The Effect of Social Networks on Market Efficiency*

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Abstract

I examine the impact of friendships on imperfectly competitive markets. First, I conduct a laboratory experiment to estimate the causal effect of real-world friendships on market prices and efficiency. Second, I use the experimental data to test a general model of friendships among sellers in markets with substitutes and complements. Like collusion, friendships among sellers of substitutes increase prices and decrease efficiency, whereas friendships between sellers of complements decrease prices and increase efficiency.

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Markets are intertwined with social relationships (Granovetter, 1985). People selling houses in Amsterdam go to church together (Lindenthal et al., 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 (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 (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, Möbius, et al., 2009)). In this model, friendships between two people affect efficiency in the same way as mergers: Friendships between sellers of complements increase 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

[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.

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).

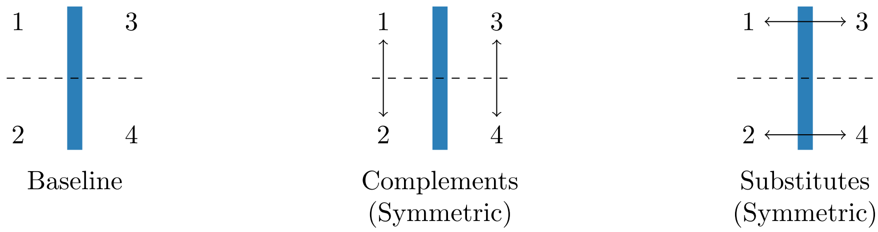


Figure 1: The experimental market with different social networks.

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].

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

[2]Chandrasekhar et al., 2018 inspired this design.

common ownership model (Rotemberg, 1984; Rubinstein and Yaari, 1983) to friendships within a market. 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, Möbius, 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.[3] 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 the lowest prices, followed by the *Baseline* network and the *Substitutes Symmetric* network as the least efficient network with the highest prices:

[3] 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.

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, Möbius, 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, Möbius, 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 include´s 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 (Chandrasekhar et al., 2018; Goeree et al., 2010; Leider, Möbius, et al., 2009; Leider, Rosenblat, et al., 2010; Ligon and Schechter, 2012). 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, Rosenblat, et al., 2010 finds that friends are not better at predicting friends' allocations than strangers' allocations, in a modified dictator game. However, Gächter, Starmer, Thöni, et al., 2022 and Chierchia et al., 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 (Bryan et al., 2019; Grossman et al., 2019; Kominers and Weyl, 2012; Sarkar, 2017). 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, I discover a fruitful connection between IO and social network research. Ederer and Pellegrino, 2022 and Backus et al., 2021 study firms, linked by common ownership. They use structural models to quantify the effect of common ownership on (real-world) market outcomes. My results suggest that friendships induce the same objective function for friends ("linear directed altruism") that common ownership induces for firms. Therefore we can repurpose existing methods for common ownership networks to quantify the effect of social networks on market outcomes. To do this, we replace the common ownership network with a friendship network.

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 incentive for top managers Anton et al., 2022). Firms' owners can staff top 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 documents that there are consultancies that could provide owners with the necessary data on social networks.

1 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.

1.1 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 $p_i \in [0, 50]$
$\forall i \in \{1, 2, 3, 4\}$ but run the experiment with discrete prizes $p_i \in \{0, 1, 2, ..., 50\}$ $\forall i \in \{1, 2, 3, 4\}$.

The buyer wants to build one, two plots wide, building that does not cross 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 Thaler. Sellers' take-it-or-leave-it offers are aggregated ($p_l = p_1 + p_2$ and $p_r = p_3 + p_4$) and transmitted to the buyer. The buyer buys the bundle of land that gives them the highest surplus ($\theta_\ell - p_l$ 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 (u_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 (this is different in Section 3.4). The utility (U_i) incorporates altruism between friends.

When a participant sells, their material utility (u_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 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 is zero. Then the utilities of all players are given by

$$\underbrace{\begin{bmatrix} U_1(p_1, p_2, p_3, p_4) \\ U_2(p_1, p_2, p_3, p_4) \\ U_3(p_1, p_2, p_3, p_4) \\ U_4(p_1, p_2, p_3, p_4) \end{bmatrix}}_{\text{expected utilities}} = \underbrace{\begin{bmatrix} u_1(p_1, p_2, p_3, p_4) \\ u_2(p_1, p_2, p_3, p_4) \\ u_3(p_1, p_2, p_3, p_4) \\ u_4(p_1, p_2, p_3, p_4) \end{bmatrix}}_{\text{material expected utilities}} + \mu \cdot M \cdot \underbrace{\begin{bmatrix} u_1(p_1, p_2, p_3, p_4) \\ u_2(p_1, p_2, p_3, p_4) \\ u_3(p_1, p_2, p_3, p_4) \\ u_4(p_1, p_2, p_3, p_4) \end{bmatrix}}_{\text{material expected utilities}}$$

In a literal interpretation, the parameter μ captures altruism between, but 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, Möbius, 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 serves as a *social collateral* (e.g., Ambrus et al., 2014) and can enforce cooperation. In practice, friends can also yell at their friends if they do not cooperate.

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. I assume price transparency increases μ.

1.2 Social Network Treatments and Theoretical Predictions

My main analysis compares symmetric social networks (Substitutes Symmetric and Complement Symmetric) to the Baseline social network without social relationships.[4] These networks are depicted in Figure 3. The market institution and each of these social networks describe a game. I analyze the symmetric equilibria of these games.

I focus on symmetric equilibria. The absence of communication and feedback lends credibility to this assumption. With feedback or communication, participants could coordinate on an asymmetric equilibrium; coordination is very hard without these elements. I focus on pure strategy equilibria for reasons of tractability. However, the structural model in 3.4 allows for mixed strategies.

Lemma 1 shows that symmetric equilibria exist in both games. This lemma uses the additional assumption that $50 > (1 + \mu) \cdot s$. In the experiment $s \leq 20$, thus the condition holds for all $\mu \in [0, 1]$. This assumption guarantees that the player's maximization problems have an interior solution. The lemma also implies concavity of the players' utility functions. Therefore the symmetric equilibrium strategies solve the player's first order conditions. I relegate this lemma's proof to Appendix A.

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.*

Definition 1 names the symmetric equilibrium prices .

Definition 1. *Denote the symmetric equilibrium price for the Substitutes Symmetric network by p_s, for the Baseline network by p_b and for the Complement Symmetric network by p_c.*

[4] I also run treatments with asymmetric social networks. I discuss these treatments in Subsection 3.5.

The Substitutes Symmetric network raises prices relative to the Baseline network, and the Complements Symmetric network lowers prices relative to the Baseline network. This effect occurs because a player raising their price reduces demand for complements to that player's product and increases demand that product's substitutes. If players are altruistic towards other players that sell complements, they internalize this externality and lower their prices. If they are altruistic toward other players that sell substitutes, the relevant externality goes the opposite, and players raise their prices. I formalize this argument in Proposition 1. I relegate this proposition's proof to Appendix A.

Proposition 1. $p_s > p_b > p_c$

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 leads to an additional 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 complement symmetric network,

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

and the substitute symmetric network

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

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 $\frac{\partial Pr_l(p_1,p_2,p_3,p_4)}{\partial p_1}$ 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 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 $p_{lr} = p_l = p_r$. The overall expected welfare is

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

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

2 Experimental Design

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

The experiment proceeded in five steps.: (1) I recruited pairs of friends, (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. Finally, (5) participants received feedback and answered some open questions. The experiment was conducted in German. The following explanation translates all terms into English.

2.1 Recruitment

I recruited participants via hroot (Bock et al., 2014) from the database of the BonnEconLab. Each participant 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. One session of the experiment needs four friendship pairs. As a precaution, for the case of no-shows, I recruited 5 friendship pairs. Redundant participants either got to participate in an unrelated individual choice experiment, or were paid a show-up fee of 7.50 Euros and left.[5]

To incentivize bringing a friend, I announced that, as in Leider, Möbius, et al., 2009, all participants could earn 5 Euro for correctly answering a trivia question about their friend. The experiment was implemented in OTreee (Chen et al., 2016). I verify in Section 3.1 with some additional survey questions that these friendships are strong and meaningful social relationships.

2.2 Survey

The experiment started with a survey. I used this survey to ask the announced trivia question. I also collected data on friendship strength and risk aversion.

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

I measured relationship closeness with the inclusion of the other in the self (IOS) scale (Aron et al., 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 finds that the IOS measure correlates strongly with six other measures of relationship closeness.

I asked four survey questions as an alternative measure of friendship strength. First (following Goeree et al., 2010), I asked participants if the friend they brought to the experiment was their best friend, how much time they spent with their friend during a week, and how much time they spent with others during a week. Second, I asked the participants if their relationship is romantic or sexual.

[5] 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.

I elicited risk aversion with a question from Falk, Becker, Dohmen, Huffman, et al., forthcoming. To save time, I only use the second item of the risk elicitation module: "Please tell me, in general, how willing or unwilling you are to take risks." I use this question in the German translation from Falk, Becker, Dohmen, Enke, et al., 2018.

2.3 Implementation of The Experimental Land Market

The experiment started with an explanation of the market's general rules (I introduced this rules at the beginning of Section 1). Then participants were asked several control questions, followed by an explanation of some features of the market related to the treatments. The experiment used the experimental currency unit Thaler. Participants had to earn two Thaler to get one Euro.

I ask participants to make slightly different choices within each treatment, to get several realizations of participants' decision errors. Keeping everything else constant, participants decided on prices for several possible subsidies. In case of a sale, the subsidy was added to the price. If realizations are not perfectly correlated, this method increases the precision of my estimates. Subjects made decisions for subsidies of 0, 5, 10, 15, and 20 Thaler.

I visualized the market with a map of the four plots. Each participant saw an individual map from their perspective. The current player was always in position 1. In the experiment, I indicated positions by UL (upper left), UR (upper right), LL (lower left), LR (lower right). If the current player's friend was in the same group, their name was shown in the correct position on the map.

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 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. After answering these questions participants read explanations of the different treatments. 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 gave participants a decision aid to help them with their decisions. This decision aid (Figure 2) simulated the consequences of their and others' decisions. Participants got one slider for each

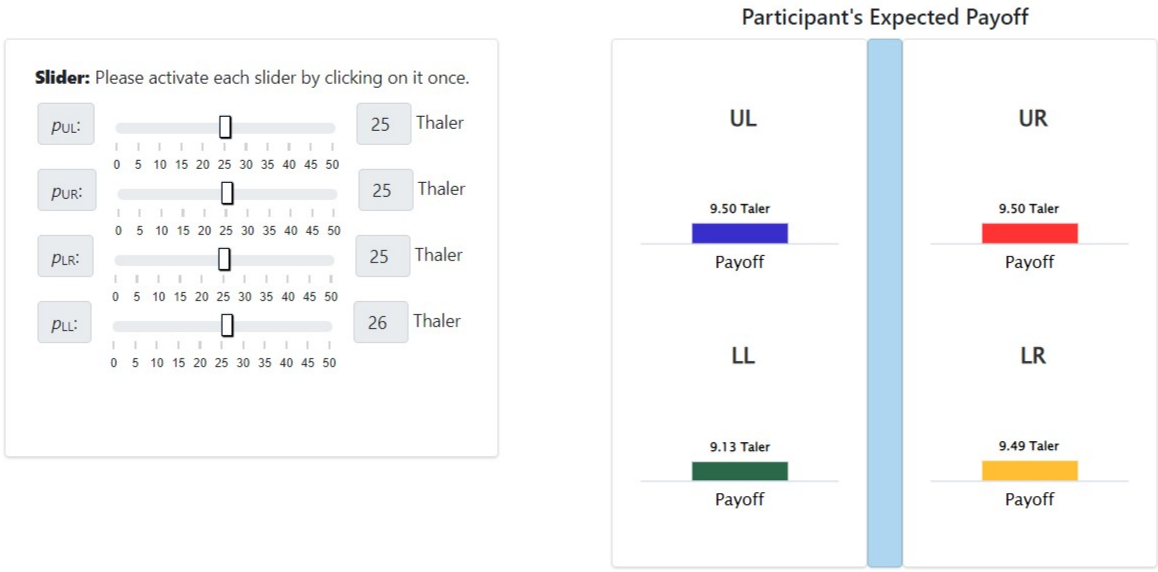


Figure 2: A decision aid that helps participants' decision making. I depict the version for the Baseline condition.

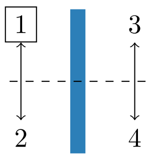
participant's price, including their own. A diagram next to the sliders showed a map of all plots, the river, and friendships between participants. Bar charts and numbers on each plot indicated the participants' expected payoffs given those strategies. Participants could now move the sliders to simulate how changes in their and others' prices affected all participant's expected payoffs. The decision aid started without the bars, and sliders started without the slider thumb to avoid anchoring. Slider thumbs appeared at the spot where the participants initially clicked the sliders. After the participants clicked on each slider, the bars appeared.

2.4 Treatment Conditions

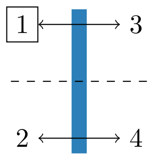
I varied three elements of the market: the social network, an individual's position in it, and price transparency. Sometimes, I also elicited beliefs about players' prices.

Before making any decisions, participants saw a diagram of the current social network treatment. 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.

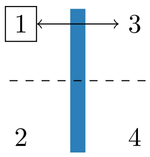
Figure 3 depicts all social network treatments. I used these conditions to identify the effect of network links on an individual's prices and equilibrium spillovers of social network links. Each sub-figure represents one treatment from the perspective of a specific participant. This participant is in position 1. Arrows depict friendships. I generated these treatments by assigning participants to different positions. I used a within subject design, and hence I have decisions from each participant for each treatment.



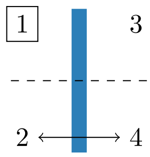
(a) Complements Symmetric



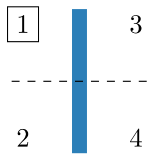
(b) Substitutes Symmetric



(c) Substitutes Asymmetric: Couple



(d) Substitutes Asymmetric: Separate



(e) Baseline

Figure 3: The experimental market with different social networks.

I elicited each player's beliefs about the other players' strategies. To save time, I elicited beliefs only for the markets without subsidies and only for some treatments. Participants stated a different belief for each other player's decisions. Belief elicitation was incentivized with the binarized scoring rule (Hossain and Okui, 2013). I told participants that more accurate beliefs result in higher payoffs, and they could open a collapsed text box to reveal the exact scoring rule. This procedure is similar to the best-practice (Danz et al., 2022), where participants can ask for the scoring rule at the end of the experiment.

Participants have three ways to earn money. They get 5 Euro for answering a trivia question about their friend, a show-up fee of 5 Euro, and the payoff for a randomly chosen decision . After the experiment, a belief task or one of the rounds was randomly selected for payout to avoid hedging.

Table 1 shows the combinations of social network and transparency treatments used in the experiment. It also indicates for which treatments I elicit beliefs.

Table 1: All combinations of treatments and belief elicitation.

Treatment	Transparent/Private	Beliefs
Baseline	Transparent	Yes
Baseline	Private	No
Complements Symmetric	Transparent	Yes
Complements Symmetric	Private	No
Substitutes Symmetric	Transparent	Yes
Substitutes Symmetric	Private	No
Substitutes Asym. Couple	Transparent	Yes
Substitutes Asym. Separate	Transparent	Yes

Participants made 40 decisions (5 subsidy conditions for each row in Table 1) in the market and participated in 8 belief elicitations. These decisions were all be payoff-relevant with equal probability (1/48). Participants did not receive any feedback or information on payoffs during the experiment.

I vary price transparency with two treatments: In the *transparent* treatment strategies could be revealed at the end of the experiment and in the *private* could not. The private condition is omitted in the asymmetric networks. In the private condition, I did not inform participants about the outcome and prices of the market. Participants only learned their total payoff, not which round was paid out. In the transparent condition, participants got feedback at the end of the experiment if the corresponding round was selected for payout. Participants learned all prices, their monetary payoff, and which plots were sold.

I framed the experiment in two ways. I used the previously described framing (building condition) and an alternative 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 condition are strategically equivalent and differ only in framing. These frames are meant to adjust for minimal group effects (Charness and Chen, 2020).

Minimal groups can make participants on the same riverside feel connected just because they are on the same riverside. In the building condition, people on the same riverside sell complements. In the bridge condition, people on the same riverside sell substitutes. I run half of the session with the building and the other half with the bridge condition. This procedure balances the potential minimal group effect since, in half of the sessions, the minimal group connects complements, and in half of the sessions, it connects substitutes.

The order of decisions varied at the session level. To reduce order effects, I used two social network treatment orders.[6] I randomized which transparency treatment comes first for each social network treatment (that has both price transparency treatments), and the order of subsidies.[7] I tried to balance the bridge and non-bridge conditions across treatment orders.[8]

3 Empirical Results

In this section, I discuss the effect of social networks on prices and efficiency, investigate alternative components of friendships (sanctioning and beliefs), estimate a structural model, and evaluate its fit. I always indicate which analyses I preregistered and which are exploratory. 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.[9]

3.1 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,

[6] 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.

[7] 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.

[8] 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).

[9] I preregistered the analysis, most hypotheses, and the sample size (240) at `https://osf.io/5ytnz`.

and one-third are romantic or sexual partners.[10]

Table 2: Summary of answers to the introductory survey.

Statistic	N	Mean	St. 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

3.2 The Effect of Social Networks on Prices and Efficiency

I test the effect of social networks on prices by comparing prices in symmetric network treatments to prices in the Baseline treatment. I use data from the "transparent" and the "private" conditions. The estimated treatment effect of substitute friendships on prices is the average difference between prices in the Substitutes Symmetric network (transparent and private) and the Baseline network (public and private). The estimated treatment effect of complement friendships is the analogous comparison for the Complements Symmetric network.

I estimate most treatment effects with the following regression, where I regress price ($p_{i,D,\iota,s}$) on a treatment indicator (T) and a constant,

$$p_{i,D,\iota,s} = \alpha + \beta \cdot T + \epsilon_{i,D,\iota,s}. \quad (1)$$

I index individuals by i in network treatment, social network treatments by D (Baseline, Substitutes Symmetric, Complements Symmetric, Substitutes Asym. Separate, Substitutes Asym. Couple), subsidies by $s \in \{0, 5, 10, 15, 20\}$ and the transparency condition by $\iota = \{transparent, private\}$. Depending on the hypothesis I change which treatments I include in the treated group and in the control group and with that in the data-set.

I run two regressions that test for the effect of social networks on prices. The first regression (effect of substitute friendships) includes data from the transparent and the private condition for

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

the Baseline and Substitutes Symmetric networks. The treatment indicator (T) is 1 for observations from the Substitutes Symmetric network and 0 for observations from the Baseline network. For each individual, the treated and control group include ten observations each (there are 5 different subsidy values for each the private and transparent treatment). I cluster standard errors at the friendship pair level. The analysis includes 4800 observations (120 clusters). Each cluster includes 40 observations. I run the analogous regressions (effect of complement friendships) comparing the Baseline and Complements Symmetric networks. I preregistered this analysis and the following hypothesis: complement friendships decrease prices and substitute friendships increase prices.

Complement friendships lower prices, and substitute friendships increase prices. Figure 4 depicts the estimated causal effect of friendships on prices. The x-axis shows the social network treatment, and the y-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.[11] At the end of this chapter I interpret these magnitudes in terms of the applied altruism parameter. Participant's beliefs about other's prices move in the same direction as the corresponding prices (See Figure Figure 9 in Appendix B).

I calculate the expected surplus to investigate the effects of social networks on efficiency. Since the buyer is computerized, his behavior is known. 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 for a specific symmetric network. These markets differ in subsidies, transparency conditions, and the players involved. Table 3 reports expected total payoffs by network (social surplus) and decomposes it into buyer and seller payoffs. All other payoffs are calculated analogously. I report the average maximum surplus ($p_l = p_r = 0$) for reference.

The causal effects of social networks imply a corresponding change in payoffs and total surplus. Since the market is imperfectly competitive (prices are too high) lower prices increase efficiency. As shown in Table 3, markets with the Symmetric Complements Network have the highest total surplus, followed by markets with the Baseline network and then the Symmetric Substitutes network. The buyer's surplus is higher for networks with a higher social surplus. Moreover, the seller's surplus is lower for networks with a higher social surplus.

[11] Prices range from 0 to 50, and one Thaler equals 0.5 Euro.

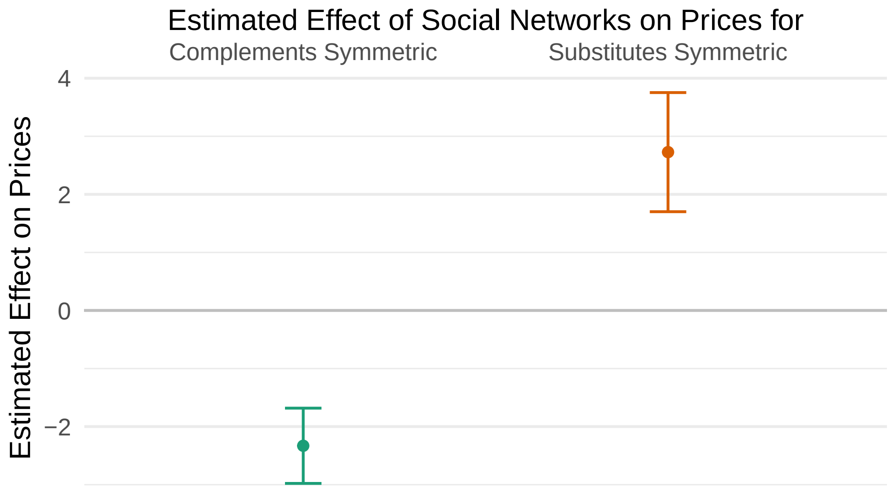


Figure 4: Estimated effects of Complement Symmetric and Substitutes Symmetric networks relative to the Baseline network. Standard errors are clustered on the friendship pair level. Error bars indicate 95% confidence intervals.

Table 3: 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

3.3 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 transparent 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 test this hypothesis by comparing prices with and without transparency in the Substitutes Symmetric and the Complements Symmetric treatment. The left part of Figure 5 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

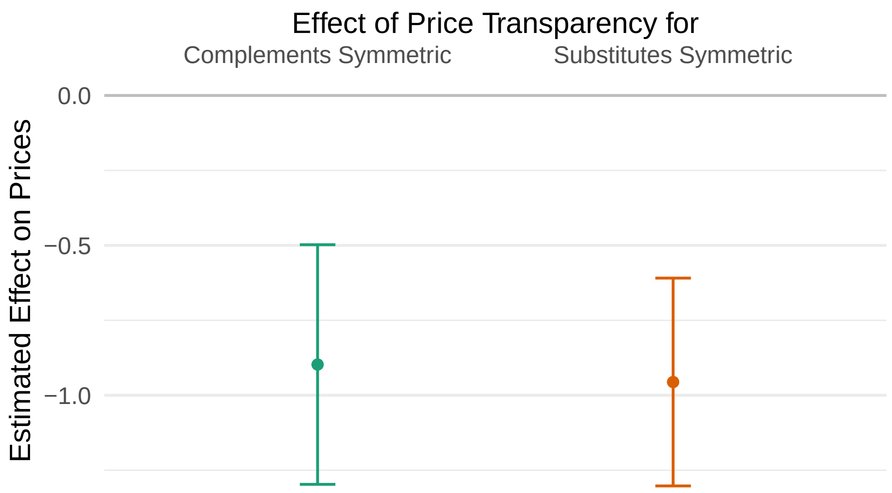


Figure 5: Estimated effects of price transparency on prices in the complement symmetric and substitute symmetric treatments. Standard errors are clustered on the friendship pair level. Error bars indicate 95% confidence intervals.

at the friendship pair level. Figure 10 in Appendix B shows that price transparency affects first order beliefs in the same way as the underlying prices. I preregistered this analysis with the hypothesis that price transparency lowers prices in the Substitutes Symmetric network and increases prices in the Complements Symmetric treatments.

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 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. I reproduce the question and the (translated) justifications of participants that lowered prices in Appendix C.1.[12] However, 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)."; "vanity"; "I was venturesome about staying secret and didn't want to quote extreme prices that would

[12] Some people gave a generic answer that applies to the transparent and private conditions, some seemed to misunderstand the incentives, and one statement was too incoherent to be translated.

portray me as greedy."

3.4 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 1 with joy of winning, decision error, social image concerns and social sanctions.

- 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 transparent 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 ($\mu(\iota)$), to capture that fact that social sanctions may intensify altruism between friends.

Recall that I use discrete prices ($\mathbb{P} = \{0, 1, ..., 50\}$). Since I focus on symmetric treatment 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,

$$u_1(p_1, p_2, p_3, p_4, s, D, \iota, \gamma) = Pr_l(p_1, p_2, p_3, p_4)(\alpha + s + p_1). \tag{2}$$

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 punishment for high prices in the transparent treatment and replacing material utility with the new specification,

$$\underbrace{\begin{bmatrix} U_1(p_1,p_2,p_3,p_4) \\ U_2(p_1,p_2,p_3,p_4) \\ U_3(p_1,p_2,p_3,p_4) \\ U_4(p_1,p_2,p_3,p_4) \end{bmatrix}}_{\text{expected utilities}} = \underbrace{\begin{bmatrix} u_1(p_1,p_2,p_3,p_4) \\ u_2(p_1,p_2,p_3,p_4) \\ u_3(p_1,p_2,p_3,p_4) \\ u_4(p_1,p_2,p_3,p_4) \end{bmatrix}}_{\text{material expected utilities}} + \mu(\iota) \cdot M \cdot \underbrace{\begin{bmatrix} u_1(p_1,p_2,p_3,p_4) \\ u_2(p_1,p_2,p_3,p_4) \\ u_3(p_1,p_2,p_3,p_4) \\ u_4(p_1,p_2,p_3,p_4) \end{bmatrix}}_{\text{material expected utilities}} - \mathbb{1}(\iota = public) \cdot \rho \cdot \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix}. \tag{3}$$

The parameter $\mathbb{1}(\iota = public) \cdot \rho$ 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 general social image concerns. This method allows me to use data from the transparent 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. Instead of best-responding players, best-respond noisily. This noise is added to the utility. If this noise is Gumbel distributed, the choice probability takes logit form. The parameter λ captures the relative size of material pay-offs 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 $p_1 \in \mathbb{P}$ is given by

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

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

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

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 ι 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: $\sigma_2(p_2, s_j, D_j, \iota_j, \gamma)$, $\sigma_3(p_2, s_j, D_j, \iota_j, \gamma)$ and $\sigma_4(p_2, D_j, \iota_j, s_j, \gamma)$. The standard approach would use the analogous equations for the other 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 $\sigma_2(p_2, s_j, D_j, \iota_j, \gamma)$, 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 ι_j.

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

$$LLH(\gamma) = \Sigma_{i=1}^{N} log(\sigma_1(p_{1i}, s_i, D_i, \iota_i, \gamma)), \tag{7}$$

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 20 and 36 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 transparent treatment. This value is small but significant, in line with the small treatment effects of price transparency.

To determine if directed altruism can rationalize behavior in the experiment, I plot the fitted model together with the data. Each point in figure 6 indicates either data or model predictions for one experimental condition. The x-axis indicates the subsidy, and the y-axis indicates average

Table 4: Parameter estimates for the QRE-Directed-Altruism model. Standard errors are clustered (Huber-White) on the friendship pair level. The parameter μ captures directed altruism, α captures the joy of winning, ρ captures social image concerns and λ captures decision error. I state 95% confidence intervals in brackets below the estimates.

$\mu(private)$	0.277^{***}
	(0.193,0.361)
$\mu(public) - \mu(private)$	0.009
	(-0.057,0.074)
α	24.600^{***}
	(20.600,28.600)
ρ	0.037^{***}
	(0.013,0.060)
λ	0.250^{***}
	(0.189,0.312)

or predicted prices. The different symbols show the social network treatments. The left panel displays data from the private condition, and the right panel displays data from the transparent condition. I plot the average prices in solid colors, with error bars that indicate 95% confidence intervals. I display model predictions in light colors and connect them by a line. I do not quantify the uncertainty of the model's predictions.

For almost all treatments the model fits the data very closely. One exception is the substitute network for low values of the subsidy.

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.

3.5 Equilibrium Effects of Friendships

Does the linear, directed altruism model also predict the equilibrium effects of friendships? Until now, we looked at changes in the social network that affected all participants equally. However,

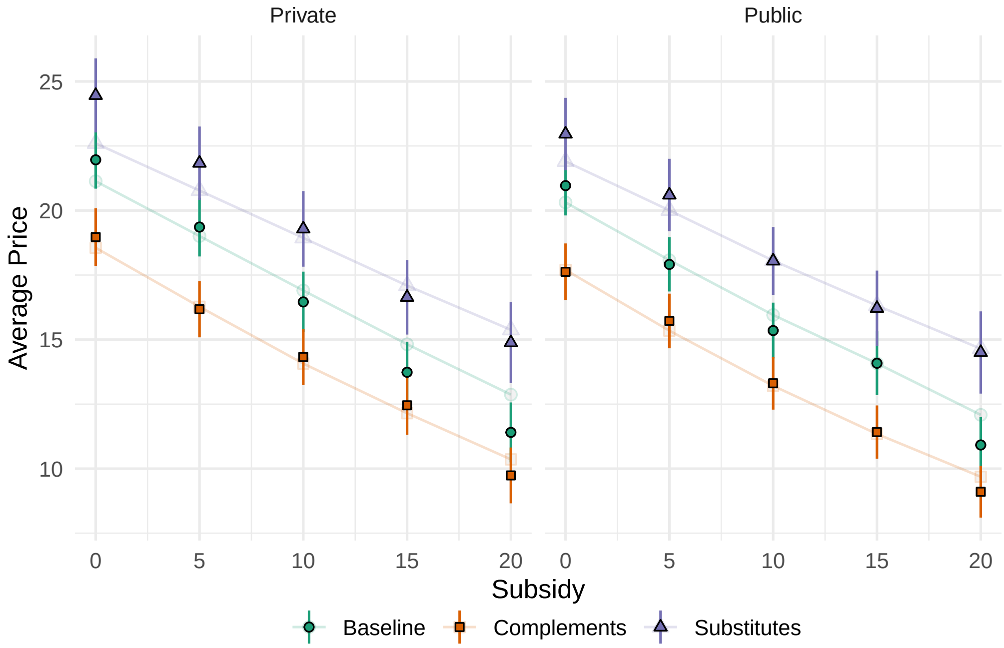
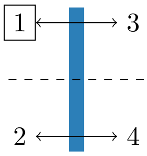
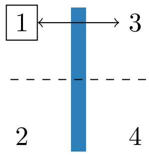


Figure 6: Model fit and means of empirical bids as a function of social-network and subsidy, split by privacy condition. I show 95% normal approximation confidence intervals for the means. Model fit is shown in light colors.

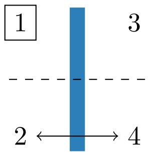
participants should also react to the friendships of other people. I use the structural model from the previous section to predict that reaction and test these predictions with the Substitutes Asymmetric treatment.



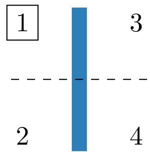
(a) Substitutes Symmetric



(b) Substitutes Asymmetric: Couple



(c) Substitutes Asymmetric: Separate



(d) Baseline

Figure 7: All social network treatments used to test for the equilibrium effects of friendships.

I keep players 1 and 3's friendship constant and vary the friendship of players 2 and 4 to test for the friendship's equilibrium effects. Figure 7 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 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 transparent condition.

The structural model from the preceding section makes quantitative out-of-sample predictions for the equilibrium effects of friendships. I assume that participants have consistent beliefs. I explain the strategy from the perspective of player 1. That is we can estimate player 1's equilibrium beliefs about other player's prices from realized price frequencies. I do this for each social network depicted in Figure 7. Then I calculate the noise best response by plugging them into Equation 4 (the QRE best response). I use the parameters that I 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 8 shows the QRE prediction as a grey line.

The friendship of 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. As we will see from the structural model prediction, the former effect is much stronger. The model predicts that player 1 will lower their price in response to 2 and 4's friendship.

The actual equilibrium effects of friendships (between 2 and 4) are estimated with a similar regression as the main effects (Equation 8). The dependent variable is the price of player one in each network from Figure 7. Each participant is player 1 in these networks for five different 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, and observations from Substitutes Asymmetric (couple) and Baseline are in the control group. I conducted 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 of Figure 8 and the treatment effect on beliefs is depicted on the right side.

Compared to the model benchmark, participants under-react to other participants' friendships. As Figure 8 shows, the model predicts participants to lower their prices in response to the other participant's friendship. Participants slightly increase their prices. The estimates are uncertain, probably the predicted effects are small. However, players do not significantly lower their prices, and the effect of price changes has a significantly lower magnitude than predicted.

I do not find evidence for the theory that players under-react because of biased beliefs. Figure 11 in Appendix B reports the effect of a substitute friendships on beliefs about the friends prices.

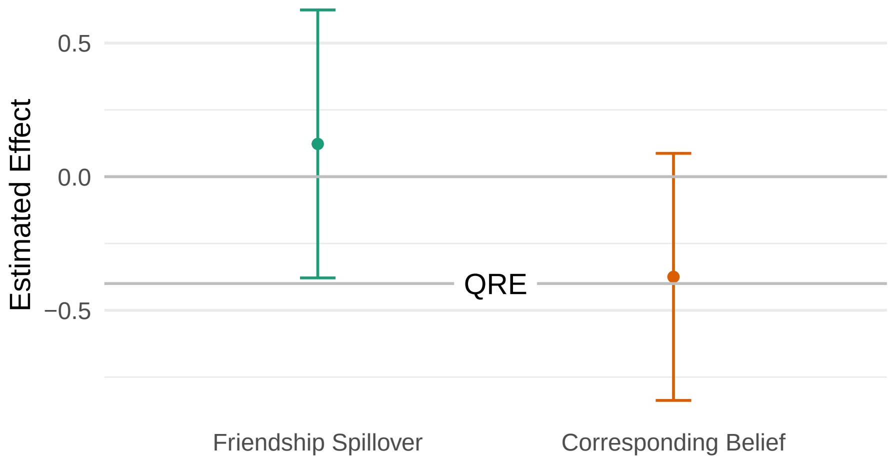


Figure 8: Estimated effects of friendships between 2 and 4 on 1's prices and beliefs about 1's prices. Standard errors are clustered on the friendship pair level. Error bars indicate 95% confidence intervals.

They are roughly the same across the two networks Substitutes Symmetric and Substitutes Asymmetric. Consequently, players should react the same if they best respond to their beliefs.

3.6 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 expected value of a person's prices maximizes this measure. I divide by the maximum possible deviation (50^2). The resulting values range from zero to one.

I test if beliefs are more accurate for friends than strangers by regressing the quadratic deviation of elicited beliefs from realized actions 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 5 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 D 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.

4 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 network. This data and structural

Table 5: 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		0.004	
		(0.003)	
Friend*IOS		−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
Adjusted R^2	0.013	0.014	0.011
Residual Std. Error	0.100 (df = 5750)	0.100 (df = 5748)	0.101 (df = 3444)
Note:	*p<0.1; **p<0.05; ***p<0.01		
	Standard errors are clusterd on the friendship pair level.		

model suggest that price transparency increases social image concerns and does not increase cooperativeness between friends.

This 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, Möbius, 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 a lack of robustness.

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 et al., 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. Further research should investigate this conjecture theoretically (for more general networks) and test it empirically (in real world data).

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

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

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

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

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

The first order condition is:

$$\frac{\partial Pr_l(p_1, p_2, p_3, p_4)}{\partial p_1} \cdot (p_1 + s) + Pr_l(p_1, p_2, p_3, p_4) + \mu \frac{\partial Pr_r(p_1, p_2, p_3, p_4)}{\partial p_1} \cdot (p_3 + s) = 0$$

and the second order condition is:

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

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

$$-(2 + \mu(p_3 + s)) < 0, \text{ if } p_l \leq p_r$$

and

$$-(p_1+s)-2(1+p_r-p_l)-\mu(p_3+s) < -(p_1+s)-\mu(p_3+s) < 0, \text{ if } p_r < p_l,$$

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:

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

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

.

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

$$max_{p_1} Pr_l(p_1,p_2,p_3,p_4)\cdot(p_1+s)+\mu\cdot Pr_l(p_1,p_2,p_3,p_4)\cdot(p_2+s)$$

The first order condition is:

$$\frac{\partial Pr_l(p_1,p_2,p_3,p_4)}{\partial p_1}(p_1+s) + Pr_l(p_1,p_2,p_3,p_4) + \mu\frac{\partial Pr_l(p_1,p_2,p_3,p_4)}{\partial p_1}\cdot(p_2+s) = 0$$

and the second order condition is:

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

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

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

and

$$-(p_1+s)-2(1+p_r-p_l)-\mu(p_3+s)<-(p_1+s)-\mu(p_3+s)<0, \text{ if } p_r<p_l,$$

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:

$$g(p_c,\mu):=\frac{\partial Pr_l(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+s)+Pr_l(p_c,p_c,p_c,p_c)+\mu\frac{\partial Pr_l(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+s)=0 \tag{12}$$

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

.

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:

$$\frac{\partial Pr_l(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+s)+Pr_l(p_s,p_s,p_s,p_s)+\mu\frac{\partial Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+s)=0 \tag{14}$$

$$\frac{\partial Pr_l(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+s)+Pr_l(p_c,p_c,p_c,p_c)+\mu\frac{\partial Pr_l(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+s)=0 \tag{15}$$

$$\frac{\partial Pr_l(p_b,p_b,p_b,p_b)}{\partial p_1}(p_b+s)+Pr_l(p_b,p_b,p_b,p_b)=0. \tag{16}$$

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

$$h(p)=\frac{\partial Pr_l(p,p,p,p)}{\partial p_1}(p+s)+Pr_l(p,p,p,p).$$

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

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:

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

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

□

B Beliefs

shows the treatment effects of friendships on first order beliefs about prices. The first two coefficients correspond to the estimate in Figure 9. I just replaced participant's prices with other

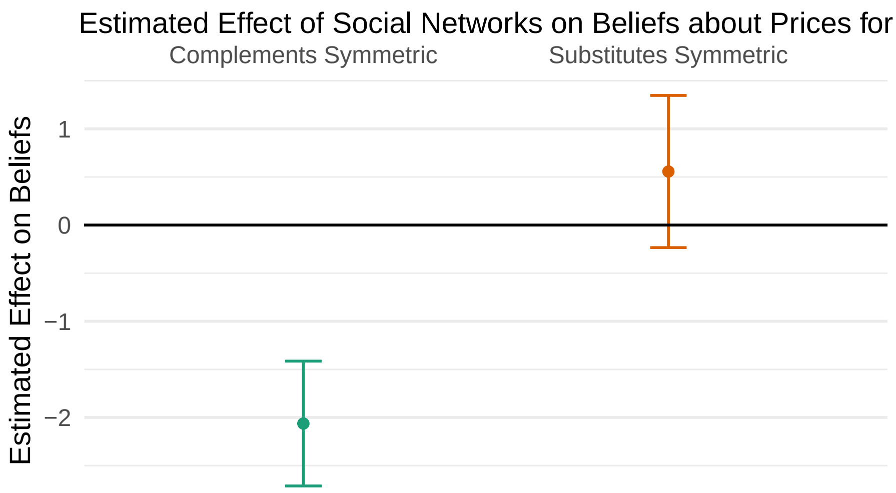

Figure 9: Estimated effect of complement and substitute friendships on first order beliefs. Standard errors are clustered on the friendship pair level.

players' first order beliefs about these prices. I preregistered this analysis with the hypothesis that beliefs react in the same way as the actual variables.

C Open Question Price Transparency

C.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 prize either. "

"vanity"

"Better lower payouts than no payouts."

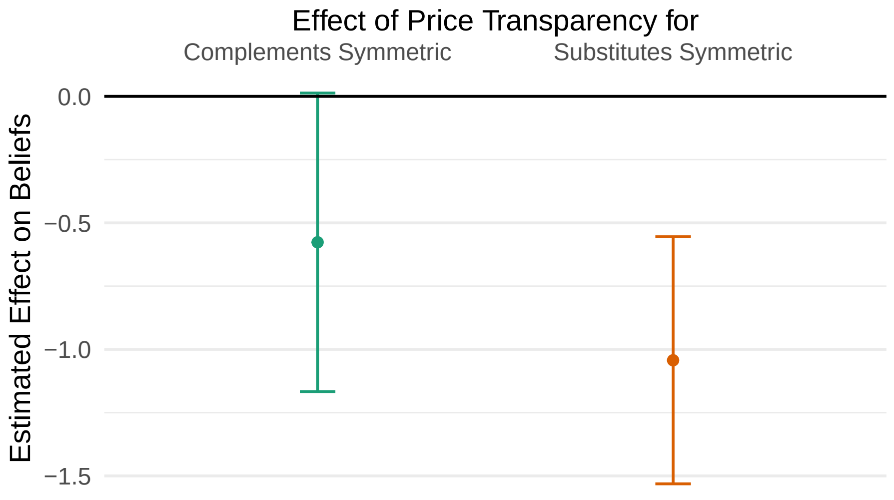

Figure 10: Estimated effects of price transparency on beliefs in the complement symmetric and substitute symmetric treatments. Standard errors are clustered on the friendship pair level.

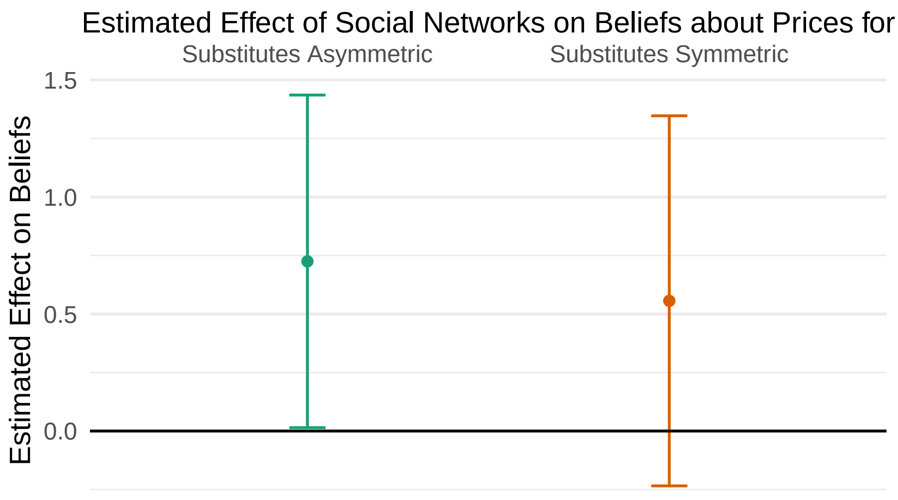

Figure 11: Effect of substitute friendships on beliefs about substitutes prices in the substitute symmetric and substitute asymmetric treatment.

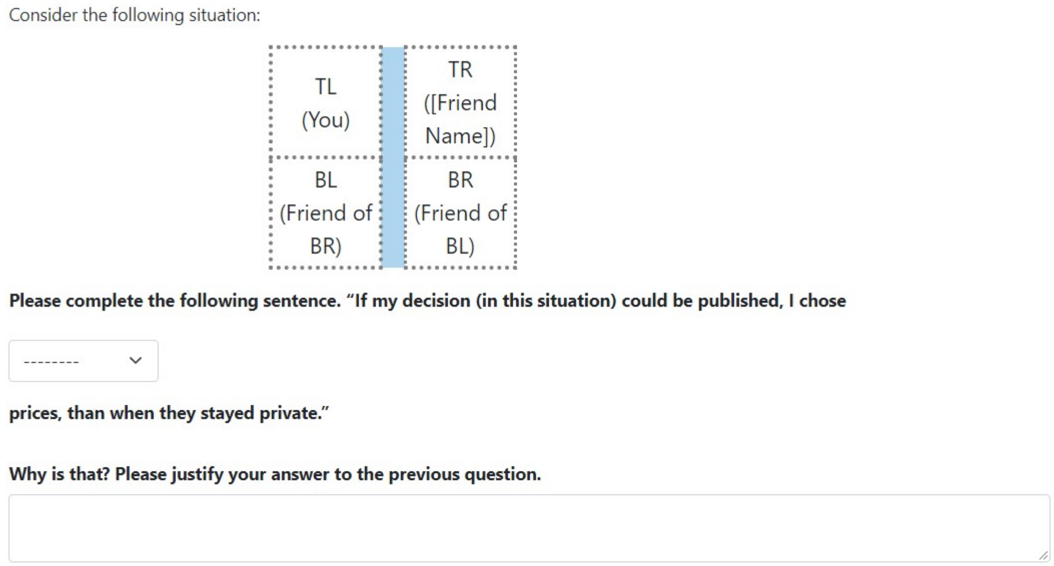

Figure 12: Open question regarding price transparency in the substitutes treatment (translated from German).

"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. ”

D 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

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

$p_{i,t,s}$ is the price of participant i in treatment t and subsidy s, $p_{-i,t,s}$ is the corresponding price of i’s friend and $S_{-i,t,s}$ is one, if the friend sells a substitute. The variable X_i includes additional controls: player i’s prices in the selfish and substitutes lonely 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. I conduct one-sided t-tests at the 5% level for $H_0 : \beta = 0$ vs. $H_1 : \beta > 0$ and $H_0 : \gamma = 0$ vs. $H_1 : \gamma < 0$.

Table 6: 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)
Treatment Dummies	Yes	Yes
Treatment Dummies	Yes	Yes
Baseline ans 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
Adjusted R^2	0.359	0.362
Residual Std. Error	9.175 (df = 2993)	9.155 (df = 2991)
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clusterd on the friendship pair level.	