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Financial Contagion in Networks: A Market Experiment

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Abstract

We investigate how the network structure of financial linkages and uncertainty about the location of a shock affect the likelihood of contagion and the formation of prices in a double auction market experiment. Core-periphery networks are highly susceptible to contagion and generate fire sales of assets that exacerbate financial contagion beyond the mechanical role of network structure. In contrast, contagion is minimal on circle networks and market prices remain stable. Uncertainty on the location of the shock has little influence. The traders' comprehension level of the network-driven risk is predictive of their behavior and the likelihood of bankruptcy.

Keywords: contagion, financial network, experimental asset market.
JEL: C92, D40, D85, L14.

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1 Introduction

The complex architecture of linkages among financial institutions is a pervasive feature of financial markets. In the aftermath of the financial crisis of 2007-2008, it was widely viewed as a critical factor in shaping systemic risk, and its impact may have been amplified by the market participants' lack of information on where a shock hits the system[1]. A growing number of theoretical studies validate these views by showing that the structure of the network of linkages and the information about where a shock hits the network are one of the determinants of the robustness of the financial system[2]. However, empirical studies struggle to identify these effects because the financial network endogenously evolves in response to incentives, including the outcomes of interest, and it is challenging to observe potential confounds such as preferences and information held by market participants.

This paper reports the results of a laboratory market experiment where we systematically vary the architecture of the financial network and the structure of information on the location of a shock in the network. We integrate the classical continuous double auction experimental asset market à la Smith [1962] with the canonical 3-period economy framework in the theoretical literature of financial contagion with economic agents connected by a network of cross-holdings (e.g., Allen and Gale [2000] and Acemoglu et al. [2015]). The 3-period economy set-up allows an investigation of the trade-off between long-term investment and holding short-term liquidity to cushion the effect of a shock where the network of cross-holdings determines the risk a trader is exposed to. The double auction institution allows us to inspect the process of price formation in the laboratory and observe anomalous market behaviors such as market freezes and fire sales. Thus, we can deepen our understanding of the decomposition between spillover effects purely driven by the mechanical network propagation process and those further amplified by fire sales of assets and resulting price collapses.

Specifically, each individual is endowed with one unit of a long-term asset, a

[1]See, for instance, Haldane [2009], Sorkin [2010], Plosser [2009], Tucker et al. [2009], and Yellen [2013].

[2]For a recent survey of the literature on financial contagion in networks, see Cabrales et al. [2016].

per-unit value of the asset, and a network of cross-holdings of short-term debts with the other participants. As Figure 1 shows, we consider treatments with both circle networks, which are the standard benchmark in the theoretical literature, as well as core-periphery networks with some highly connected individuals in the core and some poorly connected ones in the periphery, which are a stylized representation of real financial networks[3]. Before trading, one and only one participant is hit by a shock of small, medium or large size. Motivated by Caballero and Simsek [2013], we consider treatments with complete and incomplete information about the recipient of the shock, where in the latter one the recipient is the only participant who knows who was hit by the shock. In the first period, individuals can trade their assets using a continuous double auction institution. The assets yield a return only in the final period and are completely illiquid at the intermediate period, so participants have an incentive to sell to raise liquidity in case they are (directly or possibly indirectly) affected by the shock. After trading ends, in the intermediate period all short-term debts have to be repaid and individuals who are unable to do so go bankrupt and lose any assets in their possession. In the final period, participants who did not go bankrupt earn the return from any assets that they hold.

Our main results are that network structure has a substantial impact on contagion and market outcomes, whereas information has a negligible effect. The difference between the contagion rates of core-periphery and circle networks range from 19% to 46%, and these differences are generally higher than those predicted by benchmark simulations. Additionally, in core-periphery networks contagion occurs more frequently when a core, rather than a peripheral, node is hit by a shock. The contagion rates we observe in the laboratory for core-periphery networks are also significantly higher than those predicted by a benchmark simulation which only accounts for the mechanical process of shock propagation, suggesting that price reactions play a role

[3] There is a growing list of empirical studies identifying financial markets in the real world with a core-periphery network structure. To name a few, Li and Schürhoff [2014] for municipal bonds, Bech and Atalay [2010] for the federal funds market, Hollifield et al. [2014] for securitization markets, Boss et al. [2004] and Langfield et al. [2014] for interbank markets, Maggio et al. [2016] for corporate bond markets, and Battiston et al. [2012] for the US Federal Reserve Bank loans program.

in exacerbating contagion. Indeed, prices tend to collapse in core-periphery networks up to about 40% of the prices in circle networks, which remain stable and close to equilibrium values. This collapse is driven by widespread sales of assets and depressed demand for buying assets in core-periphery networks, whereas the market maintains a balanced volume of buying and selling requests in circle networks. Finally, there is no difference in contagion rates, price levels or trading behavior between the complete and incomplete information treatments.

The contagion rates observed in core-periphery networks are also higher than benchmark simulations that account for the price formation process, and we find evidence that this adverse outcome is driven by heterogeneity among participants in the comprehension of the network-driven risk. At the end of the experiment, we use an incentivized task to elicit subjects' comprehension of optimal strategies across different nodes in the network. We find that those with a higher network comprehension score tend to be more likely to sell the asset, and hence less likely to face the risk of going bankrupt. This association between a subject's comprehension and their likelihood of bankruptcy is significant in the core-periphery networks, but not in the circle networks.

Our paper relates to several strands of the literature in economics and finance. Its fundamental contribution is to be the first investigation of the causal link between financial networks and systemic risk in a setting where the price is endogenously determined through an asset market. In doing so, it brings together the large body of work on experimental asset markets with the recent theoretical literature on contagion.

A recent survey by Cabrales et al. [2016] provides a useful classification of the theoretical literature into contagion through shock transmission and informational contagion. Acemoglu et al. [2015] and Glasserman and Young [2015] are the two most relevant papers to ours in the former category[4]. Acemoglu et al. [2015] focus

[4]Allen and Gale [2000] and Freixas et al. [2000] made pioneering contributions. A separate strand of the literature analyzes a set-up where the network represents mutual ownerships of claim on underlying projects rather than borrowing and lending relationships. Selected contributions in this vein include Cabrales et al. [2014], Elliott et al. [2014], Elliott and Hazell [2016] and Galeotti et al. [2016].

their analysis on regular networks and show that the susceptibility to contagion is non-monotonic in connectedness and shock size, while Glasserman and Young [2015] give bounds on contagion independent of the network. In the information contagion category, Caballero and Simsek [2013] is the most relevant paper. They use the same framework as Acemoglu et al. [2015] and Glasserman and Young [2015], and show that contagion and fire sales of asset are more likely to occur when players do not know who is the recipient of a shock compared to the complete information benchmark. Our experimental results provide strong evidence on the causal impact of network structure on contagion by comparing circle networks and core-periphery networks, which have not been explicitly investigated by Acemoglu et al. [2015] and Caballero and Simsek [2013]. In contrast, we find little evidence on the impact of information contagion as suggested by Caballero and Simsek [2013]. A potential reason is that their theoretical model assumes agents are extremely ambiguity or risk averse, which is a behavioral assumption that is too strong to be realistic in the laboratory.

The only experimental paper that investigates the causal link between network structure and systemic risk is Duffy et al. [2016][5]. They test the 4-agent model by Allen and Gale [2000], and they find that contagion occurs in both a circle and a complete (i.e. all agents are connected) network, but it is less likely in the latter. Our work differs from theirs in several crucial aspects. First, we introduce a trading market for assets that permits an investigation of the link between the evolution of market prices and the structures of network and information, whereas Duffy et al. [2016] use a game situation of whether to withdraw subjects' deposit or not which abstracts away from the role of market pricing. Secondly, we consider a richer set of networks, including core-periphery networks that are representative of real financial networks. Third, we introduce information treatments which allow an investigation of informational contagion in addition to contagion via the transmission of shocks

[5]A large empirical literature investigates how network structure *correlates* with systemic risk. Selected contributions include Elsinger et al. [2006], Denbee et al. [2014], Battiston et al. [2012], and Bonaldi et al. [2015], but none of them manages to identify the causal channel. One possible exception is Iyer and Peydro [2011] who attempt to identify financial contagion due to interbank linkages by exploiting a natural experiment caused by the failure of a large bank.

through the network.

The comprehensive survey by Sunder [1995] gives an overview of the extensive literature on experimental asset markets. Our paper is the first one to integrate the standard double auction institution with a financial market where participants are interconnected by borrowing and lending relationships. Starting with the seminal contribution by Smith et al. [1988], a central focus of inquiry has been the emergence of asset pricing anomalies. The so-called bubble and crash literature has exclusively taken and modified the basic framework of Smith et al. [1988] and explored the extent to which irrational bubbles can be formed (see Palan [2013] for a recent review). Our market experiment differs substantially from this literature along various dimensions, but we contribute to it by identifying network structure as a novel source of price crashes in experimental asset markets.

Lastly, this paper also contributes to different strands of the large literature of experimental work on networks (see Choi et al. [2016] for a recent survey). First, it relates to papers that study the impact of network architecture on trading outcomes with various trading institutions. A non-exhaustive list includes Charness et al. [2007] and Gallo [2014] for bargaining, Judd and Kearns [2008] for bipartite exchange, Gale and Kariv [2009] for simultaneous bid-ask trading, and Choi et al. [2017] for posted-price trading. Second, a recent line of work examines how network architecture affects behavior in incomplete information settings. Previous research includes Charness et al. [2014] in the context of public goods, Gallo and Yan [2015] on cooperation, and Grimm and Mengel [2014] on social learning. Our paper sheds light on how incomplete information affects the role of network architecture in the context of trading.

The rest of the paper is organized as follows. Section 2 presents the set-up of our experiment and describes the experimental procedures. Section 3 formulates the main hypotheses based on benchmark simulations and the theoretical literature. Section 4 presents the results on contagion and the factors affecting individual bankruptcy and trading positions. Section 5 shows the evolution of prices and bidding behaviour, and section 6 concludes. Further information is available in Online Appendices containing sample instructions of the experiment and further data analysis[6].

2 Experimental Design and Procedures

2.1 Set-up

The financial market consists of 6 or 15 individuals each of whom is endowed with (i) one indivisible unit of the (long-term) asset, (ii) a per-unit value of the asset, and (iii) a relation of cross-holdings of short-term debt with the other participants. The market lasts for three periods, $t = 0, 1, 2$. Prior to the opening of the market, a shock of size s hits one and only one participant. At the initial period $t = 0$, individuals take part in a continuous double auction market for trading the long-term asset. After trading ends, at period $t = 1$ the computer clears all the debt claims, and any participant who ends up with a negative cash balance goes bankrupt and loses any units of the asset in their possession. Finally, at period $t = 2$ participants receive their payoffs including the realization of the value of any asset(s) they hold.

Each participant is endowed with one unit of the long-term asset which yields a return at period 2 that is specific to the participant. In markets with 15 participants, the per-unit values of the asset are randomly assigned from the set of 15 evenly-spaced values between 860 and 1140. In markets with 6 participants, they are randomly assigned from the set of 6 evenly-spaced values between 850 and 1150. Each of these values is assigned to one and only one participant. In our set-up the heterogeneity of the asset return is one source of trading in the market. We assume the standard liquidity and return trade-off in the literature (e.g., Diamond and Dybvig [1983]): the asset is completely illiquid at period 1 and it yields a positive return at period 2. In particular, if the individual is unable to pay fully their own debt at period 1, the individual goes bankrupt and loses all units of the asset that they hold.

Participants are also endowed with short-term debt claims on some other participants in the market. Each claim is worth y, which is the same for all debt claims

[6] Online Appendices are available on the authors' personal websites (the URLs are available on the title page).

in the market. We use a directed graph with N vertices to describe the relation of cross-holdings of short-term debt among all participants. Each vertex corresponds to an individual and a directed edge from vertex j to vertex i represents that individual i is a creditor of individual j. That is, j owes y amount of cash via short-term debt to i. The cross-debt claims among all participants form a financial network. We consider the four network structures in Figure 1 that vary in structure and size: Circle 6 (*CI6*), Circle 15 (*CI15*), Core-Periphery 6 (*CP6*), and Core-Periphery 15 (*CP15*). In circle networks each participant is the sole creditor of one participant and the sole debtor of another participant. In core-periphery networks there are participants at peripheral positions each of whom has a single creditor link to one core participant and has a single debtor link to another core participant, and participants at core positions who are connected with others at core positions, in addition to their links to peripheral participants. For instance, each core position in the *CP15* network has four incoming edges, which represent a credit of y from each of them, and four outgoing edges, representing a debit of y to each of them.

- Figure 1 here -

Prior to the opening of the market, one and only one participant is hit by a shock of size s, which is randomly and uniformly determined. The size of the shock can be small ($s = 50$), intermediate ($s = 1200$) or large ($s = 3000$ for the 6-node networks and $s = 5000$ for the 15-node networks), and it is common knowledge to all the participants and randomly determined. The recipient of the shock knows that they are hit by the shock, and suffers a loss s that needs to be recovered by selling their long-term asset in the market in order to prevent insolvency. We consider two different information treatments. In the scenario of *complete information*, every person in the network knows who received the shock. In contrast, in the scenario of *incomplete information* each participant is unaware of who got a shock, unless they are the recipient of a shock, and knows only that one participant is randomly hit by a shock of size s. The two distinct structures of information, together with the aforementioned four networks, generate 8 treatments in the experimental design.

We use a computerized continuous double auction institution for the market of the long-term asset. The market is open for 90 seconds during which participants who want to buy (sell) can submit and revise their bid (ask) prices or accept an available ask (bid) price. Participants can buy an asset by borrowing cash with zero interest rate from an outside institution, which they have to return at period 2. Once two participants agree to exchange one unit of the asset, they are no longer allowed to make another trade during the rest of the market. Trading is anonymous so a participant does not know the identity, and therefore the network position, of the other participant involved in the trade. At any point during the market, participants can see all available bid and ask offers, and the prices of completed trades[7]. At the end of the market each participant holds zero, one or two units of the asset depending on whether they sold the asset, made no trade or bought one asset respectively.

At period 1, after the market has closed, the computer clears all the debt claims, taking into account the location and size of the shock and participants' trading outcomes, and computes the leftover cash balance for each participant[8]. The recipient of the shock, who receives cash payments from their debtors and holds cash if they sold their asset, must first use the cash amount to meet losses from the shock. Any remaining cash amount can then be used for paying debt claims to their creditors on a pari-passu basis. Consequently, these losses might spill over to other participants via the financial network. If a participant ends up with negative cash balance after the clearance of debt claims, they are declared bankrupt and loses any units of the long-term asset that they hold[9].

At period 2, participants receive the information about their payoffs. Participants who were not bankrupt at period 1 receive the return from any units of the asset they had at the end of trading as well as the cash leftover after debt clearing. Participants who went bankrupt incur losses equal to their negative cash balance at the end of period 1. In addition, participants pay back the external institution for the cash they borrowed to purchase an asset.

[7]Please refer to Online Appendix 1 for screenshots of the trading interface.

[8]Eisenberg and Noe [2001] provide a computationally efficient algorithm that finds a unique payment vector for clearing the financial system.

[9]We use the terms "bankrupt" and "insolvent" interchangeably throughout the paper.

2.2 Procedures

The experiment was run at the experimental laboratory in the Economics department at University College London in June 2015 and April 2016. Subjects were recruited using the ORSEE recruitment system (Greiner [2004]) from the subject pool of students across all disciplines at UCL and from other universities in London. Each subject participated in only one of the experimental sessions. After subjects read printed instructions including sample screenshots, the instructions were also read aloud by the experimenter. Prior to the commencement of the experiment, there was an on-screen quiz to ensure that subjects had a good understanding of the experiment. The experiment was computerized and conducted using the experimental software z-Tree developed by Fischbacher [2007]. Sample instructions are reported in Online Appendix 1.

In each experimental session, subjects were matched into fixed groups and interacted with the same subjects throughout the experiment. We ran 2 sessions and collected the data of six groups for each of the four treatments with 6-person networks, and ran 4 sessions with five groups for each of the four treatments with 15-person networks. In total, 444 subjects participated in 24 sessions. Subjects earned on average about £30 in *CP6*, £31 in *CP15*, £24 in *CI6*, and £21 in *CI15* treatments, including a £5 show-up fee. During the session, we ensured anonymity and an effective isolation of subjects by separating their workstations using partitions.

The market experiment consists of 21 rounds of the continuous double auction market in each of which trading lasts for 90 seconds. At the end of each market subjects were informed of whether they went bankrupt or not and their final earnings. The first three market rounds are practise rounds, and therefore they do not count for payment. From the remaining 18 rounds, there are six rounds in which the group experiences each size of shock in a random order. From each of the six rounds, one is chosen at random for payment and subjects are paid their earnings in that round. To ensure payments were likely to be positive despite the potential differential impact of the large shock across treatments, subjects receive a cash injection of £20 for the core-periphery treatments and £10 for the circle treatments. The exchange rate is the same in all treatments so the relative incentives remain constant.[10]

At the end of the experiment, subjects answered an incentivized task to elicit their comprehension of the trade-offs involved in buying and selling assets when a shock hits a participant in the network. Subjects faced the same network as in the experiment and were informed that a shock of large size hits a specific node in the network. They were told that there is a computer player at each node who is programmed to decide optimally whether to buy or sell one unit of the asset of fixed value equal to 1200 at a fixed price equal to 600, knowing that the computer players on the other nodes are deciding optimally to maximize their payoffs. Subjects made guesses on whether the computer player on each node buys or sells the asset. Subjects in the core-periphery network treatments make decisions both when the location hit by the shock is a core and when it is a periphery. The fraction of correct answers gives us a *Network Comprehension Score* (NCS) for each subject to measure the subject's level of comprehension of the network-driven risk. Following this comprehension elicitation, subjects took a risk and loss aversion elicitation, which is a modified version of Holt and Laury [2002] (HL).

3 Benchmarks and hypotheses

To put the experimental design in perspective and derive testable hypotheses, we discuss several benchmark cases and figure out the basic workings of our experimental markets. Notice that in the case when there is no shock, the clearance of short-term debt claims is independent of the functioning of the long-term asset market because the flows of debts among market participants match perfectly with no extra cash in the clearance process. Hence, there should be no spillover effect of the network of short-term debt claims on the long-term asset market.

We consider several benchmarks in the presence of a shock and conduct a simulation exercise for each benchmark using the market conditions in the experimental data. Benchmark cases are chosen to explore the impacts of network architecture on

[10]Subjects' earnings during the experiment were calculated in terms of experimental tokens and then exchanged at the end into pounds at the following rate: 600 tokens = £1.

system-wide contagion with and without its effect on prices. We focus on the spillover of a shock through bankruptcy and report the rate of contagion in each simulation. Contagion with $x\%$ threshold is said to occur when at least $x\%$ of market participants go bankrupt. In the simulation exercise and subsequent data analysis, we report contagion rates with 60%, 80%, and 100% thresholds.

Benchmark I simulates the case where the price of the long-term asset is fixed at the competitive equilibrium level as if there is no shock and the market participants trade according to the realized values of assets. The objective is to examine the role of network architecture on the market-wide spread of bankruptcy without any endogenous response of prices. In this benchmark participants sell their assets if their asset value is lower than the competitive equilibrium price, and buy one unit of the asset from the market if it is higher than the equilibrium price. The competitive equilibrium price without a shock is $1,000$ in the 15-person networks and lies in the $[970, 1030]$ interval in the 6-person networks.

The next two benchmarks explore the effects of network structure on contagion by incorporating its influence on price formation. In Benchmark II the competitive equilibrium price is determined assuming that the shocked participant always sells their asset and the other participants decide their trading positions according to whether their asset values are lower or higher than the equilibrium price. The assumption that the shocked participant sells their asset makes the supply and the demand curves shift to the left, and therefore the equilibrium price depends on the asset value of the shocked participant. The equilibrium price for the 6-person networks is given by a price interval, whereas it is unique for the 15-person networks.

In Benchmark III the equilibrium price is determined assuming that the shocked participant as well as the neighbors of the shocked participant always sell their assets, while the remaining participants decide their trading positions according to whether their asset values are lower or higher than the equilibrium price. Compared to Benchmark II, this assumption makes the supply and the demand curves shift further to the left, and therefore equilibrium price depends on the asset values of the shocked participant and the neighbors. Again, the equilibrium price for the 6-person networks is given by a price interval, whereas it is unique for the 15-person networks.

Table 1 reports the simulated likelihood of contagion with different thresholds for the aforementioned three benchmarks using the experimental data[11]. In the 6-person networks, where competitive equilibrium prices are given by an interval, we report the frequencies of contagion for the lower bound and the upper bound of those prices.

- Table 1 here -

The simulations show the critical role of network structure on market-wide contagion. First of all, given the size of the network, we observe higher incidences of contagion in core-periphery networks than in circle networks for all the three benchmarks. For instance, focusing on the 60% threshold, the structure of the network has a clear impact on contagion in the 15-person networks. The *CI15* network yields no incidence of contagion in any of the benchmarks, whereas the *CP15* network predicts strictly positive chances of contagion in all benchmarks: the rates of 60% contagion are 9% in Benchmark I, 18% in Benchmark II, and 21% in Benchmark III. A similar effect of network structure is present for the 6-person networks, although the magnitude of the effect is smaller.

In addition to the substantial effects of network structure, the simulations also suggest that the responsiveness of prices and trading behavior to a shock can aggravate the spread of contagion in the market, and this effect is more prominent in the core-periphery networks than in the circle networks. For instance, 60%-threshold contagion rates in the *CP15* network are at least two times higher in Benchmark II and III, where prices and trading decisions are endogenous to exposure to a shock, than in Benchmark I, where prices and trading decisions are independent of the shock. An analogous pattern is present in the *CP6* network. In contrast, there is no variation across benchmarks in the *CI15* network. In the *CI6* network, we observe no variation of contagion with 100% threshold across benchmarks because there is no system-wide contagion. With either the 80% or 60% threshold, contagion rates tend to be slightly higher in Benchmark II and III than in Benchmark I [12].

[11] We pool the experimental data of the complete and incomplete information treatments to conduct the simulation. There is basically no change in the results when we only use the data of either of the two information treatments.

[12] There are countervailing forces on contagion when contrasting between Benchmark I and the

In line with these findings, the response of human subjects to a shock in a given network structure is ultimately an empirical question. We conjecture that subjects take a more cautionary action in the core-periphery networks than in the circle networks, which may result in the collapse of long-term asset prices. These observations lead us to the following hypothesis on contagion and prices.

Hypothesis 1. Holding constant network size and information structure, the likelihood of contagion is higher in a core-periphery network than in a circle network.

Hypothesis 2. Holding constant network size and information structure, the price of the long-term asset falls more in a core-periphery network than in a circle network.

In addition, the experiment tests the effect of information structure on contagion and prices with treatments that differ depending on whether subjects have complete or incomplete information on the location of the shock. Caballero and Simsek [2013] motivate our experimental investigation of this information hypothesis by constructing a model where counterparty risk originated by network uncertainty on the location of a shock compels traders to take excessively precautionary actions and cause a market freeze. While offering novel insights on market freeze and contagion, their model is based on the strong behavioral assumption that market traders are extremely ambiguity/risk averse. Given the common findings in the empirical literature that people, on average, tend to be moderately ambiguity/risk averse and hold heterogeneous preferences, it is an empirical question whether the channel of market freeze and contagion identified by Caballero and Simsek [2013] is salient. We have the following two information hypotheses on contagion and prices.

Hypothesis 3. Holding constant network structure and size, the likelihood of contagion is higher under incomplete information than under complete information.

other two benchmarks. On the one hand, in Benchmark III more traders are forced to sell their assets to raise liquidity against bankruptcy compared to Benchmark I. On the other hand, these forced sales shift market supply and demand curves lowering equilibrium prices, which can reduce the buffer against bankruptcy. Hence, contagion rates are not necessarily higher in Benchmark III than in Benchmark I in 6-person networks.

Hypothesis 4. Holding constant network structure and size, the price of the long-term asset falls more under incomplete information than under complete information.

4 Contagion and bankruptcy

In section 4.1 we begin the analysis of the experimental data by presenting network and information treatment effects on contagion at the market level to test the aforementioned hypotheses. Section 4.2 analyzes their effects on bankruptcy and trading decisions at the individual subject level.

4.1 Financial contagion

Our first objective is to understand how network structure and information on shock location determine system-wide contagion. Recall from Section 3 that contagion with $x\%$ threshold is said to occur if at least $x\%$ of market participants go bankrupt. We present results on contagion with 60% threshold, while those with different thresholds are relegated to Online Appendix II [13]. Figure 2 shows frequencies of occurrence of contagion across network and information treatments. We complements the graphical comparisons of Figure 2 with formal statistical tests for network effects and information effects in Table 2. We use the Mann-Whitney (M-W) test for the equality of average frequencies of contagion between two treatments to compare treatments with data aggregated at the session level.

- Figure 2 and Table 2 here -

Firstly, the data shows the prevalence of contagion in the laboratory. In the complete information treatments, contagion occurs in 58% of market rounds in *CP6*, 39% in *CI6*, 43% in *CP15*, and 4% in *CI15*. Likewise, in the incomplete information

[13] This means that at least 3 out of 6 subjects go bankrupt in the 6-node networks, and at least 10 out of 15 go bankrupt in the 15-node networks. Online Appendix II shows that the results in this section remain overall robust to different thresholds, although the 100% threshold yields less variations across treatments and thus less significant results.

treatments it occurs in 60% of market rounds in *CP6*, 33% in *CI6*, 50% in *CP15*, and 4% in *CI15*. Secondly, there are strong effects of network structure: contagion is substantially more likely to occur in core-periphery than in circle networks. The differences between the contagion frequencies of core-periphery and circle networks are 19% (complete information) and 27% (incomplete information) in 6-person networks, and 39% (complete information) and 46% (incomplete information) in 15-person networks. The M-W test results of Table 2 show that these differences are all highly significant (p-values are less than 0.01 in all the comparisons except for that between *CP6* and *CI6* under complete information where the p-value is 0.028)[14]. In addition to the network structure effects, we observe that network size also matters: the difference between the contagion rates of core-periphery and circle networks are about twice as large in 15-person networks than in 6-person networks. Thirdly, there is a negligible effect of information on shock location on contagion. It is evident in Figure 2 that there is little difference between the contagion rates of the two information treatments for any given network, and the statistical analysis in Table 2 confirms this.

Our findings on contagion raise the question of whether they are solely driven by mechanical differences in clearing short-term debt claims between the network structures we consider. We first note that contagion is much more prevalent in the experimental data than in the simulated data of Benchmark I in Table 1. The simulated frequencies of contagion in Benchmark I are between 15% (upper bound) and 32% (lower bound) in *CP6*, between 5% and 22% in *CI6*, 9% in *CP15*, and 0% in *CI15*. A one-sided t-test on the equality of means using paired session-level data confirms that contagion is significantly more prevalent in the experimental data than in Benchmark I for both core-periphery ($p < 0.01$ in all treatments) and circle ($p < 0.05$ in all treatments) networks. This shows that contagion in the experimental asset market occurs beyond the scale of networks serving as a purely mechanical

[14]The network effects remain similar using different thresholds of contagion. Specifically, contagion occurs significantly more frequently in core-periphery than in circle networks using the 80% thresholds in all conditions except under full information in the 6-person networks. Similarly, contagion is more frequent in core-periphery networks using the 100% thresholds, but it is only significant for the 15-person networks.

shock propagation as captured in the Benchmark I simulations that maintain the asset price exogenously fixed.

Contagion rates observed in the laboratory are also significantly higher (t-test, $p < 0.05$) than in the simulations for 15-person networks in Benchmark II and III, which account for endogenous price effects. In 6-person networks contagion rates in the experiment are significantly higher ($p < 0.05$) than all equilibria in the simulations for both benchmarks with the exception of the $CI6$ network under complete information in Benchmark II and the $CP6$ network treatments in Benchmark III.

The effect of network structure on contagion in 15-person networks is also stronger in the laboratory than the simulation exercise predicts. Observed differences between the contagion rates of *CP15* and *CI15* are 39% (complete information) and 46% (incomplete information). These differences are predicted to be only 9% in Benchmark I, 18% in Benchmark II, and 21% in Benchmark III. A similar feature emerges for 6-person networks despite the multiplicity of equilibria, although the magnitudes of the effects are smaller. Observed differences between the contagion rates of *CP6* and *CI6* are 27% (complete information) and 19% (incomplete information). The simulated differences for 6-person networks with the upper bound of equilibria are 11%, 13%, and 14% in Benchmarks I, II, and III respectively. Those with lower bound are 11%, 13%, and 49% across the three benchmarks. Overall, comparing the experimental rates of contagion with the simulated contagion rates from the benchmarks suggests that systemic risk in financial systems shapes traders' behavior and affects the formation of asset prices differently across networks, which in turn amplify financial distress beyond the scale of mechanical shock propagation.

In core-periphery networks, a potential factor in determining the extent of contagion is whether the shock hits a core or a periphery node. A priori, it is not clear which location is more susceptible to contagion. On the one hand, the financial distress of a shock directly spreads to more participants when the shock hits a core node. On the other hand, the amount of unpaid debts is equally divided among the creditors and therefore the financial distress is diluted among the neighbors. Notice that a periphery node has the same number of links in both $CP6$ and $CP15$ networks, but a core node has more links in the $CP15$ than in the $CP6$ network, and therefore any difference in contagion dependent on location should be amplified in $CP15$ compared to $CP6$.

Figure 3 shows the frequency of contagion with 60% threshold depending on the location of the shock for each core-periphery network and information treatment. In the $CP15$ network, contagion is significantly more likely (M-W, $p < 0.05$) when a core node is hit by the shock than when a periphery node is hit for both information treatments. The same holds for the $CP6$ network, but the difference is only significant for the incomplete information treatment (M-W, $p < 0.05$). A potential reason for this difference is that it is more difficult for subjects to understand the ramifications of the shock when a core node gets hit by a shock because it has a higher number of connections than a peripheral node, and, consequently, longer chains of spillovers to keep track of. The Network Comprehension Score (NCS) supports this hypothesis: subjects have a higher NCS when the shock hits a peripheral node than when it hits a core node (M-W, $p = 0.002$).

- Figure 3 here -

The analysis conducted so far has aggregated the data at the session level, and thus does not address the question of how contagion rates vary depending on the size of the shock. Figure 4 and Table 3 present the same information as Figure 2 and Table 2 disaggregated by shock size at the session level. As expected, Figure 4 shows that there is a monotonic relation between contagion and shock size: the larger the shock the more frequent the occurrence of system-wide contagion.

- Figure 4 and Table 3 here -

The disaggregated data shows that the finding that contagion is more frequent in core-periphery than in circle networks is driven by the rounds when a large or intermediate shock hits the system. As Table 3 shows, contagion with 60% threshold is significantly higher (M-W, $p < 0.05$) in core-periphery than in circle networks for both intermediate and large shocks, with the exception of the comparison between $CP6$ and $CI6$ under complete information where the difference is only qualitative.

There is no statistically significant difference when a small shock hits the system, as we would expect given that the participant hit by the shock can cushion it by selling their asset. Lastly, even with the data disaggregated by the size of a shock, we find no evidence that information on shock location plays a role in financial contagion.

We summarize the findings on contagion in our experiment as follows.

Result 1 (Contagion). *(i) Contagion rates in the laboratory are higher than those predicted by the purely mechanical process of shock propagation through networks. (ii) Core-periphery networks lead to a higher likelihood of contagion than circle networks. (iii) In core-periphery networks, contagion occurs more frequently when a core node is hit by a shock. (iv) There are negligible impacts of information on shock location on contagion.*

4.2 Bankruptcy and trading

In this section we delve deeper into the data by investigating how the bankruptcy rates of market participants depend on their position in the network structure, environmental, and behavioral factors. Starting from the role of position in the network, Table 4-A shows the observed frequencies of bankruptcy across treatments over distance from the shock. As a comparison, Table 4-B displays the same information for the benchmark simulations. Notice that we present the range of predicted bankruptcy rates in 6-person networks because of the multiplicity of competitive equilibria.

- *Table 4-A and 4-B here* -

Firstly, the insolvency rates of shock recipients in the experimental data are quite high. The participants directly hit by a shock in the experiment became insolvent in around 72% – 87% of the markets across treatments. The rates for some treatments are close to those predicted by Benchmark I, in which shock recipients ignore a shock and make trading decisions solely on the basis of asset value. The rates in all the treatments are overall higher than those simulated by Benchmark II and III, which assume, respectively, that the shock recipient and the shock recipient plus the neighbors sell their asset in order to raise liquidity to cushion the shock. Secondly, as expected, the bankruptcy rates in the data decrease in distance from the shock in each of the treatments. Compared to the simulated rates, they tend to stay persistently higher than those predicted by the three benchmarks on positions distant from the shock. This is consistent with the finding in Section 4.1 that contagion rates in the experimental data are higher than in the benchmark simulations.

Tables 5 and 6 show the results of a generalized linear random effects regression analysis to understand how environmental and behavioral factors correlate with, respectively, individual bankruptcy and trading behavior, i.e. buy or sell decisions. Environmental factors include the size of a shock, distance from the shock, and heterogeneity in asset value, as well as interaction terms between some of them and the network and information treatments. Behavioral factors contain the measures of risk preferences in the gain and loss domains and the Network Comprehension Score (NCS). Each table presents the regression analyses with all the data and with the subset of data for the circle or core-periphery networks only. Standard errors are clustered by individual subject.

- Table 5 and Table 6 here -

First, the size of the shock is positively related to bankruptcy rates, but it does not affect the likelihood of trading decisions. Bankruptcy rates when an intermediate or large shock occurs are 32% and 46% higher than when a small shock hits the system. These differences increase to 43% and 59% if we only consider core-periphery networks. On the other hand, there is little variation in the frequency of trading depending on shock size. For instance, the frequencies of buying an asset are 37%, 36% and 36% when a small, intermediate and large shock occur respectively.

Second, distance from the shock is inversely related to the likelihood of bankruptcy, and it also affects trading behavior. The farther away an individual participant is from a shock, the less likely they are to sell the long-term asset and the more likely they are to buy the asset. This endogenous response of subjects' behavior makes the bankruptcy rate fall by about 10% in each increase of distance from the shock, which is a less drastic decrease than we find in the purely mechanical process of shock propagation in the Benchmark I simulation. Network structure has an overall negligible impact on the relation between distance from the shock and bankruptcy and trading decisions. Information structure has significant but minor effects on the relation between distance from the shock and bankruptcy and trading activities: bankruptcy drops by 1% in the incomplete information treatments of the circle networks, and buy activities drop and sell activities go up by 2% in the incomplete information treatments. These information effects become stronger in the core-periphery networks. Nevertheless, these information effects do not appear to affect system-wide contagion as shown in Section 4.1. Finally, shock location in the core-periphery networks matters for bankruptcy and sell activities: when the shock recipient is located in a peripheral position, bankruptcy decreases overall by 5% and sell activities increase by 6%. There is little effect of shock location on buy activities.

Third, the higher the value of the long-term asset participants are endowed with, the less likely they are to sell it, the more likely they are to buy another unit of the asset, and, consequently, the more likely they are to go bankrupt. The association between asset value and buy or sell behavior is weaker in the core-periphery than in the circle networks, as the magnitude of the coefficient is reduced by half. The association between asset value and trading behavior is a causal determinant of the risk of bankruptcy in the experiment. Holding other factors constant, participants who are endowed with a higher asset value are less likely to sell their asset and hold cash as a liquidity cushion, which in turn increases the likelihood of insolvency, and this channel is more substantial in core-periphery networks. Finally, information structure has no impact on the relation between asset value and trading behavior as well as the likelihood of bankruptcy.

Lastly, participants' capabilities of comprehending the trade-offs involved in their decision, as captured by the Network Comprehension Score (NCS), has an explanatory power on sell decisions and the likelihood of bankruptcy in the core-periphery networks. One standard deviation increase in the NCS increases the chance of selling the long-term asset by around 4% and decreases the likelihood of bankruptcy by about 2%.[15] The complexity of the network structure appears to be a crucial factor in determining differences in understanding among participants because in circle networks, which are less complex, there is a negligible association between the *NCS* and trading behavior and/or bankruptcy. In other words, subjects who are better able to grasp how the complexity of the networks affects the trade-offs involved in the decision to buy or sell are more likely to decide to sell the long-term asset to cushion themselves from a spillover of the shock and hence less likely to face the risk of going bankrupt. Risk preferences in both gain and loss domains have a negligible association with trading behavior and/or bankruptcy.

We summarize our findings on bankruptcy and trading behavior in our experiment as follows.

Result 2 (Bankruptcy and trading). *(i) Bankruptcy rates and the tendency to sell the asset both decrease in the distance from the shock. (ii) Bankruptcy rates are high in the vicinity of the shock and higher in positions distant from the shock than those predicted by the benchmarks. (iii) The tendency to sell (buy) the asset decreases (increases) in the value of the asset. (iv) Subjects with a higher level of comprehension of the network-driven risk are more likely to sell the asset and hence less likely to face the risk of going bankrupt.*

5 Prices and bidding behavior

The double auction mechanism enables us to look closely into the formation of market prices across treatments to enhance our understanding of how network structure plays a substantial role in contagion. Tables 7-A and 7-B show the mean, standard deviations and percentile values for market prices for all treatments for, respectively, the data of all markets and the second half of each shock, i.e. the last three instances of each shock.

- Table 7-A and 7-B here -

[15]The standard deviation of *NCS* in the core-periphery network treatments is 15.24.

The descriptive data of market prices reveal a couple of noteworthy patterns. First, the mean prices in the core-periphery networks appear substantially lower than those of the circle networks. Focusing on Table 7-B, the differences between the two 15-person networks are 302 in the complete information treatment and 399 in the incomplete information treatment. These differences become smaller in the 6-person networks: 146 and 135 in the complete and incomplete information treatments respectively. These differences are largely driven by prices in the core-periphery networks collapsing to very low values from time to time. For instance, the bottom 5th percentile of prices hover between 200 and 275 in the core-periphery networks, whereas they are between 600 and 800 in the circle networks. Secondly, the information structure on the location of the shock plays a negligible role in price formation.

Figure 5 disaggregates the data further by showing the evolution of prices in cumulative seconds for each group from the first to the sixth market for a given shock size for the 15-person networks.[16] Similarly to the aggregated data, we observe a visible impact of network structure, but no discernible effect of information. More concretely, in Figures 5-B and 5-C for the intermediate and large shock sizes respectively, market prices in the core-periphery networks fall drastically after the first two or three markets in most of the groups. Given the complexity of debt settlement in the core-periphery networks, subjects learn the risk of a spillover and resort to 'flight-to-quality' trading which leads to a collapse in prices that amplifies the magnitude of market contagion beyond the role of the mechanical process of shock propagation. In contrast, market prices remain overall constant throughout the six markets in the circle networks. Prices tend to be slightly below the equilibrium value in Benchmark I, which seems to reflect the minor risk of a spillover from a shock.

- Figure 5-A, 5-B, and 5-C here -

The formal statistical analysis in Table 8 confirms that network structure has a significant impact on prices, whereas the effect of information is negligible. Table 8 reports the p-values for the M-W test for the equality of the samples of prices comparing each pair of network treatments after aggregating at the group level the

[16] See Online Appendix II for the equivalent plots for the 6-person networks.

data for the second half of the market data for each shock[17]. In the 15-person networks, prices are significantly lower in $CP15$ than in $CI15$ for all shock sizes ($p < 0.03$ for all comparisons). In the 6-person networks, prices are qualitatively lower in $CP6$ compared to $CI6$, and the difference is marginally significant for the complete information case ($p < 0.05$ for the intermediate shock, $p < 0.1$ for the large shock and all shocks combined).

- Table 8 here -

The continuous double auction set-up in the experiment allows the collection of information about bid and ask activities beyond the actual trading price. This permits the exploration of whether traders engage in panic selling to raise cash when they anticipate a liquidity crisis due to the spillover from a shock. In order to investigate this we look at the bid-ask volume ratio in the market, which we define as the number of distinct price contracts submitted to buy an asset (bid) over the number of distinct price contracts submitted to sell an asset (ask). If this ratio is equal to one then both buy and sell sides of the market submit an exactly equal number of contracts and thus put equal pressure on price formation. If it is below 1 then the sell side of the market submits more contracts than the buy side of the market, which is an indication of panic selling that may trigger a collapse of market prices.

Figure 6 displays the bid-ask volume ratios for the second half of the market data for each shock divided by network and information treatments.[18] We first note that the ratio decreases in shock size independently of treatment: it is close to 1 for the small shock, but it decreases substantially below 1 for both the intermediate and large shock cases. It suggests that the medium/large shock put more pressure on participants to sell in anticipation of a liquidity crisis. Secondly, the bid-ask volume ratios in core-periphery networks are lower than for circle networks, especially in the 15-person networks. For instance, in the medium shock case, the volume ratios are

[17] The M-W test results for the impact of the information treatment on prices are all insignificant. They are available from the authors upon request.

[18] Online Appendix II shows the equivalent figure for all the data, which displays the same qualitative features described in the text.

0.37 (*CP15*) versus 1.09 (*CI15*) and 0.32 (*CP15*) versus 0.80 (*CI15*) in the complete and incomplete information treatments respectively. The effect of network structure appears moderate in the 6-person networks. Lastly, there is a negligible effect of the information treatment.

- Figure 6 here -

A formal statistical analysis confirms that network structure has a significant impact on the bid-ask volume ratios, whereas the effect of information is negligible. Table 9 reports the p-values for the M-W test for the equality of the samples of the bid-ask volume ratios comparing each pair of network treatments after aggregating at the group level for the second half of the market data for each shock[19]. In agreement with the qualitative picture from Figure 6, the bid-ask volume ratio is significantly lower in the *CP15* than in the *CI15* networks ($p < 0.03$) and the significance of the effect is higher the larger the size of the shock. In the 6-person networks, the difference is smaller and only significant if we limit the data to markets in which a large shock occurs ($p < 0.05$). Overall, the evidence from the bid and ask data suggests that the collapse in prices in the core-periphery networks shown in Figure 5 are driven by fire-sales of assets in which most market participants are trying to sell their asset to raise liquidity, but they are only able to complete the trades at low prices because very few participants are willing to buy.

- Table 9 here -

We summarize our findings on prices and bidding behaviour in our experiment as follows.

Result 3 (Prices and bidding). *(i) Prices tend to collapse in core-periphery networks due to widespread sales of assets and depressed demand for buying assets, in particular in the medium and large shock cases; (ii) In the circle networks prices remain high in all shock regimes and the market maintains a balanced volume of bid and ask requests; (iii) There are negligible impacts of information on shock location on prices and bidding behavior.*

[19]Online Appendix II shows the same analysis for all the data, the results are unchanged.

6 Conclusion

This paper reports the results of the first experimental investigation of how the structure of financial linkages and market participants' uncertainty about the location of a shock causally determine financial contagion in a context where prices are endogenously determined through a trading process. The main results are that the network structure of linkages is an important determinant of contagion and adverse market outcomes, but uncertainty about the location of the shock has negligible effects. In particular, core-periphery networks exhibit a higher frequency of contagion than the benchmark simulations. The high contagion rates are driven by collapses in prices generated by fire sales of assets as market participants are trying to raise liquidity. In addition, participants who are better at understanding how the complex core-periphery network structure relates to the optimality of decisions tend to sell more frequently and therefore go bankrupt less often. In contrast, financial contagion is minimal in circle networks and trading happens at stable prices with a balanced number of bids and asks even in the presence of large shocks.

There are several avenues for future work to both extend and check the robustness of these results. First, one can extend the experiment by testing other network structures: a careful and systematic variation of the network would help to identify the specific features of network structure that lead to contagion. Second, the literature on experimental asset markets has investigated a large number of variations of the basic continuous double auction design and one can test the robustness of the findings in this paper in richer trading environments that allow for, e.g., multi-unit trading and arbitrage. Finally, financial networks in the real economy are not exogenously imposed but actively chosen by market participants so a future avenue of investigation is to extend our set-up to allow for endogenous network formation.

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Figure 1. Financial Networks

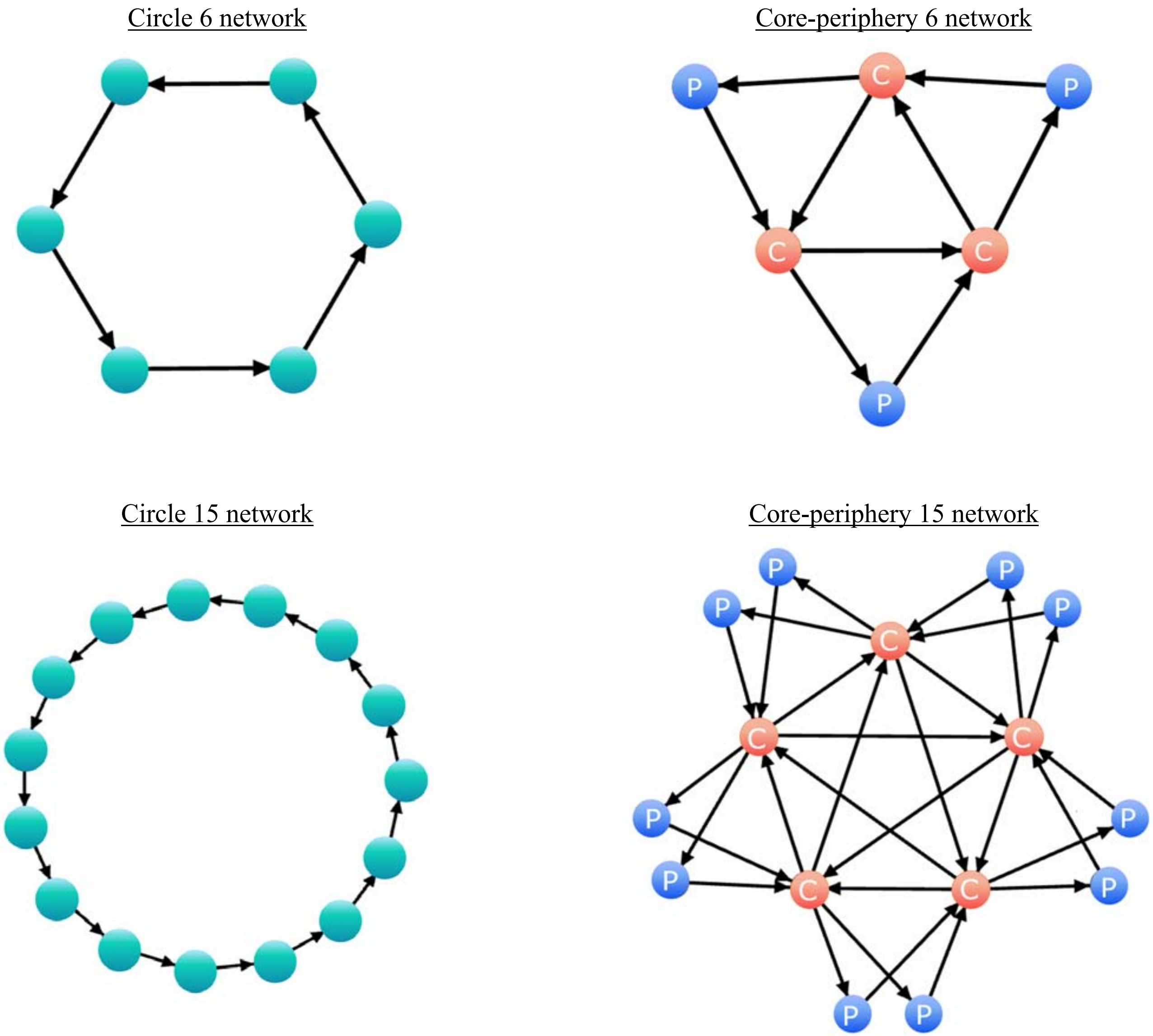


Figure 2. Frequencies of contagion: 60% threshold within a market

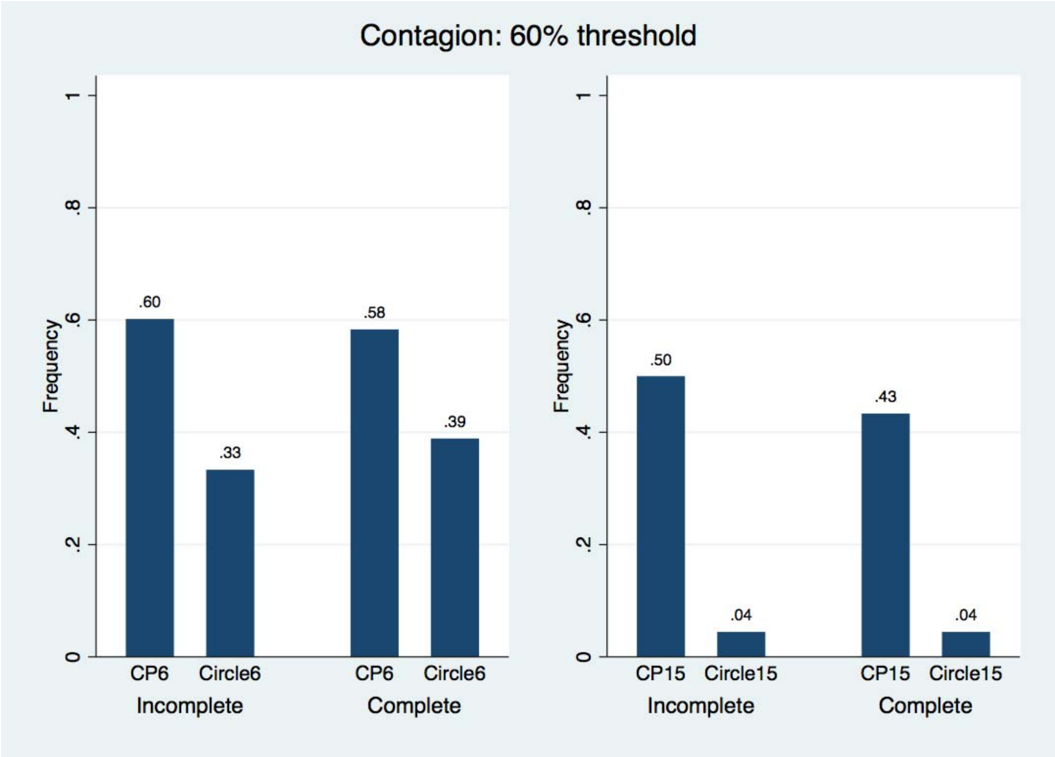


Figure 3. Frequencies of contagion in core-periphery networks over the location of a shock: 60% threshold

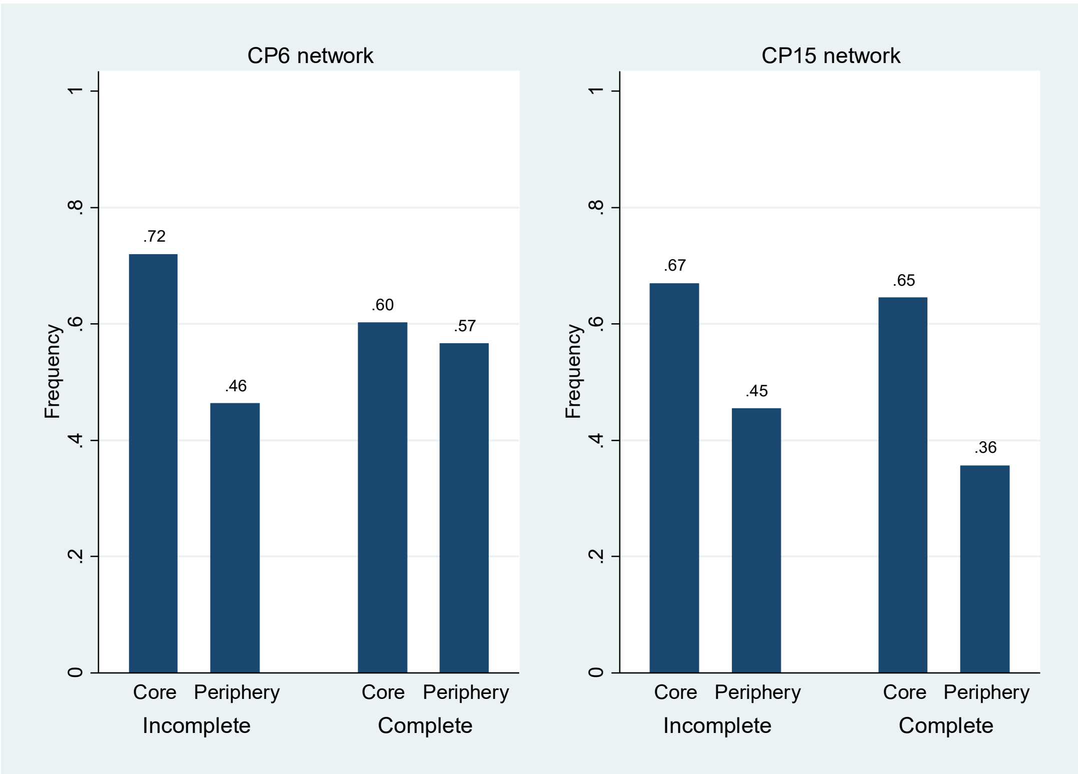


Figure 4. Frequencies of contagion over shocks: 60% threshold within a market

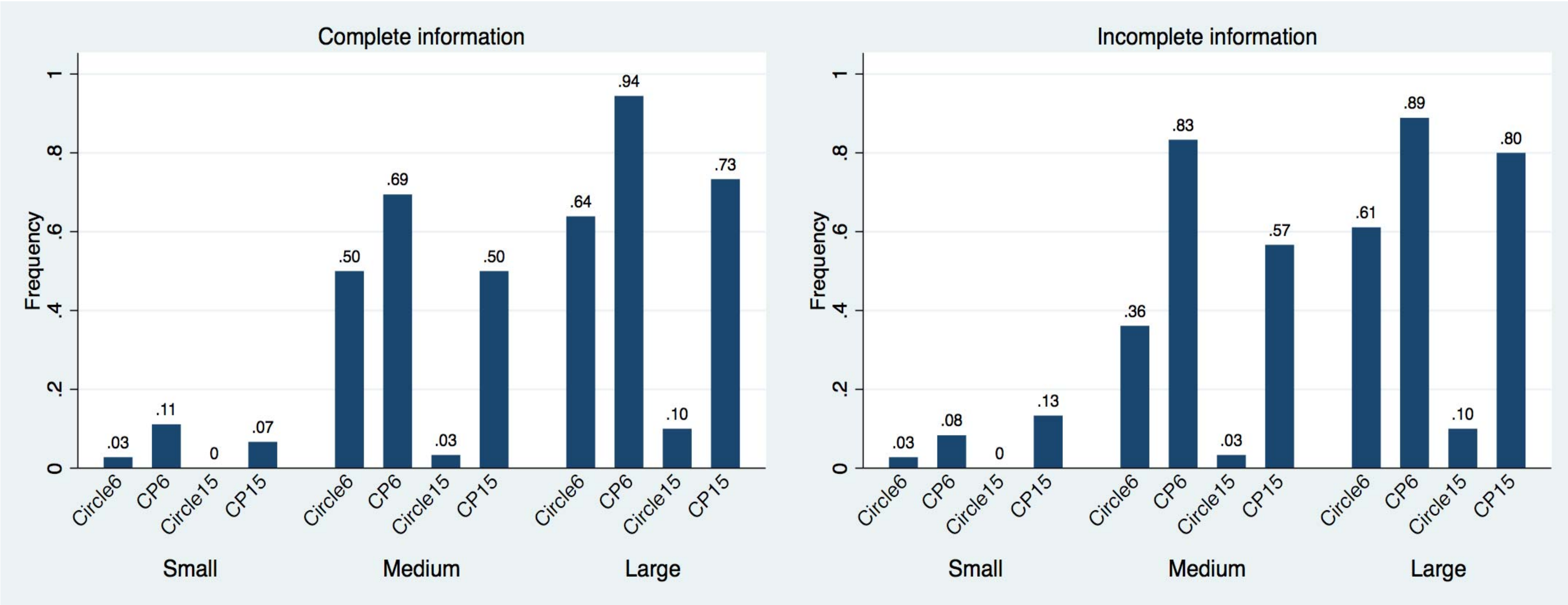
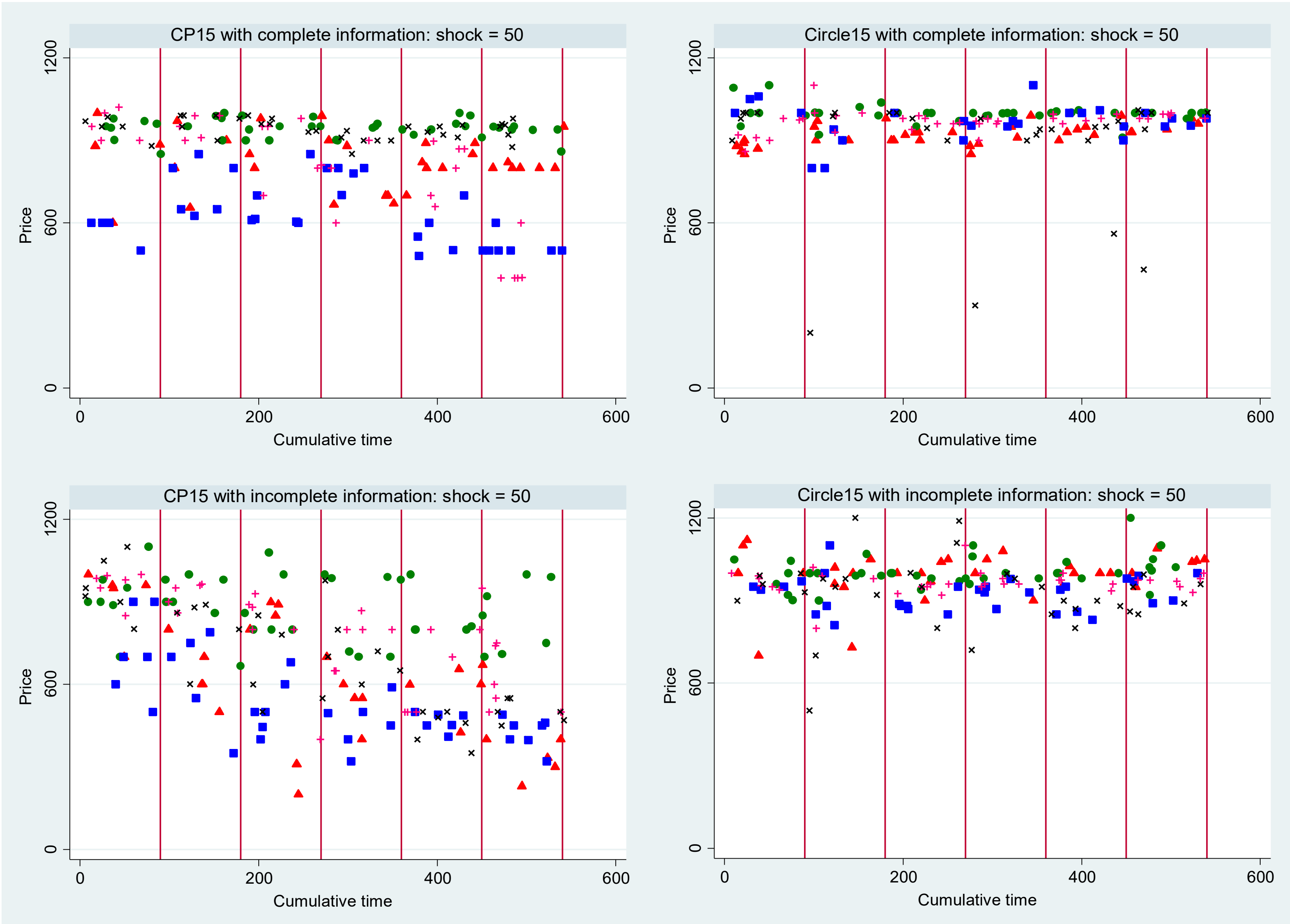


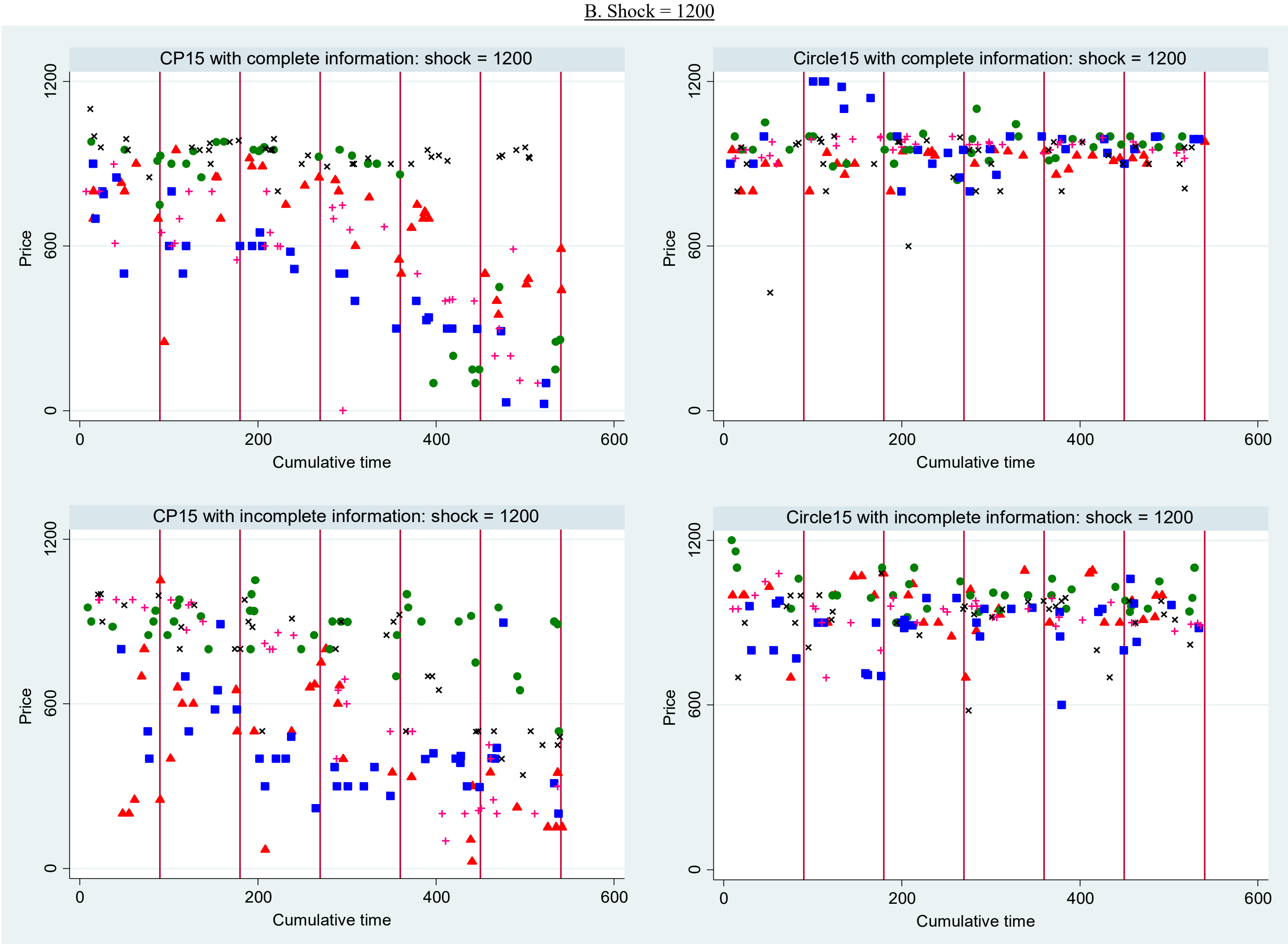
Figure 5. Dynamics of prices within and across markets over groups in 15-person networks

A. Shock = 50



Notes. (i) Each market lasts for 90 seconds. The cumulative time computes the seconds accumulated over markets. (ii) A pair of color and shape denotes one fixed group of subjects who repeated 6 markets in a session. We omit the first market which is the practice round.

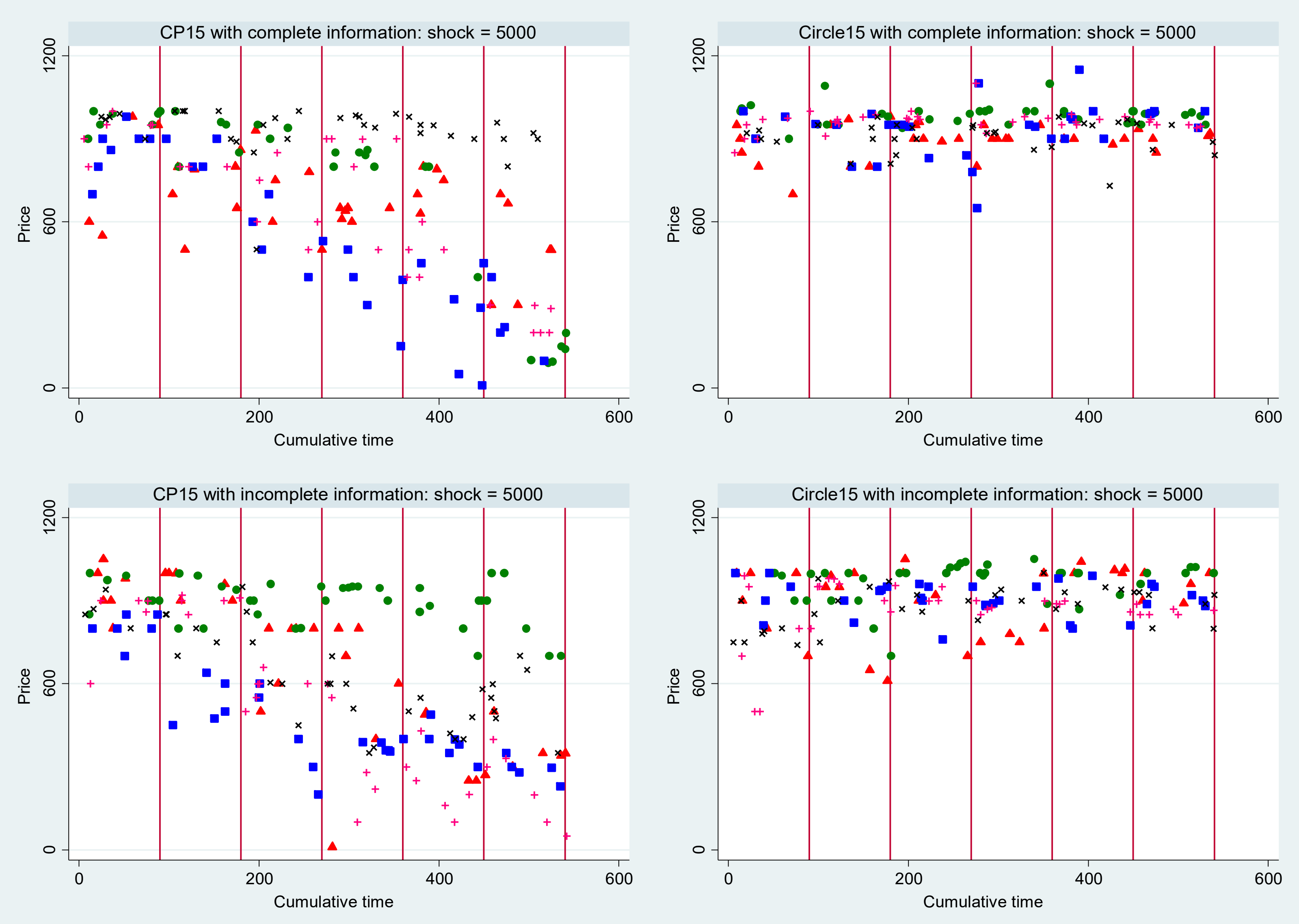
Figure 5 continued



Notes. (i) Each market lasts for 90 seconds. The cumulative time computes the seconds accumulated over markets. (ii) A pair of color and shape denotes one fixed group of subjects who repeated 6 markets in a session. We omit the first market which is the practice round.

Figure 5 continued

C. Shock = 5000



Notes. (i) Each market lasts for 90 seconds. The cumulative time computes the seconds accumulated over markets. (ii) A pair of color and shape denotes one fixed group of subjects who repeated 6 markets in a session. We omit the first market which is the practice round.

Figure 6. Average bid-ask volume ratios over shocks: data of second-half markets for each shock

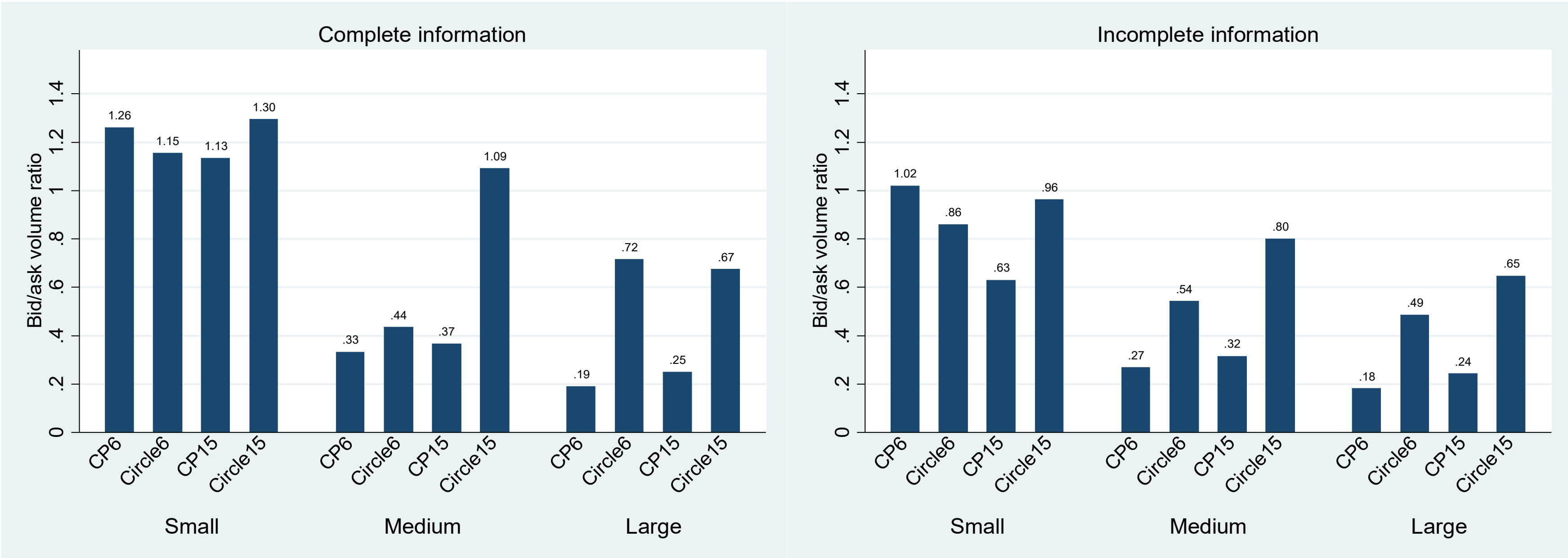


Table 1. Contagion rates in the benchmark simulations

		Benchmark I			Benchmark II			Benchmark III		
Networks	CE prices	100%	80%	60%	100%	80%	60%	100%	80%	60%
Circle 6	lower bound	0.000	0.079	0.218	0.000	0.144	0.259	0.000	0.111	0.190
	upper bound	0.000	0.000	0.046	0.000	0.065	0.176	0.000	0.083	0.157
CP 6	lower bound	0.019	0.130	0.324	0.032	0.157	0.389	0.532	0.644	0.681
	upper bound	0.000	0.019	0.153	0.014	0.069	0.310	0.176	0.273	0.301
Circle 15	unique	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CP 15	unique	0.000	0.006	0.089	0.000	0.017	0.178	0.000	0.100	0.211

Note. x% column reports relative frequencies of contagion with x% threshold

Table 2. Nonparametric tests of contagion: 60% threshold within a market

(p -value)

A. Network effects

		CP 6	CP 15
Complete info	CI 6	0.028	
	CI 15		0.007
Incomplete info	CI 6	0.004	
	CI 15		0.008

B. Information effects

		Complete	Incomplete
CP 6	Complete		0.622
CI 6	Incomplete	0.418	
CP 15	Complete		0.525
CI 15	Incomplete	0.905	

Note. Each cell reports p -values of Mann-Whitney-Wilcoxon test for the equality of average frequencies of contagion between two comparing treatments with data aggregated at the session level.

Table 3. Nonparametric tests of contagion over shocks: 60% threshold within a market

		Large shock		**Medium shock**		**Small shock**	
	Network	CP 6	CP 15	CP 6	CP 15	CP 6	CP 15
Complete info	CI 6	0.042		0.210		0.210	
	CI 15		0.008		0.010		0.320
Incomplete info	CI 6	0.032		0.009		0.460	
	CI 15		0.008		0.009		0.130

Note. Each cell reports p-values of Mann-Whitney-Wilcoxon test for the equality of average frequencies of contagion between two comparing treatments with data disaggregated by shock size at the session level.

Table 4. Frequencies of observed and simulated bankruptcy across treatments

A. Frequencies of bankruptcy in the experimental data

		Distance from the shock						
Information	Network	0	1	2	3	4	5	6 and above
Incomplete	Circle6	0.83 (108)	0.68 (108)	0.51 (108)	0.33 (108)	0.24 (108)	0.14 (108)	
	CP6	0.74 (108)	0.65 (167)	0.50 (216)	0.47 (108)	0.27 (49)		
	Circle15	0.87 (90)	0.66 (90)	0.48 (90)	0.33 (90)	0.22 (90)	0.20 (90)	0.03 (810)
	CP15	0.84 (90)	0.72 (177)	0.52 (418)	0.38 (421)	0.29 (244)		
Complete	Circle6	0.76 (108)	0.63 (108)	0.48 (108)	0.40 (108)	0.31 (108)	0.21 (108)	
	CP6	0.79 (108)	0.63 (164)	0.51 (216)	0.43 (108)	0.37 (52)		
	Circle15	0.79 (90)	0.57 (90)	0.32 (90)	0.18 (90)	0.12 (90)	0.09 (90)	0.02 (810)
	CP15	0.72 (90)	0.67 (159)	0.46 (418)	0.36 (427)	0.23 (268)		

Note. The number in parenthesis is the number of observations.

B. Frequencies of bankruptcy in the simulated data

		Distance from the shock						
Benchmark	Network	0	1	2	3	4	5	6 and above
I	Circle6	0.85	[0.42, 0.71]	[0.19, 0.44]	[0.05, 0.22]	[0, 0.08]	0.00	
	CP6	0.83	[0.41, 0.60]	[0.22, 0.34]	[0.07, 0.13]	[0, 0.02]		
	Circle15	0.84	0.44	0.17	0.08	0.03	0.02	0.00
	CP15	0.83	0.49	0.27	0.16	0.10		
II	Circle6	0.67	[0.51, 0.56]	[0.33, 0.40]	[0.18, 0.26]	[0.06, 0.14]	0.00	
	CP6	0.67	[0.46, 0.53]	[0.30, 0.35]	[0.14, 0.18]	[0.03, 0.05]		
	Circle15	0.67	0.44	0.26	0.17	0.09	0.04	0.00
	CP15	0.67	0.49	0.28	0.19	0.13		
III	Circle6	0.67	[0.28, 0.33]	[0.22, 0.26]	[0.16, 0.19]	[0.08, 0.11]	0.00	
	CP6	0.83	[0.31, 0.79]	[0.26, 0.64]	[0.27, 0.64]	[0.17, 0.19]		
	Circle15	0.67	0.24	0.15	0.08	0.06	0.02	0.00
	CP15	0.67	0.36	0.21	0.15	0.10		

Table 5. Regression analysis of individual bankruptcy

	All networks (1)	Circle networks (2)	CP networks (3)
Networks and shocks			
shock size: medium	0.324***	0.221***	0.427***
	(0.013)	(0.017)	(0.019)
shock size: large	0.463***	0.339***	0.588***
	(0.013)	(0.017)	(0.018)
distance from the shock	-0.109***	-0.109***	-0.108***
	(0.003)	(0.004)	(0.006)
distance * CP networks	-0.007		
	(0.006)		
distance * Incomplete information	-0.012***	-0.012***	-0.014
	(0.002)	(0.002)	(0.010)
periphery shocked			-0.048***
			(0.015)
Asset value			
ln (asset value)	0.224***	0.200**	0.451***
	(0.077)	(0.087)	(0.098)
ln (asset value) * CP networks	0.202**		
	(0.094)		
ln(asset value) * Incomplete information	0.072	0.116	0.026
	(0.094)	(0.117)	(0.149)
Behavioral characteristics			
network comprehension test	-0.057**	-0.023	-0.151***
	(0.024)	(0.023)	(0.057)
# of safe choices: gain	-0.001	-0.004	0.002
	(0.004)	(0.004)	(0.007)
# of safe choices: loss	-0.001	0.002	-0.006
	(0.003)	(0.003)	(0.006)
Constant	-0.991*	-0.744	-12.008***
	(0.534)	(0.608)	(2.717)
Treatment & period dummies	Yes	Yes	Yes
R squared	0.42	0.36	0.47
Observations	7,992	3,996	3,996
Number of subjects	444	222	222

Notes. Random-effects GLS model. Period effects are controlled by including period dummies. The 'distance' variable is truncated by 6. *,**, and *** represent significance at th 10%, 5%, 1% levels, respectively.

Table 6. Regression analysis of trading decisions

	Sell			Buy		
	All networks	Circle networks	CP networks	All networks	Circle networks	CP networks
	(1)	(2)	(3)	(1)	(2)	(3)
Networks and shocks						
shock size: medium	-0.012	-0.016	-0.010	-0.012	-0.016	-0.012
	(0.013)	(0.018)	(0.019)	(0.014)	(0.019)	(0.022)
shock size: large	-0.019	-0.016	-0.018	-0.014	-0.016	-0.016
	(0.013)	(0.018)	(0.020)	(0.014)	(0.019)	(0.022)
distance from the shock	-0.048***	-0.047***	-0.074***	0.048***	0.046***	0.092***
	(0.005)	(0.006)	(0.010)	(0.005)	(0.005)	(0.011)
distance * CP networks	-0.012			0.021**		
	(0.008)			(0.008)		
distance * Incomplete information	0.020***	0.018***	0.034***	-0.021***	-0.018***	-0.062***
	(0.003)	(0.003)	(0.013)	(0.003)	(0.003)	(0.014)
periphery shocked			0.061***			-0.019
			(0.016)			(0.017)
Asset value						
ln (asset value)	-1.930***	-1.919***	-0.977***	1.869***	1.836***	0.991***
	(0.118)	(0.138)	(0.123)	(0.126)	(0.149)	(0.129)
ln (asset value) * CP networks	0.968***			-0.912***		
	(0.133)			(0.136)		
ln(asset value) * Incomplete information	-0.009	-0.029	0.015	-0.054	0.006	-0.115
	(0.133)	(0.201)	(0.173)	(0.136)	(0.199)	(0.186)
Behavioral characteristics						
network comprehension test	0.124***	0.064	0.276***	-0.008	0.042	-0.134
	(0.043)	(0.052)	(0.080)	(0.047)	(0.055)	(0.089)
# of safe choices: gain	0.009	0.001	0.017	-0.008	-0.004	-0.012
	(0.007)	(0.009)	(0.010)	(0.006)	(0.008)	(0.010)
# of safe choices: loss	0.002	0.001	0.002	-0.008	-0.007	-0.008
	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)	(0.009)
Constant	13.668***	13.663***	6.935***	-12.562***	-12.413***	-6.418***
	(0.812)	(0.950)	(0.863)	(0.863)	(1.027)	(0.899)
Treatment & period dummies	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.11	0.16	0.06	0.10	0.14	0.06
Observations	7,992	3,996	3,996	7,992	3,996	3,996
Number of subjects	444	222	222	444	222	222

Notes. Random-effects GLS model. Period effects are controlled by including period dummies. The 'distance' variable is truncated by 6. *,**, and *** represent significance at th 10%, 5%, 1% levels, respectively.

Table 7. Description of Prices

A. Data of all markets

		Complete info		Incomplete info		Complete info		Incomplete info	
		Circle 15	CP 15	Circle 15	CP 15	Circle 6	CP 6	Circle 6	CP 6
Mean		945.9	742.5	936.7	656.9	911.2	791.3	894	804.4
S. D.		94.4	248.1	97	254.4	242.8	252.9	113.9	266.3
Percentile	95%	1010	990	1070	995	1090	1040	1050	1055.5
	75%	990	945	1000	900	995	980	970	930
	50%	953	830	950	700	945	850	900	850
	25%	910	600	900	450	850	700	830	700
	5%	800	200	750	220	600	250	611	275
Observations		517	497	505	523	233	226	238	240

B. Data of the second-half markets for each shock

		Complete info		Incomplete info		Complete info		Incomplete info	
		Circle 15	CP 15	Circle 15	CP 15	Circle 6	CP 6	Circle 6	CP 6
Mean		948.4	646.2	941.5	542.8	904.7	758.5	882.9	747.9
S. D.		78.9	283.3	79.4	241.7	244.8	256.4	113.9	249.8
Percentile	95%	1001	958	1050	950	1050	1000	1004.75	1000
	75%	990	900	999	710	990	970	955.5	900
	50%	960	702	950	500	918	820	899	800
	25%	930	400	899	360	811	600	815	650
	5%	850	100	800	200	600	300	670	150
Observations		265	251	250	269	122	111	120	118

Table 8. Nonparametric tests of prices: Data of the second-half markets for each shock

		All shocks		Large shock		Medium shock		Small shock	
	Network	CP 6	CP 15	CP 6	CP 15	CP 6	CP 15	CP 6	CP 15
Complete info	Circle 6	0.078		0.055		0.040		1.000	
	Circle 15		0.028		0.028		0.016		0.030
Incomplete info	Circle 6	0.337		0.262		0.150		0.200	
	Circle 15		0.009		0.028		0.009		0.009

Note: Each cell reports the p-value of Mann-Whitney-Wilcoxon test for the equality of two samples at the group

Table 9. Nonparametric tests of bid-ask volume ratio: Data of the second-half markets for each shock

		All shocks		Large shock		Medium shock		Small shock	
	Network	CP 6	CP 15	CP 6	CP 15	CP 6	CP 15	CP 6	CP 15
Complete info	Circle 6	0.337		0.025		0.631		1.000	
	Circle 15		0.028		0.047		0.076		0.465
Incomplete info	Circle 6	0.522		0.007		0.337		0.150	
	Circle 15		0.009		0.009		0.009		0.047

Note: Each cell reports the p-value of Mann-Whitney-Wilcoxon test for the equality of two samples.