for the expected profits and the expectation of the value function, gives the coefficients \(\alpha_n, \mu_n, \psi_n\) and \(\delta_n\) in eq. (29).

**Step 3: Market maker updates**

Finally, we consider the market maker’s problem. By plugging the equilibrium trades in eq. (18) into the order flow in eq. (3) gives

\[
y_n = \sum_{i=1}^{M} \hat{G} \beta_n \bar{s}_{i,n-1} + u_n = \hat{G} M \beta_n \left[ \frac{1}{M} \sum_{i=1}^{M} (\bar{s}_{i,0} - t_{n-1}) \right] + u_n.
\]

31
where the second line follows by the market maker’s update in eq. (14). By the definition of \( \bar{s} \), and the equality \( t_{n-1} = \theta^{-1} p_{n-1} \) in eq. (13),

\[
y_n = GM \beta_n \left( \bar{s} - \frac{p_{n-1}}{\theta} \right) + u_n = \frac{GM \beta_n}{\theta} (\theta \bar{s} - p_{n-1}) + u_n.
\]  

(C8)

By eqs. (C8) and (5), and the Law of Iterated Expectations,

\[
cov (f, y_n | F_{M+1,n-1}) = cov (\theta \bar{s} - p_{n-1}, y_n | F_{M+1,n-1})
\]

Therefore,

\[
cov (f, y_n | F_{M+1,n-1}) = \frac{GM \beta_n}{\theta} \text{var} (\theta \bar{s} - p_{n-1} | F_{M+1,n-1})
\]

\[
= \frac{GM \beta_n}{\theta} \sigma_{f,n-1}^2,
\]  

(C9)

where the first line follows because \( p_{n-1} \in F_{M+1,n-1} \), the second line is obtained through the order flow in eq. (C8), and the third line is due to the expression of the residual variance in eq. (15). We now re-write the recursion of \( \Lambda_n \) in terms of equilibrium parameters. Using the order flow in eq. (C7),

\[
c_n \equiv cov (s_{i,n-1}, y_n | F_{M+1,n-1})
\]

\[
= \hat{G} \beta_n cov \left( s_{i,n-1}, \sum_{i=1}^M s_{i,n-1} | F_{M+1,n-1} \right)
\]

\[
= \hat{G} \beta_n (\Lambda_{n-1} + (M-1) \Omega_{n-1})
\]

\[
= \frac{M \hat{G} \beta_n}{\theta^2} \sigma_{f,n-1}^2,
\]

where the third line follows by the expression of the residual variances in eq. (15), and the last line holds by the expression of \( \sigma_{f,n}^2 \) in eq. (16). Therefore, by eqs. (B1), (B2), the expression for \( c_n \) found above, and eq. (21),

\[
\Lambda_n = \Lambda_{n-1} - \zeta_n c_n = \Lambda_{n-1} - \frac{M \hat{G} \beta_n \lambda_n}{\theta^3} \sigma_{f,n-1}^2.
\]  

(C10)

Again by the above expression for \( c_n \), eqs. (21) and (B2),

\[
\lambda_n = \theta \zeta_n = \frac{\theta c_n}{\text{var} (y_n | F_{M+1,n-1})} = \frac{M \hat{G} \beta_n \sigma_{f,n-1}^2}{\theta \cdot \text{var} (y_n | F_{M+1,n-1})}.
\]
But
\[
\text{var } (y_n | F_{M+1,n-1}) = \left(\theta^{-1}\hat{G}M\beta_n\right)^2 \text{var } (\theta s - p_n-1 | F_{M+1,n-1}) + \sigma_u^2
\]
\[
= \left(\theta^{-1}\hat{G}M\beta_n\right)^2 \sigma_{f,n-1}^2 + \sigma_u^2.
\]

Therefore, the price sensitivity in eq. (19) can be represented as:
\[
\lambda_n = \frac{\theta M\hat{G}\beta_n\sigma_{f,n-1}^2}{\left(\hat{G}M\beta_n\right)^2 \sigma_{f,n-1}^2 + \theta^2 \sigma_u^2}.
\]

(C11)

After \( n \) trading rounds, the full information fundamental value has residual variance given by:
\[
\sigma_{f,n}^2 = \sigma_{f,n-1}^2 - \lambda_n \text{cov } (f, y_n | F_{M+1,n-1}) = \left(1 - \theta^{-1}\beta_n\lambda_n\hat{G}M\right) \sigma_{f,n-1}^2,
\]
where the last equality follows by the eq. (C9) and the first equality holds because \( E (y_n | F_{M+1,n-1}) = 0 \), and by the Law of Iterated Expectations,
\[
\text{cov } (f, y_n | F_{M+1,n-1}) = E (f \cdot y_n | F_{M+1,n-1})
\]
\[
= E(E(f \cdot y_n | F_{M+1,n}) | F_{M+1,n-1})
\]
\[
= E(p_n \cdot y_n | F_{M+1,n-1})
\]
\[
= E(p_{n-1} \cdot y_n | F_{M+1,n-1}) + E(\lambda_n \cdot y_n^2 | F_{M+1,n-1})
\]
\[
= \lambda_n \cdot \text{var } (y_n | F_{M+1,n-1}).
\]

Next, we plug eq. (C11) into eq. (C12) and obtain:
\[
\sigma_{f,n}^2 = \frac{\theta^2 \sigma_n^2 \sigma_{f,n-1}^2}{\left(\hat{G}M\beta_n\right)^2 \sigma_{f,n-1}^2 + \theta^2 \sigma_u^2}.
\]

(C13)

By combining eqs. (C11) and (C13) we find an alternative expression for \( \lambda_n \),
\[
\lambda_n = \frac{\hat{G}M\beta_n \sigma_{f,n}^2}{\theta \sigma_{f,n-1}^2}.
\]

(C14)

or equivalently eq. (27). By solving eq. (C13) for \( \sigma_{f,n-1}^2 \) gives
\[
\sigma_{f,n-1}^2 = -\frac{\theta^2 \sigma_n^2 \sigma_{f,n}^2}{\left(\hat{G}M\beta_n\right)^2 \sigma_{f,n}^2 - \theta^2 \sigma_u^2}.
\]

(C15)
By combining eqs. (C10), (C14) and (C15), we find that \( \Lambda_n \) solves,

\[
\Lambda_{n-1} - \Lambda_n = -\frac{\sigma_u^4}{(\hat{G}M\beta_n)^2\sigma_{f,n}^2 - \theta^2\sigma_u^2} \lambda_n^2 = -\frac{\lambda_n^2\sigma_u^2\sigma_{f,n}^2}{\theta^2(\lambda_n^2\sigma_u^2 - \sigma_{f,n}^2)}.
\]

(C16)

where the last equality follows because \( (\hat{G}M\beta_n)^2\sigma_{f,n}^2 = \theta^2\lambda_n^2\sigma_u^4\sigma_{f,n}^{-2} \) [due to eq. (27)]. Also, eqs. (17c) and (17e) imply that

\[
\frac{\hat{\Gamma}_{n-1}}{\Lambda_{n-1}} = \frac{\hat{\Gamma}_n + (M-1)(\Lambda_{n-1} - \Lambda_n)}{\Lambda_n + (\Lambda_{n-1} - \Lambda_n)}.
\]

(C17)

Furthermore, by eqs. (30)-(31):

\[
\frac{\hat{\Gamma}_{n-1}}{\Lambda_{n-1}} = (M-1)\phi_n = \frac{\hat{G}M}{\theta}\eta_n - 1.
\]

(C18)

By combining eqs. (27) and (C4), we find that

\[
\theta\sigma_u^2\lambda_n^2 [1 + (1 - \theta^{-1}\lambda_n\psi_n) (1 + (M-1)\phi_n)] = (\hat{G}\eta_n - \lambda_n\psi_n) M\sigma_{f,n}^2.
\]

Substituting eqs. (30)-(31) in the previous equation leaves

\[
\theta\sigma_u^2\lambda_n^2 [1 + (1 - \theta^{-1}\lambda_n\psi_n) \left(1 + \frac{\hat{\Gamma}_{n-1}}{\Lambda_{n-1}} \right)] = \left[\frac{\theta}{M} \left(1 + \frac{\hat{\Gamma}_{n-1}}{\Lambda_{n-1}} \right) - \lambda_n\psi_n\right] M\sigma_{f,n}^2.
\]

The quartic equation \( F(\lambda_n) = 0 \) in eq. (26) is obtained by substituting eqs. (C16), (C17), (16), (7) and (9) evaluated at \( n \) into the previous equation, and by tedious but straightforward computations available upon request from the authors. To show that eq. (26) admits a unique positive solution, note that the constant and the coefficient of \( \lambda_n^4 \) are both positive, and that the coefficient of \( \lambda_n^2 \) is negative.\(^5\) On the other hand, the sign of \( \psi_n \) determines the sign of the terms in \( \lambda_n^2 \) and \( \lambda_n \). However, regardless of whether \( \psi_n \) is positive or negative, there are only two sign changes. By Descartes’ rule, eq. (26) has at most two real positive roots. By eq. (C12), \( \sigma_{f,n}^2 < \sigma_{f,n-1}^2 \Leftrightarrow \theta^{-1}\beta_n\lambda_n\hat{G}M < 1 \). By eq. (27) this restriction becomes \( \lambda_n^2 < \sigma_{f,n}^2\sigma_u^{-2} \) or equivalently \( \lambda_n < \sigma_{f,n}\sigma_u^{-1} \). By eq. (26), \( F(\lambda = 0) = \frac{\theta}{\hat{G}M}[\Lambda_n + (M-1)\Omega_n] > 0 \), \( F(\lambda = \sigma_{f,n}\sigma_u^{-1}) = -\frac{\theta}{\hat{G}M} (\Lambda_n + (M-1)\Omega_n) < 0 \) and \( F(\lambda = +\infty) = +\infty \); hence, there is one and only one positive root between 0 and \( \sigma_{f,n}\sigma_u^{-1} \).

\(^5\)Let \( \rho_n = \Omega_n/\Lambda_n \) be the correlation coefficient between individual signals. Since \( |\rho_n| \leq 1 \), then \( \Lambda_n - \Omega_n \geq 0 \) and the coefficient for \( \lambda_n^4 \) is non-negative. Moreover \( \Lambda_n + (M-1)\Omega_n \) is positive due to (6), and a fortiori \( 2\Lambda_n + (M-1)\Omega_n > 0 \) since \( \Lambda_n > 0 \).
D. Computation of the equilibrium

We solve for the equilibrium using backward induction. By eq. (17a), \( \Lambda_n - \Omega_n = \Lambda_0 - \Omega_0 \). We fix a terminal value for \( \Lambda_N \) and compute \( \Omega_N = \Lambda_N + \Omega_0 - \Lambda_0 \). \( \sigma^2_{f,N} \) then follows by eq. (16). Since \( \alpha_N = \psi_N = \mu_N = \delta_N = 0 \), we solve for \( \lambda_N \) in eq. (26), which yields \( \beta_N \) and \( \gamma_N \) through eqs. (27)-(28). To compute the value function coefficients as of at time \( N - 1 \), one needs to express \( \Lambda_{N-1} \) and \( \Omega_{N-1} \) in terms of variables known at time \( N \). Below, we show that:

\[
\Lambda_{n-1} = \frac{\theta \Lambda_n - \tilde{G} (M - 1) \lambda_n \beta_n (\Lambda_n - \Omega_n)}{\theta - GM \lambda_n \beta_n}. \tag{D1}
\]

Then, \( \Lambda_{N-1} \) is obtained by evaluating eq. (D1) at \( n = N \), and \( \Omega_{N-1} \) is obtained by the equality \( \Omega_{N-1} = \Lambda_{N-1} + \Omega_0 - \Lambda_0 \). Finally, we retrieve regression coefficients \( \phi_N \) and \( \eta_N \) through eqs. (30)-(31) and the equality \( \tilde{\Gamma}_{N-1} = \tilde{\Gamma}_N + (M - 1) (\Lambda_{N-1} - \Lambda_N) \) [see eq. (17e)]. The value function coefficients at time \( N - 1 \) are therefore uniquely determined by eq. (29).

The above procedure is then applied at each trading round \( n \in [1, N] \) yielding the initial value of \( \Lambda_0 \) implied by the choice of the terminal value of \( \Lambda_N \). The resulting initial value of \( \Lambda_0 \) is then compared to the one we posited as initial parameter, and the procedure is repeated for different choices of \( \Lambda_N \) until convergence is achieved.

**Derivation of eq. (D1).** Taking one lag in eq. (16) and substituting the result into eq. (C10) yields:

\[
\Lambda_{n-1} = \Lambda_n + \frac{\tilde{G} \beta_n \lambda_n}{\theta} [\Lambda_{n-1} + (M - 1) \Omega_{n-1}] .
\]

Since \( \Omega_{n-1} - \Omega_n = \Lambda_{n-1} - \Lambda_n \) [see eq. (17a)],

\[
\Omega_{n-1} = \Omega_n + \frac{\tilde{G} \beta_n \lambda_n}{\theta} (\Lambda_{n-1} - \Omega_{n-1} + M \Omega_{n-1}) = \frac{\theta \Omega_n + \tilde{G} \beta_n \lambda_n (\Lambda_{n-1} - \Omega_{n-1})}{\theta - GM \beta_n \lambda_n}.
\]

By solving for \( \Omega_{n-1} \) we find that

\[
\Omega_{n-1} = \frac{\theta \Omega_n + \tilde{G} \beta_n \lambda_n (\Lambda_{n-1} - \Omega_{n-1})}{\theta - GM \beta_n \lambda_n} . \tag{D2}
\]

Finally,

\[
\Lambda_{n-1} = \Lambda_n + \Omega_{n-1} - \Omega_n = \frac{\theta \Lambda_n - \tilde{G} \beta_n \lambda_n [M (\Lambda_n - \Omega_n) - (\Lambda_{n-1} - \Omega_{n-1})]}{\theta - GM \beta_n \lambda_n} ,
\]

where we have used eq. (D2). Eq. (D1) follows by replacing \( \Lambda_n - \Omega_n = \Lambda_{n-1} - \Omega_{n-1} \) in the previous equation.
References


Figures

Figure 1: Geographical location of traders \((G = 1)\)
All traders are physically located around a circle. Every filled circle represents the signal available at the location of traders. Every trader has \((M - 1)/2\) traders to his left and \((M - 1)/2\) traders to his right. In this particular example, every trader has \(2G = 2\) information linkages. The signal available at the location of trader \(i\) (empty circle) is also observed by one trader on his left and one trader on his right.
Figure 2: Overlapping information sets \((G = 2, M \geq 11)\)

Empty circles denote signals available at the location of a given trader. Filled circles are signals every trader observes on top of the signal available at his location. Left (to empty) signals are signals available at the location of left neighbors, and right (to empty) signals are signals available at the location of right neighbors.
Figure 3: “Double overlap”
Traders on the left semicircle share bits of information with traders on the right semicircle sharing information with trader \# i.
Figure 4: Rat race versus waiting game

The dynamics of volume in a market without information linkages, three informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. The left-hand side panel depicts the dynamics of volume when the correlation amongst all traders’ signals is so low that traders play a waiting game ($\rho = 0.01$). The right-hand side panel depicts the dynamics of volume in the rat race case arising when the initial correlation is high ($\rho = 0.99$).
Figure 5: Volume
The dynamics of (traders) volume in a market with information linkages, seven informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. The left-hand side panel depicts the dynamics of volume when the initial correlation amongst all signals is low ($\rho = 0.10$). The right-hand side panel depicts the dynamics of volume when the initial correlation is high ($\rho = 0.90$). In each panel, we display the dynamics of volume arising when each trader has a number of information linkages equal to $2G$, with $G = 0, 1$ and 2.
Figure 6: Efficiency
Price-discovery in a market with information linkages, seven informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. The left-hand side panel depicts price-discovery patterns arising when the initial correlation amongst all signals is low ($\rho = 0.10$). The right-hand side panel depicts price-discovery patterns arising when the initial correlation is high ($\rho = 0.90$). In each panel, we display price-discovery patterns arising when each trader has a number of information linkages equal to $2G$, with $G = 0, 1$ and 2.
Figure 7: Liquidity
Liquidity in a market with information linkages, seven informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. The left-hand side panel depicts liquidity dynamics arising when the initial correlation amongst all signals is low ($\rho = 0.10$). The right-hand side panel depicts liquidity dynamics arising when the initial correlation is high ($\rho = 0.90$). In each panel, we display liquidity dynamics arising when each trader has a number of information linkages equal to $2G$, with $G = 0, 1$ and 2.
Figure 8: Volatility

Asset return volatility in a market with information linkages, seven informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. The left-hand side panel depicts volatility dynamics arising when the initial correlation amongst all signals is low ($\rho = 0.10$). The right-hand side panel depicts volatility dynamics arising when the initial correlation is high ($\rho = 0.90$). In each panel, we display volatility dynamics arising when each trader has a number of information linkages equal to $2G$, with $G = 0, 1$ and 2.
**Figure 9: Heterogeneity in correlation amongst trades**

Correlation amongst trades in a market with information linkages, seven informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. The left-hand side pictures depict correlation amongst trades arising when the initial correlation amongst all signals is low ($\rho = 0.10$). The left-hand side picture at the top depicts the correlation between two close neighbors (i.e. the correlation between trader $i$ and $i - 1$). The left-hand side picture at the bottom depicts the correlation between two distant traders (i.e. the correlation between trader $i$ and $i - 3$). In each case, we display trades correlation dynamics arising when each trader has a number of information linkages equal to $2G$, with $G = 0, 1$ and 2. The right-hand pictures depict trades correlation dynamics arising when the initial correlation amongst signals is high ($\rho = 0.90$), and are otherwise as the left-hand pictures.
Figure 10: Traders’ welfare
The traders expected profits in a market with seven informed traders, one unit of initial variance of information, one unit of liquidity trader variance across all periods and ten trading rounds. Displayed are the expected profits arising when each trader has a number of information linkages equal to $2G$, with $G = 0, 1$ and $2$; and the initial correlations amongst individual signals equals $\rho = 0.01, 0.1, 0.2, \ldots, 0.9$, and $0.99$. 