The Effect of Social Networks on Market Efficiency*

Paul Ivo Schäfer†

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Abstract

I examine the impact of friendships on imperfectly competitive markets with substitutes and complements. I test a model of friendships in these markets. In the model, people are (linearly) altruistic towards their friends (like firms with common owners). The model predicts that friendships among sellers of substitutes increase prices and decrease efficiency, whereas friendships between sellers of complements decrease prices and increase efficiency. I invite pairs of (real-world) friends to the laboratory and assign them different roles within a market experiment. Each individual chooses a price for different social networks within the same market. In some social networks, their friend sells a complement; in some, they sell a substitute; and in some, they do not participate. The estimated causal effects of friendships confirm the model's predictions. A structural model with a homogeneous parameter for altruism among friends rationalizes the experimental data. I also investigate asymmetric social networks, the effect of price transparency, and the accuracy of people's beliefs about their friend's prices.

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†Department of Economics, University of Bonn, paul.schaefer@uni-bonn.de

1 Introduction

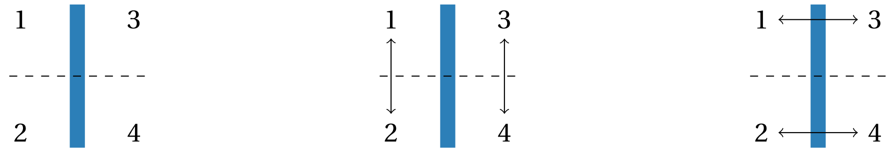
Markets are intertwined with social relationships (Granovetter 1985). People selling houses in Amsterdam go to church together (Lindenthal, Eichholtz, and Geltner 2017), friends of rival CEOs serve on a company's board (Westphal and Zhu 2019), and hotel managers in Sydney befriend the managers of their competition (Ingram and Roberts 2000). How do these friendships interact with the market? Do friends conspire and raise prices (A. Smith 1776, p. 130), or can their cooperation benefit consumers?

Little is known about the causal effects of network structure on market efficiency. Three problems explain lack of knowledge. First, we need exogenous variation in social networks to estimate their causal effects. Without exogenous variation, treatment effect estimates may be confounded by common causes. For example, physical distance facilitates both trade and social network connections. Second, market efficiency is unobservable because we need to know individuals' private costs and values. These data are necessary to compute the gains from trade and, thus, market efficiency. Third, we need a theoretical model of social relationships and market efficiency. Social networks are high dimensional: There are many possible ways to link market participants. Each social relationship can have many aspects: Friendships can affect markets because friends are more altruistic towards each other (altruism or social sanctions) or because they know more about each other. We need a model to learn which social relationships and which aspects of them are essential.[1]

My solution to these problems is a controlled laboratory experiment. First, I make the social network exogenous by assigning real-world friends to different roles in a market experiment. Second, the experiment solves the problem of private values and costs, because it induces them (V. L. Smith 1976): The experimenter knows and controls private values and costs because they can set participants' monetary rewards for the experiment.

I assume that friends are more altruistic towards each other than towards strangers (directed altruism, Leider et al. 2009). In this model, friendships between two people affect efficiency in the same way as mergers: Friendships between sellers of complements increase

1. While we have theoretical models of contract enforcement through social networks (Karlan et al. 2009) and enabling exchange (Kranton 1996), we lack a model of how social networks affect efficiency inside formal market institutions.



a. Baseline

b. Complements (Symmetric)

c. Substitutes (Symmetric)

Figure 1: The experimental market with different social networks.

efficiency, and friendships between sellers of substitutes decrease it.

I confirm this prediction in an experiment and estimate the altruism parameter with a structural model. The model fits the data well. The familiarity between friends does not affect market outcomes in my experiment. Consequently, directed altruism between friends is a helpful model for analyzing social networks' effect on market efficiency.

I conduct my experiment in a simple market that includes substitutes and complements (from the buyers perspective). Four participants are assigned the role of sellers that each own one plot of land. Sellers 1 and 2 own land to the left side of a river, and sellers 3 and 4 own land to the right side of a river (see Panel a of Figure 1). A computerized buyer wants to buy precisely two plots on the same side of the river. Thus, plots on the same side of the rivers are complements, and plots on different sides are substitutes. Each seller makes a (simultaneous) take-it-or-leave-it offer to the buyer. The buyer aggregates the prices and buys the bundle of land that gives them the highest surplus (or abstains from buying).

I test if friendships between owners of substitutes (substitute friendships) and owner of complements (complement friendships) have different effects. I compare substitute and complement friendships by comparing three symmetric social networks. These networks are depicted in Panels a–c of Figure 1, where arrows indicate friendships. I name social network treatments after the properties of their friendships. In the *Complements Symmetric* treatment, friendships are between people that sell complements. In the *Substitutes Symmetric* treatment, friendships are between people that sell substitutes. In the *Baseline* treatment, all players are strangers. I create these friendships exogenously in the lab by inviting pairs of friends and assigning them to different roles.[2]

2. Chandrasekhar, Kinnan, and Larreguy (2018) inspired this design.

I exploit an analogy between friendships and partial mergers to derive my predictions. Friends might want their friends to get higher payoffs, and partially merged firms would like each other to make higher profits and set prices correspondingly. I formalize this argument by applying the common ownership model (Rubinstein and Yaari 1983; Rotemberg 1984; Azar, Schmalz, and Tecu 2018) to friendships within a market.[3] This model is observationally equivalent to linear altruism among firms with common owners. Applied to friendships, this model is a linear version of directed altruism among friends (e.g. Leider et al. 2009). I test if the linear, directed altruism model predicts the empirical effects of friendships.

The merger analogy suggests that friendships between sellers of complements and sellers of substitutes have different effects on prices. Mergers between sellers of complements decrease prices, whereas mergers between sellers of substitutes increase prices (See in particular chapter IX of Cournot (1897), which has been reproduced and extended in Economides and Salop (1992)). Friendships might behave similarly.

Compared to the benchmark without friendships, friendships between sellers of complements (same side friendships) should decrease prices, and friendships between sellers of substitutes (cross-river friendships) should increase prices. The reason is that directed altruism partially internalizes an externality between friends: Lower prices increase the demand for complements (plots on the same side of the river) and decrease the demand for substitutes (plots on different sides of the river). Sellers want to increase the demand for their friend's product. Thus, compared to the benchmark without friendships, sellers with friends that sell complements (same side friendships) decrease their prices, and sellers with friends that sell substitutes (cross-river friendships) increase their prices.

The effect of friendships on prices translates into an effect on market efficiency.[4] Since we are in an imperfectly competitive market, prices start above the competitive level. Therefore, increasing them lowers efficiency, and lowering them increases it as long as prices remain above the competitive benchmark.

The experiment's results are consistent with the qualitative predictions of directed altruism theory. The markets with the *Complements Symmetric* network are the most efficient and have

3. For a survey of the more recent literature see Schmalz (2021).

4. I define *efficiency* as the expected realized material gains from trade. If there is a trade, the gains from trade are the difference between the seller's costs and the buyer's values.

the lowest prices, followed by the *Baseline* network and the *Substitutes Symmetric* network as the least efficient network with the highest prices:

This finding suggests a policy implication: Social networks that connect sellers of Complements boost efficiency and social networks that connect sellers of substitutes decrease it. Consequently, we should boost the former's effects and dampen the latter's. In my experiment, I increase price transparency to facilitate social sanctions.

Leider et al. (2009) suggests that altruistic behavior among friends increases when friends can be socially sanctioned. I test this by adding a price transparency treatment in which the chosen prices are revealed, which allows participants to sanction their friends for their choices. The theory predicts that transparency leads to lower prices in the *Complements Symmetric* networks and to higher prices in the *Substitutes Symmetric* network. In the experiment, however, transparency lowers prices in both cases. The answers to open questions after the experiment suggest a possible reason: Participants lower their prices because they do not want to appear greedy. That is they have social image concerns (e.g. Andreoni and Bernheim 2009). This unexpected effect of price transparency indicates that findings from two person experiments, such as Leider et al. (2009), do not necessarily generalize to larger markets. Further, in my setting, price transparency does not increase the effects of social networks.

Do friendships behave like partial mergers qualitatively as well as quantitatively? To answer this question, I need to calculate the linear directed altruism model predictions. These predictions depend on directed altruism's strength. I estimate this parameter with a structural model. The estimated model makes in-sample and out-of-sample predictions which I can compare to the data. Additionally, it allows me to disentangle the effect of price transparency on social image concerns from its effect on altruistic behavior.

In addition to linear directed altruism the structural model includes decision error, joy of winning and social image concerns. I model decision errors with a quantal response equilibrium (QRE) (McKelvey and Palfrey 1995). I use a homogeneous parameter for altruism among friends and add two other parameters to the utility function: First, a constant to rationalize a downward shift of all prices compared to the Nash Equilibrium, capturing for example joy of winning and risk aversion, and second a penalty for high prices in the transparency treatment, capturing the social norm for low prices.

The good fit of the structural model suggests that one parameter, directed altruism, rationalizes the effects of different social networks. Besides the altruism parameter, all parameters mainly affect the average magnitude and variance of prices and not the treatment effects of different social networks. The model fits the data well. Therefore a single altruism parameter can rationalize the effects of complement and substitute friendships. The representative participant is willing to pay 20 and 36 cents for their friend to receive one dollar.

To know if directed altruism should be the workhorse theory for the effects of friendships on market efficiency, we need to compare it to other theories. Independently from altruism, a friendship might have strategic effects if participants have more accurate beliefs about their friend's actions than about strangers' (familiarity). Although 60% of the participants state that they have more accurate beliefs about their friend's actions, it does not seem to be true: I elicit beliefs about other players' actions with the binarized scoring rule (Hossain and Okui 2013) and measure belief accuracy by the quadratic distance of beliefs from the corresponding actions. Conditional on the treatment, beliefs about a friend's actions are roughly as accurate as beliefs about a stranger's actions.

My paper contributes to the experimental literature on the effects of social networks on economic decision-making. The existing literature shows that tighter social network links facilitate informal contract enforcement and increase cooperative behaviors and equitable sharing among friends (Leider et al. 2009; Leider et al. 2010; Goeree et al. 2010; Ligon and Schechter 2012; Chandrasekhar, Kinnan, and Larreguy 2018). I complement this literature and investigate the effect of social networks in small markets with more than two people. Consistent with the literature, friends are more altruistic towards each other than strangers. However, my richer setting puts some of the results that were obtained in simple games into a new perspective: in my setting price transparency fails to increase altruistic behavior among friends.

Friends are not better at predicting friends' actions than strangers' actions. While this finding is unexpected for the participants it is mostly in line with the literature. Leider et al. (2010) finds that friends are not better at predicting friends' allocations than strangers' allocations, in a modified dictator game. However, Gächter et al. (2022) and Chierchia, Tufano, and Coricelli (2020) find that friends coordinate better than strangers in some coordination games.

My paper contributes to the literature on market design for the assembly of complements, for example: plots of land into a building site, patents into an invention, components into a car (Kominers and Weyl 2012; Sarkar 2017; Grossman et al. 2019; Bryan et al. 2019). This paper suggests that social network data can help market-designers to decide when it might be worthwhile to harness social relationships to increase market efficiency.

Furthermore, the paper connects IO and social network research. I connect to an older qualitative literature about the role of informal social contacts for oligopolistic coordination (Scherer and Ross 1990, p.311-315) and the literature on common ownership.

My empirical results establish a link between research on firms with common owners and friendships in markets. The same utility function that rationalizes the behavior of friends in this study is used to model firms with common owners (linear-directed altruism).

We can use this bridge to import methods from common ownership research to analyze friendships. Backus, Conlon, and Sinkinson (2021) test the common ownership model with field data. Ederer and Pellegrino (2022) use a structural common ownership model to quantify the effect of common ownership on (real-world) market outcomes. We can repurpose these existing methods for common ownership networks to quantify the effect of friendship networks on market outcomes and test the linear, directed altruism model with field data. To do this, we could replace the common ownership network with a friendship network.

The connection also suggests individual-level friendships as an additional mechanism behind firm-level common ownership preferences. The literature on common ownership also looks for mechanisms by which a firm's owners can induce common ownership preferences in their managers. This paper suggests a complementary approach to the one already discussed in the literature (less sensitive incentives for top managers as in Anton, Gine, and Schmalz (2022) and others discussed in Schmalz (2021)). Firms' owners could staff management positions with friends and pay these friends directly for their firm's performance. The altruism between managers then induces common ownership preferences. Westphal and Zhu (2019) document that there are consultancies that could provide owners with the necessary data on social networks.

2 Theoretical Framework

I model a symmetric market to test for different effects of friendships between sellers of substitutes (*substitute friendships*) and sellers of complements (*complement friendships*). In this section, I outline this experimental market, apply the linear directed altruism model to this market, and derive predictions for the effect of different social networks on prices.

2.1 Model

Participants play one of four human sellers that sell land to a computerized buyer. Sellers 1 and 2 own land to the left side of a river, and sellers 3 and 4 own land to the right side of a river. Sellers make a simultaneous take-it-or-leave-it price offers. Seller i's offer is denoted p_i, $i \in \{1,2,3,4\}$. I develop the theory for the continuous case where $p_i \in [0,50]\ \forall i$, but run the experiment with discrete prices ($p_i \in \{0,1,2,...,50\}\ \forall i$).

The buyer wants to build a single building that spans two plots on the same side of the river. He has i.i.d. uniform private values θ_ℓ and θ_r for two plots on the left or right sides, respectively. The value distribution's support reaches from 0 to 100. Sellers' take-it-or-leave-it offers are aggregated ($p_\ell = p_1 + p_2$ and $p_r = p_3 + p_4$) and transmitted to the buyer. The buyer buys the bundle of land that gives him the highest surplus ($\theta_\ell - p_\ell$ or $\theta_r - p_r$) if this surplus is positive. In some rounds of the experiment, I pay a subsidy of s for successful sales.

I distinguish between a participant's material utility (m_i) and their utility (U_i). In this section I assume that the material utility is equal to the expected monetary pay-off from the experiment. The utility (U_i) incorporates altruism between friends.

If a participant sells, their material utility (m_i) is their price plus the subsidy; in all other cases, it is zero.

I use the simplest possible model of friendships and cooperation: linear directed altruism with a homogeneous altruism parameter $\mu \in [0,1]$. The model allows us to define a player's utility in terms of all players' material utility. Define the adjacency matrix $\boldsymbol{M}$. This matrix has dimensions 4×4, and its typical element m_{kl} is equal to 1 if players k and l are friends and equal to 0 otherwise. The main diagonal is zero. Then the utilities of all players are given by

$$\underbrace{\begin{bmatrix} U_1(p_1,p_2,p_3,p_4) \\ U_2(p_1,p_2,p_3,p_4) \\ U_3(p_1,p_2,p_3,p_4) \\ U_4(p_1,p_2,p_3,p_4) \end{bmatrix}}_{\text{expected utilities}} = \underbrace{\begin{bmatrix} m_1(p_1,p_2,p_3,p_4) \\ m_2(p_1,p_2,p_3,p_4) \\ m_3(p_1,p_2,p_3,p_4) \\ m_4(p_1,p_2,p_3,p_4) \end{bmatrix}}_{\text{material utility}} \underbrace{+\mu \cdot \boldsymbol{M} \cdot \begin{bmatrix} m_1(p_1,p_2,p_3,p_4) \\ m_2(p_1,p_2,p_3,p_4) \\ m_3(p_1,p_2,p_3,p_4) \\ m_4(p_1,p_2,p_3,p_4) \end{bmatrix}}_{\text{altruism term}}$$

In a literal interpretation, the parameter μ captures altruism between friends. I also interpret it as a reduced form summary of all cooperation effects of friendships, such as social sanctions.

Social sanctions work better between friends than strangers because friends value their friendship and can use it as *social collateral* (e.g., Leider et al. 2009). In theory, friends derive utility from their friendships. If someone observes that their friend does not cooperate, they can stop being friends and withdraw that utility. This threat can enforce cooperation.

I conceptualize changes in social sanctions as shocks to the directed altruism parameter (μ). In the experiment, I run a price transparency condition. This condition facilitates social sanctions. Consequently, I assume price transparency increases μ.

2.2 Social Network Treatments and Theoretical Predictions

My main analysis compares symmetric social networks (Substitutes Symmetric and Complement Symmetric) to a Baseline social network without social relationships.[5] These networks are depicted in Figure 1. Market institutions and social networks jointly induce a game.

I analyze the symmetric equilibria of these games. Participants did not receive any feedback before making their last decision and were not able to communicate. With feedback or communication, participants could coordinate on an asymmetric equilibrium; coordination is very hard without these elements. Therefore the symmetric equilibrium is a better prediction for participant's behavior.

I can analyze each round of the experiment as a separate game, because participants do

5. I also run treatments with asymmetric social networks. I discuss these treatments in Subsection 4.7.

not get feedback in between decisions. Therefore they cannot condition their action on other participants' actions in previous rounds. This prevents repeated game effects.

I focus on pure strategy equilibria for reasons of tractability. However, the structural model in Section 4.6 allows for mixed strategies.

Lemma 1 shows that symmetric equilibria exist in all games with symmetric networks. Further, the symmetric equilibrium strategies solve the player's first order conditions. This Lemma's proof is in Appendix A.

This Lemma uses the additional assumption that $50 > (1+\mu)\cdot s$. This assumption guarantees that the player's maximization problems have an interior solution. In the experiment $s \leq 20$, thus the assumption holds for all $\mu \in [0, 1]$.

Lemma 1. *If $50 > (1 + \mu) \cdot s$, the games generated by the Substitutes Symmetric, Baseline and Complement Symmetric networks have a unique symmetric equilibrium. The symmetric equilibrium price solves the players first order conditions and is always on the interior of the price interval.*

Prices in the Substitutes Symmetric network are higher than in the Baseline Network, and prices in the Complements Symmetric network are lower than in the Baseline network. This effect occurs because friends internalize externalities between them more, and externalities between sellers of substitutes and sellers of complements go in opposite directions. If a plot's price rises, the demand for its complement falls, and the demand for its substitute rises. High prices have negative externalities on sellers of complements and positive externalities on sellers of substitutes. If sellers of complements are friends, they internalize the negative externality of high prices and lower their prices. If sellers of substitutes are friends, they internalize the positive externality between them and increase their prices. I formalize this argument in Proposition 1. This proposition's proof is in Appendix A.

Proposition 1. *The symmetric equilibrium price in the Substitutes Symmetric network (p_s) exceeds the price in the Baseline network (p_b), which exceed the price in the Complement Symmetric network (p_c): $p_s > p_b > p_c$.*

We can get an economic intuition for this result by looking at price and quantity effects. Classically, IO decomposes the revenue effect of an increase into a *price effect* and a *quantity* *effect*. The price effect is the rise in revenue through higher prices, keeping quantities constant. The quantity effect is the fall in revenue through lower quantities, keeping prices constant. A revenue maximizing firm (marginal costs are zero) balances price and quantity effect.

Introducing friendships adds an additional element to this decomposition. We can decompose the quantity effect into an *own quantity effect* and a *friend quantity effect*. The own quantity effect is the traditional quantity effect, whereas the friend quantity effect is the effect of a price increase on a friend's quantity. We can see this decomposition in the first-order conditions (FOC) (example for player 1) from the Complements Symmetric network,

$$\underbrace{\frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1}(p_1 + S)}_{\text{own quantity effect (-)}} + \underbrace{\mu \frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1}(p_2 + S)}_{\text{friend quantity effect (-)}} + \underbrace{\Pr_\ell(p_1, p_2, p_3, p_4)}_{\text{own price effect (+)}} = 0,$$

and the Substitute Symmetric network

$$\underbrace{\frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1}(p_1 + S)}_{\text{own quantity effect (-)}} + \underbrace{\mu \frac{\partial \Pr_r(p_1, p_2, p_3, p_4)}{\partial p_1}(p_3 + S)}_{\text{friend quantity effect (+)}} + \underbrace{\Pr_\ell(p_1, p_2, p_3, p_4)}_{\text{own price effect (+)}} = 0.$$

For $\mu = 0$ these FOC coincide with the FOC of the baseline case.

The friend quantity effect in the complement symmetric network leads to lower prices in the Symmetric Complements than in the Baseline network. A higher p_1 makes it less likely that the buyer buys on the left side (the side of players 1 and 2). Consequently, the cross price elasticity of demand ($\frac{\partial \Pr_\ell(p_1,p_2,p_3,p_4)}{\partial p_1}$) is negative. The friend price effect decreases the marginal utility from higher prices.

The effect is reversed in the Substitutes Symmetric network. Hence $p_s > p_b > p_c$.

In the symmetric equilibrium efficiency (total expected material surplus) is highest for the Complements Symmetric network, second highest for the Baseline network, and third highest for the Substitutes Symmetric network. If all prices are the same, the buyer either buys on the side where he has the highest value or does not buy. Prices are a transfer and do not change overall welfare. When the buyer buys, the social surplus is the utility of the buyer ($\max\{\theta_\ell, \theta_r\}$) and the subsidy for the sellers (s); if he does not buy, there is no social surplus. Define the symmetric equilibrium price $p_{\ell r} = p_\ell = p_r$. The overall expected welfare is

$$\int \underbrace{\mathbb{1}[\max\{\theta_\ell, \theta_r\} > p_{lr}]}_{\text{successful trade}}(\max\{\theta_\ell, \theta_r\} + S) f(\theta_r) f(\theta_\ell) \mathrm{d}\theta_\ell \mathrm{d}\theta_r.$$

This expression falls in $p_{\ell r}$. Consequently, social networks with lower prices have a higher expected surplus.

3 Experimental Design

The experiment investigated the effect of social networks on market efficiency. I varied participants' social networks in an experimental market.

The experiment proceeded in five steps: (1) I recruited pairs of friends to participate in the experiment; (2) participants filled out a survey about their friendship; (3) they read an explanation of the experiment's rules and answered control questions. Then, in the central part of the experiment, (4) participants made decisions in the experimental market for different social networks. Throughout this process, participants did not receive any feedback and were not able to communicate. Finally, after making all of their decisions, (5) participants received feedback and answered some open-ended questions.

The experiment was conducted in German. The following explanation translates all terms into English. The experiment was implemented in oTree (Chen, Schonger, and Wickens 2016).

3.1 Recruitment

I recruited participants from the database of the BonnEconLab (via hroot (Bock, Baetge, and Nicklisch 2014)). Each participant, from the database, acted as an anchor and had to bring one friend to the experiment. The anchor participants got an e-mail with an invitation and a link. Participants were told to forward this link to their respective friend who used it to register for the experiment.

The experiment requires precisely four pairs of participants to generate the Baseline network, consisting of four strangers.

As a precaution, for the case of no-shows, I recruited an extra pair of participants. Redundant participants either got to participate in an unrelated individual choice experiment, or were paid a show-up fee and left. [6]

To incentivize bringing a friend, I announced that, as in Leider et al. (2009), all participants could earn 5 Euro for correctly answering a trivia question about their friend. I verify in Section 4.1 with some additional survey questions that the participants' friendships are strong and meaningful social relationships.

3.2 Payoffs

Participants in the experiment were compensated through a combination of show-up fees, trivia question rewards, and decision payoffs. To begin with, each participant received a show-up fee of 7.50 Euro. Additionally, they had the opportunity to earn 5 Euro by successfully answering a trivia question about their friend.

Throughout the experiment, participants made 40 decisions in the market and participated in 8 belief elicitations. These decisions were all payoff-relevant, each with an equal probability of 1/48. Payoffs in the experiment are the same as in Section 2 (the theory section). The theory section omits units; the experiment uses the experimental currency unit, Thaler. Two Thaler correspond to one Euro.

Participants, on average, earned an additional 10.44 Euros based on their choices and their answer to the trivia question.

3.3 Survey

The experiment started with a survey. I reproduce this survey in Appendix B.

I used this survey to ask the announced trivia question. At the beginning of the experiment, participants were asked when they usually get up and when their friends usually get up. Then, participants could enter their and their friend's wake-up times in brackets of one hour that reach from 5 to 11 a.m. They won 5 Euros if they guessed the correct bracket for their friend's

6. I preregistered the design, the analysis, most hypotheses and the sample size (240) at https://osf.io/5ytnz. With a minor deviation, which I discuss later, I stuck to the preregistered design.

wake-up time. To avoid participants preparing for this question, I later switched it to another question: "Is your friend a vegetarian?"

I measured friendship closeness with the inclusion of the other in the self (IOS) scale (Aron, Aron, and Smollan 1992). This scale asks participants to pick one of seven pictures with overlapping rings that best describe their friendship. These pictures range from (1) no overlap to (7) almost complete overlap. Gächter, Starmer, and Tufano (2015) find that the IOS measure correlates strongly with six other measures of relationship closeness.

I asked four survey questions as an alternative measure of friendship closeness. First, I asked if participants brought their best friend to the experiment. Then, I separately inquired about the hours spent with the friend they brought and the hours spent with other friends each week. Lastly, I asked if their relationship with their friend was romantic or sexual, allowing participants to decline answering due to privacy concerns.

I elicited risk aversion with a question from Falk et al. (forthcoming).

3.4 Implementation of the Experimental Land Market

The experiment started with an explanation of the market's general rules (see Section 2.1). Then participants were asked several control questions, followed by an explanation of some features of the market related to the treatments.

Control questions tested participant's knowledge about the cross-price derivatives of the seller's probability to buy a specific plot of land (demand) (for more details see Appendix C). For example (fill in the blanks): "The probability that you sell your plot of land [rises/falls] if player LL increases their price." I asked 5 questions of this type. I did not exclude any participants from the experiment. On average participants answered 4.8 questions correctly and approximately 88% of participants got every question right.

I visualized the market with a map of the four plots. In the experiment, I indicated positions by UL (upper left), UR (upper right), LL (lower left), and LR (lower right). Each participant saw an individual map from their perspective, as UL. I showed this map when explaining the game and when asking the control questions. I also used it to explain each social network treatment and incorporated it into a decision aid.

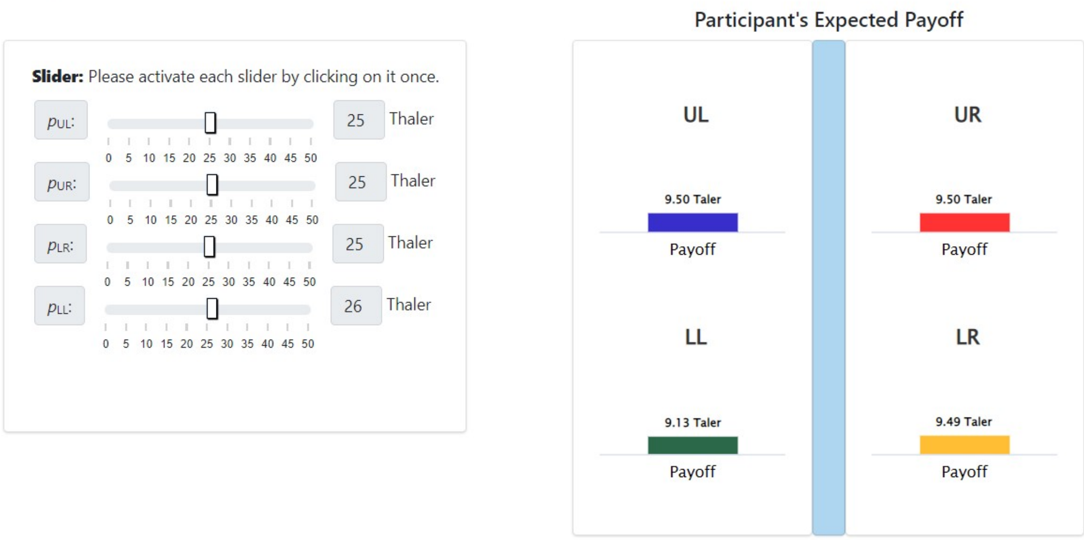


Figure 2: A decision aid that helps participants' decision making. I depict the version for the Baseline network.

I gave participants this decision aid to reduce decision error (Figure 2) . It calculates each player's expected pay-off from all player's prices. Participants received one slider for each participant's price, including their own. A map of all plots, the river, and friendships between participants is displayed next to the sliders. Bar charts and numbers on each plot indicated the respective participants' expected payoffs. Participants could simulate how changes in their and others' prices affected everyone's expected payoffs by moving the sliders.

To avoid anchoring, I started the decision aid without the bars and the sliders without the slider thumbs. Slider thumbs appeared at the spot where the participants initially clicked the sliders. After the participants clicked on each slider, the bars appeared.

I asked participants to make choices in slightly varying market environments to further increase statistical power. While keeping all other variables, including the treatments, constant, participants were asked to decide on prices for several possible subsidies, ranging from 0 to 20 Thaler. When a sale occurred, the subsidy was added to the price. This method increases the precision of my estimates if decisions for different subsidies are not perfectly correlated.

Table 1: All combinations of treatments and belief elicitation.

Treatment	Public/Private	Beliefs
Baseline	Public	Yes
Baseline	Private	No
Complements Symmetric	Public	Yes
Complements Symmetric	Private	No
Substitutes Symmetric	Public	Yes
Substitutes Symmetric	Private	No
Substitutes Asymmetric Couple	Public	Yes
Substitutes Asymmetric Separate	Public	Yes

3.5 Treatment Conditions

I varied two elements of the market: the social network, and price transparency. Sometimes, I also elicited beliefs about players' prices.

Table 1 shows the combinations of social network and transparency treatments used in the experiment. It also indicates for which treatments I elicit beliefs. Each participant makes 5 decisions for each row in this table (within subject design). That is one decision for each possible value of the subsidy.

Figure 3 depicts all social network treatments. I used these conditions to identify the effect of network links on an individual's prices and equilibrium spillovers of social network links. Each sub-figure represents one treatment from the perspective of a specific participant. This participant is in position UL. Arrows depict friendships. I generated these treatments by assigning participants to different positions in the experimental market.

Before making any decisions, participants saw a diagram of the current social network treatment (see Figure 11 in Appendix D). This diagram was based on the map of the four plots. I indicated friendships between other players without revealing their names. For example if the player 3 was friends with player 4, I indicted this by writing "LL (Friend of LR) "and "LR (Friend of LL)" in the positions of player 3 and 4, respectively. I remind participants of the current social network by adding the same labels to the diagram on the right side of the decision aid.

I vary price transparency with two treatments: In the *public*, treatment prices could be

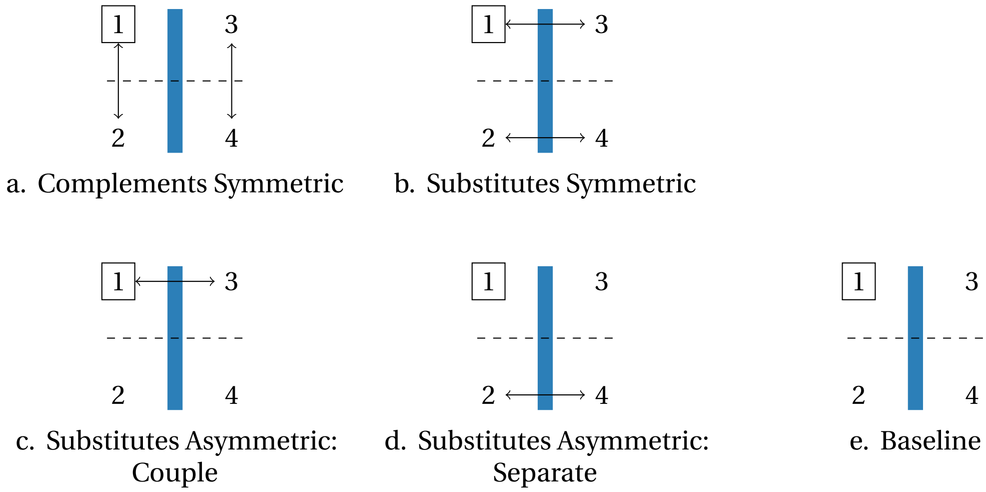


Figure 3: The experimental market with different social networks.

revealed at the end of the experiment, and in the *private* treatment, they always stayed private. Recall that in both treatments, there were no feedback in-between decisions. At the end of the experiment, participants learned their total payoff. They also received feedback if the computer selected a decision from the public treatment for payout. In this case, participants learned all prices, their monetary payoff, and which plots were sold. I omit the private treatment for the asymmetric networks (see Table 1).

Participants made their decisions, on screens that showed the current transparency treatment and subsidy as well as the decision aid. I reproduce such a screen in Figure 12 in Appendix D.

3.6 Belief Elicitation

I elicited each player's beliefs regarding the expected value of other players' prices. To save time, I concentrated on markets without subsidies and selected treatments (refer to Table 1). Participants had to express distinct beliefs about each other player's price.

The belief elicitation process was incentivized with the binarized scoring rule (Hossain and Okui 2013). Players could win a prize based on a specific probability. This probability increased with the squared distance between the belief and the actual price. This scoring rule is incentive compatible for expected utility maximizers.

I took additional steps to ensure participants stated their expected value of other players' prices. I informed participants that more accurate beliefs would result in higher payoffs, and they could open a collapsed text box to view the exact scoring rule. This approach aligns with best-practice methods (Danz, Vesterlund, and Wilson 2022), wherein participants can request the scoring rule at the end of the experiment. Participants could not hedge because either a belief task or one of the rounds was randomly chosen for payout (Blanco et al. 2010).

3.7 Avoiding Possible Confounds

I took steps to address two potential confounds: minimal group effects and order effects.

Minimal group effects can lead participants to feel a sense of connection with others who are arbitrarily grouped with them, even if the group has no actual significance (Charness and Chen 2020). In this experiment the river could lead to such groups. To prevent this effect from influencing my results, I used an alternative frame to balance the minimal group effect across sellers of substitutes and complements.

Specifically, I framed the experiment in two ways: a building condition (the one that I used to describe the experiment in the preceding sections) and a bridge condition. In the bridge condition, the buyer wants to build a bridge across the river instead of building on one side. To do so, the buyer wants to buy two adjacent plots on different sides of the river. Both the building and the bridge treatment are strategically equivalent and differ only in framing. These frames are meant to adjust for minimal group effects.

In the building condition, people on the same riverside sell complements, while in the bridge condition, people on the same riverside sell substitutes. I balanced the potential minimal group effect across substitutes and complements by running half of the sessions with the building condition and half with the bridge condition.

Order effects can occur when the order in which participants make decisions affects their subsequent decisions. To minimize this effect, I used two social network treatment orders.[7] I randomized the transparency treatment order and the order of subsidies within each social

7. Treatment order A is: Substitute Asymmetric, Substitutes Symmetric, Baseline, Complements Symmetric, Substitutes Asymmetric 2; and treatment order B is: Substitute Asymmetric, Complements Symmetric, Baseline, Substitutes Symmetric, Substitutes Asymmetric.

network treatment.[8] I tried to balance the bridge and building conditions across treatment orders.[9]

4 Empirical Results

In this section, I discuss the effect of social networks on prices and efficiency an how it varies with price transparency. I investigate an alternative theory of friendships: higher belief accuracy among friends. After ruling out this theory, I compare an estimated structural directed altruism model to the data to test its quantitative implications and gain further insights.

I always indicate which analyses I preregistered and which are exploratory. I preregistered the analysis, most hypotheses, and the sample size (240) at https://osf.io/5ytnz I preregistered the direction of all effects and one-sided t-tests. My analysis deviates by presenting coefficient plots with 95% confidence intervals instead of these tests.

4.1 Friendship Strength

The introductory survey's results suggest that participants have strong and meaningful social connections with their friends (Table 2). Participants have an average value of 5 on the IOS scale. This value compares to 3.7 for friends and 5.7 for close friends in Gächter, Starmer, and Tufano (2015). Participants spend 33 hours per week with their friends compared to slightly below twenty hours found by Goeree et al. (2010), who find strong effects of friendship on dictator game contributions. The majority answered the trivia question correctly, two-thirds are best friends, and one-third are romantic or sexual partners.[10]

8. For example participants could make decisions in the following order: (Substitute Asymmetric Transparent: 10, 0, 20, 5, 15), (Substitute Asymmetric Private: 10, 0, 20, 5, 15), (Baseline Transparent: 10, 0, 20, 5, 15), (Baseline Private: 10, 0, 20, 5, 15), and so on.

9. I ran 15 session in the bridge and 15 in the building condition. In the building condition I ran 8 sessions with treatment order A and 6 sessions with treatment order B. In the bridge condition I ran 7 sessions with treatment order A and 8 sessions with treatment order B. This differs slightly from the pre-registration (by accident).

10. Answering this question was voluntary, since romantic or sexual relationships are a sensitive topic. Seven people declined to answer.

Table 2: Summary of answers to the introductory survey.

Statistic	Obs	Mean	Std. Dev.	Min	Max
Romantic Relationship	233	0.33	0.47	0	1
Time with Friend (h/week)	240	33.80	39.49	0	168
Time with Others (h/week)	240	14.61	13.54	0	100
Best Friend	240	0.60	0.49	0	1
IOS	240	4.96	1.50	1	7
Correct Trivia	240	0.87	0.34	0	1

4.2 Estimation Framework

The following sections describe various treatment effect estimates, all of which employ the same regression equation, unless specified otherwise. I regress the price ($p_{i,D,O,S}$) on a treatment indicator (T) and a constant:

$$p_{i,D,O,S} = \alpha + \beta \cdot T + \epsilon_{i,D,O,S}. \tag{1}$$

The treatment indicator (T) and the sample vary across analyses. I index individuals by i, social network treatments by D (Baseline, Substitutes Symmetric, Complements Symmetric, Substitutes Asym. Separate, Substitutes Asym. Couple), the transparency condition by $O = \{public, private\}$, and subsidies by $S \in \{0, 5, 10, 15, 20\}$. Unless specified otherwise, I pool data from both the "public" and "private" treatments and always pool data from different subsidy levels. I cluster standard errors at the friendship pair level.

4.3 The Effect of Social Networks on Prices and Efficiency

I examine the impact of social networks on prices by comparing prices in symmetric network treatments to those in the Baseline network. For example, to estimate the treatment effect of substitute friendships, I subtract average prices in the Baseline network from average prices in the Substitutes Symmetric network.

I implement the estimation with the regression from the preceding Subsection. In the example, the sample comprises data from the Substitutes Symmetric and Baseline networks. The

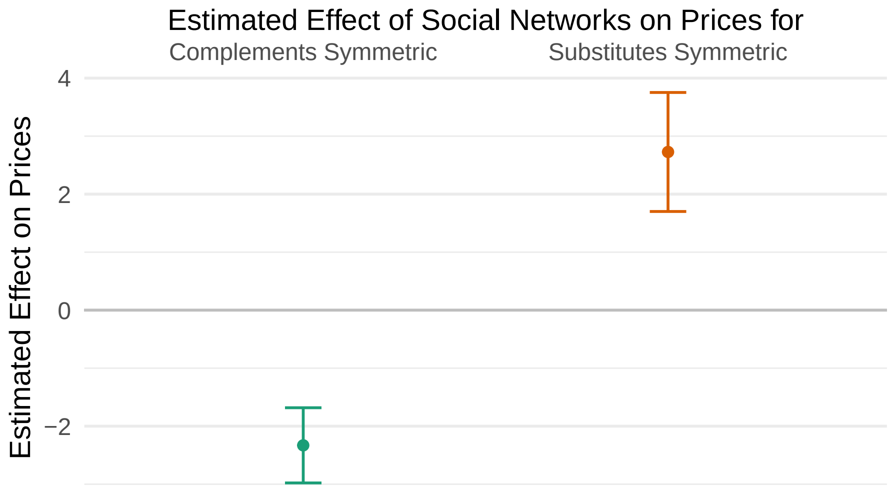


Figure 4: Estimated effects of Complement Symmetric and Substitutes Symmetric networks relative to the Baseline network. Standard errors are clustered on the friendship pair level. Error bars indicate 95% confidence intervals. Each analysis includes 4800 observations from 120 friendship pairs.

treatment indicator (T) is set to 1 for observations from the Substitutes Symmetric network and 0 for those from the Baseline network. I estimate the treatment effect of complement friendships through a parallel comparison for the Complements Symmetric network. Both analyses encompass 4800 observations.[11]

I preregistered these analyses and the following hypotheses: *complement friendships decrease prices, and substitute friendships increase prices.*

Empirically, complement friendships lower prices, and substitute friendships increase prices. Figure 4 depicts the estimated causal effect of friendships on prices. The horizontal axis shows the social network treatment, and the vertical axis shows the effect on Thaler prices. Prices are approximately 2 Thalers lower in the complement network and approximately 2.5 Thalers higher in the substitute network.[12] At the end of this Section I interpret these magnitudes in terms of the directed altruism parameter (μ). Participant's beliefs about other's prices move in the same direction as the corresponding prices (See Figure 13 in Appendix E).

11. These observations are from 240 participants $\times$ 2 Networks $\times$ 2 Transparency Treatments $\times$ 5 subsidies. Since standard errors are clustered by friendship pairs, the sample includes 120 clusters.

12. Prices range from 0 to 50, and one Thaler equals 0.5 Euro, paid out with a probability of 1/48.

I calculate the expected total surplus to investigate the effects of social networks on efficiency. Since the buyer is computerized, I know his behavior. Consequently, I can take the expected value over the buyers' actions. I do this for each iteration of the market. Then I average over all markets I observed. These markets differ in subsidies, transparency conditions, and the players involved. Figure 5 reports average expected total payoffs by network (social surplus). Table 9 in Appendix J decomposes this surplus into buyer and seller payoffs. I report the average maximum surplus ($p_\ell = p_r = 0$) for reference.

The causal effects of social networks on prices imply a corresponding change in total surplus. Since the market is imperfectly competitive (prices are too high) lower prices increase efficiency. As shown in Figure 9, markets with the Complements Symmetric Network have the highest total surplus, followed by markets with the Baseline network and then the Substitutes Symmetric network.

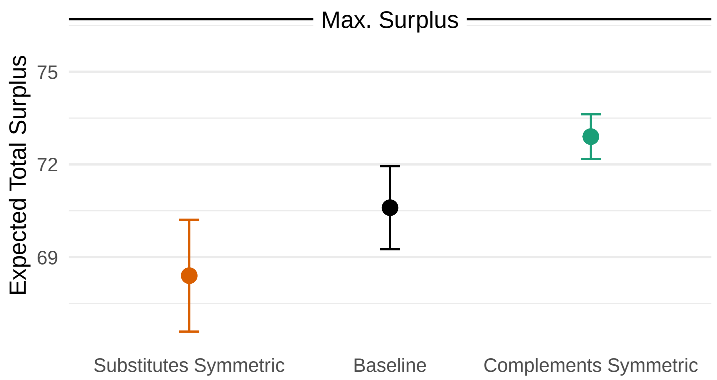


Figure 5: Average expected total surplus for all symmetric social networks. Confidence intervals are 95%. Standard errors are taken from a network-wise linear regression of average prices on a constant, with standard errors clustered by session. Each regression uses 600 observations for 29 sessions.This includes 18 sessions with 8 people each and one session with 16 people.

Efficiency in the Substitutes Symmetric network is significantly lower and efficiency in the Complements Symmetric network is significantly higher than in the Baseline network (at the 5% level). To test this I regress total surplus on a Dummy for the each of the two networks with the Baseline network as the reference category. I cluster standard errors at the session level. Both dummies significantly differ from zero at the 5% level in the expect direction.

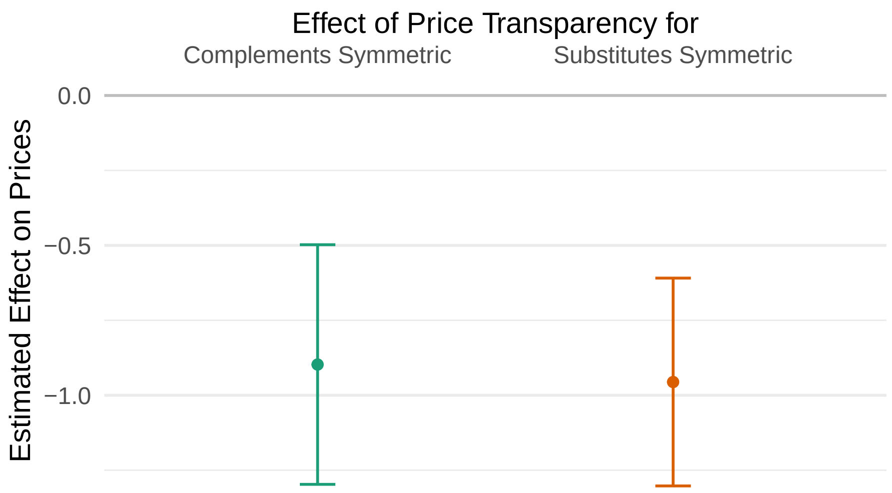


Figure 6: Estimated effects of price transparency on prices in the Complements Symmetric and Substitutes Symmetric treatments. Standard errors are clustered by friendship pair. Error bars indicate 95% confidence intervals. Each regression includes 2400 observations in 120 clusters.

4.4 The Effects of Transparency on Prices

Social collateral theory predicts that price transparency lowers prices in the substitutes' symmetric network and increases prices in the complements symmetric network.

To sanction your friends, you must know what they did to you. Consequently, social sanctioning is easier in the public than in the private condition. If social sanctioning facilitates cooperation, it should increase the effects of social networks, *raising prices for the Substitutes Symmetric network and lowering them for the Complements Symmetric network.* I preregistered this hypothesis.

I test this hypothesis by comparing prices with and without transparency in the Substitutes Symmetric and the Complements Symmetric treatment. The left part of Figure 6 shows the difference in prices between decisions in the complements symmetric network with and without price transparency. The right part shows the corresponding difference for the Substitutes Symmetric network. Error bars indicate 95% confidence intervals with standard errors clustered at the friendship pair level. Figure 14 in Appendix E shows that price transparency affects first order beliefs in the same way as the underlying prices.

Contrary to my hypothesis, price transparency lowers prices in both networks. Since this finding was unexpected, I started to ask participants, after the experiment, how they reacted to price transparency in the Substitute Symmetric treatment. I also asked them to justify their answer (exploratory and not preregistered). The majority (107) said they did not change their price, 25 said they lowered their price, and 12 said they increased their price. I reproduce the question and the (translated) justifications of participants that lowered their prices in Appendix F.1.[13]

Many answers point toward social image concerns (e.g. Andreoni and Bernheim 2009). In particular, people did not want to appear risk-seeking or greedy. Some of the most explicit statements were:

- "Social desirability. You didn't want to disappoint the others by gambling too high."
- "Because I think that many people are more willing to take risks anonymously (myself included)."
- "I was venturesome about staying secret and didn't want to quote extreme prices that would portray me as greedy."
- "vanity"

4.5 Friendship and Belief Accuracy

The familiarity between friends could also affect behavior in the experimental market. I conducted a pilot with strangers instead of friends and asked these strangers to speculate about the effects of friendship. Many of them stated that they know how their friend "ticks", which might affect their behavior. After the experiment, a subset of participants was asked (not preregistered) if they agreed with the following statement "I am a better judge of the price [Name of my Friend] is asking for than what a stranger is asking for." Approximately 63% answered yes (n = 144). Are they right, and does it affect prices?

I address this question by comparing belief accuracy between friends and strangers. I measure belief accuracy by the quadratic deviation of elicited beliefs from realized actions. The

13. Some people gave a generic answer that applies to the public and private treatments, some seemed to misunderstand the incentives, and one statement was too incoherent to be translated.

expected value of a person's prices maximizes this measure. I divide by the maximum possible deviation (50^2), to normalize the values from 0 (lowest deviation/highest accuracy) to 1 (highest deviation/lowest accuracy).

I test if beliefs are more accurate for friends than strangers by regressing this quadratic deviation on a dummy for friendship, a complement dummy, and dummies for each treatment. This regression includes one observation per belief. The complement dummy is one for beliefs about the prices of other participants that sell complements to the person who believes and zero for beliefs about the prices of participants who sell substitutes. The friendship dummy is one if the person having the belief is friends with the person about whom they have the belief. I cluster standard errors on the friendship pair level for the believers. This analysis was preregistered.

Participants' beliefs are not significantly more accurate for friends than for strangers. Row one of Table 3 reports the result of the preregistered specification. The coefficient of the friendships dummy is insignificant and small. Consequently, beliefs are likely not more accurate for friends than for strangers. The other rows report exploratory analyses that I did not pre-register. These analyses indicate that closer friends (as measured by the standardized IOS value) are not better at predicting their friends' actions. People who stated that they had more accurate beliefs about their friends than strangers (Better Beliefs Dummy) do not have significantly more accurate beliefs about their friends than strangers.

We would expect to find a correlation between friends' prices if they had more accurate beliefs about their friend's strategies than strangers'. In the experimental market, prices of substitutes are strategic complements, and prices of complements are strategic substitutes. Thus we would expect a positive correlation between friends' prices if they sell complements and a negative correlation if they sell substitutes. I test this theory in Appendix G and do not find any evidence for it. Consequently, participants' choices are consistent with the finding that beliefs are not more accurate for friends than for strangers.

Table 3: Do participants have more accurate beliefs about friends? Regressions of belief accuracy on a friendship dummy an additional controls. All regression controll for treatment dummies and a dummy that indicates if the belief is about a person selling a complement.

	Dependent variable:		
		$\frac{(Belief-Price)^2}{50^2}$	
	(1)	(2)	(3)
Friend	0.005	0.005	0.020*
	(0.007)	(0.007)	(0.012)
IOS Scale (standardized)		0.004	
		(0.003)	
Friend*IOS (standardized)		−0.005	
		(0.005)	
Better Beliefs			−0.003
			(0.007)
Friend*Better Beliefs			−0.021
			(0.013)
Observations	5,757	5,757	3,453
R^2	0.014	0.015	0.013

Notes: *p<0.1; **p<0.05; ***p<0.01; Standard errors are clusterd on the friendship pair level.

4.6 Structural Model

I test if the data fit the theory quantitatively and qualitatively, by comparing the data to a fitted structural model. I did not pre-register the specification of my structural model. I estimate the model only on the symmetric network treatments (Symmetric Substitutes, Symmetric Complements and Baseline).

To get accurate estimates of the directed altruism parameter (μ), I amend the model from Section 2 with joy of winning, decision error, social image concerns and social sanctions. Recall that I denote the subsidy by S, the transparency treatment by O and the social network treatment by D. I write the adjacency matrix as a function of D ($\boldsymbol{M}(D)$) to indicate that the social network treatment determines it.

- My experiment shares a lot of features with a reverse auction. Auction participants often bid above the risk-neutral Nash equilibrium (John H Kagel 1995; Kagel and Levin 2016). Since my experiment is akin to a reverse auction, on average bids are below the risk-neutral Nash equilibrium. I model this by adding a constant joy of winning (α) to the utility function. This parameter also captures all other forces that may push bids downwards (e.g., risk-aversion, a norm against high prices in the private condition).

- I model the effect of price transparency (social image concerns) with a "tax" (ρ) on high prices in the public treatment.

- Real-world choices are noisy; I model this noise as decision error and estimate a Quantal Response Equilibrium (QRE; McKelvey and Palfrey (1995)).

- I let the directed altruism parameter depend on the transparency condition ($\mu(O)$), to capture that fact that social sanctions may intensify altruism between friends.

Since I focus on symmetric treatments, I focus on player 1's perspective. I collect all parameters in the vector $\gamma = (\mu(public), \mu(private), \alpha, \rho, \lambda)$.

Player 1's material utility is given by,

$$m_1(p_1, p_2, p_3, p_4, S, \gamma) = Pr_\ell(p_1, p_2, p_3, p_4)(\alpha + S + p_1). \tag{2}$$

The only difference to the initial theory section is that players get an additional utility of α when they sell their land.

We obtain the vector of utility functions by adding a tax on high prices in the public treatment and replacing material utility with the new specification,

$$\underbrace{\begin{bmatrix} U_1(p_1, p_2, p_3, p_4, S, D, O, \gamma) \\ U_2(p_1, p_2, p_3, p_4, S, D, O, \gamma) \\ U_3(p_1, p_2, p_3, p_4, S, D, O, \gamma) \\ U_4(p_1, p_2, p_3, p_4, S, D, O, \gamma) \end{bmatrix}}_{\text{expected utilities}} = \underbrace{\begin{bmatrix} m_1(.) \\ m_2(.) \\ m_3(.) \\ m_4(.) \end{bmatrix}}_{\text{own payoff}} \underbrace{+ \mu(O) \cdot \boldsymbol{M}(D) \cdot \begin{bmatrix} m_1(.) \\ m_2(.) \\ m_3(.) \\ m_4(.) \end{bmatrix}}_{\text{altruism term}} \underbrace{- \mathbb{1}(O = public) \cdot \rho \cdot \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix}}_{\text{tax on high prices}}. \tag{3}$$

The parameter ρ captures participants' social image concerns when their prices can get published. This term is motivated by my previous results on price transparency. I include it to separate the effects of friendships from the impact of social image concerns. This method allows me to use data from the public and private treatments without confounding the estimate of the friendship parameter. In particular, I can see if transparency increases cooperation between friends, net of the social image concerns.

QRE generalizes discrete-choice, random-utility models to games.[14] Instead of best-responding players, best-respond noisily. This noise is added to the utility. I use the parametrized version Logit-QRE. The parameter λ captures the relative size of material payoffs and noise. Higher values of λ, lower the noise. If incentives decrease, decisions become noisier.

I denote player i's probability distribution over prices by σ_i. The probability of player 1, choosing p_1 is given by

$$\sigma_1(p_1, S, D, O, \gamma) = \frac{exp(\lambda \mathbb{E}_{p_2,p_3,p_4}[U_1(p_1, p_2, p_3, p_4, S, D, O, \gamma)])}{\Sigma_{p_1' \in \mathbb{P}} exp(\lambda \mathbb{E}_{p_2,p_3,p_4}[U_1(p_1', p_2, p_3, p_4, S, D, O, \gamma)])} \tag{4}$$

$$\mathbb{E}_{p_2,p_3,p_4}[U_1(p_1, p_2, p_3, p_4, S, D, O, \gamma)] = \tag{5}$$

$$\sum_{p_2 \in \mathbb{P}} \sum_{p_3 \in \mathbb{P}} \sum_{p_4 \in \mathbb{P}} \sigma_2(p_2, S, D, O, \gamma)\sigma_3(p_3, S, D, O, \gamma)\sigma_4(p_4, S, D, O, \gamma)U_1(p_1, p_2, p_3, p_4, S, D, O, \gamma). \tag{6}$$

The probabilities for the other players are analogous.

I estimate the model by maximum likelihood and introduce some additional notation to state the likelihood function. Observations are indexed by $j \in \{1, ..., N\}$. The price of player 1 in observation j is p_{1j}. Treatment D and O differ across observations j, I show this by adding the index j to these variables.

Usually, estimating a QRE model requires solving for the equilibrium for many different parameter values. I use a trick from structural auction models to avoid this. Equation 4 depends on the strategies of all other players: $\sigma_2(p_2, S_j, D_j, O_j, \gamma)$, $\sigma_3(p_2, S_j, D_j, O_j, \gamma)$ and $\sigma_4(p_2, D_j, O_j, S_j, \gamma)$. The standard approach would use the analogous equations for the other

14. Recall that I use discrete prices ($\mathbb{P} = \{0, 1, ..., 50\}$).

players and solve for these quantities as equilibrium objects. Following Bajari and Hortaçsu (2005), I plug in these quantities' empirical analogs instead. For example I substitute $\sigma_2(p_2, S_j, D_j, O_j, \gamma)$, with the empirical frequency that a player plays p_2, when the subsidy is S_j, for social network treatment D_j, and transparency condition O_j.

I estimate the model with quasi-maximum likelihood. I maximize the log-likelihood function,

$$LLH(\gamma) = \Sigma_{j=1}^{N} \log(\sigma_1(p_{1j}, S_j, D_j, O_j, \gamma)), \tag{7}$$

with respect to the parameter vector γ. This process generates a covariance matrix under the assumption of independent observations. I adjust these standard errors for clustering with the Huber-White sandwich estimator as implemented in Zeileis (2006).

Table 4 lists the estimated parameters with 95% confidence intervals. Directed altruism in the private condition ($\mu(private)$) is between 0.2 and 0.36. This implies that a participant is willing to pay approximately 30 cents for their friend to receive one dollar. Directed altruism does not significantly differ between public and private treatments. The estimated joy of winning parameter (α) is larger than 20. Social image concerns impose a tax of 4% on prices in the public treatment. This value is small but significant, in line with the small treatment effects of price transparency.

Table 4: Parameter estimates for the QRE-Directed-Altruism model.

Parameter	Explanation	Estimate	95% CI
Directed Altruism			
$\mu(private)$	private	0.277^{***}	(0.193, 0.361)
$\mu(public) - \mu(private)$	increase public	0.009	(−0.057, 0.074)
ρ	social image concerns	0.037^{***}	(0.013, 0.060)
α	constant	24.600^{***}	(20.60, 28.60)
λ	QRE-parameter	0.250^{***}	(0.189, 0.312)

Notes: *p<0.1; **p<0.05; ***p<0.01; standard errors are clusterd on the friendship pair level.

I plot the fitted model alongside the data to determine if directed altruism can rationalize behavior in the experiment. Figure 7 shows the treatment effects of the symmetric networks compared to the Baseline network. I reproduce the empirical treatment effect estimates from

Figure 4 (Main Effect) with yellow triangles labeled "Data." I conduct the same analysis used to come up with these estimates on the structural model predictions. These predictions are depicted with purple dots. Model predictions and treatment effect estimates are similar and not significantly different. I do not quantify the uncertainty of the model's predictions.

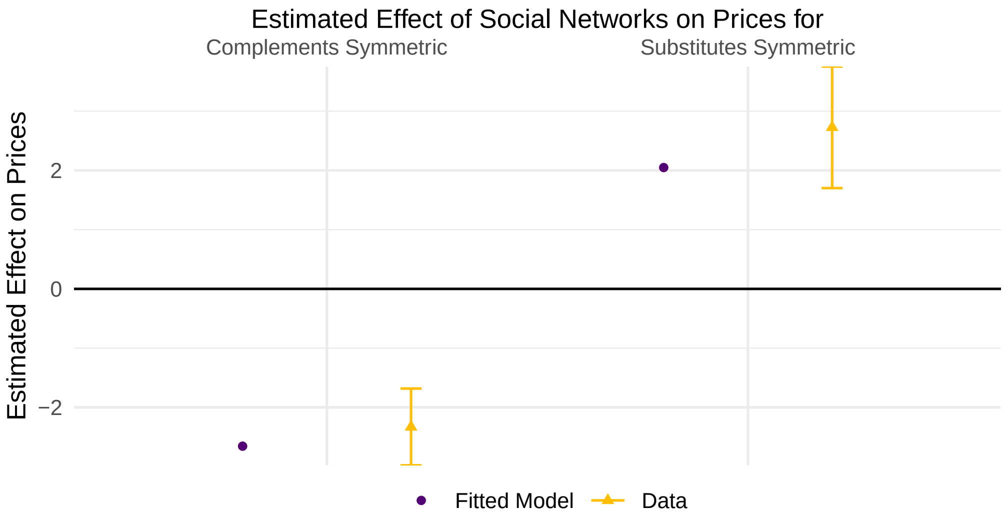


Figure 7: This figure shows the estimated treatment effects predicted by the fitted structural model and the reduced form treatment effect estimates, along with 95% confidence intervals calculated using standard errors clustered at the friendship pair level. The estimated treatment effects are drawn from the main analysis, which is reported in Figure 4.

Homogeneous linear directed altruism rationalizes the data after accounting for lower bids and decision errors. While the model includes other parameters, these parameters are not concerned with fitting the effects of social networks on prices. Decision error mainly fits the variance of prices. Joy of winning explains the general level of prices without reacting to the social network. The parameter ρ mainly fits the differences between the transparency and private condition. Only the altruism parameter μ directly interacts with the network's structure. This parameter fits two treatment effects: the effect of symmetric substitute friendships and the effect of symmetric complement friendships.

Introducing altruism among strangers has minimal impact on the structural estimates. The experiment is primarily designed to uncover the consequences of altruism among friends rather than strangers. As a result, altruism among strangers is not expected to substantially affect prices, making it challenging to estimate. Appendix I presents a variant of the model incorporating linear altruism among strangers. The confidence interval for the altruism parameter among strangers is broad, while other parameter estimates remain similar to those in this section.

Closer friends exhibit higher directed altruism parameters. I generate a friendship closeness index using responses from the introductory survey. By fitting a unique directed altruism parameter for each tercile of this index, I find that participants in the lowest tercile have significantly lower directed altruism parameters. For additional details, refer to Appendix H.

4.7 Equilibrium Spillover of Friendships

Does the linear, directed altruism model also predict the equilibrium spillovers of friendships? Participants should anticipate that they face different prices dependent on other participants' friendships. In equilibrium, they should react to these changed expectations about other participants' prices. Friendships should have spillovers on people that are not directly affected by them. For friendships among sellers of substitutes, the structural model from the previous section predicts these spillovers to be one-fourth of the size of the direct effect. I use data from the asymmetric substitutes treatment to estimate the spillovers and find that they do not significantly differ from zero.

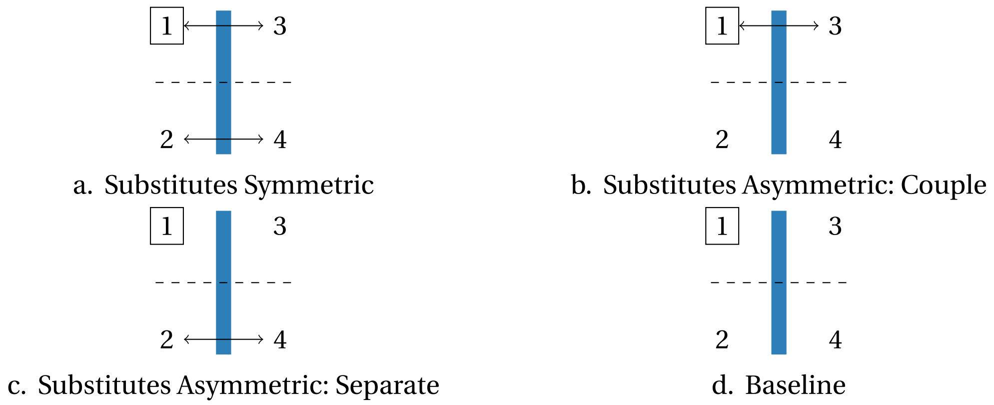


Figure 8: All social network treatments used to test for the equilibrium effects of friendships.

To test for the equilibrium effects of friendships, I keep players 1 and 3's friendship constant and vary the friendships of players 2 and 4. Figure 8 reports the social network treatments used for this comparison. In the Substitutes Symmetric treatment (row one on the left), players 2 and 4 are friends; in the Substitutes Asymmetric couple (row one on the right) treatment, they are not. The second row shows the same comparison, with a slight difference: players 1 and 3 are friends in both cases.

I estimate the treatment effect of players 2 and 4's friendship as the difference between two means: The treated mean is the average price in the Substitutes Symmetric" and Substitutes Asymmetric: Separate" treatments, where 2 and 4 are friends, and the control mean is the average price in the Substitutes Asymmetric: Couple" and Baseline" treatments, where 2 and 4 are strangers. Both treatment and control groups include an equal number of observations where 1 and 3 are friends and where they are strangers. I run both networks only in the public treatment.

The structural model from the preceding section makes quantitative out-of-sample predictions for the equilibrium effects of friendships. Assuming that participants have consistent beliefs, I can estimate player 1's equilibrium beliefs about other players' prices from realized price frequencies, considering each social network depicted in Figure 8. Then, I calculate the noise best response by plugging them into Equation 4 (the QRE best response) and use the parameters estimated from the symmetric treatments. I average over all subsidies and calculate the predicted treatment effect of a friendship between players 2 and 4 on player 1's prices. Figure 9 shows the QRE prediction as a grey line.

The friendship between players 2 and 4 should lower player 1's prices. Since players 2 and 4 sell substitutes for each other's goods, their friendship raises their prices. Player 1 is now faced with a higher price for their complement (p_2) and slightly higher prices for their substitutes ($p_3 + p_4$). The higher p_2 raises the price for both plots on the left. Player 1 should react by lowering their price. The higher price on the right softens competition and would allow player 1 to lower their price. The structural model predicts that the former effect is much stronger. The model predicts that player 1 will lower their price in response to the friendship between 2 and 4.

The actual equilibrium effects of friendships (between 2 and 4) are estimated with a similar regression as the main effects (Section 4.2). The dependent variable is the price of player one in each network from Figure 8. Each participant is player 1 in these networks for five different

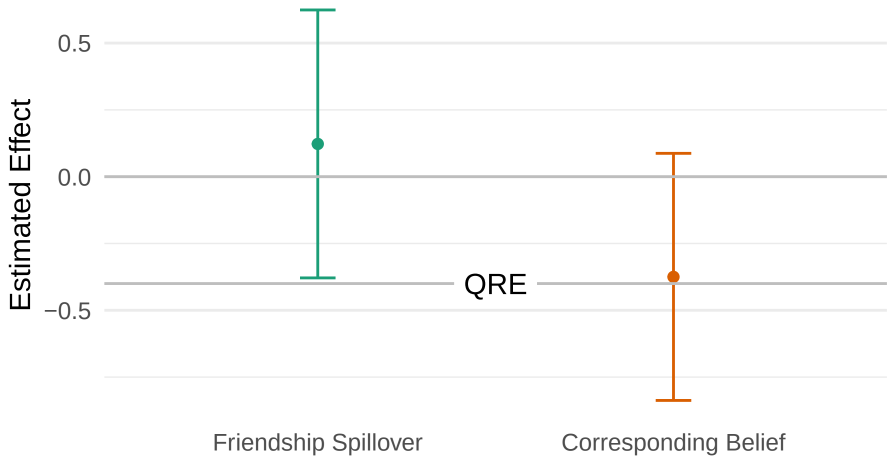


Figure 9: Estimated effects of friendships between 2 and 4 on 1's prices and beliefs about 1's prices. Standard errors are clustered on the friendship pair level. Error bars indicate 95% confidence intervals. The analyses uses 4800 observations in 120 clusters.

subsidies. Consequently, we observe each player ten times when 2 and 4 are friends and ten times when they are not. Observations from Substitutes Symmetric and Substitutes Asymmetric (separate) are in the treated group, and observations from Substitutes Asymmetric (couple) and Baseline are in the control group. I conduct this regression twice: once with the actual prices as the dependent variable and once with all other players' beliefs about these prices. I cluster standard errors at the friendship pair level for the participants that decided on the price and the participants that stated the belief. I preregistered this analysis with the hypothesis that the friendship between 2 and 4 lowers 1's price and that first-order beliefs behave accordingly. The estimated treatment effect on prices is depicted on the left side and the treatment effect on beliefs on the right side of Figure 9.

Compared to the model benchmark, participants under-react to other participants' friendships. As Figure 9 shows, the model predicts participants to lower their prices in response to the other participant's friendship. The data do not show any evidence for that.

I do not find evidence for the theory that players under-react because of biased beliefs. Figure 15 in Appendix E reports the effect of a substitute friendships on beliefs about the friends prices. Participants always (in symmetric and asymmetric networks) belief that substitute friends charge higher prices than strangers. Consequently they should reduce their prices when they face substitute friendships, as predicted by the structural model.

5 Conclusion

I conduct an experiment with real world friendships in a laboratory market with substitutes and complements. In this experiment, complement friendships decrease prices and increase efficiency and substitute friendships do the opposite. The linear directed altruism model fits the data well. Price transparency reduces prices for all symmetric social networks. This data and the estimated structural model suggest that price transparency increases social image concerns and does not increase cooperativeness between friends. In this experiment, participants' beliefs about their friend's actions are not more accurate than about strangers' actions.

The unexpected effect of price transparency suggests that more than findings from simple two-person experiments on cooperation in markets is needed to predict behavior in more complex markets with more participants. With more than two persons, a player's action may affect people other than their friend. Adding these people to the situation may alter the effects of friendship. Leider et al. (2009) vary the ability for social sanctions in a modified dictator game by hiding and revealing the dictator's identity. They find that the ability for social sanctions increases altruistic behavior. I vary the ability for social sanctions by hiding and revealing players' actions and find no effect of transparency on altruistic behavior but uniformly lower prices. This price reduction could be due to increased social image concerns. Participants care how they look in front of their friends and strangers. While the discrepancy could also stem from the difference in how this paper facilitates social sanctioning, the finding still suggests that previous results on friendship and social sanctioning might not be applicable to price transparency in larger markets.

My results suggest that markets for the assembly of complements can be particularly efficient when there are complement friendships. This result suggests a lower need for government intervention in markets with complement friendships.

The result also suggests that market designers want to emphasize social networks when there are complement friendships. This can occur through, reducing anonymity and using mechanisms that retain externalities between participants instead of reducing them like Bierbrauer et al. (2017). In this experiment price transparency does not boost the effects of social networks.

One example for markets with complement friendships are land markets with geographic social networks (Ambrus, Mobius, and Szeidl 2014). In land markets often close plots are complements and distant plots are substitutes. In geographic networks neighbors are more likely to be friends. Consequently, these two properties lead to complement friendships.

This experiment indicates that friendships in markets can be described by the same preferences as firms with common owners. However, We need further research to investigate the connection between common ownership and friendship. In this paper, firms are unitary actors. Each participant owns one piece of land that they can sell. Real-world firms have a more complex corporate governance structure. Directed altruism at the level of individual decision-makers is embedded in this structure. To understand the firm-level impact of linear, directed altruism preferences, we must understand the interplay between these preferences and corporate governance. How can individual-level directed altruism translates to firm-level common ownership preferences?

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A Proof of Proposition 1

Proof of Lemma 1. I write this proof for a uniform value distribution from 0 to 1 and prices from 0 to 0.5. It also holds for a uniform value distribution from 0 to 100 (which I use in the main text) and prices from 0 to 50.

Recall that $p_\ell = p_1 + p_2$ and $p_r = p_3 + p_4$. The probability that the buyer buys on the left-side is,

$$\Pr_\ell(p_1, p_2, p_3, p_4) = \int_0^1 \int_0^1 \mathbb{1}(\theta_\ell - p_\ell > \theta_r - p_r)\mathbb{1}(\theta_\ell - p_\ell > 0) f(\theta_r) f(\theta_\ell) d\theta_\ell d\theta_r \tag{8}$$

$$= \begin{cases} (1 - p_\ell) - 0.5(1 - p_r)^2 & \text{if } p_\ell \leq p_r \\ (1 - p_\ell) \cdot p_r + 0.5(1 - p_\ell)^2 & if\ p_r < p_\ell \end{cases}. \tag{9}$$

I start by characterizing the symmetric equilibrium of the Substitutes Symmetric network. Player 1 solves

$$\max_{p_1 \in [0, 0.5]} \Pr_\ell(p_1, p_2, p_3, p_4) \cdot (p_1 + S) + \mu \cdot \Pr_r(p_1, p_2, p_3, p_4) \cdot (p_3 + S)$$

The first order condition is:

$$\frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1} \cdot (p_1 + S) + \Pr_\ell(p_1, p_2, p_3, p_4) + \mu \frac{\partial \Pr_r(p_1, p_2, p_3, p_4)}{\partial p_1} \cdot (p_3 + S) = 0$$

and the second order condition is:

$$\frac{\partial^2 \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1^2} \cdot (p_1 + S) + 2 \cdot \frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1} + \mu \cdot \frac{\partial^2 \Pr_r(p_1, p_2, p_3, p_4)}{\partial p_1^2} \cdot (p_3 + S) < 0$$

By plugging in the derivatives of Equation 9 into the second order condition we get

$$-(2 + \mu(p_3 + S)) < 0, \text{ if } p_\ell \leq p_r$$

and

$$-(p_1+S)-2(1+p_r-p_\ell)-\mu(p_3+S)<-(p_1+S)-\mu(p_3+S)<0,\ \text{if}\, p_r<p_\ell,$$

which is true and implies that player 1's utility function is strictly concave in p_1. Therefore all players ($i \in \{1,2,3,4\}$) utility functions are strictly concave in their own price (p_i).

Any symmetric equilibrium strategy p_s satisfies the first order condition:

$$g(p_s,\mu) := \frac{\partial Pr_\ell(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)+\Pr_\ell(p_s,p_s,p_s,p_s)+\mu\frac{\partial \Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)=0 \tag{10}$$

$$\Leftrightarrow g(p_s,\mu)=-(p_s+S)+(1-2p_s)-0.5(1-2p_s)^2+\mu(1-2p_s)(p_s+S)=0 \tag{11}$$

.

I use the intermediate value theorem to show that this equation has a solution. The function g is continuous because it is a composition of continuous functions. I calculate that $g(0,\mu)=(-1+\mu)S+0.5$ and $g(0.5,\mu)=-(1+S)$. The first expression is larger than 0 if $(-1+\mu)S+0.5>0 \Leftrightarrow 0.5>(1-\mu)\cdot S$. This is true because $0.5>(1+\mu)\cdot s$. The second $(g(0.5,\mu))$ is always larger than zero. Consequently, the FOC has an interior solution by the intermediate value theorem. Furthermore this solution is the symmetric equilibrium price $0<p_s<0.5$.

Now I characterize the symmetric equilibrium of the Complements Symmetric network. Player 1 solves

$$\max_{p_1} \Pr_\ell(p_1,p_2,p_3,p_4)\cdot(p_1+S)+\mu\cdot\Pr_\ell(p_1,p_2,p_3,p_4)\cdot(p_2+S)$$

The first order condition is:

$$\frac{\partial \Pr_\ell(p_1,p_2,p_3,p_4)}{\partial p_1}(p_1+S)+\Pr_\ell(p_1,p_2,p_3,p_4)+\mu\frac{\partial \Pr_\ell(p_1,p_2,p_3,p_4)}{\partial p_1}\cdot(p_2+S)=0$$

and the second order condition is:

$$\frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial^2 p_1}(p_1 + S) + 2\frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial p_1} + \mu \frac{\partial \Pr_\ell(p_1, p_2, p_3, p_4)}{\partial^2 p_1} \cdot (p_2 + S) < 0$$

By plugging in the derivatives of Equation 9 into the second order condition we get

$$-2 < 0, \text{ if } p_\ell \leq p_r$$

and

$$-(p_1 + S) - 2(1 + p_r - p_\ell) - \mu(p_3 + S) < -(p_1 + S) - \mu(p_3 + S) < 0, \text{ if } p_r < p_\ell,$$

which is true and implies that player 1's utility function is strictly concave in p_1. Therefore all players utility functions are strictly concave in their own price p_i.

Any symmetric equilibrium strategy p_s satisfies the first order condition:

$$g(p_c, \mu) := \frac{\partial \Pr_\ell(p_c, p_c, p_c, p_c)}{\partial p_1}(p_c + S) + \Pr_\ell(p_c, p_c, p_c, p_c) + \mu \frac{\partial \Pr_\ell(p_c, p_c, p_c, p_c)}{\partial p_1}(p_c + S) = 0 \tag{12}$$

$$\Leftrightarrow g(p_c, \mu) = (1 - 2p_c) - 0.5(1 - 2p_c)^2 - (1 + \mu)(p_c + S) = 0. \tag{13}$$

I use the intermediate value theorem to show that this equation has a solution. The function g is continuous because it is a composition of continuous functions. I calculate that $g(0, \mu) = 0.5 - (1+\mu)S$ and $g(0.5, \mu) = -(1+\mu)(1+S)$. The first expression is larger than 0 if $0.5 - (1+\mu)S > 0 \Leftrightarrow 0.5 > (1 + \mu) \cdot S$, which is true by assumption. The second $(g(0.5, \mu))$ is always larger than zero. Consequently, the FOC has an interior solution by the intermediate value theorem. Furthermore this solution is the symmetric equilibrium price $0 < p_c < 0.5$.

In conclusion the Substitute Symmetric and Complement Symmetric networks have an interior symmetric equilibrium: In each of these networks player's utility functions are strictly concave in their own price. Since both networks nest the Baseline network, for $\mu = 0$, this also holds for the Baseline network. □

Proof of Proposition 1. In all three symmetric networks the equilibrium is on the interior of the price space and the objective function is concave. Therefore symmetric equilibrium prices solve the first order conditions:

$$\frac{\partial \Pr_\ell(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)+\Pr_\ell(p_s,p_s,p_s,p_s)+\mu\frac{\partial \Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)=0 \tag{14}$$

$$\frac{\partial \Pr_\ell(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+S)+\Pr_\ell(p_c,p_c,p_c,p_c)+\mu\frac{\partial \Pr_\ell(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+S)=0 \tag{15}$$

$$\frac{\partial \Pr_\ell(p_b,p_b,p_b,p_b)}{\partial p_1}(p_b+S)+\Pr_\ell(p_b,p_b,p_b,p_b)=0. \tag{16}$$

Define the marginal private gain from higher prices in the symmetric equilibrium as:

$$h(p)=\frac{\partial \Pr_\ell(p,p,p,p)}{\partial p_1}(p+S)+\Pr_\ell(p,p,p,p).$$

This expression ($h(p)$) falls in p because $\frac{\partial \Pr_\ell(p,p,p,p)}{\partial p_1}=-1$.

Taking the difference between Equations 14 and 16 and rearranging yields:

$$h(p_b)-h(p_s)=\mu\frac{\partial \Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)>0 \tag{17}$$

$$\leftrightarrow h(p_b)>h(p_s)\Leftrightarrow p_s>p_b. \tag{18}$$

Taking the difference between Equations 15 and 16 and rearranging yields:

$$h(p_b)-h(p_c)=\mu\frac{\partial \Pr_\ell(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+S)<0 \tag{19}$$

$$\leftrightarrow h(p_b)<h(p_c)\Leftrightarrow p_b>p_c. \tag{20}$$

□

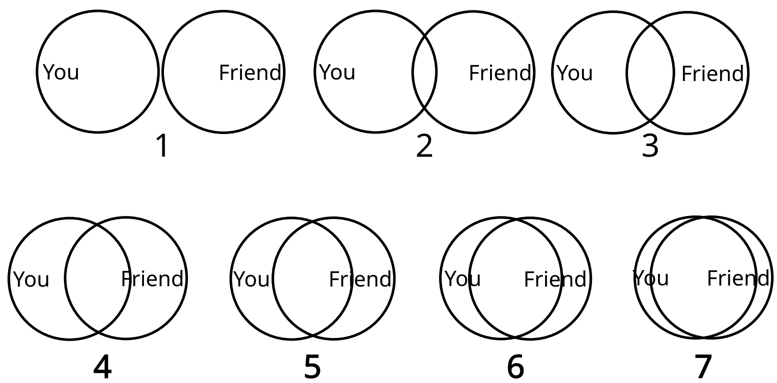
B Survey Questions

I asked the following Survey questions. I give possible answers in square brackets.

- Did you bring your best friend with you? [yes, no]
- How many hours do you and the friend you brought with you spend together every week?

[number between 0 and 168]

- How many hours do you spend with other friends each week in total? [number between 0 and 168]
- Trivia question (one of the following):
  - Are you vegetarian or vegan? [yes, no]
  - What time do you usually wake up on weekdays? [hourly brackets from before 5 am to after 11 am]
- What do you think your friend answered to the last question? If you are correct, you will receive a prize of 10 Thalers. [same as the trivia question]
- Which of the following pictures best describes your friendship?



- Are you in a romantic or sexual relationship with your friend? [yes, no, do not want to say]
- In general, how willing or unwilling are you to take risks? [integers from "0 - Not at all willing to take risks" to "10 - Very willing to take risks"]

C Control Questions

I asked the following control questions in two batches (1-3 and 4-5).

1. The probability that you (Participant UL) will sell your property, [*decreases*, *increases*], when Participant LL raises the price.

2. The probability that you (Participant UL) will sell your property, [*decreases, increases*], when Participant UR raises the price.

3. The probability that you (Participant UL) will sell your property, [*decreases, increases*], when Participant LR raises the price.

4. When you (Participant UL) raise your price, [*decreases, increases*] the probability that the buyer will purchase property LL.

5. When you (Participant UL) raise your price, [*decreases, increases*] the probability that the buyer will purchase properties UR and LR.

After each batch I gave participants feedback that corrected the wrong answers. Together with each batch I showed participants a map of the experimental land market (see Figure 10).

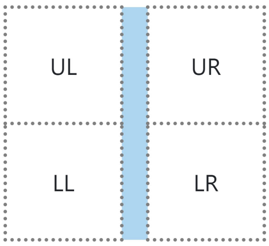


Figure 10: Map that I showed before each batch of control questions.

D Screenshots from The Experiment

Figure 11: Overview of the social network treatment: An example of the Complements Symmetric network in the building condition, with the participant's friend's name set to Peter.

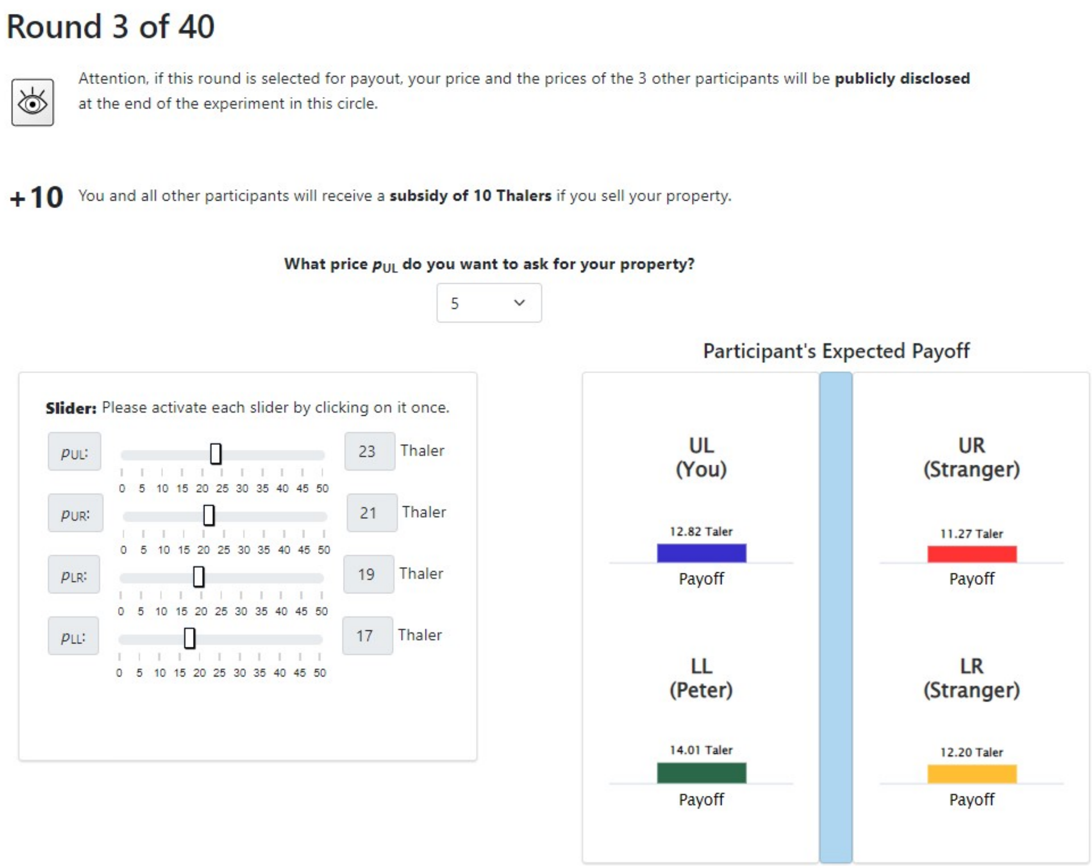


Figure 12: Screenshot of the decision screen used in the experiment to elicit participant choices for different subsidy levels. The top of the screen displays information about the subsidy and the transparency treatment, which varied between public and private. Participants were asked to enter a price for their property (indicated by UL on the map) and were provided with a decision aid (shown in Figure 2) to simulate the consequences of their and others' decisions.

E Beliefs

Figures 13 and 14 revisit analyses from Section 4, using beliefs as the dependent variables instead of participants' prices. The belief data contain three observations for each observation in the price data since for each price there are three participants who have a belief about it. This analysis was preregistered with the hypothesis that beliefs would react in the same direction as the actual variables. Standard errors are clustered at the friendship pair level of those who formed the belief. Clustering at the individual level yields identical results since individuals are nested within friendship pairs. Each table caption refers to a figure for the corresponding analysis, where prices serve as the dependent variable instead of beliefs.

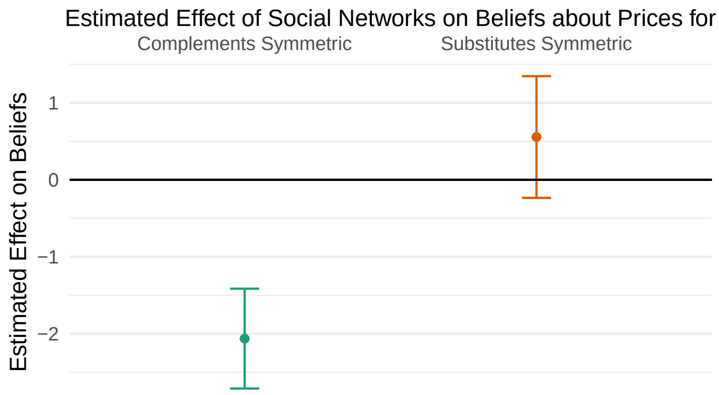


Figure 13: Estimated effect of complement and substitute friendships on first-order beliefs. Standard errors are clustered at the friendship pair level. This figure is analogous to Figure 4.

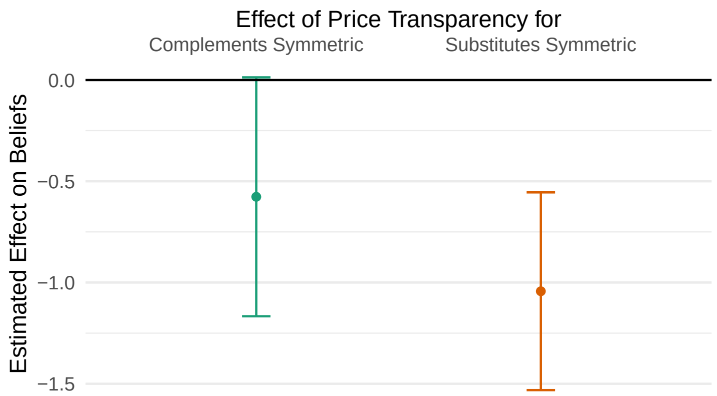


Figure 14: Estimated effects of price transparency on beliefs in the complement symmetric and substitute symmetric treatments. Standard errors are clustered at the friendship pair level. This figure is analogous to Figure 6.

The left side of Figure 15 examines asymmetric networks, focusing on how a participant's (he) belief about another participant (she) changes when she transitions from being isolated to being friends with a seller of a substitute, while his friendships remain constant. To estimate this effect, I compare beliefs about participants in the Substitutes Symmetric and Substitutes Asymmetric Couple treatments to beliefs about participants in the Baseline and Substitutes Asymmetric: Separate treatments. This analysis corresponds to the left part of Figure 9, with prices replaced by first-order beliefs about them.[15]

The right side of Figure 15 investigates symmetric networks, replicating the right side of Figure 13.

In both asymmetric and symmetric networks, participants expect prices to be higher when individuals are friends with others selling a substitute, as opposed to when their friends do not participate in the market. The coefficients on both sides of Figure 15 are very similar, indicating that participants anticipate similar effects of substitute friendships in both asymmetric and symmetric networks. The consistency in belief-changes across different network structures indicates that an under-reaction in asymmetric networks compared to symmetric networks is unlikely to be the source of a lack of equilibrium spillovers.

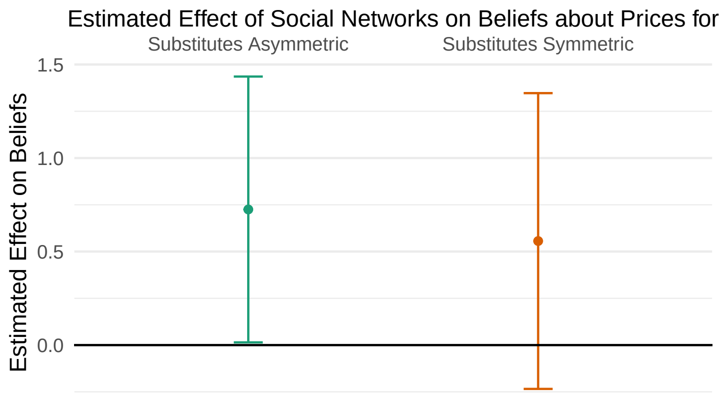


Figure 15: Effect of substitute friendships on beliefs about substitute prices in the substitute symmetric and substitute asymmetric treatments.

15. The right part of Figure 9 also reports an analysis about beliefs. However, this analysis considers the mirror image of the analysis reported in Figure 15. It looks at the belief of people who change from being isolated to selling substitutes about people whose friendships do not change.

F Open Question Price Transparency

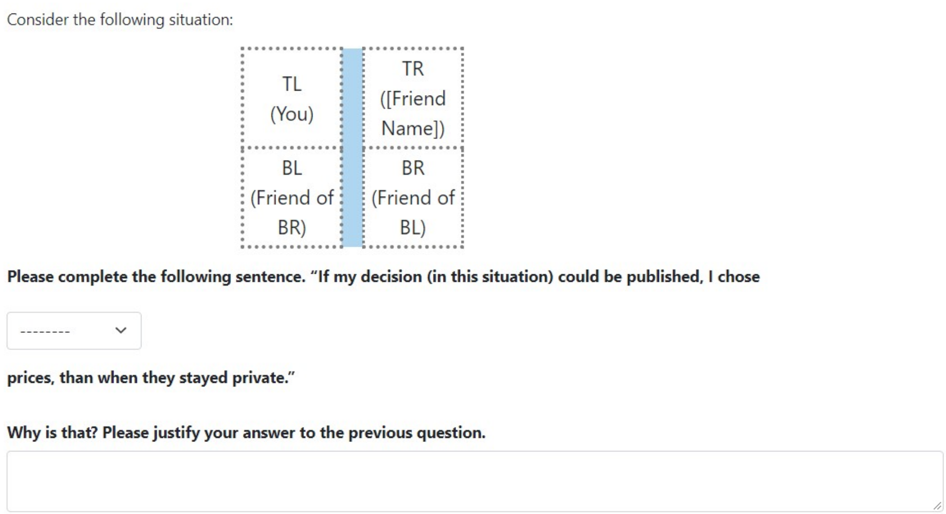


Figure 16: Open question regarding price transparency in the substitutes treatment (translated from German).

F.1 Answer of Participants that Lowered Prices

"I think in this situation I could have brought a win for both sides."

"If there is no payout, the disclosed price is not too risky."

"So that I can sell my property with a higher probability."

"Because I feel safer with a lower price."

"I was venturesome about staying secret and didn't want to quote extreme prices that would portray me as greedy. I also expected that a decision that could be published, would be selected."

"Because I didn't want to be responsible for a failed sale because I set a high price. "

"You don't want to come across in front of others as if you're just out for the money. In addition, people does not want to be publicly responsible if the other does not receive a price either. "

"vanity"

"Better lower payouts than no payouts."

"So my chances of winning are higher."

"I chose low prices because I suspect that the knowledge about my higher pricing could potentially negatively impact trading."
"I wanted to choose a lower price so that the probability of selling the property is higher. If I had chosen the price too high and we had not sold, I would have felt guilty to my counterpart."
"Because I believe that if the decision could be announced, [name] also chose lower prices."
"Because I think that many people are more willing to take risks anonymously (myself included)."
"So that I have not chosen too high prices and therefore the upper plots are not sold by me."
"[name] would see that I chose too high, unpleasant."
"If it is not anonymous, I do not want to take too high prices myself."
"Because that decides whether you get the profit."
"So that I don't look greedy and I'm not fault that our site is not bought."
"So that nobody is angry if they don't earn money because of me."
"Probably I would have compared my prices with those of [name] and noticed that hers are lower than expected, so I would have started to set lower ones as well."
"Social desirability. You didn't want to disappoint the others by gambling too high."
"Because you may be fault afterwards if a purchase does not take place."
"I didn't want to overestimate my prices when other participants see that. "

G Correlation Between Prices

I test for the correlation between friend's prices by regressing a person's price on their friend's price. I restrict the sample to the Complements Symmetric and substitutes treatments, as well as the substitutes asymmetric couple treatment. I estimate the following regression

$$p_{i,D,O,S} = \alpha + \beta * p_{-i,D,O,S} * S_{-i,D,O,S} + \gamma * p_{-i,D,O,S} * (1 - S_{-i,D,O,S}) + \delta * X_i + \epsilon_{i,D,O,S},$$

$p_{i,D,O,S}$ is the price of participant i in network D, transparency treatment (O) and subsidy S, $p_{-i,D,O,S}$ is the corresponding price of i's friend and $S_{-i,D,O,S}$ is one, if the friend sells a substitute. The variable X_i includes additional controls: player i's prices in the Baseline and Substitutes Asymmetric: Separate treatments, a social network treatment indicator and fixed effect for a player's answer on the risk aversion questions. I cluster standard errors at the friendship pair level.

Table 5: Estimated relationship between friends' prices.

	Dependent variable:	
	Price	
	(1)	(2)
Complements · Price Friend	−0.009	−0.031
	(0.053)	(0.055)
Substitute · Price Friend	−0.024	−0.034
	(0.044)	(0.046)
Controll Variables		
Treatment Dummies	Yes	Yes
Baseline and Sep. Prices	Yes	Yes
Risk Aversion	Yes	Yes
Cost	No	Yes
Secret	No	Yes
Observations	3,000	3,000
R^2	0.361	0.364

Notes: *p<0.1; **p<0.05; ***p<0.01; Standard errors are clustered on the friendship pair level.

H Friendship Closeness and the Strength of Directed Altruism

I investigate the relationship between friendship closeness and market cooperation, hypothesizing that closer friends exhibit greater cooperation. Specifically, closer friends should raise prices more when selling complements and less when selling substitutes. In my model, the closer friendships should exhibit a higher directed altruism parameter.

To create a friendship closeness index, I conducted a principal component analysis using responses from the introductory survey's friendship questions, as outlined in Appendix B. I incorporated a dummy variable for accurate guesses in the trivia question and log-transformed the values for time spent with friends and others. I addressed missing data on romantic or sexual relationships by employing a dummy variable that indicates if this question has a missing

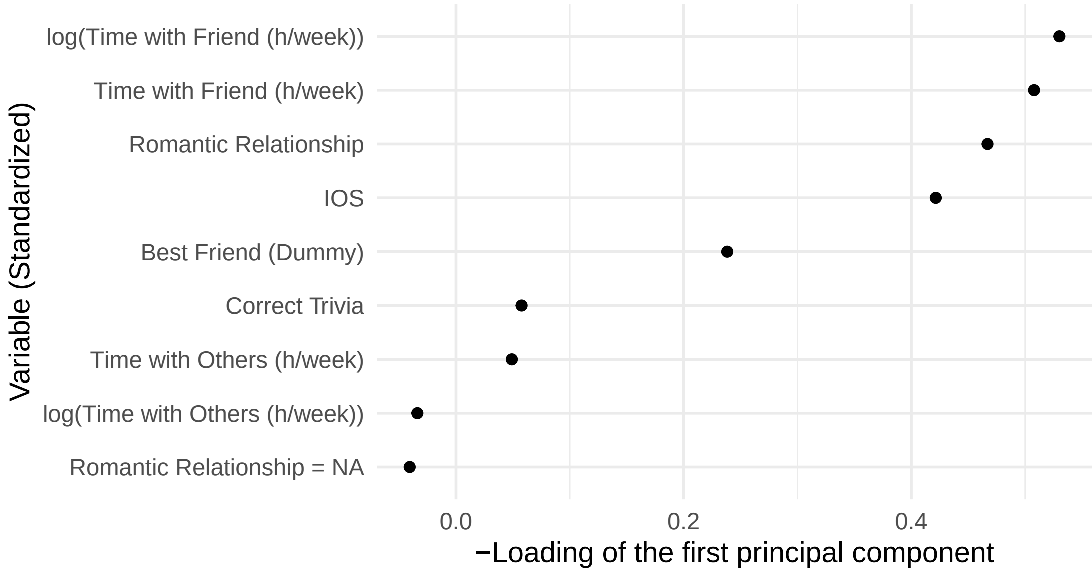


Figure 17: Factor loadings of the first principal components of friendship measures. All factor loadings are multiplied by -1, because I use -1 times the first principal component to measure friendship strength.

value. In this case, the original variable is coded as zero. The resulting index is the first principal component, multiplied by (-1). I conduct this analysis on an individual level; therefore, friends have correlated but different values for this index.

The friendship closeness index is positively related to all variables representing strong and meaningful friendships. Figure 17 displays the factor loadings for the first principal component multiplied by (-1). Since the friendship closeness index is derived from the first principal component multiplied by (-1), a positive factor loading, after being multiplied by (-1), indicates a positive relationship between that variable and the friendship closeness index. All variables, except for the log of time spent with others and missing values in the romantic relationship question, have a positive association with the friendship index.

A reduced form analysis is not powerful enough to test for the hypothesized effect. I use data for all symmetric social networks and regress prices on social network dummies interacted with my friendship closeness indicator. If closer friends act more altruistically, the coefficient of Complements × Friendship Closeness Index” should be negative and the coefficient of Substitutes × Friendship Closeness Index” should be positive. These coefficients have the expected sign, but they are not significantly different from zero. This is due to the fact that I am making a between-subject comparison in an experiment that is powered to detect a within-subject treatment effect. I can increase power by enforcing that friendship closeness should act similarly in the Complements and Substitutes networks, but in different directions. I do this with the help of a structural model.

Table 6: Do closer friends behave more altruistically? Regression of prices on social network treatments interacted with the friendship closeness index.

	Dependent variable:
	Price
Substitutes	−2.15***
	(0.31)
Complements	2.61***
	(0.48)
Friendship Index	−0.25
	(0.26)
Substitutes x Friendship Closeness Index	−0.08
	(0.18)
Complements x Friendship Closeness Index	0.30
	(0.24)
Constant	16.04***
	(0.44)
Observations	9,600
R^2	0.03

Notes: *p<0.1; **p<0.05; ***p<0.01; Standard errors are clustered on the friendship pair level.

I estimate a version of the structural model where the directed altruism parameter can vary with relationship closeness. I define a participant's directed altruism parameter as a function of transparency treatments and the friendship closeness index (FCI). To facilitate my estimation, I bin the FCI into terciles ($FCI_{1/3}, FCI_{2/3}$). The lowest tercile forms the Baseline, and belonging to the middle tercile can change the Baseline directed altruism parameter by δ_m, while belonging to the highest tercile can change it by δ_h,

$$\mu(T, FI) = \mu(private) + \mathbb{1}(T = public) \cdot (\mu(public) - \mu(private))$$
$$+ \mathbb{1}(FCI_{1/3} < FCI < FCI_{2/3})\delta_m + \mathbb{1}(FCI_{2/3} < FCI)\delta_h.$$

Participants who are not very close to their friends exhibit lower directed altruism. Table 7 reports the parameter estimates from the structural model where the directed altruism parameter can vary with relationship closeness. I find lower directed altruism parameters for participants whose friendship closeness falls in the bottom tercile. The directed altruism parameters for the top two terciles are very similar.

Table 7: Parameter estimates for the QRE-Directed-Altruism model, when the altruism parameter varies with relationship closeness (measured by the friendship index).

Parameter	Explanation	Estimate	95% CI
Directed Altruism			
$\mu(private)$	bottom tercile & private	0.14^{***}	$(0.072, 0.21)$
δ_m	increase medium tercile	0.24^{***}	$(0.060, 0.41)$
δ_h	increase top tercile	0.18^{***}	$(0.062, 0.30)$
$\mu(public) - \mu(private)$	increase public	0.009	$(-0.037, 0.054)$
ρ	social image concerns	0.037^{***}	$(0.016, 0.058)$
α	constant	25^{***}	$(21, 28)$
λ	QRE-parameter	0.25^{***}	$(0.20, 0.30)$

Notes: *p<0.1; **p<0.05; ***p<0.01; tandard errors are clustered on the friendship pair level.

I Structural Model with Baseline Altruism

I re-estimate the structural model with a Baseline Altruism parameter. In this specification, participant 1's utility is as follows:

$$U_1(p_1, p_2, p_3, p_4, S, D, O, \gamma) = m_1(.) + \mu_{bl}(O) \sum_{i=2}^{4} m_i(.) + \mu(o) m_{friend},$$

where μ_{bl} is the baseline altruism parameter. This implies that people weigh their friend's payoff with $\mu_{bl}(O) + \mu(O)$.

The baseline altruism parameter is likely difficult to estimate from my experiment. Baseline altruism should push participants' actions closer to the collusive outcome. This shift is very small and unlikely to differ with the social network. The constant (α) in the utility function has similar consequences. Therefore, it is hard to disentangle the two.

I test if changes in baseline altruism can explain the effect of price-transparency. If participants' prices become more observable, they could react by behaving more altruistically towards all other participants. I estimate different baseline altruism parameters for each price-transparency condition (O) and drop the term for social image concerns from the participant's utility. If participants do indeed become more altruistic, their baseline altruism parameter should increase when switching from the private to the public treatment ($\mu(public) - \mu(private) > 0$).

The estimation reflects that the level of baseline altruism is difficult to estimate from the data. Table 8 reports the parameter estimates for the model with baseline altruism. The confidence interval for $\mu_{bl}(private)$ ranges from -0.99 to 0.19.

Table 8: Parameter estimates for the QRE-Directed-Altruism model, incorporating baseline altruism.

Parameter	Explanation	Estimate	95% CI
Baseline Altruism			
$\mu_{bl}(private)$	private	-0.40	$(-0.99, 0.19)$
$\mu_{bl}(public) - \mu_{bl}(private)$	increase public	-0.16^{***}	$(-0.26, -0.047)$
Directed Altruism			
$\mu(private)$	private	0.24^{***}	$(0.17, 0.31)$
$\mu(public) - \mu(private)$	increase public	-0.003	$(-0.077, 0.071)$
α	constant	23^{***}	$(19, 27)$
λ	QRE-parameter	0.25^{***}	$(0.18, 0.31)$

Notes: *p<0.1; **p<0.05; ***p<0.01; standard errors are clusterd on the friendship pair level.

The model estimates indicate that an increase in Baseline altruism cannot explain the fall in prices due to increased transparency. Table 8 reports a significant decrease in baseline altruism in response to increasing price transparency. This suggests that a model that uses baseline altruism to explain the effect of increasing price transparency is misspecified.

The decrease in estimated baseline altruism can be explained by examining the externalities between participants. From the perspective of a specific player, higher prices benefit the two other participants selling substitutes and harm the one participant selling a complement. On average, across all experimental conditions, the first externality outweighs the latter. Therefore, the model estimates a decrease in baseline altruism to rationalize the decrease in prices.

J Buyer and Seller Payoffs

I calculate buyer and seller payoffs analogously to total welfare. The sellers' payoff is higher for networks with higher prices. The buyer's payoff is lower for networks with higher prices.

Table 9: Empirical expected profits and expected total surplus.

	Seller	Buyer	Total	Max Total
Complements	17.30	40.00	57.30	76.70
Baseline	19.30	34.30	53.60	76.70
Substitutes	20.50	30.60	51.10	76.70