EIEF WORKING PAPER SERIES

EIEF

Einaudi Institute for Economics and Finance

EIEF Working Paper 11/10
May 2010

Are Networks Priced?
Network Topology and Order Trading Strategies in High Liquidity Markets

by
Ethan Cohen-Cole
(University of Maryland - College Park)
Andrei Kirilenko
(Commodity Futures Trading Commission)
Eleonora Patacchini
(University of Rome "La Sapienza")

Are Networks Priced? Network Topology and Order Trading Strategies in High Liquidity Markets

Ethan Cohen-Cole*
University of Maryland - College Park

Andrei Kirilenko
Commodity Futures Trading Commission

Eleonora Patacchini
University of Rome - La Sapienza

April 29, 2010

Abstract

Network spillovers explain as much as 90% of the individual variation in returns in a fully electronic market. We study two fully electronic, highly liquid markets, the Dow an S&P 500 e-mini futures markets. Within these markets, we use a unique dataset of realized trades that includes the precise topology of transactions; this topology allows us to identify precisely both the relevance of network structure as well as endogenous network spillovers. Within these markets, we will show that network positioning on the part of trader leads to remarkable spillovers in return. Empirically, we estimate that the implied average multiplier, the ratio of a individual level shock to the total network one, is as large as 20. A gain of $1 for a trader leads to an average of $20 in gains for all traders and much more for connected ones. In a zero-sum market, such as the one in this study, this suggests a very large re-allocation of returns according to network structure.

Keywords: Financial networks, interconnections, network centrality, spatial autoregressive models

JEL Classification: G10, C21

*Ethan Cohen-Cole: Assistant Professor of Finance, Robert H Smith School of Business. 4420 Van Munching Hall, University of Maryland, College Park, MD 20742. email: ecohencole@rhsmith.umd.edu. +1 (301) 541-7227. Andrei Kirilenko: Senior Financial Economist; Commodity Futures Trading Commission; 1155 21st Street, N.W. Washington, DC 20581; tel: +1 (202) 418-5587. email: akirilenko@cftc.gov. Eleonora Patacchini University of Roma La Sapienza. Box 83 Roma 62, P.le A. Moro 5, I-00185 Roma eleonora.patacchini@uniroma1.it; tel: +39-06-44284 200. We are very grateful to Ana Babus, Lauren Cohen, Rod Garratt, Todd Prono, Julio Rotemberg, Jose Scheinkman as well as conference participants at Centre for Financial Analysis and Policy (CFAP) conference on Financial Interconnections. Benjamin Enowitz provided research assistance. All errors are our own.

1 Introduction

Network spillovers can explain as much as 90% of the individual variation in returns in a fully electronic market. We study two fully electronic, highly liquid markets, the Dow and S&P 500 E-mini futures markets. Within these markets, we show that a trader's empirical network positioning is strongly correlated with her returns; that is, the patterns of returns earned by my network 'neighbors' has a direct influence on my own return. From an empirical perspective, the impact is large: a one-standard deviation improvement in one's position is associated with an 450 percentage point larger annualized return. We further estimate that the implied average 'social' multiplier, the ratio of an individual level shock to the total network one, is as large as 20. A gain of $1 for a trader leads to $20 in gains for all traders. This multiplier is an average across all agents; for agents that directly experience the shock it is considerably larger.[1] In a zero-sum market, such as the one in this study, this suggests a very large re-allocation of returns according to network structure.

In our markets, as any other, traders earn returns by buying and selling assets. These returns can potentially be influenced by the implementation of order trading strategies. These strategies consist of buy and sell limit orders. Orders are matched with other orders exclusively by a computer based on the presence of other positions in the limit order book, the aggregation of the orders in place by all other traders in the market. Following the realization of all agents' trades, one observes a defacto empirical network topology. Each trade forms a link (edge) between two traders (nodes) in the network. Of course, this network is conceptually and functionally distinct from widely studied social networks, principally due to the fact that traders in this network have no tangible ability to choose their partners. Indeed, without direct choice over their position in a network, agents optimize profits only by changing their limit orders conditional on similar optimization by all other agents.

Because each set of strategies produces a network topology and these topologies have an empirical relationship to returns, one can use the network topologies themselves to identify the presence of spillovers.

Our methodology proceeds as follows. Because order strategies generate both network topologies and returns, agents must choose strategies cognizant that these choices link them with a set of other agents pursuing complementary ones. A different choice of strategies links a trader with a different set of counterparties. Thus, the only way to determine the Nash equilibrium of this trading game without knowledge of the strategies themselves is to infer payoffs from the resulting network topology.

In short, we will be using the precise empirical topology of realized trades to determine the paths by which returns spillover. This will involve estimating two objects, the role of the network structure, and endogenous spillovers (Manski 1993). The first of these can be thought of as the

[1] The average impact includes a zero effect for agents not connected and a larger one for those connected to the agent that experiences a shock.

benefit or cost to one's network positioning; sit closer to the center and earn more money. The second can be understood as the direct impact of a trading partners' gains or losses on my gains or losses. The joint analysis of these effects will describe the link between network position and profitability.

Specifically, the first object is the output for a weighted Bonacich (1987) centrality measure. The Bonacich provides a specific measure of an agent centrality in the network. As we describe in detail below, we augment the measure by weighting it to reflect a network measure of transaction volume. The second object is what Manski (1993) called endogenous effects. This is a measure of the spillovers from one agent's returns to the returns of others. We will show that our estimation technique explains nearly the entire distribution of returns and thus provides an outstanding proxy for the underlying trading strategies.

For identification, we rely on the nature of our data to provide a couple of benefits. First, Manski's (1993) reflection problem, that one could not identify the linear projection of group-level decisions on individual ones, can be resolved in a number of ways.[2] We use Bramoullé, Djebbari and Fortin's (2009) method of drawing on the specific architecture of trading networks. This technique, applied in Calvo-Armengol, Patacchini, and Zenou (2009), uses the presence of intransitivities in network structure to break the reflection problem. Because we have all realized trades in our database, we can build the full network map and exploit their work. Second, because our data consists of order matched by computer based on price and time priority, there is little opportunity to choose partners. As a result, we can claim exogenous sorting into groups in a fashion akin to freshman roommate selection in Sacerdote (2001).

Our paper extends existing literature on financial networks in that we seek to understand the functional spillovers that emerge out of an equilibrium trading strategy. Others in this space include evaluations of correlations in the collapse of assets prices, such as real estate (Herring and Wachter, 2001), or through contagion propagated through counterparty exposure.[3] Each of these effects would require distinct modeling; however, they are highly unlikely to apply in the case of individual trader's returns in liquid futures markets. Bech, Chapman and Garratt (2010) use empirical network techniques to evaluate the Canadian payment system. The closest to our work in this literature is the model of financial connections that leads to correlated exposures (Allen, Babus and Carletti, 2009) and Babus (2009). Allen and Babus (2009) survey the growing literature on network connections in finance.

The growth in interest in network spillovers in finance stems from an increased recognition that

[2] Brock and Durlauf (2001) use a structural approach to identification, Glaeser, Sacerdote and Scheinkman (1996) use the variance of group average outcomes, and Cohen-Cole (2006) uses the presence of multiple group influence. Each of the latter two were later formalized further by Graham (2008) and Bramoullé, Djebbari and Fortin (2009), respectively. Topa (2001) and Conley and Topa (2002) use spatial clustering techniques to identify spillovers, and De Paula (2005) uses a dynamic model to identify.

[3] Allen and Gale (2000) and Freixas, Parigi and Rochet (2000) provide examples. Adrian and Brunnermeier (2009) provide a mechanism for measuring linked exposures.

economic theory has difficulties in explaining a number of economic phenomena without acknowledging the importance of interdependence between preferences, constraints, and expectations. To capture the strategic behavior in networks, models of social interactions describe individual behavior, outcomes, and characteristics as depending in some fashion on the behavior and the characteristics of other individuals within reference groups. Typically such models assume a non-market mechanism such as a preference for assortative matching. Because we work in financial market context, we do not need to resort to non-market incentives.

Our paper is linked to several finance research agendas. Concerning the presence of spillovers through connected individuals in a financial services context, a number of papers find a role for individual-level link and financial decisions. Kaustia and Knüpfer (2008) find evidence in IPO participation; Kaustia and Knüpfer (2009), Hong, Kubik, and Stein (2004) and Brown, Ivkovich, Smith, and Weisbenner (2008) find a link to stock market participation; Shive (2009) finds interactions in trading activity; Topa, Bayer, and Ross (2009) find a link to workplace choice. Guiso, Sapienza, and Zingales (2004) find a link between social spillovers and financial development. Grinblatt, Keloharju, and Ikäheimo (2008) find interactions in automobile purchases. Mas and Moretti (2009) find that cashiers respond to the speed of co-workers and Cohen-Cole and Duygan-Bump (2009) find individual-level local spillovers in bankruptcy decisions. Cohen, Malloy and Frazzini (2008, 2010) find peer networks in a couple of contexts. Faulkender and Yang (2010) find evidence that peer networks influence executive compensation and Leary and Roberts (2009) find that peers influence corporate financing policy. Each of these emphasizes non-market interactions that influence market prices in some fashion. We focus exclusively on market interactions.

We proceed in Section 2 to describe our data and their institutional features. Section 3 presents the revisitation of a basic asset pricing model that proves useful to our analysis. In Section 4 we explain our methodology. Specifically, we introduce the notation and definitions at the core of our network-based analysis, and discuss the identification of pricing interactions using a network perspective. Section 5 details our empirical model and presents the results. Section 6 concludes with suggestions for future work.

2 Data and Institutional Features

Our data of interest are the actual trades completed on the Chicago Mercantile Exchange (CME) for two contracts, the S&P 500 and Dow futures. The trades we observe are the result or orders placed by traders in these markets. These orders are matched by a trading algorithm implemented by the CME. Using the audit trail-level of detail from the S&P 500 futures market, we uniquely identify two trading accounts for each transaction: one for the broker who booked a buy and the opposite for the broker who booked a sale. For these two markets, First In, First Out (FIFO) is used. FIFO uses price and time as the only criteria for filling an order: all orders at the same price level are filled according to time priority.

Each financial transaction has two parties (e.g., A and B), a direction (buy or sell), a transaction ID number, a time stamp, a quantity, and a price. We have transaction-level data for all regular transactions that took place in August of 2008 for the September 2008 E-mini S&P 500 futures and the Dow futures contracts. The transactions take place during August 2008 during the time when the markets for stocks underlying the S&P 500 Index are open: weekdays between 9:30 a.m. EST and 4:00 p.m EST. Both markets are highly liquid, fully electronic, and have cash-settled contracts traded on the CME GLOBEX trading platform.

Our dataset consists of over 7,224,824 transactions that took place among more than 31,585 trading accounts that belong to 346 brokers. Similarly, the DOW futures dataset consists of 1,163,274 transactions between approximately 7,335 traders.

2.1 Empirically Observed Networks

Because these two markets are characterized by the use of price and time priority alone in determining trading partners, the only phenomenon that generates the appearance of networks is the pattern of trading strategies that probabilistically links traders with each other. From an empirical perspective, we define a trading network as a set of traders engaged in conducting financial transactions within a period of time; the presence of a link is simply a reflection of the ex-post realization of a cleared trade.

The fact that we measure networks empirically by observing the presence of consummated trades, the choice of network time is important. Of course, in using ultra high-frequency data, one must also choose an appropriate sampling frequency in order to maintain important microstructure information but also minimize the effect of market microstructure noise in this data.[4] However, the number of transactions, i.e. the time span within which a network is defined, contains valuable information on the resulting network structure. Indeed, with more time, more transactions are formed and more participants can form accurate beliefs about the valuation of a given asset. An interdependence of expectations and beliefs across traders can result in a more accentuated cross-sectional dependence of their observed returns in more complex transaction network architectures. An assessment of the importance of a traders centrality measure within the network which takes into considerations such interdependencies (see below) thus requires consideration of different levels of network architecture complexity. Throughout, we will use a range of densities in order to ensure that our results are robust to this choice.

Empirically, we construct trading networks as follows. At 9:30:00 a.m EST on August 1, 2008, we start counting transactions in the September 2008 E-mini S&P 500 futures contract. For each transaction, we know the account identity for buyer and seller as well as the price of the transaction and the quantity changing hands. We designate a sequence of consecutive transactions as one period. For example, transactions 1 through 1000 mark the first period, transactions 1001-2000

[4] Adamic et al (2009) for a discussed on this issue CME data.

mark the second period, and so on. While for each period, we do not observe the limit order book itself, we know that transactions occurred because market orders or limit orders were matched with existing orders in the limit order book. We can then trace the pattern of order execution or a trading network within each period. Even though the number of transactions for each period is the same, a pattern for a large market order executed over the period will look very different compared to a pattern for several smaller limit orders. Metrics that we compute for each network should be interpreted as quantitative measures of the pattern of order execution in the limit order book.

Mathematically, a trading network can be represented as a graph $g \equiv g(N, L)$, in which the $N = \{1, \ldots, n\}$ nodes (or vertices) represent the traders involved and the set of links, L, expresses the financial transactions among them. The $N-$square adjacency matrix $\mathbf{G}(g) = \{g_{ij}\}$ of a network g (we will write $\mathbf{G}$ where there is no ambiguity), keeps track of the direct connections in the network g. Here $g_{ij} = 1$ if trader i and j have concluded a transaction during a period of time, and $g_{ij} = 0$, otherwise.

In the language of graph theory, in a directed graph, a link (edge) has two distinct ends: a head and a tail. Each end is counted separately. The sum of head endpoints count toward the indegree and the sum of tail endpoints count toward the outdegree. We can thus construct two types of directed networks, one based on indegrees and the other based on outdegrees. Formally, in our context a definition of networks based on indegrees would imply an adjacency matrix $\mathbf{G}(g) = \left\{g_{ij}^{+}\right\}$, where $g_{ij}^{+} = 1$ represents a sale of a futures contract from trader j to trader i and $g_{ij} = 0$, otherwise; whereas a definition of networks based on outdegrees implies an adjacency matrix $\mathbf{G}(g) = \left\{g_{ij}^{-}\right\}$, where $g_{ij}^{-} = 1$ represents a sale of a futures contract from trader i to trader j and $g_{ij} = 0$, otherwise. By definition, while in undirected networks the adjacency matrix $\mathbf{G}$ is symmetric, in directed networks it is asymmetric. We focus on the undirected case only.

We define returns for an individual trader as one of two values. In the case that a trader both opens and closes a position during a single time period, we assign the trader returns equal to the actual realized gains and losses from that time period. If the trader maintains an open positions, either a long or a short, until the end of the time period, we mark the position to market in order to calculate his or her period specific returns.

We show in Table 1 some sample statistics of the data for each of the two markets that we analyze. For each definition of networks, we compute returns for each trader, volumes for each trader as well as the variance of returns across traders.

3 The Empirical Model

Our core question is now whether the presence of networks impacts trader level idiosyncratic returns. Our claim is that idiosyncratic returns are a function of the trading network that emerges from an equilibrium set of interlinked trading strategies. In other words, we would like to investigate whether the returns of traders i and j in a given network are correlated:

$$Er_{it}r_{jt} \neq 0$$

If returns are correlated, and traders are not subject to other idiosyncratic shocks, one can describe the distribution of returns using the topology of the resultant network.

More precisely, assume that there are K networks in the economy, each of them connecting n_κ different agents, $\sum_{\kappa=1}^{K} n_\kappa = N$.

Consider the following model:

$$r_{i,\kappa} = \alpha + \theta \sum_{j=1}^{n_\kappa} g_{ij,\kappa} r_{j,\kappa} + v_{i,\kappa}, \qquad \text{for } i = 1, ..., n_\kappa \ ; \ \kappa = 1, ..., K. \tag{1}$$

where $r_{i,\kappa}$ is the idiosyncratic return of trader i in the network k, $\sum_{j=1}^{n_\kappa} g_{ij,\kappa} r_{j,\kappa}$ is the spatial lag term and $v_{i,k}$ is a random error term. Observe that in this expression, α can be used as a short-hand for $\sum_{m=1}^{M} \beta^m x_{i,\kappa}^m$, where $x_{i,\kappa}^m$ is a set of M control variables at the individual and/or network level and including a constant term. This model is the so-called *spatial lag model* in the spatial econometric literature (see, e.g. Anselin 1988).

Because of the typical simultaneity problem in dealing with spatial lag models,[5] which yields inconsistent OLS estimators, we use Maximum Likelihood (see Anselin, 1988).

The estimate of θ will capture the level of correlation in the idiosyncratic returns, over and above the effects due to the (individual and network) characteristics included in the set $x_{i,\kappa}^m$.

3.1 Weighted Bonacich Centrality

We begin by presenting an adaptation of a network centrality measure originally due to Katz (1953), and later extended by Bonacich (1987), suited to financial markets.

Let the matrix $\mathbf{W} = \mathbf{GD}$, where $\mathbf{G}$ is as defined above and $\mathbf{D} = \{d_{ij}\}$ is a matrix the weights the links within the network. The scalar d_{ij} is a scaling factor, calculated as the total trading volume in the same trading period of each i and j. Total trading volume is defined as the sum of all trades, both buys and sells, made by trader i with all other traders. As a result, $\mathbf{W} = \{w_{ij}\}$ represents now a weighted network w. An example of how we construct this measure is in figure 2. In the original Bonacich (1987) paper, $\mathbf{W} = \mathbf{G}$, i.e. the centrality measure is presented for unweighted networks. However, all the techniques apply to the weighted network case (see Newman, 2004, for a discussion).[6]

[5] This stems from the fact that the spatial lag term contains the dependent variable for neighboring observations, which in turn contains the spatial lag for their neighbors, and so on, leading to a nonzero correlation between the spatial lag and the error terms.

[6] Only the interpretation differs, as we will discuss in Section 5.1.

Given a small-enough scalar $\theta \geq 0$, one can define the matrix

$$\mathbf{M}(w, \theta) = [\mathbf{I} - \theta\, \mathbf{W}]^{-1} = \sum_{k=0}^{+\infty} \theta^k \mathbf{W}^k \tag{2}$$

where the parameter θ is a decay factor that scales down the relative weight of longer paths. Provided the matrix $\mathbf{M}(w, \theta)$ is non-negative, its coefficients $m_{ij}(w, \theta,)$ count the number of paths in w starting at i and ending at j, where paths of length k are weighted by θ^k. It turns out that an exact strict upper bound for the scalar θ is given by the inverse of the largest eigenvalue of $\mathbf{W}$ (Debreu and Herstein, 1953). In a row-standardized matrix, the largest eigenvalue is 1. Let us then use a row-standardized $\mathbf{W}$ matrix and take $|\theta| < 1$, so that expression is well-defined (i.e. the infinite sum converges). Let $\mathbf{1}$ be the $n-$dimensional vector of ones.

Definition 1 *Consider a network w with adjacency $N-$square matrix $\mathbf{W}$ and a scalar θ such that $\mathbf{M}(w, \theta) = [\mathbf{I} - \theta\, \mathbf{W}]^{-1}$ is well-defined and non-negative. The vector of centralities of parameter θ in g is:*

$$\mathbf{b}(w, \theta) = [\mathbf{I} - \theta\, \mathbf{W}]^{-1} \cdot \mathbf{1}. \tag{3}$$

The centrality of node i is thus $b_i(w, \theta) = \sum_{j=1}^{n} m_{ij}(w, \theta)$, and counts the total number of paths in g starting from i. It is the sum of all loops $m_{ii}(w, \theta)$ starting from i and ending at i, and all outer paths $\sum_{j \neq i} m_{ij}(w, \theta)$ that connect i to every other player $j \neq i$, that is:

$$b_i(w, \theta) = m_{ii}(w, \theta) + \sum_{j \neq i} m_{ij}(w, \theta).$$

By definition, $m_{ii}(w, \theta) \geq 1$, and thus $b_i(w, \theta) \geq 1$, with equality when $\theta = 0$.

Our modification is to adapt the Bonacich centrality measure to better capture the role of a trader's role in a financial network. Large traders are large due to the nature of their order strategy; weighting by volume allows us to capture a feature of the otherwise unobserved strategy. We will show below that because this measure maintains the form of the original Bonacich measure, we can use existing methods for estimation and interpretation.

3.2 Interpretation

For ease of interpretation, let us write model (1) in matrix notation:

$$\mathbf{r} = \alpha \boldsymbol{\iota} + \theta \mathbf{W} \mathbf{r} + \gamma \mathbf{x} + \delta \mathbf{W} \mathbf{x} + \boldsymbol{\epsilon}, \qquad E\left[\boldsymbol{\epsilon} | \mathbf{x}\right] = 0 \tag{4}$$

where $\mathbf{r}$ is a $N \times 1$ vector of returns of N traders, $\mathbf{x}$ is a $N \times M$ matrix of M variables that may influence individual behavior but are not related to networks, $\mathbf{W}$ is the row standardized $N \times N$ adjacency matrix from above that formalizes the network structure of the agents, $\boldsymbol{\iota}$ is a $N \times 1$ vector of ones and $\boldsymbol{\epsilon}$ is a $N \times 1$ vector of error terms, which are uncorrelated with the regressors.

If one solves for $\mathbf{r}$ in model (4), the result is a reduced form relationship under the assumption that $|\theta| < 1$:

$$\mathbf{r} = \alpha \left[\mathbf{I} - \theta\mathbf{W}\right]^{-1} \boldsymbol{\iota} + \left[\mathbf{I} - \boldsymbol{\theta}\mathbf{W}\right]^{-\mathbf{1}} \left[\boldsymbol{\gamma}\mathbf{I} - \boldsymbol{\delta}\mathbf{W}\right] \mathbf{x} + \left[\mathbf{I} - \boldsymbol{\theta}\mathbf{W}\right]^{-\mathbf{1}} \boldsymbol{\epsilon} \tag{5}$$

Considering equation (3), it is now apparent that the estimate of the intercept of model (5), $\widehat{\alpha}$, will capture the effect of the individual position within a network (measured by the weighted centrality measure) in shaping returns. When $\mathbf{W}$ is constructed while taking into account total trade volume, $\widehat{\alpha}$ estimates the impact of our centrality measure, thus yielding an assessment of the link between network position and profitability in a financial network.

3.3 Estimation issues

The aim of our empirical analysis is to assess whether and to what extent network structure matters in shaping individual returns. Because, as explained before, such an influence can be affected by the level of network interactions, i.e. the weighted centrality measure is not parameter-free, we need to offer a credible identification strategy for the strength of network effects (i.e. for θ) in financial networks. We turn to this now. Recall from above that θ is a measure of the marginal change in returns trader i receives as a function of the average returns of her trading partners.

An empirical assessment of network effects is quite problematic because of well-known issues that render the identification and measurement of such effects quite difficult: (i) reflection, which is a particular case of simultaneity (Manski, 1993) and (ii) endogeneity, which may arise for both network self-selection and unobserved common (group) correlated effects.

The main novel feature of our estimation with respect to previous works is the use of the architecture of networks to evaluate network effects. Let us explain this more clearly.

Reflection As many starting with Manski (1993) have observed, the coefficients of equation (4) cannot be estimated from OLS if $\mathbf{W}$ is a complete network. This is called the reflection problem. This arises from the fact that if we calculate the expected mean outcome of the group, then the expectation of $\mathbf{r}$ will appear on both sides of the equation. This generates a particular type of endogeneity problem. That is, the expected mean outcome is perfectly collinear with the mean background of the group

$$E(\mathbf{Wr}|\mathbf{x}) = \alpha/(1 - \beta)\boldsymbol{\iota} + (\gamma + \delta)/(1 - \beta)\mathbf{Wx} \tag{6}$$

This leads to a loss of a degree of freedom because we now have only two regressors to identify three structural parameters. Thus, identification fails. To obtain an estimate of the additional parameter, one needs a method to break the reflection problem.

That is, how can we distinguish between trader $i's$ impact on j and $j's$ impact on i? Effectively, we need to find an instrument: a variable that is correlated with the behavior of i but not j.

Bramoullé, Djebbari and Fortin (2009) noticed that in incomplete networks, one observes 'intransitivities.' These are connections that lead from i to j then to k, but not from k to i. Thus, we can use the partial correlation in behavior between i and j as an instrument for the influence of j on k. Because there are no connections between k and i, these are valid instruments by construction. That is, network effects are identified if we can find two agents in the economy that differ in the average connectivity of their direct contacts. A formal proof is in Bramoullé, Djebbari and Fortin (2009). Of course, in a complex trading network such as the one we are concerned with, $\mathbf{W}$ has a very rich structure and identification never fails. Thus, using the architecture of networks we can obtain estimates of our full vector of relevant structural parameters: $[\alpha\ \theta\ \gamma\ \delta]$.

Correlated effects Although this setting allows us to solve the reflection problem, the estimation results might still be flawed because it is difficult to disentangle endogenous network effects from correlated effects, i.e. from effects arising from the fact that agents in the same group tend to behave similarly because they face a common environment or common shocks. These are typically unobserved factors. For example, traders with similar training, that sit in similar rooms or use trading screens that show different types of data, may be influenced in their trading patterns in ways that generate correlations in returns. The point is that we could potentially interpret those effects as network effects if the correlations lay along similar network lines as the observed trades. While we believe this to be very unlikely, we can control for these unobserved effects by re-estimating our results after taking deviations in returns with respect to the group-specific means, i.e. from the average returns of trading partners in the prior trading period. Of course, our primary specification already nets out market level returns by virtue of the fact that aggregate market levels returns are zero. In this case, we also control for group-level unobserved heterogenerity. We will show below in the robustness section that this change is not relevant to our results.

Self-selection If individuals are not randomly assigned into groups, this problem might originate from the possible sorting of agents. Given our definition of networks based on high-frequency data, we have no reason to believe that any selection effects exist in this context. Agents are assigned to trading partners as we described above, based on time and price priority. As such, we have a plausible claim that individuals cannot choose their network partners and thus no selection effects should be present.

4 Results

One can observe two phenomena in our results. For each specification, we estimate two key coefficients. As mentioned above, we obtain estimates of two key coefficients. The first, α, indicates the role of network structure. This term reflects the importance of network position on individual level returns. Better positioning in the network, as measured by weighted Bonacich centrality, leads to increased returns. We find that a one standard deviation improvement in positioning is associated with an approximately two percentage point increase in daily returns. As shown above, such an impact also depends on the strength of network interactions that stems from the network architecture. This is the our second parameter of interest, θ. It measures the spillover in returns. This measures the impact that an increase in a single trader's return has on his trading partner's returns. We find a very, very large spillover. Indeed, we find that a single dollar increase in returns leads to 5-20 additional dollars earned by the traders' neighbors. This ratio 5/1, which measures the ratio of total network outcome over an individual level shock is often referred to as the social multiplier. For a complete network, it can be calculated as $1/(1-\theta)$. Since θ in our results ranges from approximately .8-.95, the average social multiplier for all agents in the network ranges from approximately 5 to 20. For directly connected agents, the multiplier is much larger. Of course, because futures markets are zero-sum, local spillovers in returns imply re-allocations rather than aggregate increases.

We begin by grounding our claims using the results reported in Table 2. Table 2 has the following structure. Panel A shows the primary results from the S&P 500 futures market. Panel B shows the results from the Dow futures market. Each of the two panels shows three ranges of results, which are obtained by estimating model (1) for different levels of network structure complexity. Each column thus shows the results from sparse, moderately dense and dense networks, respectively. For each type of network in each market, we estimate 21 days of results and report the range of estimation results and t-stats across these time periods. The first and second rows of each panel shows the estimates of the constant term, α, and of the extent of the spillover effects, θ, respectively. The third row shows the adjusted R squared from each specification.

We can view the day-by-day results as well in Table 4. Each row of this table shows the estimation results for each day. The extent of the spillover effects are plotted in Figure 4. Each point of Figure 4 below shows the coefficient estimate of θ in equation (1) above. The horizontal axis displays the trading day for the month of August 2008, numbered sequentially from 1 to 21. Each of the 21 estimated coefficients are thus obtained from a single day of transaction data. The solid (red) line shows the results from the S&P sparse network data, the dotted (green) line shows the S&P moderate network data and the marked (blue) line the dense network data. As should be apparent, the results are largely consistent across trading days and across network definition.

In Figures 5 and 6 we show the empirical distribution of networks. Figure 5 shows three plots, one each for sparse, moderate and dense networks. For each day of data in each network, we sub-divide the day into 10 time periods and estimate our model on this sample. The plot shows the distribution of networks by the estimated strength of interactions, θ . Dense network coefficient densities are shown in black, moderate in grey and sparse in white. Figure 6 shows the corresponding distribution based on the adjusted R2 statistics.

Regardless of the density of network structure, our estimates of θ are strongly and always statistically significant pointing towards the existence of a cross-sectional dependence of returns that is not explicitly mediated by the market. Such a pattern is consistent with the existence of interdependent preferences, expectations and beliefs of the traders embedded in a given transaction network. As conjectured before, when the network architecture gets richer and traders have more time to form accurate beliefs about the valuation of the asset, the effects are more pronounced in our data. Our estimates of θs are in fact increasing in magnitude as networks get more complex. Looking at our results within network type, our estimates are remarkably consistent in magnitude within each network type.

Our estimates of α, which capture the impact of the individual position within a given transaction network in shaping returns, also appear statistically significant in every network architecture. This evidence indicates that network centrality is a relevant (and so far unnoticed) factor that plays a role in explaining the cross-sectional variation of returns.

The specifications in Table 2 (and Table 4) explain more than 80% of the variation of individual level returns in the Dow futures market and more than 90% of the variation in the S&P futures market. These results are consistent across the density of network structure.

Networks thus appear as an important determinant of pricing that acts through two different but strictly related channels. First, networks intermediate interdependent expectations and beliefs which spillover into returns. Secondly, such spillovers differs according to the network structure. As a result, the centrality measure that depends on both network topology and on the extent of such effects is found to capture a relevant portion of the observed cross-sectional variation in returns.

5 Robustness checks

5.1 Weighted vs Unweighted networks

Let us compare the explanatory power of our model specification based on a weighted network scheme with respect to the one of a traditional unweighted network definition (i.e. no weights, $\mathbf{W} = \mathbf{G}$). This is helpful in isolating the impact of our weighting scheme and allows us to provide an interpretation of our modification of the traditional (unweighted) Bonacich centrality measure in financial markets. We thus run our estimation using the same model (1) on identical data using an unweighted network topology definition.

The results for this exercise are in Table 3. Confirming the work in Ballester, Calvo-Armengol and Zenou (2006), we find strong results for the role of network structure. The network structure coefficients range from .79 to over 0.9, suggesting that being central in a trading network is very important. On its own, this would suggest a role similar to those found in social contexts. The adjusted R-squared for these specifications range from 4-45%. Indeed, in social contexts, explaining 4-45% of the extant variation would be remarkable. However, once we apply our weighted network measure, we are able to explain an even greater fraction of the distribution of returns.

In comparison to the weighted network results (Table 2), we find two key differences. First, our specification based on weighted networks explains more of 90% of the variation in returns. Second, the estimate of the spillover effect, θ, in the weighted results is much larger, implying an average social multiplier of 5-20 instead of 1-2 for the unweighted case.

The key difference between the two tables is the weighting network scheme based on trading volume. Going back to the definition of Bonacich centrality (3), one can notice that the parameter θ captures the relative importance of local and global network structure. Small values of θ heavily weight the local structure, while large values take into account the position of agents in the structure as a whole (Bonacich, 1987). In social networks, where typically a social network is defined by using information on pure contacts between agents, the local structure, i.e. the number of direct ties, is typically crucial to measure centrality. In our context, however, not only the quantity but also the quality of contacts can be of fundamental importance. In other words, by using a weighted measure using trading volume we allow for the possibility that a trader is highly central even if she/he is connected to few others with high trading volumes (which in turn engage in highly volume transactions, and so on...). Under this circumstance, the global network structure may play the most relevant role. Our results, showing a drastically larger explicative power of the specification based on weighted networks, suggest that an unweighted network definition can be inappropriate in our context.

As we discussed above, our data show only the realized trade network structure that occurs as a result of the pattern of trading strategies. Ideally we would have a measure of the trading strategies themselves. Trading volumes are part of such strategies. As a result, the use of a network link weighting scheme by volume permits an outstanding proxy for the underlying trading strategies.

5.2 Control Variables

Our next exercise checks the sensitivity of our results when including control variables in our specification (i.e. values for the $\mathbf{x}$ variables in model (4)). In this context, there is little information on appropriate control variables or theory to guide what variables should be included. However, in light of our results in the previous section , in Table 6, we estimate model (4) using an unweighted network scheme (i.e. no weights, $\mathbf{W} = \mathbf{G}$) and including volume as a control variable. We find little differences between these results and the results in Table 3 that used an unweighted network scheme but did not include volume as a control. Our interpretation is consequently that volume serves as an effective proxy for order strategies only when included as part of the network structure definition. That is, it helps explain returns indirectly via its impact on the role of network structure, but does not directly explain differences in returns.

Nonetheless, we have little reason to believe that individual level control variables will have any impact in an electronic market of this sort. Our intuition as to why our weighting network scheme generates differences in explanatory power but the addition of trading volume as a regressor does not is precisely that an automated intermediary will prevent individual level differences from driving profits. However, the nature and frequency of interconnections provides a potential mapping to the order strategies that do indeed differentiate returns.

5.3 Levels vs Deviations in Returns

Finally, in order to control for additional group-level variations that may not be captured in our primary model specification, we re-estimate model (4) after re-calculating returns. Our new measure of returns is the deviation of individual returns from traders' group-level average return. Group-level average return are calculated as the average returns of trading partners in the prior trading period. Results are in Table 5 and illustrate very small differences from those in Table 2 (results on levels).

These results are useful for a couple of reasons. First, the market that we are discussing is a zero-sum one; benefits to a given individual are necessary reflected in losses to another. As a result, complementarities in returns must necessarily be reflected in losses elsewhere in the network. By estimating our results in deviations from average level returns for an individuals own 'network,' we sidestep this issue. In deviations, complementarities will no longer be reflected elsewhere in the network structure and we can consequently directly interpret our spillover effects.

Second, as mentioned in Section 3.3 estimating our results in deviations allows us to screen for potential unobserved contextual effects. That is, if agents in a given empirically observed network have some similarity that leads them to earn higher returns as a group, we will average out this group-level effect and look only for the presence of spillovers. That said, there is little reason to believe that in an electronically matched market one would observe any type of contextual effects.

5.4 Discussion: why would individual returns be correlated?

We propose a couple of reasons why individual returns would be correlated via interdependent trading strategies. We explain one such pattern here. Consider the presence of two large traders that have fundamental liquidity demands, one positive and one negative. A distinct set of traders implements rapid offers to buy and sell. The combination of these trades will generate a diamond-shaped network pattern illustrated in Figure 1, Panel a. As the agents in the center line of diamond earn excess returns, a new set of trading strategies can emerge. Figure 1, Panel b shows the emergence of additional agents that capitalize on the opportunities shown in 1a.

As should be apparent, in this network, position is particularly important. Indeed, sitting along the center line of the diamond will yield profits through intermediation of fundamental liquidity needs. Consequently, a potential trading strategy would be to look for large orders that indicate a liquidity need and to intermediate these orders with other that have off-setting needs. To ensure that the two offsetting needs are not themselves matched, a very fast trader, typically a computer, can ensure that his order is the one matched. However, we can neither observe the strategy itself nor the response time of traders. As a result, we wish to observe ex-post patterns of trading that would help infer the strategies.

Let us provide more intuition on our results. Our analysis starts from a simple observation: the collection of trading relationships constitutes a network. At each point in time, each agent chooses an order strategy to maximize her payoff. For network connected agents, however, payoffs are interdependent. Although the payoff interdependence is such that each agent only cares about the behavior of her direct partners, in equilibrium each agent has to anticipate the actual behavior of her partners to take on an optimal action herself. Because the network we model here is based on a matching algorithm, partners are chosen based solely on the order strategy used. For these reason, in equilibrium, when agents choose their levels of activity simultaneously, individual decisions emanate from all the existing network chains of direct and indirect contacts stemming from each agent. The exact mapping between network location and equilibrium outcome is thus more intricate than simply counting direct network links, and also requires to account for indirect network links.

6 Conclusions

We have provided a methodology for the estimation of network influences in financial markets. Using our proposed centrality measure on these two markets, we have explained nearly all of the individual level variation in returns. The implication of this finding is that the pattern of traders in a fully electronic market has enormous salience.

One of our results is that individual level shocks are greatly amplified and spread in these markets. A one unit change in individual level returns can be amplified more than 20 times. This implies very rapid propagation of shocks and little ability to avoid contagion. Because these results are a function of the network structure, these results point policymakers in the direction of potential interventions. Notice that the rapid spread and amplification derives from the network structure; adjust the structure and adjust the speed of spillovers. This points towards interventions in the matching algorithm, potentially during times of anticipated crisis.

A long literature in sociology and economics would suggest that network patterns are important in non-market interactions based on a variety of plausible mechanisms. These include social stigma, information sharing, peer pressure, and more. The difficulty in translation of the methodologies developed in the social science to financial markets, particularly electronic ones, is that there is little basis to believe that any of the mechanisms are at work. Orders are matched at random by a computer based on time and price priority, leaving little room for social impact even if traders had a motivation to do so.

Thus, our conclusions are statements about the empirical importance of the networks that emerge as a result of equilibrium order strategies. We find that these strategies not only lead to networks of note, but that an empirical mapping of the networks to returns shows important effects.

References

[1] Adamic, L, C. Brunetti, J. Harris, and A. Kirilenko. 2009, "On the Informational Properties of Trading Networks" Commodity Futures Trading Commission, mimeo.

[2] Adrian, T., and M. Brunnermeier, 2009, "CoVaR," Federal Reserve Bank of New York, mimeo.

[3] Allen, F., and A. Babus, 2009, "Networks in Finance," in The Network Challenge, edited by P. Kleindorfer and J. Wind, Wharton School Publishing, 367-382.

[4] Allen, F, A. Babus and E. Carletti, 2009, "Financial Connections and Systemic Risk" University of Pennsylvania

[5] Allen, F., and D. Gale, 2000, "Financial Contagion," Journal of Political Economy 108,1-33.

[6] Anselin, L. (1988), *Spatial Econometrics: Methods and Models* (Boston: Kluwer Academic Publishers).

[7] Babus, A. (2009). "Strategic Relationships in OTC Markets"

[8] Ballester, C., A. Calvo-Armengol, A. and Y. Zenou, 2006, "Who's Who in Networks. Wanted: The Key Player", Econometrica, 74, 1403-1417.

[9] Bech, M., J. Chapman, and R. Garratt (2010), "Which Bank Is the "Central" Bank? An Application of Markov Theory to the Canadian Large Value Transfer System," Journal of Monetary Economics, forthcoming.

[10] Bonacich, P. (1987), "Power and Centrality: A Family of Measures", American Journal of Sociology, 92, 1170-1182.

[11] Bramoullé, Y., H. Djebbari, and B. Fortin, 2009, "Identification of Peer Effects through Social Networks," Journal of Econometrics, 150(1), 41-55.

[12] Brock, W. and S. Durlauf, 2001, "Discrete Choice With Social Interactions," Review of Economic Studies 68(2): 235–60.

[13] Brown, J., Ivkovich, Z., Smith, P., Weisbenner, S., 2008, "Neighbors Matter: Causal Community Effects and Stock Market Participation." Journal of Finance, LXII: 1509-1531.

[14] Calvo-Armengol, A., E. Patacchini, and Y. Zenou, 2009, "Peer Effects and Social Networks in Education," Review of Economic Studies, 76, 1239-1267.

[15] Cohen, L., C.Malloy, and A. Frazzini, 2010. "Sell Side School Ties." Journal of Finance, forthcoming

[16] Cohen, L., A. Frazzini, and C. Malloy. 2008. "The Small World of Investing: Board Connections and Mutual Fund Returns." Journal of Political Economy 116(5), 951-979.

[17] Cohen-Cole, E., 2006, "Multiple Groups Identification in the Linear-in-Means Model," Economics Letters 92(2), 753–58.

[18] Cohen-Cole, E. and B. Duygan-Bump, 2009, "$10,000 bills on the table: Social Influence and Choosing Not to File for Bankruptcy." University of Maryland - College Park, mimeo.

[19] Cohen-Cole, E. and G. Zanella, 2008, "Unpacking Social Interactions," Economic Inquiry 46(1), 19–24.

[20] Conley, T. and G. Topa, 2002, "Socio-economic Distance and Spatial Patterns in Unemployment" Journal of Applied Econometrics, 17 (4), 303-327.

[21] Debreu, G. and Herstein, I.N. (1953), "Nonnegative Square Matrices", Econometrica, 21, 597-607.

[22] De Paula, A. 2009. "Inference in a Synchronization Game with Social Interactions" Journal of Econometrics, 148(1), 56-71.

[23] Durlauf, S. 2004 "Neighborhood Effects" in: J. V. Henderson&J. F. Thisse (ed.), Handbook of Regional and Urban Economics, 1(4), chapter 50, 2173-2242.

[24] Faulkender, M and J Yang ""Inside the Black Box: The Role and Composition of Compensation Peer Groups" Journal of Financial Economics forthcoming

[25] Freixas, X., B. Parigi, and J. Rochet, 2000, "Systemic Risk, Interbank Relations and Liquidity Provision by the Central Bank," Journal of Money, Credit and Banking 32, 611-638.

[26] Glaeser, E., B. Sacerdote and J. Scheinkman, 1996, "Crime and Social Interactions," Quarterly Journal of Economics, CXI, 507–548.

[27] Glaeser, E., B. Sacerdote and J. Scheinkman, 2003, "The Social Multiplier," Journal of the European Economic Association, 1(2-3), 345-353.

[28] Graham, B., 2008, "Identifying Social Interactions through Conditional Variance Restrictions" Econometrica 76(3): 643-660.

[29] Grinblatt, M. and M. Keloharju, 2001, "How Distance, Language and Culture Influence Stockholdings and Trades", Journal of Finance 56, 1053-1073.

[30] Grinblatt, M., M. Keloharju, and S. Ikäheimo, 2008, "Social Influence and Consumption: Evidence from the Automobile Purchases of Neighbors", Review of Economics and Statistics 90, 735-753.

[31] Herring, R. and S. Wachter, 2001, "Real Estate Booms and Banking Busts: An International Perspective," University of Pennsylvania, mimeo.

[32] Jackson, M. and A. Wolinsky, 1996, "A Strategic Model of Social and Economic Networks," Journal of Economic Theory 71, 44-74.

[33] Katz, L. (1953), "A New Status Index Derived from Sociometric Analysis", Psychometrika, 18, 39-43.

[34] Kaustia, M. and S. Knüpfer, 2008, "Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions", Journal of Finance 63, 2679-2702.

[35] Kaustia, M. and S. Knüpfer, 2009, "Learning from the outcomes of others: Stock market experiences of local peers and new investors' market entry" Finnish School of Economics, mimeo.

[36] Leary, M. and M. Roberts, 2009, "Do Peer Firms Affect Corporate Financial Policy" University of Pennsylvania, mimeo.

[37] Manski, C., 1993, "Identifications of Endogenous Social Effects: The Refection Problem," Review of Economic Studies, 60: 531–42.

[38] Newman, M., 2004, "Analysis of weighted networks" Physical Review E 70.

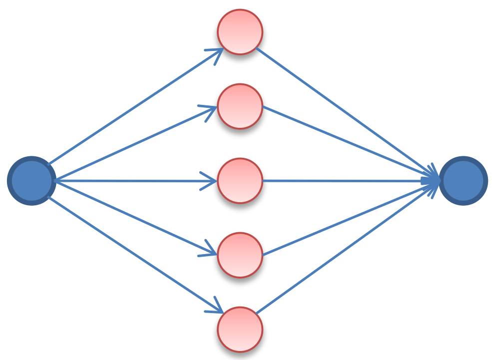
[39] Sacerdote, B., 2001, "Peer Effects With Random Assignment: Results for Dartmouth Roommates." Quarterly Journal of Economics, 116(2), 681-704.

[40] Shive, S., 2009, "An Epidemic Model of Investor Behavior", Journal of Financial and Quantitative Analysis, Forthcoming.

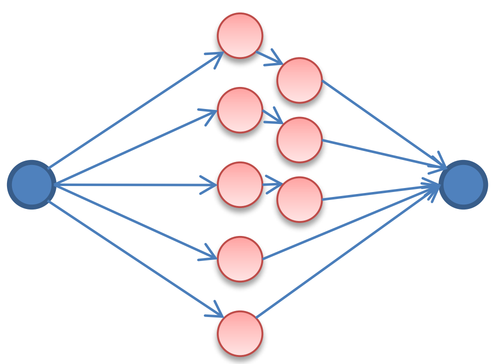
[41] Topa, G., 2002, "Social Interactions, Local Spillovers and Unemployment" Review of Economic Studies 68(2), 261-95.

Figure 1

Panel A

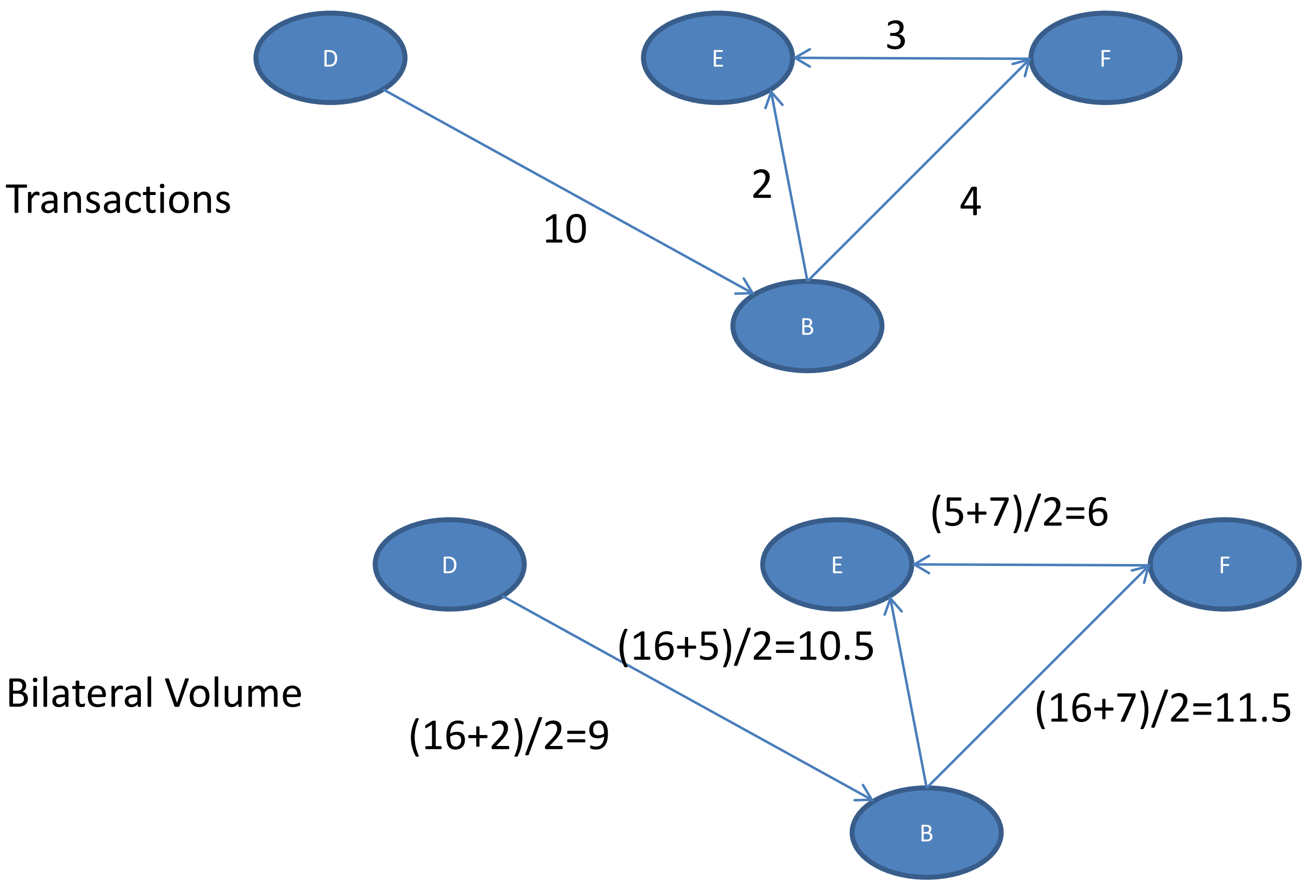


Panel B



note: Panel A shows two agents with fundamental liquidity needs, marked A and B, and a series of agents that have traded with them. Each edge is marked as an arrow, pointing from the seller to the buyer. Panel B shows the same configuration with the addition of a few additional agents.

Figure 2



note: Panel A shows two agents with fundamental liquidity needs, marked A and B, and a series of agents that have traded with them. Each edge is marked as an arrow, pointing from the seller to the buyer. Panel B shows the same configuration with the addition of a few additional agents.

Figure 3

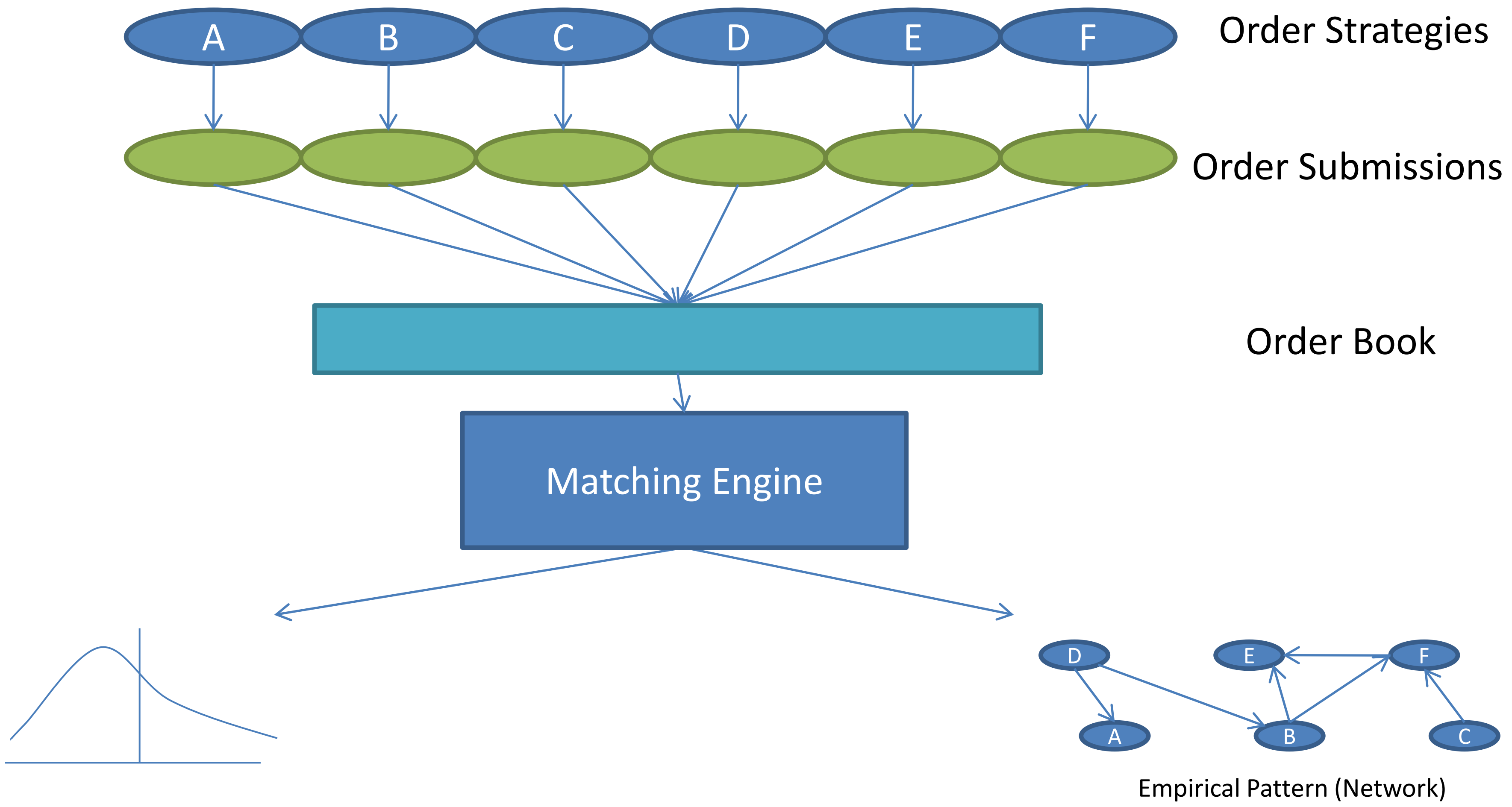
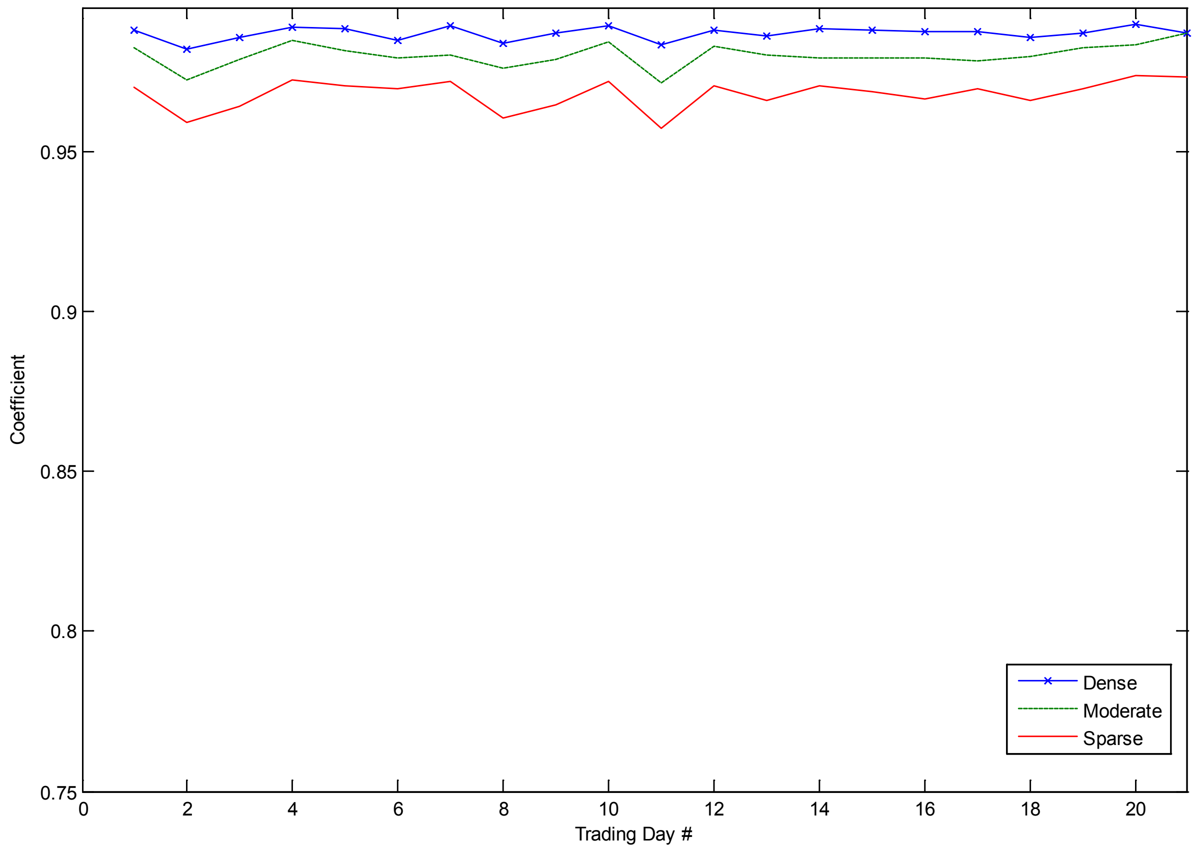
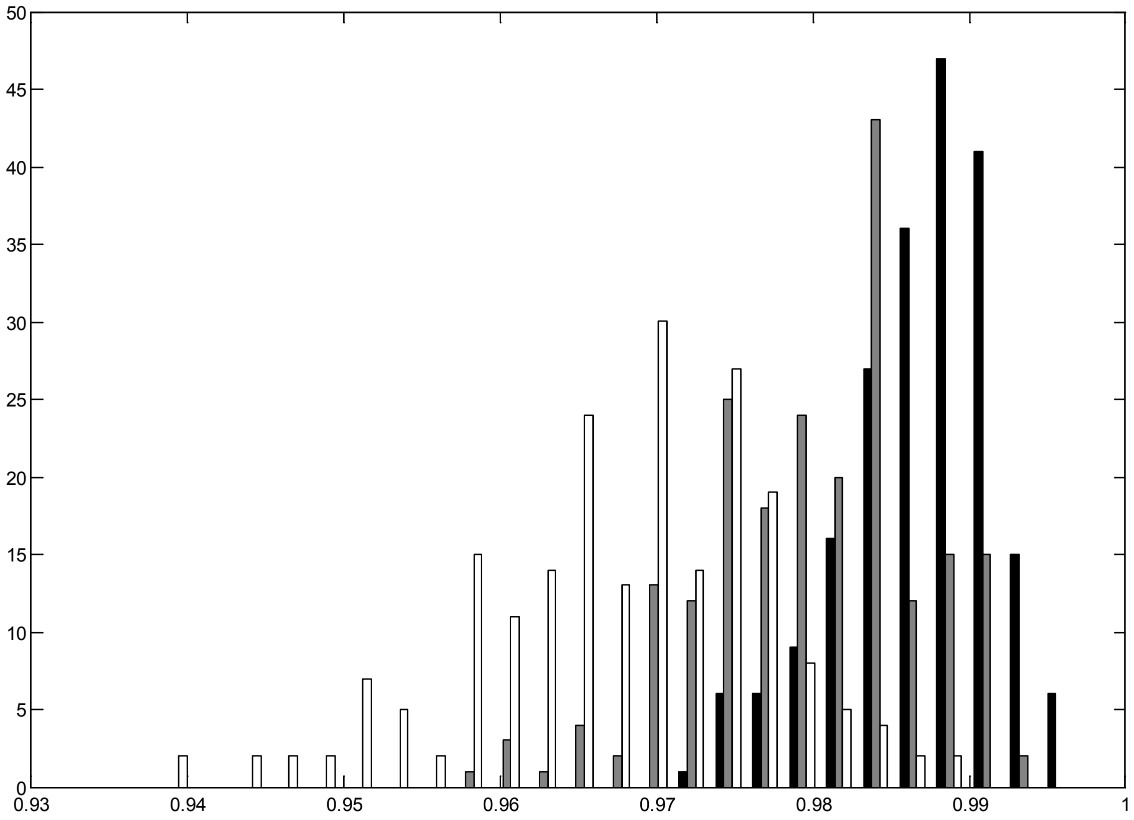

A
B
C
D
E
F
Order Strategies
Order Submissions
Order Book
Matching Engine
D
E
F
A
B
C
Empirical Pattern (Network)

Figure 4: Network Spillovers effects



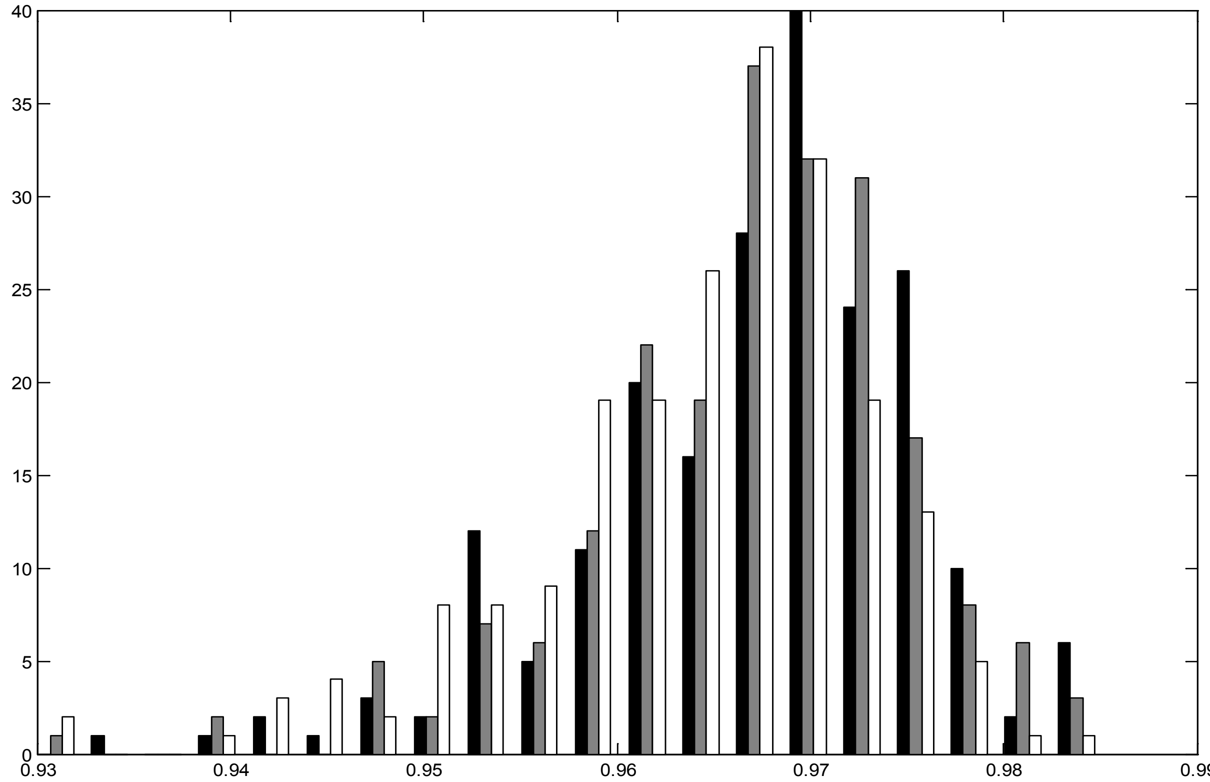
Note: Each point shows the coefficient estimate of the θ parametr in model (1) from a single day of transaction data (21 trading days). The solid (red) line shows the results from the S&P sparse network data, the dotted (green) line shows the S&P moderate network data and the marked (blue) line the dense network data.

Figure 5: Empirical Distribution of networks
by network complexity and network spillovers effects



Note: Each column counts the number of networks showing the estimated value of spillovers in the x-axes (approximation at the third decimal) . For each of dense, moderate and spare networks, we estimate 210 models, 10 each from 21 days of transaction data. Dense networks are shown in black, moderate in grey and sparse in white.

Figure 6: Empirical Distribution of networks by network complexity and adjusted R2



Note: Each column counts the number of networks showing the adjusted R2 statistic value of spillovers in the x-axes (approximation at the third decimal) . For each of dense, moderate and spare networks, we estimate 210 models, 10 each from 21 days of transaction data. Dense networks are shown in black, moderate in grey and sparse in white.

Table 1: Summary Statistics

	Mean	Standard Deviation	Min	Max
S&P 500 e-mini				
Sparse Networks				
Average daily Returns (unweighted)	0.98	0.01	0.00	1.04
Volume (daily)	5.94	4.98	0.00	1903.00
Moderately Dense				
Average Returns (unweighted)	0.96	0.02	0.00	1.03
Volume (daily)	5.73	7.90	0.00	2,253.0
Dense				
Average Returns (unweighted)	0.92	0.02	0.00	1.106
Volume (daily)	5.32	12.68	0.00	212.0
	min	max		
# traders (daily)	9,175	11,597		
Dow				
Sparse Networks				
Average Returns (unweighted)	0.99	0.03	0.00	1.02
Volume (daily)	6.39	1.42	0.00	150.00
Moderately Dense				
Average Returns (unweighted)	0.98	0.05	0.00	1.03
Volume (daily)	6.33	2.60	0.00	190.0
Dense				
Average Returns (unweighted)	0.95	0.07	0.00	1.04
Volume (daily)	5.91	4.86	0.00	341.0
# traders	7,335			

Note: Sparse networks are defined as containing 250 transactions, moderately dense networks as containing 500 transactions and dense networks as containing 1000 transactions. The top half of the table includes statistics from the S&P 500 e-mini futures market. The bottom half includes statistics from the Dow futures market. Return means are defined as the average across individual level trader returns. These are unweighted by volume; volume weighted returns are identically zero. Volumes statistics are average daily volumes at the level of the trader. Variance is measured as the variance over the returns at the trader level, again unweighted. Minimums and maximums are the smallest and largest for a trader on any day.

Table 2: ML Estimation results on weighted networks

	Sparse Networks		**Moderately Dense Networks**		**Dense Networks**	
	low	***high***	***low***	***high***	***low***	***high***
Panel A						
S&P 500 e-mini futures						
Network structure (weigthed Bonacich centrality)	0.01	0.03	0.01	0.01	0.00	0.01
	113.75	449.75	15.91	31.73	3.51	6.12
Network spillovers	0.94	0.96	0.96	0.98	0.97	0.98
	1488.42	2594.92	619.46	619.46	516.89	669.17
R-Squared	0.94	0.99	0.93	0.98	0.93	0.98
Panel B						
DOW futures						
Network structure (weigthed Bonacich centrality)	0.10	0.18	0.07	0.14	0.04	0.09
	42.48	101.96	32.46	55.48	14.92	27.47
Network spillovers	0.82	0.89	0.85	0.92	0.90	0.95
	355.26	475.98	316.51	415.36	233.36	309.37
R-Squared	0.71	0.80	0.71	0.79	0.71	0.78

Note: Panel A shows the results from the S&P 500 futures market. Panel B shows the resuls from the Dow futures market. Each of the two panels shows three ranges of results from the estimation of model (1), distinguishing between different levels of network structure complexity. The weight matrix W is defined in the paper as the product of the adjancency matrix of realized trades and the sum of trading volume. Each column shows the results from sparse, moderately dense and dense networks, respectively. For each type of network, we estimate 21 days of results and report the range of estimation results and t-stats across these time period. The first and second rows shows the estimates of the parameters α and θ respectively. The third row shows the adjusted R squared from each specification. See Table I for summary statistics on networks and markets. T-statistics are reported below coefficient estimates.

Table 4: ML Estimation results on unweighted networks

	Sparse Networks		Moderately Dense Networks		Dense Networks	
	low	***high***	***low***	***high***	***low***	***high***
Panel A						
S&P 500 e-mini futures						
Network structure (CKP centrality)	0.90	0.95	0.80	0.89	0.59	0.79
	35.48	1674.42	41.19	1106.76	24.09	583.96
Network spillovers	0.02	0.05	0.05	0.11	0.10	0.27
	0.90	38.24	4.55	46.51	6.94	47.60
R-Squared	0.04	0.10	0.09	0.21	0.18	0.46
Panel B						
DOW futures						
Network structure (CKP centrality)	0.95	0.96	0.91	0.92	0.82	0.84
	310.41	16292.46	198.13	245.04	101.01	3537.70
Network spillovers	0.02	0.02	0.04	0.05	0.08	0.10
	7.75	50.09	8.05	11.38	9.06	50.00
R-Squared	0.04	0.04	0.07	0.08	0.14	0.17

Note: Panel A shows the results from the S&P 500 futures market. Panel B shows the resuls from the Dow futures market. Each of the two panels shows three ranges of results from the estimation of model (1), distinguishing between different levels of network structure complexity. The weight matrix W is equal to the adjacency matrix of the realized trade network G. Each column shows the results from sparse, moderately dense and dense networks, respectively. For each type of network, we estimate 21 days of results and report the range of estimation results and t-stats across these time period. The first and second rows shows the estimates of the parameters α and θ respectively. The third row shows the adjusted R squared from each specification. See Table I for summary statistics on networks and markets. T-statistics are reported below coefficient estimates.

Table 4: Daily Output (S&P)

	Number of Traders	Network structure (Constant Term)		Network spillovers		R-Squared
S&P 500 e-mini futures		***Coefficient***	***tstat***	***Coefficient***	***tstat***	
August-3	10566	0.016	7.0	0.983	404.5	0.966
August-4	10253	0.026	12.1	0.972	429.0	0.957
August-5	10917	0.020	15.5	0.979	774.0	0.965
August-6	10867	0.014	11.9	0.984	967.3	0.972
August-7	11579	0.017	10.2	0.981	568.9	0.968
August-10	9175	0.019	11.1	0.979	523.4	0.965
August-11	10860	0.018	9.4	0.980	485.7	0.967
August-12	11366	0.023	14.6	0.976	662.1	0.962
August-13	10435	0.020	10.3	0.979	482.3	0.965
August-14	10590	0.015	11.6	0.984	762.8	0.973
August-17	10248	0.027	15.5	0.971	581.5	0.956
August-18	10525	0.016	10.9	0.983	753.5	0.974
August-19	11597	0.019	15.9	0.980	1006.4	0.968
August-20	9985	0.019	8.4	0.979	403.2	0.970
August-21	10703	0.019	10.9	0.979	632.7	0.967
August-24	10487	0.019	8.3	0.979	393.0	0.966
August-25	10998	0.020	13.9	0.978	786.1	0.966
August-26	10140	0.019	12.5	0.980	718.7	0.966
August-27	11504	0.017	20.9	0.982	1366.3	0.970
August-28	10358	0.015	8.5	0.983	523.8	0.970
August-31	9978	0.012	6.9	0.987	549.0	0.973

Note: The results correspond to the 21 trading days used in the estimation results in Table 2, Panel A, moderately dense networks. Column 1 reports the number of traders active that day. Column 2 the estimates of the parameter α and column 3 the estimates of the parameter θ. Finally, column 4 reports the R-squared of the specification. T statistics are reported to the right of coefficient estimates. See Table I for summary statistics on networks and markets.

Table 5: Robutness checks - ML Estimation results on weighted networks and data in deviations

	Sparse Networks		**Moderately Dense Networks**		**Dense Networks**	
	low	***high***	***low***	***high***	***low***	***high***
Panel A						
S&P 500 e-mini futures						
Network structure (CKP centrality)	0.01	0.03	0.01	0.02	0.00	0.01
	103.69	557.94	8.86	42.76	2.73	6.68
Network spillovers	0.94	0.96	0.95	0.98	0.97	0.99
	964.33	2917.94	544.24	718.19	438.62	666.50
R-Squared	0.94	0.99	0.93	0.98	0.93	0.98
Panel B						
DOW futures						
Network structure (CKP centrality)	0.12	0.17	0.07	0.15	0.05	0.09
	54.52	89.67	28.99	57.26	15.92	25.81
Network spillovers	0.82	0.88	0.84	0.92	0.90	0.95
	385.74	448.79	307.21	411.65	237.46	310.21
R-Squared	0.71	0.78	0.70	0.79	0.71	0.78

Note: Panel A shows the results from the S&P 500 futures market. Panel B shows the resuls from the Dow futures market. Each of the two panels shows three ranges of results from the estimation of model (1), where the returns are expressed in deviations from the individual network average, distinguishing between different levels of network structure complexity. The weight matrix W is defined in the paper as the product of the adjancency matrix of realized trades and the sum of trading volume. Each column shows the results from sparse, moderately dense and dense networks, respectively. For each type of network, we estimate 21 days of results and report the range of estimation results and t-stats across these time period. The first and second rows shows the estimates of the parameters α and θ respectively. The third row shows the adjusted R squared from each specification. See Table I for summary statistics on networks and markets. T-statistics are reported below coefficient estimates.

Table 6: Robutness checks - ML Estimation results on unweighted networks and volume as additional regressor

	Sparse Networks		Moderately Dense Networks		Dense Networks	
	low	***high***	***low***	***high***	***low***	***high***
Panel A						
S&P 500 e-mini futures						
Network structure (CKP centrality)	0.91	0.94	0.82	0.88	0.63	0.77
	94.00	187.22	63.36	1109.54	38.52	346.68
Network spillovers	0.02	0.04	0.05	0.08	0.10	0.17
	38.01	38.02	37.13	42.66	38.18	44.59
R-Squared	0.05	0.09	0.09	0.17	0.19	0.37
Panel B						
DOW futures						
Network structure (CKP centrality)	0.91	0.96	0.91	0.92	0.81	0.83
	198.29	10794.69	198.42	3249.07	101.16	15080.15
Network spillovers	0.02	0.04	0.04	0.05	0.08	0.10
	7.77	49.47	8.19	44.81	9.07	50.68
R-Squared	0.04	0.08	0.07	0.09	0.14	0.18

Note: Panel A shows the results from the S&P 500 futures market. Panel B shows the resuls from the Dow futures market. Each of the two panels shows three ranges of results from the estimation of model (1), where an exogenous regressor has been added, distinguishing between different levels of network structure complexity. The weight matrix W is equal to the adjacency matrix of the realized trade network G. Each column shows the results from sparse, moderately dense and dense networks, respectively. For each type of network, we estimate 21 days of results and report the range of estimation results and t-stats across these time period. The first and second rows shows the estimates of the parameters α and θ respectively. The third row shows the adjusted R squared from each specification. See Table I for summary statistics on networks and markets. T-statistics are reported below coefficient estimates.