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# A LABORATORY INVESTIGATION OF NETWORKED MARKETS*

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When contracts are not perfectly enforceable, can interpersonal networks improve market efficiency? We introduce certain exogenous networks into laboratory markets in which traders can cheat in 'international' but not in 'domestic' transactions. We examine four network configurations, one of which has the potential to achieve 100% efficiency. Theoretical upper bounds correctly predict the main qualitative trade patterns across our network configurations but overpredict observed efficiency. Our networks increase international trade volume, reduce domestic volume and divert high surplus transactions to international networks.

Economists traditionally regard markets as impersonal auctions, in which buyers and sellers interact only via prices. By contrast, other social scientists focus on complex networks of interpersonal relations with little regard for price. Recently economists in several fields – including history, international, development, labour and law – have begun to realise that these perspectives are complementary and that interpersonal networks may play an important role when markets have frictions.

Frictions such as the imperfect enforcement of contracts loom large not just in major markets of the ancient and medieval world (Greif, 1993) but also in many contemporary markets. In international trade, the 'missing trade puzzle' is that the actual volume of international trade is far smaller than the volume predicted by traditional models, even when formal trade barriers are taken into account (Trefler, 1995; Helliwell, 1998). A possible explanation is that the lack of contract enforcement and trust[1] reduce the volume of international trade (Anderson and Marcouiller, 2002).

Several observers have conjectured that when contract enforcement is weak or non-existent, transnational networks – e.g., immigrant networks or business groups that include multinational firms – might bolster trust and therefore trade among their members (Cohen, 1969, 1971; Curtin, 1984; Greif, 1989, 1993; Weidenbaum and Hughes, 1996). Several empirical studies show that information sharing through immigrant networks (Gould, 1994; Head and Ries, 1998) or business groups (Belderbos and Sleuwaegen, 1998; Head and Ries, 2001; Rauch and Trindade, 2002) seems to increase trade volume. Of course, such networks can divert trade towards well-connected but inefficient producers and consumers (Taylor, 2000; Fafchamps, 2002), so the efficiency implications are unclear.

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[1] Defined as in Bradach and Eccles (1989, p. 99): 'the expectation that an exchange partner will not engage in opportunistic behavior despite short-term rewards.'

The present article reports laboratory results on how networks affect efficiency and trade patterns. The laboratory setup is inspired by the international trade literature but the underlying issues span several fields.

Frictions and networks abound in labour markets. In particular, interpersonal relationships play a crucial role in helping job-seekers find a job (Granovetter, 1995); for a survey see Ioannides and Loury (2004). Even for domestic e-commerce in developed economies, where frictions would seem minimal, networks can be crucial; for example, eBay's main competitive advantage may be its reputation rankings which effectively reduce cheating (Anderson *et al.*, 2004; Resnick *et al.*, 2006). Networks also loom large in recent work on economic development. Following the seminal work by Putnam *et al.* (1993), numerous studies find that faster economic growth is associated with more social capital, which often is measured as the number of network links per person. Fafchamps (2004) notes that many agricultural traders in Sub-Saharan Africa rely on their personal network of relationships to identify trade opportunities. When court enforcement of contracts is unreliable (Fafchamps and Minten 2001), personalised trust and informal institutions – e.g., reputation sharing within business networks and communities – help to take up the slack,[2] but only up to a point. Fafchamps (2002, 2004) conjectures that networks help mainly at intermediate levels of development. Networks foster exchange beyond the limits of personalised trust, but once strong market institutions boost generalised trust, the networks are no longer necessary and can actually reduce efficiency by diverting trade to better connected but less efficient traders. In a variation on this theme, interpersonal trade networks seems to have played a dubious role in Russia's economic implosion in the 1990s (Craver and Leijonhufvud, 2001; Klebnikov, 2000).

Empirical knowledge lags on markets and networks, despite a recent flowering of theoretical work (Kranton, 1996; Kranton and Minehart, 2001); for surveys see Rauch and Casella (2001), Goyal (2007) and Jackson (2008). Field evidence is problematic for several reasons. First of all, one can seldom observe networks directly. For example, one might relate bilateral balance of payments data to census data on immigration, or one might survey some export–import business managers about ethnic ties but one cannot directly observe the implicit contracts or the information flows in any one link, much less observe the full set of links that constitutes an immigrant network supporting international trade. Even worse, the field data are difficult to interpret because of problems of identification, unobserved group effects, self-selection, individual effects, endogeneity and reverse causation (Fafchamps, 2003). For example, the existence of international trade in memory chips might be the cause and not an effect of an international network, and the Russian economic collapse might have caused the expansion of interpersonal trading networks. Moreover, it is hard to measure efficiency in the field.

In the present article we study how laboratory markets respond to different architectures of buyer–seller networks. We build on a baseline study of market frictions

[2] For example, the field experiments of Cassar *et al.* (2007) provide evidence that the success of microfinance may be due more to personal trust and social homogeneity between group members than on more general societal trust.

(Cassar *et al.*, 2009), specifically, the imperfect enforcement of contracts or (to be blunt) cheating. The idea is that the seller might ship an item of lower quality or delay delivery and the buyer might bounce a cheque or send partial or late payment. In the Cassar *et al.* (2009) experiment, buyers and sellers operate in a domestic ('Local') market in which contracts are strictly enforced and also in an international ('Distant') market that allows cheating.

To the Cassar *et al.* (2009) setup we now add exogenous interpersonal networks. We consider four simple network architectures, involving fully connected subsets of traders ('cliques'). Thus trades within the network are observable by all members, while international trade outside the network is anonymous. Our focus on cliques can be explained in part by theoretical work that, in a variety of contexts, shows that such architectures often emerge spontaneously when network formation is endogenous (Vega-Redondo, 2006; Haag and Lagunoff, 2006). The focus also can be justified by the fact that medieval and modern trade associations can be regarded as cliques. Bernstein (2001) explains why contract enforcement in the cotton industry, international as well as domestic, relies on reputation-based extra-legal sanctions within the trade association, and Bernstein (1996, 1992) explains similar dispute resolution in US grain markets and the diamond industry.

The networks in our experiment are exogenous in order to avoid endogeneity confounds such as self-selection. For example, with endogenous networks, the more trusting and reliable subjects might form more (or fewer) networks links and one might falsely attribute the outcomes to the observed network architecture rather than to the unobserved personal traits. With exogenous networks and random assignments of subjects, we can isolate the impact of network structure and make valid causal inferences.

We chose the particular cliques that seemed most diagnostic. Network $A$ consists of the highest value buyers in one market and the lowest cost sellers in the other market, so there are very large potential gains from exchange within it. Network $B$ consists of a set of buyers and sellers with smaller potential gains. We compare market performance under four conditions: NoNet (neither network active), Net $A$ (only network $A$ active), Net $B$ (only network $B$ active) and Net$AB$ (both networks $A$ and $B$ active). This last network is particularly interesting since it could potentially achieve 100% efficiency. More details on the design are reported in Section 1.

Section 2 derives the theoretical benchmarks. We extend textbook competitive equilibrium to our multi-market situation. The analysis is intricate because there are up to eight theoretically distinct markets: two domestic markets, a cheat and a no-cheat international market outside the networks and a cheat and a no-cheat international market within each network. Nevertheless, we obtain an essentially unique competitive equilibrium under each of the four network conditions, and note that it predicts an upper bound for market performance. The Section closes with more general hypotheses about the impact of networks on market efficiency, trading volume, market segmentation and trade diversion.

The empirical results are collected in Section 3. In our experiment, networks significantly reduce cheating and increase efficiency. Traders do not achieve competitive equilibrium (CE) efficiencies but the CE upper bounds correctly predict the efficiency rankings across the four network conditions. CE also predicts the main qualitative changes in trade patterns across conditions, e.g. networks lure high surplus transactors out of domestic trade and into international trade. We find no evidence of inefficient trade diversion. CE prices tend not to respond much to changes in network architecture and neither do our data.

Following a concluding discussion, Appendix A provides details of the CE derivation. Appendix B, which reproduces the instructions to subjects, and an additional full set of figures and tables reporting details are available at the authors' webpage, at http://www.usfca.edu/fac-staff/acassar.

## 1. Experimental Design

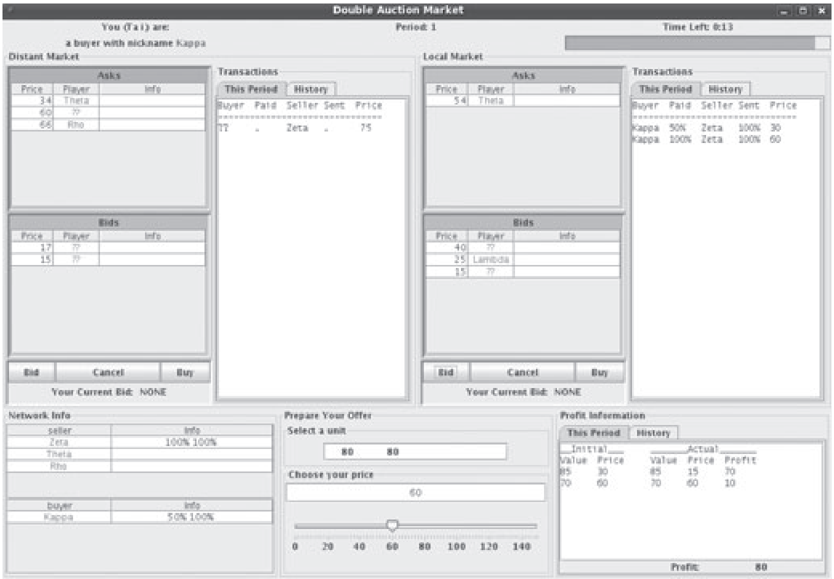
Our laboratory markets use the well-known continuous double auction (CDA) format. At any instant during a trading period, each buyer can post a public bid (offer to buy a unit at a given price or lower) and each seller can post a public ask (offer to sell a unit at a given price or higher). Each trader also at any instant can accept another trader's offer and immediately transact at the posted price $p$. A buyer with unit value $v$ earns the profit or surplus $v - p$ on the transaction and a seller with cost $c$ on the unit earns $p - c$, so the overall gains on the transaction are $v - c$.

Figure 1 shows an example of the user interface. In each period two markets run simultaneously, one labelled 'Distant' and the other labelled 'Local'. Each period each trader can transact up to 4 units with different costs or values. Each trader has a 'nickname' that identifies her in her Local market and to the other members of her network (if any) in the Distant market, as explained below. Between trading periods traders can view past transactions and profits by clicking the history tab.

Each laboratory session was comprised of sixteen human subjects (recruited by email from a list of hundreds of volunteers, mostly UCSC undergraduates). Some sessions used only subjects with no prior experience with our laboratory market. Other sessions used only experienced subjects, who had participated in a prior session. In each session each subject was randomly assigned to one of four buyer or seller roles in one of the two different Local markets, referred to below as the Red market and the Blue market. Table 1 reports all induced values and costs assigned to the traders, as well as the network architectures.

Each session began by going through the first part of the instructions (reproduced in Appendix B which can be accessed from the author's website, http://www.usfca.edu/fac-staff/acassar), followed by a practice period. Next came the first block of 3 or 4 periods, and then later parts of the instructions and later blocks of periods using different treatments. Buyer values and seller costs were reshuffled once about half-way through the two-hour sessions with experienced subjects. (Otherwise subjects would have very unequal profit opportunities because, as a stress test for Competitive Equilibrium, these sessions used treatments disadvantaging Blue buyers and Red sellers.) Each trading period lasted 240 seconds with a 10-second break between periods. The subjects could not talk to each other either during a trading period or between periods. After the last period, subjects were paid a \$5 show-up fee plus earnings for all periods; most subjects earned between \$20 and \$40. Tables 2$a$ and 2$b$ report the treatments used in each block per session.

Sessions with inexperienced traders began with 3 periods of autarchy (denoted Aut below), in which subjects can buy and sell only in their Local market. As shown in




Trading Screen. The subject a buyer nicknamed Kappa, actually named Tai. He can post a bid in either market using the Prepare your Offer box at lower centre screen, by clicking on a unit (here one of the two units valued at 80), choosing the desired price (by typing it in or by dragging the slider to the desired value), and then clicking the Bid button of either the Local or the Distant market. His bids and those of other buyers appear in the lower boxes for both markets. The color highlighted upper boxes show asks posted by sellers.

Buyer Kappa can transact a single unit either by clicking an existing ask and then clicking the Buy button (and the seller confirms it), or by waiting until some seller clicks on his bid (and he confirms it). All current period transaction prices and performance in both markets appear in the Transactions boxes: clicking the History tab switches the display to previous periods. In the Net treatments, Kappa will see nicknames of members his own network (Zeta, Theta and Rho, as shown in the lower left box) in Distant market transactions, while other traders' nicknames are replaced by ??. The 'Profit Information' box at the bottom right of the screen shows Kappa's previous transactions and profit.

Buyer Kappa's screen shows that he bought 2 units from network member Zeta, and paid only 50% of the price on the first unit but paid 100% on the second, while Zeta sent 100% value for both units. In his Distant Market window Kappa sees that Zeta sold another unit at price 75 to a buyer outside their network.

Sellers' trading screens are similar, with Ask and Sell buttons instead of Bid and Buy etc.

Fig. 1. *Trading Screen*

Figure 2 and Table 1, supply and demand are higher in the Red market than in the Blue market. These sessions continued with a block (3 or 4 periods)[3] of frictionless free trade (FFT).

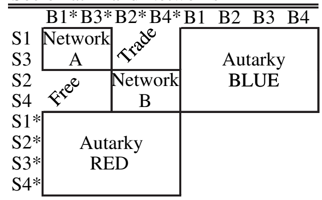
*FFT Treatment*. Here each trader can participate in both markets at the same time. Side-by-side colour-coded copies of the main window allow each trader to post, observe and accept offers in the Distant market as well as in the Local market. The third panel of Figure 2 shows the total demand and supply when cross market trade is allowed.

[3] As shown in Table 2*a*, the initial inexperienced sessions CHEAT05-07 have 3 period blocks but we shifted to 4 period blocks for subsequent inexperienced sessions to reduce the cognitive load on our subjects.

Table 1
*Parameters*

| Market BLUE | | | | | Market RED | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Buyers' Values | | | | | Buyers' Values | | | | |
| Buyer ID | Unit 1 | Unit 2 | Unit 3 | Unit 4 | Buyer ID | Unit 1 | Unit 2 | Unit 3 | Unit 4 |
| B1 | 45 | 45 | 20 | 20 | B1* | 85 | 85 | 80 | 80 |
| B2 | 40 | 40 | 15 | 15 | B2* | 60 | 60 | 55 | 55 |
| B3 | 35 | 35 | 10 | 10 | B3* | 75 | 75 | 50 | 50 |
| B4 | 30 | 30 | 5 | 5 | B4* | 70 | 70 | 45 | 45 |
| Sellers' Costs | | | | | Sellers' Costs | | | | |
| Seller ID | Unit 1 | Unit 2 | Unit 3 | Unit 4 | Seller ID | Unit 1 | Unit 2 | Unit 3 | Unit 4 |
| S1 | 10 | 10 | 15 | 15 | S1* | 50 | 50 | 65 | 65 |
| S2 | 25 | 25 | 30 | 30 | S2* | 55 | 55 | 70 | 70 |
| S3 | 20 | 20 | 35 | 35 | S3* | 60 | 60 | 75 | 75 |
| S4 | 25 | 25 | 40 | 40 | S4* | 65 | 65 | 80 | 80 |

Sociomatrix and Networks




Networks

Network A: S1, S3, B1*, B3*
Network B: S2, S4, B2*, B4*

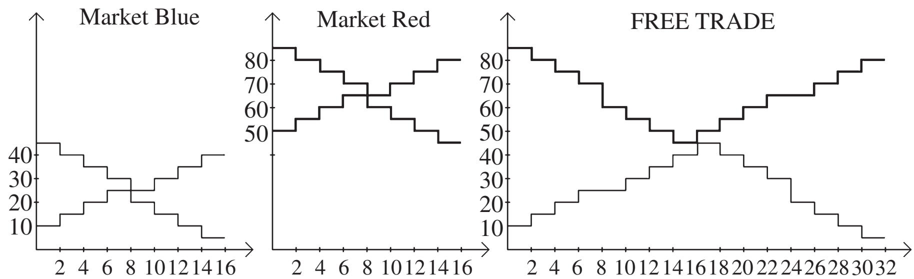



Fig. 2. *Demand and Supply Schedules*

Note that in equilibrium, only Red buyers and Blue sellers transact, and all Red sellers and all Blue buyers are extramarginal.

*NoNet Treatment.* The next 4 period block in sessions with inexperienced traders, and the first block of 4 periods with experienced players, provide the option to cheat a fixed exogenous degree $\pi = 0.5$ in trades in the Distant market. Cheating is never allowed in local trades, e.g., in the Blue market between two Blue traders. The choices are sequential. First the trader accepting a Distant offer chooses whether to cheat. That choice is observed by the trader who posted the offer, who then decides whether to cheat. Sellers cheat by delivering a good that costs $\pi c$ instead of $c$ and that provides value $\pi v$ instead of $v$. Buyers cheat by paying only $\pi p$ instead of $p$. (Instructions avoid the word 'cheat' and just mention the choice of paying $100\pi$% or 100% etc.)

For example, suppose that a buyer posts bid price $p = 50$ on a unit he values at $v = 60$. If a seller from the Distant market with cost $c = 40$ accepts and decides not to cheat but the buyer then decides to cheat, then the buyer surplus is $v - \pi p = 60 - 0.5 \times 50 = 35$ and the seller surplus is $\pi p - c = 0.5 \times 50 - 40 = -15$.

It should be emphasised that in this treatment, all cross market transactions are anonymous. Traders' nicknames are shown in all Local market transactions, but are replaced by '??' when they post or accept bids and asks in their Distant market.

*Network Treatments.* When a network is present, its members can see the nicknames of all other members in all bids, asks and transactions in all markets. In particular, they can see whether fellow members paid (or shipped) in full (100%) or not

(50%). The information is useful because the trading screen allows each trader to accept any existing offer, not just the best (as in the standard CDA), which may be held by a known cheater or by an anonymous trader. Each trader knows from the outset the identities of her network's members. As trading progresses, she benefits from her fellow members' experience as well as her own. Thus traders know which network members cheated and which did not, and they can build reputations within their network.

The right side of Table 1 shows the links among traders used in the experiment to exogenously assign networks. Network *A* is comprised of the two Blue sellers with lowest costs and the two Red buyers with highest values. Thus membership in Network *A* is especially valuable. Network *B* is comprised of the remaining two Blue sellers and two Red buyers. In treatment Net*AB*, both networks are present at the same time. In treatments Net*A* and Net*B* only the indicated network is present while the other is shut off. Table 2 shows how treatments were assigned in each session.

## 2. Theoretical Predictions

Cassar *et al.* (2009) derive the competitive equilibrium (CE) outcomes for the Autarky, Frictionless Free Trade (FFT) and NoNet treatments. Appendix A extends the analysis to the three Net treatments. In this Section we sketch the methods and results, and summarise the main testable implications.

One maintained assumption is that traders are price-takers, so CE is the relevant equilibrium concept. That assumption once might have seemed controversial, but not since the work of dozens of experimentalists summarised in Smith (1982). A second maintained assumption, justified in Cassar *et al.* (2009), is that everyone cheats in cross market trade outside the network. The analysis presented below introduces a third assumption: nobody cheats within the network. As noted in Appendix A, this assumption allows us to derive upper bounds on CE efficiency.

Is it reasonable to assume that networks completely deter cheating? Standard theory, e.g., Kreps *et al.* (1982), suggests that reputational concerns can deter cheating when trades are not anonymous but that deterrence will decay later in the session. The assumption is also consistent with 'strong reciprocity' as in Fehr *et al.* (2002) and related behavioural theory, as well as with the evidence presented in the Bernstein articles noted earlier. Empirically, we will see that the assumption does not do too much violence to our data.

It is straightforward to obtain CE for Net*AB*. Take Network *A* as a separate market in which cheating does not occur. Equate the demand (from Red buyers *B*1* and *B*3*) to the supply (from Blue sellers *S*1 and *S*3), and obtain the range [45, 50] for market-clearing prices, each of which supports 8 units traded and a realised surplus (sum of buyer values less seller costs) of 420. Likewise, the Network *B* market segment yields a surplus of 220 on 8 units traded at a market clearing price of 45. No further gains from exchange are available. Thus the CE prediction for Net*AB* is for 640 surplus (the same as in FFT, so efficiency is 100%) on 16 units traded (again, the same as in FFT) with some units at price 45 and others at prices in the interval [45, 50].

Table 2

*Experimental Design*

| Session | Period | Treatment | Session | Period | Treatment |
|---|---|---|---|---|---|
| (*a*) *Inexperienced Subjects* | | | | | |
| CHEAT05 | 1–3 | Aut | NETCHEAT04 | 1–4 | Aut |
| (Jan 16, 2004) | 4–6 | FFT | (Mar023, 2005) | 5–8 | FFT |
| | 7–9 | NoNet | | 9–12 | NoNet |
| | 10–15 | Net*AB* | | 13–16 | Net*AB* |
| CHEAT06 | 1–3 | Aut | NETCHEAT06 | 1–4 | Aut |
| (Feb06, 2004) | 4–6 | FFT | (Mar10, 2005) | 5–8 | FFT |
| | 7–10 | NoNet | | 9–12 | NoNet |
| | 11–14 | Net*AB* | | 13–16 | Net*AB* |
| CHEAT07 | 1–3 | Aut | NETCHEAT08 | 1–4 | Aut |
| (Feb13, 2004) | 4–6 | FFT | (Mar31, 2005) | 5–8 | FFT |
| | 7–10 | NoNet | | 9–12 | NoNet |
| | 11–15 | Net*AB* | | 13–16 | Net*AB* |
| NETCHEAT01 | 1–4 | Aut | NETCHEAT09 | 1–4 | Aut |
| (Feb10, 2005) | 5–8 | FFT | (Apr07, 2005) | 5–8 | FFT |
| | 9–12 | NoNet | | 9–12 | NoNet |
| | 13–16 | Net*AB* | | 13–16 | Net*AB* |
| NETCHEAT02 | 1–4 | Aut | NETCHEAT11 | 1–4 | Aut |
| (Feb24, 2005) | 5–8 | FFT | (May05 2005) | 5–8 | FFT |
| | 9–12 | NoNet | | 9–12 | NoNet |
| | 13–16 | Net*AB* | | 13–16 | Net*AB* |
| (*b*) *Experienced Subjects* | | | | | |
| CHEAT08 | 1–4* | NoNet | NETCHEAT10 | 1–4 | NoNet |
| (Feb20, 2004) | 5–8 | Net*AB* | (Apr07, 2005) | 5–8 | Net*AB* |
| | 9–12 | Net*A* | | 9–12 | Net*A* |
| | 13–16 | Net*B* | | 13–16 | Net*B* |
| | 17-20 | NoNet** | | 17–20 | Net*B*** |
| | 21–24 | Net*B* | | 21–24 | Net*A* |
| | 25–28 | Net*A* | | 25–28 | Net*AB* |
| CHEAT09 | 1–4 | NoNet | NETCHEAT12 | 1–4 | Net*AB* |
| (Feb27, 2004) | 5–8 | Net*AB* | (May11, 2005) | 5–8 | NoNet |
| | 9–12 | Net*B* | | 9–12 | Net*A* |
| | 13–16 | Net*A* | | 13–16 | Net*A* |
| | 17–20 | Net*A*** | | 17–20 | NoNet** |
| | 21–24 | Net*B* | | 21–24 | Net*A* |
| | 25–28 | Net*AB* | | 25–28 | Net*B* |
| NETCHEAT05 | 1–4 | NoNet | | 29–32 | Net*B* |
| (Mar10, 2005) | 5–8 | Net*AB* | NETCHEAT13 | 1–4 | Net*B* |
| | 9–12 | Net*A* | (May18, 2005) | 5–8 | Net*A* |
| | 13–16 | Net*B* | | 9–12 | Net*AB* |
| NETCHEAT07 | 1–4 | NoNet | | 13–16 | NoNet |
| (Mar31, 2005) | 5–8 | Net*AB* | | 17–20 | Net*AB*** |
| | 9–12 | Net*A* | | 21–24 | Net*B* |
| | 13–16 | Net*B* | | 25–28 | Net*A* |
| | 17–20 | Net*B*** | | | |
| | 21–24 | Net*A* | | | |
| | 25–28 | Net*AB* | | | |

Legend: Aut=Autarky; FFT=Frictionless Free Trade; NoNet=Cheat Friction with Anonymity; Net*AB*= Cheat&Network*AB*; Net*A*=Cheat&Network*A*; Net*B* =Cheat&Network*B*.
* These four periods were discarded because of a software problem.
** Buyer values and seller costs were reshuffled just before period 17.

The derivation of CE for Net*A* is more complicated because we have to equilibrate four market segments: the domestic Red and Blue markets, the cheat cross market and the no-cheat Network *A* market. We also need to check whether traders in each segment could increase profit by transacting in another segment. It turns out that Network *A* members find it most profitable to transact within the network as above, generating a surplus of 420 on 8 transactions at a price between 45 and 50. Two of the highest surplus units remaining transact most profitably in the domestic Red market at a price between 52.5 and 57.5, and two other units transact in the domestic Blue market at a price of 35. Of the remaining units, six transact profitably in the cross market (with cheating) at a price of 45.

Similar analysis produces an essentially unique CE when only Network *B* is present. Here it turns out that 8 units trade in Network *B* at a price of 45 and generate a surplus of 220, as in Net*AB*, but the domestic markets are more active than in the other network treatments: 6 units transact in Blue at a price between 32.5 and 35, and 6 more units transact in Red at price 60, while 2 remaining units transact in the cross market (with cheating) at a price of 45.

Given the maintained assumptions, the CE trades have the Nash property that no player can profitably deviate if all other traders accept only CE (or more advantageous) trades. The resulting outcomes represent upper bounds on the efficiency we might actually observe in the experiment. A theoretical lower bound is obtained by replacing the third maintained assumption by the contrary assumption that everyone cheats whenever possible. The result, of course, is just the NoNet CE.

Table 3 collects the CE predictions. Note that quantity and surplus predictions vary strikingly by treatment. By contrast, most price predictions remain at (or near) 45 and therefore are less distinctive. Besides the specific CE predictions, there are four general hypotheses we shall test with the laboratory data.

H1 Networks enhance efficiency. The efficiency rankings will be as in CE, so FFT $\geq$ Net*AB* $>$ Net*A* $>$ Net*B* $>$ NoNet.

H2 Networks facilitate international trade. Trade volume rankings also will be as in CE. In particular, although overall trade volume rankings will be NoNet $\geq$ Net*B* $>$ Net*A* $>$ Net*AB* $\geq$ FFT, the rankings restricted to 'international' cross-market trade volume will be FFT $\geq$ Net*AB* $>$ Net*A* $>$ Net*B* $\geq$ NoNet.

Table 3

*Benchmarks: Autarky, Frictionless Free Trade, Cheating Friction, Networks*

| | Red Market | | | Blue Market | | | Cross Market | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | No Cheating | | | Cheating | | | Network*A* | | | Network*B* | | |
| | | | | | | | | | | | | | No Cheating | | | No Cheating | | |
| | $p_R$ | $q_R$ | $S_R$ | $p_B$ | $q_B$ | $S_B$ | $p_{NC}$ | $q_{NC}$ | $S_{NC}$ | $p_C$ | $q_C$ | $S_C$ | $p^A_{NC}$ | $q^A_{NC}$ | $S^A_{NC}$ | $p^B_{NC}$ | $q^B_{NC}$ | $S^B_{NC}$ |
| Aut | 65 | 8 | 160 | 25 | 8 | 160 | | | | | | | | | | | | |
| FFT | – | 0 | 0 | – | 0 | 0 | 45 | 16 | 640 | | | | | | | | | |
| NoNet | 60 | 6 | 150 | 32.5-35 | 6 | 150 | – | 0 | 0 | 45 | 10 | 125 | | | | | | |
| Net*AB* | – | 0 | 0 | – | 0 | 0 | – | 0 | 0 | – | 0 | 0 | 45–50 | 8 | 420 | 45 | 8 | 220 |
| Net*A* | 52.5–57.5 | 2 | 60 | 35 | 2 | 60 | – | 0 | 0 | 45 | 6 | 75 | 45–50 | 8 | 420 | | | |
| Net*B* | 60 | 6 | 150 | 32.5–35 | 6 | 150 | – | 0 | 0 | 45 | 2 | 5 | | | | 45 | 8 | 220 |

H3: Networks segment markets. As in CE, high-surplus traders will remain in the domestic market in the NoNet treatment but when networks become available the high surplus traders will use them to engage in international trade.

H4: Networks divert trade. As in CE, traders included in a network will earn higher profit when that network is present than when that network is not present. Due to trade diversion, the opposite will be true for traders not included in a network.

## 3. Results

Figure 3 provides an overview of experienced sessions in the double network treatment Net*AB*. In Panel 3*a* we see that, as predicted, there are very few domestic trades in most sessions. Most prices cluster around 40 in the Blue market and around 55 in the Red market. Panel 3*b* shows trades within Network *A*. Evidently our upper benchmark assumption of no cheating within a network is not precisely satisfied. (Here cheating includes partial cheating, in which a buyer or seller does not cheat but his transaction partner does.) On average there is about 1 cheating episode per period and such episodes seem a bit more prevalent in the last few transactions in the last two periods. Most prices lie within the predicted range of 45–50; the more distant outliers are only 10 outside the range and occur in the first period. Panel 3*c* shows similar behaviour in the other network in this treatment, Network *B*. Finally, Panel 3*d* shows a substantial number of international transactions outside the network. Here the prices are more dispersed and cheating prevails.

Similar figures for other treatments and experience levels are omitted to conserve space; they can be found on the webpage of the first author.

*Mean Surplus, Trading Volume and Price.* Recall that in the NoNet treatment, the competitive equilibrium surplus is 425 compared to 640 in FFT, so the predicted efficiency is 66.4% of the maximum possible. Table 4*a* shows that actual efficiency on average is a bit lower in the inexperienced sessions and is almost exactly as predicted in experienced sessions.

The Table shows that our networks do increase efficiency. In the experienced sessions, actual surplus in the Net*AB* treatment rises about 13% above that in the NoNet treatment and rises more modestly in the Net*A* and the Net*B* treatments. The actual efficiency ranking is exactly as predicted but the realised surplus in all the Net treatments falls well short of the CE upper bound.

Where does the realised surplus come from? The upper bound CE for Net*AB* predicts that it will come entirely from no-cheat transactions within each network. With experienced subjects about a fifth of the realised surplus comes from domestic transactions and a bit more than that from international transactions outside each network, most of which involve (at least partial) cheating. About a tenth comes from cheating within the network, leaving almost half $(143.5 + 83.3)/484.9 = 46.8\%$ from the predicted source. With inexperienced subjects, only about 35.8% comes from the predicted source. (Of course, these fractions would increase if we adopted the less conservative convention that partial cheating is only partially contrary to the no-cheat prediction.) The predictions for the single network treatments involve domestic transactions and international transactions outside the network, and the data reflect

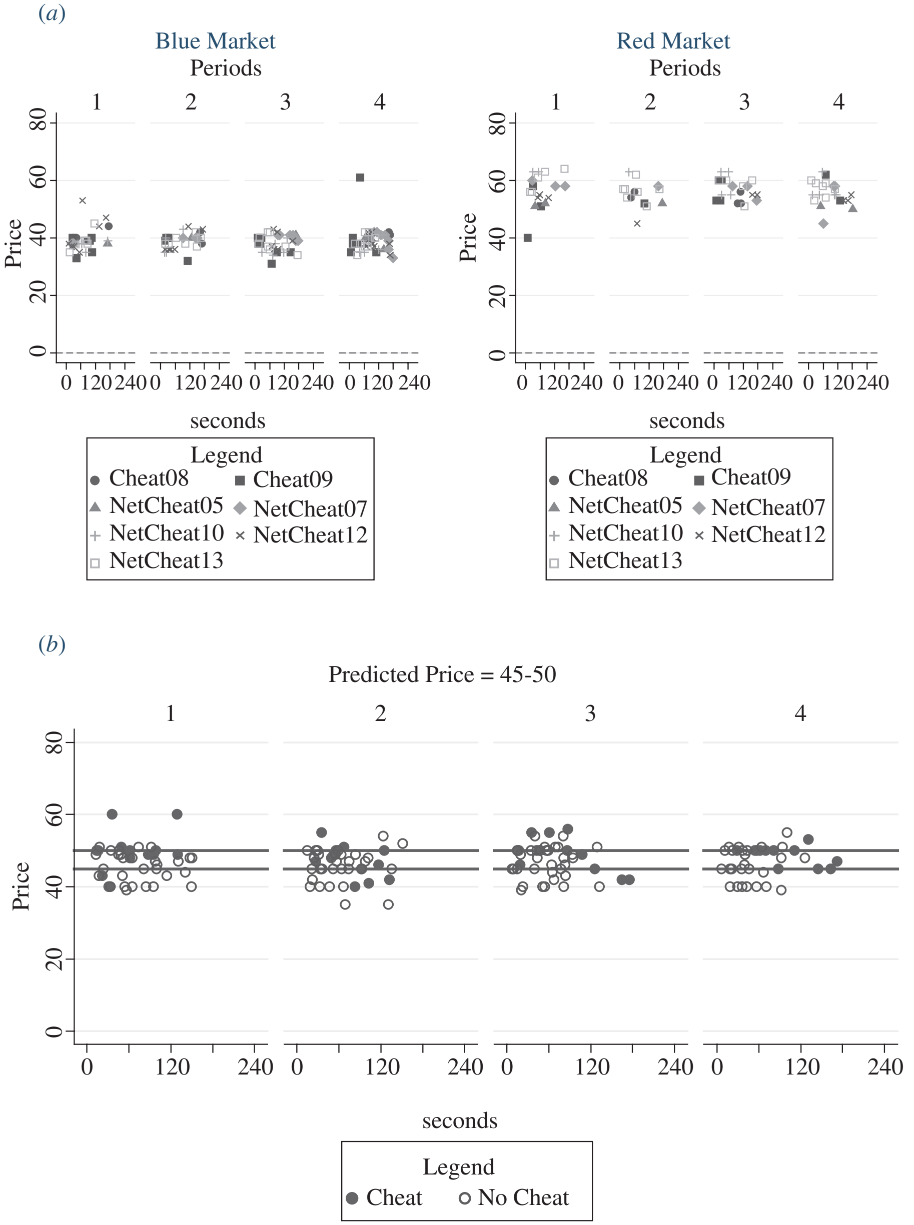
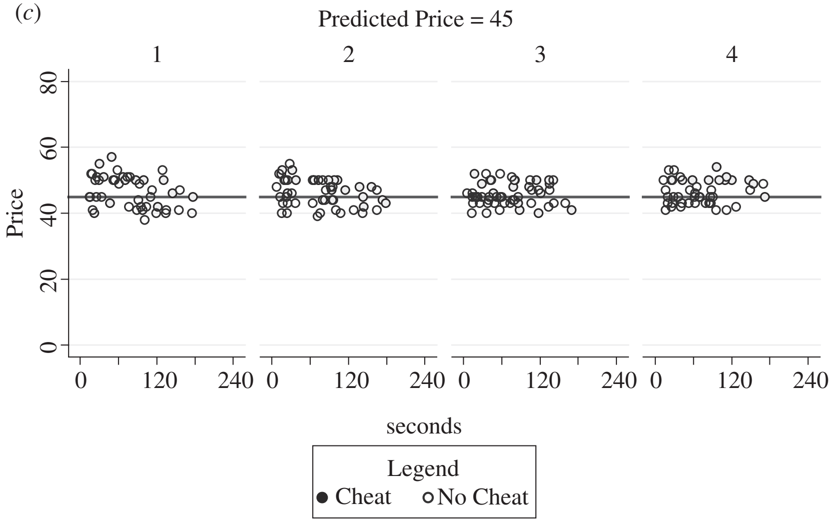



Fig. 3. *Free Trade with Cheating and Networks A & B* (Net*AB*) – *Experienced Subjects.* (*a*) *Domestic Transanctions;* (*b*) *Transactions with Network A;* (*c*) *Transactions with Network B;* (*d*) *Cross Market Transactions – Other*

this. The most striking quantitative departure is the large share of international transactions outside the network, especially in the Net*B* treatment.

Table 4*b* shows that trading volume exhibits similar patterns: our data generally follow the directional predictions but the actual quantities exhibit interesting departures. With *NoNet* and *NetAB*, the experienced session data are modestly closer to

(*c*)




(*d*)

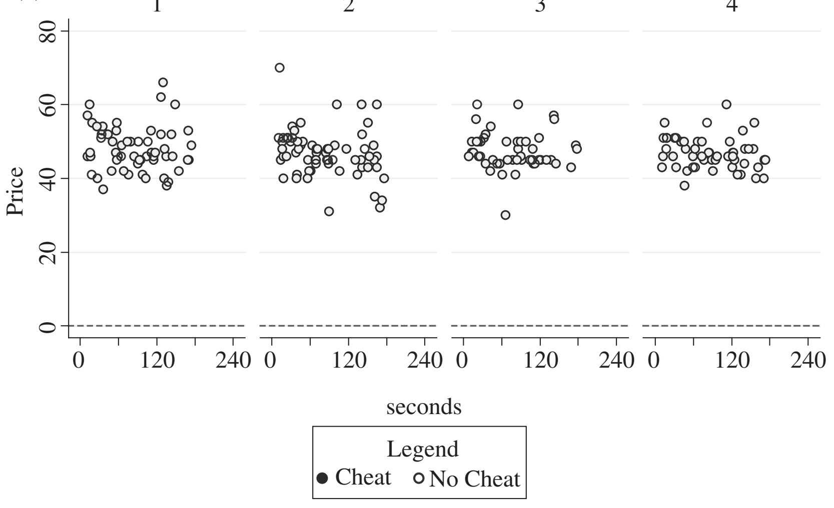



Fig. 3. *Continued*

forecast than the inexperienced session data. The data do not move as sharply as the predictions as the treatment changes, e.g., domestic transactions average between 2 and 3 units per period in all network treatments while predictions move from 0 in Net*AB* to 2 in Net*A* and 6 in Net*B*. Consistent with earlier discussions of the missing trade puzzle, cheating indeed decreases the volume of international trade that we observe. The CE prediction is that cross-market trade volume will decrease from 16 in free trade FFT to 10 in NoNet, or 37.5%, and the experienced session data show a similar decline from 15.2 to 10.1, or 33.6%. When both networks are opened, the prediction is a complete recovery of international trade to 16 units; in the data we see only a partial recovery, to 13.5 in inexperienced sessions and to 12.3 in experienced

Table 4

| | | | | | Cross – *NoNet* | | Cross – NetA | | Cross – *NetB* | |
|---|---|---|---|---|---|---|---|---|---|---|
| Treatments | Nobs | Total | Blue | Red | Cheat | No Cheat | Cheat | No Cheat | Cheat | No Cheat |
| (*a*) *Predicted and Actual Mean Surplus* | | | | | | | | | | |
| FFT | | 640 | 0 | 0 | – | 640 | – | – | – | – |
| Inexp | 37 | 606.9 | 17.0 | 15.7 | – | 574.2 | – | – | – | – |
| NoNet | | 425 | 150 | 150 | 125 | – | – | – | – | – |
| Inexp | 39 | 385.6 | 33.5 | 41.3 | 236.3 | 74.6 | – | – | – | – |
| Exp | 32 | 428.7 | 73.5 | 45.7 | 169.9 | 94.0 | – | – | – | – |
| Net*AB* | | 640 | 0 | 0 | 0 | 0 | 0 | 420 | 0 | 220 |
| Inexp | 40 | 451.4 | 51.5 | 44.8 | 72.2 | 31.4 | 47.5 | 114.9 | 42.5 | 46.8 |
| Exp | 48 | 484.9 | 59.7 | 38.0 | 76.0 | 29.8 | 32.6 | 143.5 | 22.0 | 83.3 |
| Net*A* | | 615 | 60 | 60 | 75 | 0 | 0 | 420 | – | – |
| Exp | 52 | 447.2 | 62.2 | 45.1 | 126.8 | 37.0 | 36.1 | 140.0 | – | – |
| Net*B* | | 525 | 150 | 150 | 5 | 0 | – | – | 0 | 220 |
| Exp | 52 | 443.2 | 69.4 | 48.9 | 158.1 | 70.5 | – | – | 12.4 | 83.9 |
| (*b*) *Predicted and Actual Mean Quantity* | | | | | | | | | | |
| *FFT* | | 16 | 0 | 0 | – | 16 | – | – | – | – |
| Inexp | 37 | 17.3 | 1.1 | 1.0 | – | 15.2 | – | – | – | – |
| NoNet | | 22 | 6 | 6 | 10 | – | – | – | – | – |
| Inexp | 39 | 18.5 | 1.7 | 1.9 | 13.2 | 1.7 | – | – | – | – |
| Exp | 32 | 17.2 | 3.1 | 2.1 | 7.7 | 2.4 | – | – | – | – |
| Net*AB* | | 16 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 8 |
| Inexp | 40 | 17.8 | 2.3 | 2.0 | 5.3 | 0.8 | 1.3 | 2.3 | 2.3 | 1.5 |
| Exp | 48 | 16.7 | 2.8 | 1.6 | 4.1 | 0.6 | 1.0 | 2.5 | 1.3 | 2.8 |
| Net*A* | | 18 | 2 | 2 | 6 | 0 | 0 | 8 | – | – |
| Exp | 52 | 16.8 | 3.0 | 2.0 | 7.4 | 0.9 | 1.1 | 2.4 | – | – |
| Net*B* | | 22 | 6 | 6 | 2 | 0 | – | – | 0 | 8 |
| Exp | 52 | 17.1 | 3.2 | 2.1 | 7.1 | 1.4 | – | – | 0.8 | 2.6 |
| (*c*) *Predicted and Actual Mean Price* | | | | | | | | | | |
| FFT | | – | – | – | – | 45 | – | – | – | – |
| Inexp | 641 | 45.3 | 40.3 | 60.4 | – | 44.7 | – | – | – | – |
| NoNet | | – | 32.5-35 | 60 | 45 | – | – | – | – | – |
| Inexp | 720 | 46.5 | 40.3 | 56.5 | 45.9 | 46.3 | – | – | – | – |
| Exp | 549 | 46.8 | 36.2 | 56.4 | 48.4 | 46.4 | – | – | – | – |
| Net*AB* | | – | – | – | – | – | – | 45-50 | – | 45 |
| Inexp | 713 | 46.2 | 38.5 | 58.0 | 47.0 | 45.1 | 45.6 | 44.3 | 45.9 | 44.3 |
| Exp | 799 | 46.3 | 38.8 | 56.0 | 47.1 | 48.6 | 48.7 | 46.0 | 48.0 | 45.4 |
| Net*A* | | – | 35 | 52.5-57.5 | 45 | – | – | 45-50 | – | – |
| Exp | 873 | 46.4 | 36.4 | 56.8 | 47.1 | 47.9 | 48.2 | 47.2 | – | – |
| NetB | | – | 32.5–35 | 60 | 45 | – | – | – | – | 45 |
| Exp | 891 | 45.6 | 37.1 | 54.1 | 46.8 | 45.7 | – | – | 47.3 | 44.9 |

ones. When only Net*A* is present, the predicted decline in international trade is to 14; the actual decline is to 11.8. When only Net*B* is present, cross-market trade is expected to decline further down to NoNet levels; the actual decline is not as sharp, to 11.9 on average.

Panel 4*c* shows that our mean transaction prices also respond sluggishly to treatment changes. Actual mean prices have an ordering quite consistent with predictions. As expected, domestic prices in the Blue market are significantly lower than the domestic prices in the Red for all networks and NoNet treatments. Observed cross market transactions are not far from the predicted price of 45 (45–50 within Net*A*).

*Cheating In and Outside of Networks.* When networks are not present, we observe rampant cheating in cross market transactions. Table 5 shows that when no networks are present the trader initiating a transaction cheats 577 of 939 possible times or 61.4%. Even when the initiator does not cheat, the responder cheats 61.0% of the time, so honest transactions represent less than 15% of the total. When networks are present, transactions outside networks suffer very similar rates of cheating. Within networks, however, the cheating rate drops sharply, to less than half (28.7%) in Net*B* and to about a third (19.7%) in Net*A*. Moreover, within networks responders cheat honest initiators only 12.2–15.4% of the time. By contrast, responders reciprocate cheating initiators over 90% of the time.

We conclude that our trading networks, although far from perfect, actually do prevent most cheating. Unless otherwise noted, we conservatively classify a transaction as cheating if either the initiator or the responder cheats, i.e., partial cheating is classified as cheating.

*Hypothesis Tests: Efficiency.* Table 6 confirms hypothesis H1, that our networks significantly enhance efficiency. Relative to the NoNet treatment (and including inexperienced as well as experienced sessions), the surplus is on average about 16% higher under Net*AB*, a highly significant difference by both the standard parametric t-test and the non-parametric Mann-Whitney (MW) test. The single network treatments Net*A* and Net*B* increase surplus about 10%, also significant at one-sided MW p-values of better

Table 5

*Cheating Rates in Cross Market Transactions*

| Network | Initiator Cheat Rate (%) | Non-Initiator Cheat Rate (%) given Initiator: Did not Cheat | Cheated |
|---|---|---|---|
| Within Net*A* | 19.7 (97/493)* | 15.4 (61/396) | 92.8 (90/97) |
| Within Net*B* | 28.7 (151/527) | 12.2 (46/376) | 94.7 (143/151) |
| Other | 56.9 (763/1340) | 68.6 (396/577) | 97.5 (744/763) |
| Total** | 42.8 (1011/2360) | 37.3 (503/1349) | 96.6 (977/1011) |
| No Network | 61.4 (577/939) | 61.0 (221/362) | 92.2 (532/577) |

* Number of observations are reported in parentheses.
** Cross market transactions only.

Table 6

*Efficiency Rankings*

| | Nobs | Mean Surplus | Tests against *NoNet*: t (p) | MW (p) |
|---|---|---|---|---|
| NoNet | 71 | 405.0 | – | – |
| Net*AB* | 88 | 469.7 | 5.43 (0.000) | 5.44 (0.000) |
| Net*A* | 52 | 447.2 | 2.08 (0.020) | 2.16 (0.015) |
| Net*B* | 52 | 444.3 | 1.61 (0.055) | 2.35 (0.009) |
| Net*AB* vs. Net*A* | | | 1.18 (0.120) | 2.32 (0.010) |
| Net*AB* vs. Net*B* | | | 1.12 (0.133) | 1.94 (0.026) |
| Net*A* vs. Net*B* | | | 0.09 (0.466) | 0.16 (0.438) |

than 1% for Net*B* and 1.5% for Net*A*. The double network Net*AB* increases surplus significantly over that for the single networks Net*A* and Net*B* according to the one-sided non-parametric test, while the efficiency difference between the two single networks is insignificant.

*International Trade Volume*. The results collected in Table 7*a* support the first part of hypothesis H2. NoNet indeed has significantly higher mean overall trading volume than either Net*AB* and Net*A* at p-values of 1.8% or better and also higher than Net*B* according to the non-parametric test. Recall that the second part of H2 reverses the ordering when restricting comparisons to international trade. Using the largest possible balanced sample with experienced subjects, Table 7*b* shows that on average networks do boost international trade but the boost is significant only for Net*AB*, i.e. when both networks are operating.

*Market Segmentation*. Table 8 confirms H3 that buyers transacting domestically indeed have significantly higher values than those transacting internationally in the NoNet condition. The Table shows that this segmentation persists, within treatment, in the presence of both networks whether we look only at experienced subjects or at both experienced and inexperienced. Similarly for sellers, the average cost of the units sold domestically in the Blue market is always lower than that of the units traded in the cross market. Across treatment, comparing Net*AB* to the NoNet condition, the presence of both networks does not affect the values of the units traded domestically in the Red market significantly but it does for the units sold cross market. When all level of experience is taken into consideration, segmentation reverts and the highest value units are now sold in the cross market. Similarly for the Blue market, the presence of both networks induces the highest cost units to be transacted domestically (significantly with experience) and the lower cost units to get traded cross market (only marginally significant).

Table 7

(*a*) *Volume Rankings*; (*b*) *Restricted Sample – Cross Market*

| | Prediction | Nobs | Mean Volume | Tests against *NoNet* t (p) | MW (p) |
|---|---|---|---|---|---|
| (*a*) | | | | | |
| NoNet – T | 22 | 71 | 17.9 | – | – |
| Net*AB* – T | 16 | 88 | 17.2 | −2.12 (0.018) | −2.39 (0.008) |
| Net*A* – T | 18 | 52 | 16.8 | −2.26 (0.013) | −3.19 (0.001) |
| Net*B* – T | 22 | 52 | 17.2 | −0.86 (0.196) | −1.92 (0.028) |
| Net*AB* vs. Net*A* – T | | | | 0.86 (0.804) | 1.43 (0.424) |
| Net*AB* vs. Net*B* – T | | | | 0.01 (0.505) | −0.22 (0.411) |
| Net*A* vs. Net*B* – T | | | | −0.38 (0.352) | −1.42 (0.078) |
| (*b*) | | | | | |
| NoNet – EC | 10 | 32 | 11.3 | – | – |
| Net*AB* – EC | 16 | 48 | 12.3 | 2.04 (0.022) | 2.29 (0.011) |
| Net*A* – EC | 14 | 52 | 11.8 | 0.70 (0.244) | 0.80 (0.212) |
| Net*B* – EC | 10 | 52 | 11.9 | 0.56 (0.288) | 1.23 (0.109) |

*Notes*. T refers to all data reported in Tables 2*a* and 2*b*, while *E* refers to sessions in 2*b* (experienced subjects only). C refers to cross market (non-domestic transactions). Student's t and the Mann Whitney test statistics (p value) appear in the last two columns.

Table 8
*Market Segmentation*

| | Nobs | Mean (Red, Cross) | t (p) | MW (p) |
|---|---|---|---|---|
| Red Market (Buyers' Values) | | | | |
| NoNet – T | (150, 942) | (75.5, 62.2) | 10.18 (0.00) | 9.87 (0.00) |
| Net*AB* – T | (155, 1129) | (76.1, 63.4) | 10.11 (0.00) | 9.94 (0.00) |
| NoNet – E | (77, 362) | (74.6, 65.3) | 5.67 (0.00) | 5.32 (0.00) |
| Net*AB* – E | (76, 588) | (75.5, 64.8) | 6.20 (0.00) | 5.98 (0.00) |
| Net*AB* vs. NoNet – T (Red) | | | 0.59 (0.72) | 0.52 (0.20) |
| Net*AB* vs. NoNet – E (Red) | | | 0.62 (0.73) | 0.49 (0.19) |
| Net*AB* vs. NoNet – T (Cross) | | | 1.82 (0.03) | 1.86 (0.03) |
| Net*AB* vs. NoNet – E (Cross) | | | −0.51 (0.69) | −0.24 (0.09) |
| Blue Market (Sellers' Costs) | | | | |
| NoNet – T | (177, 942) | (19.6, 28.4) | −8.63 (0.00) | −8.85 (0.00) |
| Net*AB* – T | (228, 1129) | (20.7, 27.5) | −8.00 (0.00) | −8.00 (0.00) |
| NoNet – E | (110, 362) | (18.1, 27.5) | −8.27 (0.00) | −8.39 (0.00) |
| Net*AB* – E | (135, 588) | (20.7, 26.6) | −5.68 (0.00) | −5.77 (0.00) |
| Net*AB* vs. NoNet – T (Blue) | | | 1.33 (0.09) | 1.22 (0.11) |
| Net*AB* vs. NoNet – E (Blue) | | | 2.52 (0.01) | 2.20 (0.01) |
| Net*AB* vs. NoNet – T (Cross) | | | −1.46 (0.07) | −1.13 (0.13) |
| Net*AB* vs. NoNet – E (Cross) | | | −1.23 (0.11) | −1.30 (0.10) |

*Notes.* T refers to all data reported in Tables 2*a* and 2*b*, while E refers to sessions in 2*b* (experienced subjects only). Student's t and Mann Whitney test statistics (p value) appear in the last two columns.

Table 9
*Profits Rankings*

| | | | Net*AB* against NoNet* | |
|---|---|---|---|---|
| | Nobs (Net*AB*, NoNet) | Mean Profit (Net*AB*, NoNet) | t (p) | MW (p) |
| Blue Buyers | (327, 303) | (2.4, 1.1) | 1.84 (0.033) | 2.71 (0.003) |
| Blue Sellers | (1273, 1026) | (15.8, 13.7) | 4.35 (0.000) | 4.44 (0.000) |
| Red Buyers | (1185, 966) | (16.7, 14.2) | 3.44 (0.000) | 3.52 (0.000) |
| Red Sellers | (239, 243) | (3.0, 2.8) | 0.18 (0.426) | 0.93 (0.177) |

*Notes.* Includes all data reported in Tables 2*a* and 2*b*. Check Table 1 for details on each player's values or costs.

*Trade Diversion.* Table 9 confirms the first part of H4. Unsurprisingly, both t- and MW-tests show that members of both networks (Red Buyers and Blue Sellers) capture significantly more surplus when both networks are present than they do in the NoNet treatment. Indeed, each individual member (the four Blue Buyers and the four Red Sellers) does better on average when both networks are present. Surprisingly perhaps, the traders outside the networks do at least as well in Net*AB* as in NoNet; overall mean profit is slightly higher (albeit still rather small) for Red Sellers and significantly so for Blue Buyers. More detailed tables, available on the website, show these and other similar results when only one network is present. The surplus captured by each trader type is significantly higher in Net*A* and in Net*B* than in NoNet, except for Red Sellers in Net*B* for whom the difference is insignificant. Rather than diverting surplus away from non-members, our networks seem to have slight positive spillovers.

## 4. Discussion

Our laboratory study introduces exogenous interpersonal networks for traders who can transact in two markets: a domestic (Local) market where contracts are perfectly enforced and an international (Distant) market where cheating is possible. Traders are anonymous outside their network but inside it they can build reputations for honesty. Such networks might help to overcome cheating frictions in international trade and thereby boost efficiency, or they might reduce efficiency by diverting trade to insiders with higher costs and lower values.

We chose supply and demand schedules and network architectures that produce distinctive competitive equilibrium (CE) predictions regarding trade surplus and trade volume. We tested these predictions in 17 laboratory sessions, each with 16 traders.

In our data, networks significantly reduce cheating and increase efficiency. Traders do not achieve the CE (upper bound) efficiencies when networks are present but the CE predictions correctly rank the average efficiency achieved in the four network architectures we examine. In our setup, CE prices tend not to respond much to changes in network architecture and neither do our data.

CE also correctly predicts most of the qualitative trade patterns we observed. Networks indeed support increased international trade volume and (in our distinctive setup) reduced domestic volume, especially in our double network condition. The networks segment our markets, moving transactions in the highest value (lowest cost) units from domestic markets to international networks. The impact on traders outside the networks is small but usually positive.

Quantitatively, our data do not change as sharply as the CE predictions with changes in network architecture. This is as expected for two reasons. First, of course, is that we chose the architectures (and supply/demand schedules) to produce extreme changes in CE efficiency and volume. A second reason is our conservative within-subject design. Varying treatments such as network architectures within each session tends to dampen the impact; e.g., see Friedman and Cassar (2004, Ch.4, p.35).

In terms of the wider questions raised in the Introduction, our results support an insight for the missing trade puzzle. Market frictions indeed can drastically reduce international volume and associated surplus, and trading networks can partially counteract such frictions. Our results likewise support the insight that interpersonal networks might increase trade and efficiency in developing countries where even domestic transactions are not perfectly enforceable. The results suggest, however, that the network solution is second best. In our most favourable architecture, the networks could potentially restore 100% efficiency but the network data fall well short of that mark. Observed efficiencies are much closer to 100% when all contracts are perfectly enforced.

Several caveats are in order. We have examined only four network architectures and one set of supply/demand schedules. Different architectures and schedules should be examined to assess the robustness of our results within the laboratory.

Equally important, one should investigate the endogenous formation of networks. Given the inference problems noted in the Introduction, it is appropriate to start with exogenous networks. The results for exogenous networks will make it easier to interpret results from future work investigating which network architectures emerge spontaneously and how they affect market performance.

Most importantly, we hope our laboratory work inspires new theoretical work on networks, and new studies with field data. There are strong complementarities between lab, field and theory. Definitive answers to questions regarding market frictions and networks will emerge only with advances on all three fronts.

## Appendix A. Competitive Equilibrium Predictions

This Appendix derives upper bound Competitive Equilibrium (CE) for the three network treatments Net*AB*, Net*A* and Net*B*. To set the stage, it summarises the derivation (in Cassar *et al.*, 2009) of CE for the non-network treatments Aut, FFT and NoNet.

The classic maintained assumption in CE is:

Assumption 1. *All traders take as given the vector of CE prices and trade units to maximise payoff.*

Computing the competitive equilibrium (CE) predictions is straightforward under autarchy (Aut) and free trade (FFT). Inspection of Figure 2 shows that in Red market autarchy, the CE price is $p^*_{RA} = 65$, quantity is $q^*_{RA} = 8$ and the resulting Red market surplus is 160. The autarchy CE in the Blue market has the same quantity and surplus but at CE price $p^*_{BA} = 25$. Overall surplus in autarchy is $S_A = S_{RA} + S_{BA} = 320$. In frictionless free trade, inspection of the last panel in Figure 2 yields the CE price $p^*_{FT} = 45$, quantity $q^*_{FT} = 16$, and a resulting surplus $S_{FT} = 640$. Note that CE trade volume in frictionless free trade remains the same as in autarchy, but the CE surplus doubles to 640, of which 360 is Blue seller surplus and 280 is Red buyer surplus. The environment is a challenge for theory, especially because CE surplus falls to 0 for Blue buyers and for Red sellers.

In deriving CE with cheating in international trade Cassar *et al.*, 2009 argue that in Nash equilibrium with no networks, traders will cheat whenever possible. Here we simply impose:

Assumption 2. *Traders cheat whenever possible in anonymous transactions.*

In NoNet under Assumptions 1 and 2, there are just are three distinct markets in equilibrium, denoted *R* (Red domestic), *B* (Blue domestic) and *C* (cheat or cross). In any competitive equilibrium, traders take as given a vector of prices and choose quantities so as to maximise profit. The resulting supply and demand schedules then must clear at the given prices. A CE with cheating $\pi \in (0,1)$ thus is a price vector $\mathbf{p}^* = (p^*_R, p^*_B, p^*_C)$, together with the associated trades, such that, given $\pi$ and $\mathbf{p}^*$:

(1) Every Blue trader transacts each unit in market *B* or *C* or holds the unit, whichever is more profitable.
(2) Every Red trader transacts each unit in market *R* or *C* or holds the unit, whichever is more profitable.
(3) Supply equals demand in each of the three markets.

Using a close linear approximation of the laboratory parameters, we can derive closed form expressions for an essentially unique CE for arbitrary $\pi \in [0,1]$. The expressions coincide with the autarchy CE for $\pi = 0$ and coincide with the frictionless free trade CE for $\pi = 1$. In between, the CE varies smoothly but non-linearly between the two extremes. It allows some traders that are extramarginal in autarchy and frictionless free trade to be able to earn profits.

We need the CE for $\pi = 0.5$ and for the exact discrete supply and demand used in the experiment. It turns out that one of the price predictions is no longer unique but still lies in a narrow interval. CE prices are: 45 in the cross market, 32.5–35 in the Blue market and 60 in the Red market. CE trading volume increases from 16 to 22 units: 10 units trade across markets and involve cheating by both buyer and seller, while 6 units trade domestically in each home market.

Despite the higher overall trading volume, the CE surplus decreases to 425. An intuitive explanation is that relative to frictionless trade, actual cheating cuts the surplus in half in each transaction in *C*. Moreover, the threat of cheating in *C* causes high-surplus traders to retreat to their home markets where they transact with low surplus traders (high cost sellers in *R* and low value buyers in *B*). Transactions involving these low surplus traders are inefficient, so the mere threat of cheating also reduces the surplus while reducing the volume of cross market trade.

To obtain predictions for the new network treatments, we impose a third assumption:

ASSUMPTION 3. *Traders never cheat members of their own networks.*

Although traders cheat far less often within the networks than outside, the assumption is not literally true. It is useful in establishing an upper bound on what networks can do to restore efficiency.

Net*AB*. A linear approximation of the network *A* Red inverse demand function is $p^{D}_{R,NetworkA} = 85 - 5q$ for $q \in [0,8]$ and 0 for $q > 8$. The network *A* Blue inverse supply function can be linearly approximated by $p^{S}_{B,NetworkA} = 5 + 5q$ for $q \in [0,8]$ and $\infty$ for $q > 8$. In equilibrium $p^{\star}_{NetworkA} = 45$, $q^{\star}_{NetworkA} = 8$. The associated buyer surplus is $\int_0^{q^*} [p^D(q) - p^*]\mathrm{d}q = 160$ which goes all to network *A* Red buyers, seller surplus is $\int_0^{q^*} [p^* - p^S(q)]\mathrm{d}q = 160$ which goes all to Network *A* Blue sellers, so the upper-bound for cross-market surplus between network *A* traders is $S_{NetworkA} = 320$.

Similarly, network *B* Red buyers' values can be approximated by $p^{D}_{R,NetworkB} = 65 - \frac{5}{2}q$ for $q \in [0,8]$ and 0 for $q > 8$ , and network *B* blue sellers' costs by $p^{S}_{B,NetworkB} = 25 + \frac{5}{2}q$ for $q \in [0,8]$ and $\infty$ for $q > 8$. In equilibrium $p^{\star}_{NetworkB} = 45$, $q^{\star}_{NetworkB} = 8$, network *B* Red buyer surplus $\int_0^{q^*} [p^D(q) - p^*]\mathrm{d}q = 80$, network *B* Blue seller surplus $\int_0^{q^*} [p^* - p^S(q)]\mathrm{d}q = 80$, so the upper-bound for cross-market surplus between network *B* members is $S_{NetworkB} = 160$.

When all the units which constitute the Red demand are traded cross-market between network members with all the units which constitute the Blue supply, no units are left for cheating in the cross market nor for either Red or Blue domestic markets. Therefore, when both networks are present, the upper bound predictions are: $p^{\star}_{C,NetworkA\&B} = 45$, $q^{\star}_{C,NetworkA\&B} = 16$, $S_{C,NetworkA\&B} = 480$.

Only a few minor modifications are needed for the exact step functions used in the experiments. Within network *A*: $p^{\star}_{NetworkA} = 45 - 50$, $q^{\star}_{NetworkA} = 8$, $S_{NetworkA} = 420$. In fact, given network *A* Red values and Blue costs, the price range would be 35–50. But Blue buyers whose values are 40 and 45 could compete with network *A* Red buyers for Blue sellers driving up the price till 45. On the other side, the lowest Red seller costs are 50, so they cannot compete for network *A* Red buyers (since their values start at 50). The price should then be 45–50, for a quantity of 8.

Similarly within network *B*: $p^{\star}_{NetworkB} = 45$, $q^{\star}_{NetworkB} = 8$, $S_{NetworkB} = 220$. Given network *B* members' values and costs, the price would be 40–45. But Blue buyers whose values are 45 could compete with network *B* Red buyers driving up the price till 45. On the other side, the lowest Red seller costs are 50, so they cannot compete for Red buyers. The price should then be 45.

As with the linear approximations, no other units are left to be traded in the cross-market. Networks members earn higher profit with non cheating network members than cheating in cross market with non-network members. Domestic trade also vanishes in CE: no units are left to be bought in the Red market, while in the Blue market no units are left to be sold.

Summing up: $p^{\star}_{C,NetworkA\&B} = 45 - 50$, $q^{\star}_{C,NetworkA\&B} = 16$, $S_{C,NetworkA\&B} = 640$.

Net*A*. When only network *A* is present we have to equilibrate four markets: the domestic Red and Blue markets, the cheat cross market and the no-cheat network *A* market. As above, the equilibrium within network *A* is $p^{\star}_{NetworkA} = 45$, $q^{\star}_{NetworkA} = 8$ and $S_{NetworkA} = 320$.

Removing the values associated with network *A* members, we can approximate the remaining Red market inverse demand function as $p^{D}_{R,NetworkA} = 65 - \frac{5}{2}q$ for $q \in [0,8]$, 0 for $q > 8$. The Red market inverse supply function remains $p^{S}_{R} = 45 + \frac{5}{2}q$ for $q \in [0,16]$ and $\infty$ for $q > 16$.

Similarly for the Blue market. The inverse supply function excluding network $A$ members' costs can be approximated as $p^S_{B,NetworkA} = 25 + \frac{5}{2}q$ for $q \in [0,8]$ and $\infty$ for $q > 8$, while the inverse demand function remains $p^D_B = 45 - \frac{5}{2}q$ for $q \in [0,16]$, 0 for $q > 16$.

We need to find $p_{C,NetworkA}$, $p_{R,NetworkA}$, $p_{B,NetworkA}$, $v^\star_{NetworkA}$, $c^\star_{NetworkA}$ (which in the derivation we call simply $p_C$, $p_R$, $p_B$, $v^\star$, $c^\star$). As in Cassar *et al.* (2009) we obtain indifference conditions (IC) and equilibrium conditions (EC) whose simultaneous solution gives us the needed prices, value and cost. The conditions now are

*IC for marginal Red buyer*: $\pi(v^\star - p_C) = v^\star - p_R$, which yields $v^\star = (p_R - \pi p_C)/(1-\pi)$

*IC for marginal Blue seller*: $\pi(p_C - c^\star) = p_B - c^\star$, which yields $c^\star = (p_B - \pi p_C)/(1-\pi)$

*EC in Red market*: $D_{R,NetworkA}(v^\star) = S_R(p_R)$ or $26 - \frac{2}{5}v^\star = -18 + \frac{2}{5}p_R$ which gives $p_R = [\pi p_C + (1-\pi)110]/(2-\pi)$

*EC in Blue market*: $D_B(p_B) = S_{B,NetworkA}(c^\star)$ or $18 - \frac{2}{5}p_B = -10 + \frac{2}{5}c^\star$, so that $p_B = [\pi p_C + (1-\pi)70]/(2-\pi)$

*EC in Cross market*: $D_{R,NetworkA}(p_C) - D_{R,NetworkA}(v^\star) = S_{B,NetworkA}(p_C) - S_{B,NetworkA}(c^\star)$ or $26 - \frac{2}{5}p_C - (26 - \frac{2}{5}v^\star) = -10 + \frac{2}{5}p_C - (-10 + \frac{2}{5}c^\star)$ which yields $p_C = (p_R + p_B)/2$.

Putting everything together we find:

$$p_{C,NetworkA} = 45, \tag{1}$$

$$p_{R,NetworkA} = \frac{110 - 65\pi}{2 - \pi}, \tag{2}$$

$$p_{B,NetworkA} = \frac{70 - 25\pi}{2 - \pi}, \tag{3}$$

$$v^\star_{NetworkA} = \frac{130 - 85\pi}{2 - \pi}, \text{and} \tag{4}$$

$$c^\star_{NetworkA} = \frac{50 - 5\pi}{2 - \pi} \tag{5}$$

which when $\pi = 0.5$ yields: $p_{C,NetworkA}, = 45$, $p_{R,NetworkA} = 51.\bar{6}$, $p_{B,NetworkA} = 38.\bar{3}$, $v_{NetworkA}\star = 58.\bar{3}$, $c_{NetworkA}\star = 31.\bar{6}$ so that cross-market trade is $q_{C,NetworkA} = 5.\bar{3}$ and $q_{R,NetworkA} = q_{B,NetworkA} = 2.\bar{6}$.

Now we derive the equilibrium for the step functions used in the experiment. Within network $A$ is the same as explained in the above network $A\&B$ case: $p^\star_{NetworkA} = 45 - 50$, $q^\star_{NetworkA} = 8$, $S_{NetworkA} = 420$. In order to find how many units get traded domestically and how many go in the cheat market, we need to find the price ranges for which the domestic Red, Blue and the cross-market are in equilibrium. Table A1 report for each price range how many units are offered domestically (profit domestic > profit in cheat market), how many cross-market, how much is the domestic demand or supply. The underlying assumption is $p_{C,NetworkA} = 45$.

Table A1

*Supply and Demand When Only Network A is Present*

| Blue market | No. of units offered | | | |
|---|---|---|---|---|
| $p_{B,NetworkA}$ | Cross-market $\prod_C > \prod_B$ | $\prod_C = \prod_B$ | Domestic (Blue) $\prod_C < \prod_B$ | No. of units demanded up to domestically (Blue) |
| <35 | 8 | 0 | 0 | 6 |
| 35 | 4 | 4 | 0 | 6 |
| (35, 37.5) | 4 | 0 | 4 | 4 |
| 37.5 | 2 | 2 | 4 | 4 |
| (37.5, 42.5) | 2 | 0 | 6 | 4 if (37.5, 40]<br>2 if (40, 42.5) |
| 42.5 | 0 | 2 | 6 | 2 |
| >42.5 | 0 | 0 | 8 | 2 if (42.5, 45]<br>0 if >45 |

| Red market | No. of units demanded | | | |
|---|---|---|---|---|
| $p_{R,NetworkA}$ | Cross-market $\prod_C > \prod_R$ | $\prod_C = \prod_R$ | Domestic (Red) $\prod_C < \prod_R$ | No. of units offered up to domestically (Red) |
| <45 | 0 | 0 | 8 | 0 |
| 45 | 0 | 2 | 6 | 0 |
| (45, 50) | 2 | 0 | 6 | 0 |
| 50 | 2 | 2 | 4 | 2 |
| (50, 52.5) | 4 | 0 | 4 | 2 |
| 52.5 | 4 | 2 | 2 | 2 |
| (52.5, 57.5) | 6 | 0 | 2 | 2 if (52.5, 55)<br>4 if [55, 57.5) |
| 57.5 | 6 | 2 | 0 | 4 |
| >57.5 | 8 | 0 | 0 | 4 if (57.5, 60)<br>6 if [60, 65) |

From the Table, there are 2 possibilities:

$$q_C = 8,\ p_C = 45,\ p_R \text{ indef.},\ q_R = 0,\ p_B \text{ indef.},\ q_B = 0$$

$$q_C = 6,\ p_C = 45,\ p_R \in [52.5{,}57.5],\ q_R = 2,\ p_B = 35,\ q_B = 2$$

but domestic competitive forces should drive the equation to the last one only: $q_C = 6$, $p_C = 45$, $p_R \in [52.5, 57.5]$, $q_R = 2$, $p_B = 35$, $q_B = 2$.

Net*B*. We follow a similar analysis for the case in which only network *B* is present. Again, the benchmark in which everybody cheat cross-market is the same as described above and derived in Cassar *et al.* (2009). Here we derive the benchmark in which network *B* members do not cheat with the same procedure as above.

Let us start analysing what happens when network *B* members trade among each other without cheating. Using the linear approximations described above for network *B* members, the equilibrium is as before: $p^{\star}_{NetworkB} = 45$, $q^{\star}_{NetworkB} = 8$ and $S_{NetworkB} = 80$.

Removing the values associated with network *B* members, we can approximate the remaining Red market inverse demand function as $p^{D}_{R,NetworkB} = 85 - 5q$ for $q \in [0,8]$, 0 for $q > 8$. The Red market inverse supply function stays the same as $p^{S}_{R} = 45 + \frac{5}{2}q$ for $q \in [0,16]$, and $\infty$ for $q > 16$.

Similarly for the Blue market, the inverse supply function excluding network B members' costs can be approximated as $p^S_{B,NetworkB} = 5 + 5q$ for $q \in [0,8]$, and $\infty$ for $q > 8$, while the inverse demand function stays the same $p^D_B = 45 - \frac{5}{2}q$ for $q \in [0,16]$, 0 for $q > 16$.

We need to find simultaneously $p_{C,NetworkB}$, $p_{R,NetworkB}$, $p_{B,NetworkB}$, $v^\star_{NetworkB}$, $c^\star_{NetworkB}$ (which in the derivation we call simply $p_C$, $p_R$, $p_B$ , $v^\star$, $c^\star$) and we invite the reader to see the derivation in Cassar *et al.* (2009).

*IC for marginal Red buyer*: $\pi(v^\star - p_C) = v^\star - p_R$, which yields $v^\star = (p_R - \pi p_C)/(1 - \pi)$

*IC for marginal Blue seller*: $\pi(p_C - c^\star) = p_B - c^\star$, which yields $c^\star = (p_B - \pi p_C)/(1 - \pi)$

*EC in Red market*: $D_{R,NetworkB}(v^\star) = S_R(p_R)$ or $17 - \frac{1}{5}v^\star = -18 + \frac{2}{5}p_R$ which gives $p_R = [\pi p_C + (1 - \pi)175]/(3 - 2\pi)$

*EC in Blue market*: $D_B(p_B) = S_{B,NetworkB}(c^\star)$ or $18 - \frac{2}{5}p_B = -1 + \frac{1}{5}c^\star$, so that $p_B = [\pi p_C + (1 - \pi)95]/(3 - 2\pi)$

E*C in Cross-market*: $D_{R,NetworkB}(p_C) - D_{R,NetworkB}(v^\star) = S_{B,NetworkB}(p_C) - S_{B,NetworkB}(c^\star)$ or $17 - \frac{1}{5}p_C - (17 - \frac{1}{5}v^\star) = -1 + \frac{1}{5}p_C - (-1 + \frac{1}{5}c^\star)$ which yields $p_C = (p_R+p_B)/2$.

Putting everything together we find:

$$p_{C,NetworkB} = 45, \tag{6}$$

$$p_{R,NetworkB} = \frac{175 - 130\pi}{3 - 2\pi}, \tag{7}$$

$$p_{B,NetworkB} = \frac{95 - 50\pi}{3 - 2\pi}, \tag{8}$$

$$v^\star_{NetworkB} = \frac{175 - 90\pi}{3 - 2\pi}, \text{ and} \tag{9}$$

$$c^\star_{NetworkB} = \frac{95 - 90\pi}{3 - 2\pi} \tag{10}$$

which when $\pi = 0.5$ yields: $p_{C,NetworkB} = 45$, $p_{R,NetworkB} = 55$, $p_{B,NetworkB} = 35$, $v^\star_{NetworkB} = 65$, $c^\star_{NetworkB} = 25$ so that cross-market trade is $q_{C,NetworkB} = 4$ and $q_{R,NetworkB} = q_{B,NetworkB} = 4$.

Let us now derive the equilibrium for the step functions used in the experiment. Within network *B* is the same as explained in the above network *A&B* case: $p^\star_{NetworkB} = 45$, $q^\star_{NetworkB} = 8$, $S_{NetworkB} = 160$. As above, in order to find how many units get traded domestically and how many go in the cheat market, we need to find the price ranges for which the domestic Red, Blue and the cross-market are in equilibrium. The following Tables report for each price range how many units are offered domestically (profit domestic > profit in cheat market), how many cross-market, how much is the domestic demand or supply. The underlying assumption is $p_{C,NetworkB} = 45$

Table A2

*Demand and Supply When Only Network B is Present*

| Blue market | No. of units offered | | | |
|---|---|---|---|---|
| $p_{B,NetworkB}$ | Cross-market $\prod_C > \prod_B$ | $\prod_C = \prod_B$ | Domestic (Blue) $\prod_C < \prod_B$ | No. of units demanded up to domestically (Blue) |
| <27.5 | 8 | 0 | 0 | 8 if (20, 27.5) |
| 27.5 | 6 | 2 | 0 | 8 |
| (27.5, 30) | 6 | 0 | 2 | 8 |
| 30 | 4 | 2 | 2 | 8 |
| (30, 32.5) | 4 | 0 | 4 | 6 |
| 32.5 | 2 | 2 | 4 | 6 |
| (32.5, 40) | 2 | 0 | 6 | 6 if (32.5, 35)<br>4 if [35, 40) |
| 40 | 0 | 2 | 6 | 4 |
| >40 | 0 | 0 | 8 | 2 if (40, 45]<br>0 if >45 |

| Red market | No. of units demanded | | | |
|---|---|---|---|---|
| $p_{R,NetworkB}$ | Cross-market $\prod_C > \prod_R$ | $\prod_C = \prod_R$ | Domestic (Red) $\prod_C < \prod_R$ | No. of units offered up to domestically (Red) |
| <47.5 | 0 | 0 | 8 | 0 |
| 47.5 | 0 | 2 | 6 | 0 |
| (47.5, 60) | 2 | 0 | 6 | if <50<br>2 if [50, 55)<br>4 if [55, 60) |
| 60 | 2 | 2 | 4 | 6 |
| (60, 62.5) | 4 | 0 | 4 | 6 |
| 62.5 | 4 | 2 | 2 | 6 |
| (62.5, 65) | 6 | 0 | 2 | 6 |
| 65 | 6 | 2 | 0 | 10 |
| >65 | 8 | 0 | 0 | 10 if (65, 70)<br>12 if [70, 75)<br>14 if [75, 80)<br>16 if $p \geq 80$ |

From the Table, there are 4 possibilities:

$q_C = 8$, $p_C = 45$, $p_R$ indef., $q_R = 0$, $p_B$ indef., $q_B = 0$

$q_C = 6$, $p_C = 45$, $p_R \in [62.5, 65]$, $q_R = 2$, $p_B \in [27.5, 30]$, $q_B = 2$

$q_C = 4$, $p_C = 45$, $p_R \in [60, 62.5]$, $q_R = 4$, $p_B \in [30, 32.5]$, $q_B = 4$

$q_C = 2$, $p_C = 45$, $p_R = 60$, $q_R = 6$, $p_B \in [32.5, 35)$, $q_B = 6$

and, again, competitive forces in the domestic Blue market should drive the Blue price up, in the domestic Red market should drive the Red price down till the only equilibrium is the last one: $q_C = 2$, $p_C = 45$, $p_R = 60$, $q_R = 6$, $p_B \in [32.5, 35)$, $q_B = 6$.

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