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 model of friendships among sellers in markets with substitutes and complements. Friendship among sellers of substitutes increases prices and decrease efficiency, whereas friendship between sellers of complements decreases prices and increases efficiency. My results suggest a way to connect research on friendship with the wider Industrial Organization literature. In particular the literature on common ownership.

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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 this lack of knowledge. First, social networks are high dimensional: There are many ways to link market participants. Each social relationship can have many aspects. For example, Friendships can affect markets because friends are more altruistic towards each other or because they know more about each other. ¹ Second, social networks are endogenous and hard to manipulate: Friendships develop over a long time, and natural experiments that change them are rare ². Finally, market efficiency is unobservable because we need to know individuals' private costs and values, which we need to compute the gains from trade. I combine a laboratory experiment with a theoretical model to address these issues.

I propose a model of friendships in markets to isolate the features of a social network that are likely to affect market efficiency. I assume that the main aspect of friendship is that friends act more altruistically towards each other. These preferences are called directed altruism (Leider et al. 2009). I integrate directed altruism preferences into an imperfect competition model with complements and substitutes (closely related to Economides and Salop 1992). This model suggests that market efficiency in a social network is most influenced by whether friendships are mainly between sellers of complements or substitutes.

I propose a controlled laboratory experiment to manipulate if friendships are between sellers of substitutes or complements. This variation allows me to estimate the causal effects of different friendship networks among sellers on market efficiency and prices and test directed altruism and a likely alternative theory, in a market setting. I invite real world friends to participate in laboratory markets and assigning them to different roles in a market experiment. This

^{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.

^{2.} For some exceptions see Festinger, Schachter, and Back (1950), Sacerdote (2001), and Goette, Huffman, and Meier (2006).

results in a within subject design, where the same individual makes choices in different social networks, keeping everything else constant. The social network is exogenous.

The experiment also solves the problem of private values and costs, because I can set and thus observe participants' monetary rewards for the experiment. Therefore I observe gains from trade and can use them to calculate market efficiency.

The directed altruism model predicts that friendships between sellers of complements decrease prices, and friendships between sellers of substitutes increase prices. The reason is that directed altruism partially internalizes an externality between friends: Lower prices increase the demand for complements and decrease the demand for substitutes. Sellers want to increase the demand for their friend's product, so they adjust their own price accordingly. The incentives here are the same as in Cournot 1897's original results on complement and substitute mergers.

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.

I use the experimental results to test this theory. Friendships among sellers' of substitutes increase prices and decrease efficiency and friendships among sellers' of complements do the reverse. This confirms the predictions of directed altruism theory.

I benchmark directed altruism theory against a likely alternative An alternative theory to directed altruism is that friends have more accurate beliefs concerning their friends' actions (familiarity), which would make them act differently.⁴ My experiment finds no evidence for this: Measured beliefs about a friend's actions are roughly as accurate as beliefs about a stranger's actions. As beliefs are the same for friends and strangers, familiarity among friends does not influence their actions.

By estimating a structural model, I verify that a single underlying directed altruism parameter can explain the magnitudes of different treatment effects. That is the same parameter can

^{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.

^{4.} I selected this theory because it was the second most popular among participants in the pilot. Indeed 60% participants in the experiment still belief in it.

justify the increase in prices due to a friendship between sellers of complements and the decrease in prices due to a friendship between sellers of substitutes. A simple structural model that features homogeneous directed altruism with some modifications fits the data well. A representative participant will pay 20 and 36 cents for their friend to receive one dollar.

Industrial Organization (IO) economists regard social relationships as an important impediment to competition that is "beyond the reach of conventional analysis" (Ross 1990, p.311). This paper shows that we can model friendship, an important social relationship, with a conventional tool that is shared between behavioral economics (Leider et al. 2009; Leider et al. 2010; Goeree et al. 2010; Ligon and Schechter 2012; Chandrasekhar, Kinnan, and Larreguy 2018) and IO: Edgeworths coefficient of effective sympathy (Edgeworth 1881 p.53, Vives 2020). The coefficient of effective sympathy models to which degree firms internalize other firms profits. A recent application of this idea is the common ownership literature where firms with common owners partially internalize each other's profits (Rubinstein and Yaari 1983; Rotemberg 1984; Azar, Schmalz, and Tecu 2018; Backus, Conlon, and Sinkinson 2021). Mergers between two firms are mostly equivalent to full profit internalization. In the case of friendship Edgeworths coefficient is the directed altruism parameter. This paper indicates that, friends do indeed replicate one particularly salient feature of merger analysis. Like mergers, friendships between sellers of complements increase efficiency and friendships between sellers of substitutes decrease it.

This positive impact of friendships between sellers of complements is due to the holdout problem (Cournot 1897; Kominers and Weyl 2011, 2012; Sarkar 2017; Grossman et al. 2019; Bryan et al. 2019). Raising the price of my product has a negative externality on the seller of a complement (lower demand) and on the demand side (higher prices, less trade). We find that friendships among sellers of complements internalize this externality and raise efficiency. This finding introduces a social network perspective into market design with complements.

1 Theoretical Framework

The experiment features differentiated products Bertrand competition in a market, with complements and substitutes. 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.

The theory builds on a standard results in IO theory: mergers among sellers of complements increase efficiency and mergers among sellers of substitutes decrease it (Cournot 1897). My main theoretical contribution is to draw the analogy between mergers and directed altruism. I apply the existing theory to the setting of the experiment. The closest treatment is Economides and Salop (1992) who considers discrete mergers instead of continuous profit weights/altruism in a differentiated Bertrand oligopoly with composite goods.

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 $p_i \in [0, 50] \forall i$.

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. Sellers may receive 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. The probability that the seller buys on the left side is $Pr_{\ell}(p_1, p_2, p_3, p_4) = P(\theta_{\ell} - p_1 - p_2 > \theta_r - p_3 - p_4)$. Consequently, the material utility of player 1 is

$$m_1(p_1, p_2, p_3, p_4) = Pr_\ell(p_1, p_2, p_3, p_4)(p_1 + s).$$

The material utilities of the other players (m_2, m_3, m_4) are defined analogously.



Figure 1: The experimental market with different social networks. The different plots are separated by the river (in blue) and the dotted line. Bi-directional arrows indicate friendships.

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 diagonal is zero. Then the utilities of all players are given by

expected utilities	- `	material utility		altruism term
$U_4(p_1, p_2, p_3, p_4)$		$m_4(p_1, p_2, p_3, p_4)$		$m_4(p_1, p_2, p_3, p_4)$
$U_3(p_1, p_2, p_3, p_4)$		$m_3(p_1, p_2, p_3, p_4)$	· /· -·-	$m_3(p_1, p_2, p_3, p_4)$
$U_2(p_1, p_2, p_3, p_4)$	=	$m_2(p_1, p_2, p_3, p_4)$	$+\mu \cdot M \cdot$	$m_2(p_1, p_2, p_3, p_4)$
$U_1(p_1, p_2, p_3, p_4)$		$m_1(p_1, p_2, p_3, p_4)$		$m_1(p_1, p_2, p_3, p_4)$

1.2 Social Network Treatments and Theoretical Predictions

I compare different social networks to a Baseline social network without social relationships. These networks are depicted in Figure 1. The sub-captions indicate the social network treatment of player 1. The different plots are separated by the river (in blue) and the dotted line. Bi-directional arrows indicate friendships.

Social networks, combined with market institutions, give rise to several games. I focus on

analyzing the symmetric equilibria within these games. In this context, players with identical utility functions adopt the same symmetric equilibrium strategy. In symmetric networks, this results in uniform pricing. Conversely, in the Substitutes Asymmetric network, each couple sets an identical price, and similarly, each individual acting alone chooses a uniform price.

Lemma 1 shows that there are unique symmetric Nash equilibria in all games with symmetric networks. These symmetric equilibria are interior equilibria in pure strategies. This Lemma uses the additional assumption, which guarantees that the player's maximization problems have an interior solution. This assumption holds for reasonable values of the directed altruism parameter and the parameters used in the experiment.⁵ This Lemma's proof is in Appendix A.

Lemma 1. If $50 > (1 + \mu) \cdot s$, the games generated by the Substitutes Symmetric, Baseline and Complement Symmetric networks have a symmetric equilibrium. This symmetric equilibrium is the only symmetric equilibrium, interior and in pure strategies. Best responses are interior, unique and deterministic everywhere.

Friendships among sellers of complements decrease prices, and friendships among sellers of substitutes increase prices. The reason for this difference is how sellers in these networks respond to externalities, which vary based on the relationships between their goods.

When the price of a good increases, it affects the demand for related goods differently: the demand for its complement decreases while the demand for its substitute increases. These changes have varying impacts on sellers. Higher prices result in negative externalities on sellers of complements and positive externalities on sellers of substitutes.

When sellers are friends, they internalize these externalities in their pricing decisions. If a seller's friend sells a complement, the seller lowers their price to increase their friend's demand. Conversely, if the friend sells a substitute, the seller increases their price to increase their friend's demand.

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 exceeds the price in the Complement Symmetric network (p_c^*) : $p_s^* > p_b^* > p_c^*$.

^{5.} I assume that $50 > (1 + \mu) \cdot s$. In the experiment $0 \le s \le 20$, thus the assumption holds for all $\mu \le 1.5$.

In the following I, compare the Substitutes Asymmetric (Figure 1, Sub-figure d) to the Substitutes Symmetric(Figure 1, Sub-figure c) network. In Both networks, players 1 and 3 are friends. If we move from the Substitutes Asymmetric to the Substitutes Symmetric network, players 2 and 4 on the bottom also become friends. The following paragraphs examine the comparative statics of this friendship on players 1 and 3's prices.

The friendship between 2 and 4 directly increases the prices of plots 2 and 4. Players 2 and 4 sell substitutes. Therefore, their friendship internalizes the positive externality of higher prices among them. This price increase has equilibrium spillovers on players 1 and 3's prices. I explain these spillovers for the case of player 1.

An increase in the price of plot 2 will lower the price of plot 1 (strategic substitutability). Plots 2 and 1 are both on the left side of the river. Therefore, they are complements. A rise in the price of plot 2 will increase the total price of plots on the left side. Player 1 lowers their price to compensate for this price increase.

On the other hand, An increase in the price of plot 4 will increase the price of plot 1 (strategic complementarity). As opposed to plot 1, plot 4 is on the right side of the river. Therefore, these plots are substitutes. A rise in the price of plot 4 will lower the total price of plots on the right side. Consequently, plots on the left face less competition, and player 1 can raise their price.

Putting these two effects together, the friendship between players 2 and 4 lowers players 1 and 3's prices. Strategic substitutability outweighs strategic complementarity due to the higher cross-price elasticity between complements. Therefore, the joint increase in the prices of 2 and 4 (due to the friendship) lowers the price of player 1. By symmetry, it also lowers player 3's price.

The above arguments are encapsulated in Proposition 2. This proposition's proof (in Appendix A) confirms the equilibrium's interiority in the asymmetric game. Additionally, it shows that the aggregate best responses exist, are continuous, and exhibit strategic substitutability.

Proposition 2. The Substitutes Asymmetric game has a unique symmetric pure strategy equilibrium. The equilibrium strategy profile is (p_{isol}^*, p_{pair}^*) , where $p_1 = p_3 = p_{pair}$ and $p_2 = p_4 = p_{isol}$. Further $p_{isol}^* < p_s^*$ and $p_s^* < p_{pair}^*$.

Proposition 2 demonstrates one case in which a friendship among sellers of substitutes is predicted to decreases the price of the two other players ($p_s^* < p_{pair}^*$), by an analogous argument

this effect also occurs when the two other players are strangers $(p_{isol}^* < p_b^*)$.

1.3 Efficiency

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. For the networks that I study, the symmetric equilibrium price is the same on both sides of the river: $p_{\ell r} = p_{\ell} = p_r$. The overall expected welfare is

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

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

1.4 Mechanisms Behind Directed Altruism Behavior

In a literal interpretation, the parameter μ captures altruism between friends. We can 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., Karlan et al. 2009; 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.

Social collateral theory can predict more potent effects of friendship when other players' prices are observable. To sanction my friend, I need to observe what they did to me. If my friend believes that they can avoid these sanctions by behaving more altruistically towards me, price

transparency should increase altruistic behavior and, with that, the observed directed altruism parameter. Consequently, social collateral theory predicts that price transparency raises prices when sellers of substitutes are friends and lowers prices when sellers of complements are friends.

2 Experimental Design

The experiment is designed to estimate the effect of social networks on market efficiency and investigate the underlying mechanisms. I achieve the former by exogenously varying the social network and the latter by varying price transparency, eliciting beliefs about other players' strategies, and surveying them about their friendships. The experiment follows a withinsubject design. ⁶

3 Implementing the Land Market in the Experiment

Participants in the experiment take part in laboratory versions of the market from Section 1.1. I induce all material components of the model through monetary rewards (V. L. Smith 1976).

Participants did not receive any feedback before making their last decision and were not able to communicate. This ensures that I can analyze the data as independent equilibria from different games instead of one equilibrium of a larger super-game.

I asked participants to make choices in slightly varying market environments to increase statistical power. While keeping all other variables, including the treatments, constant, participants had to decide on prices for five possible subsidies, ranging from 0 to 20 Thaler. When the participants sold successfully, they received the subsidy on top of the price. The subsidy corresponds to the parameter *S* in section 1.1.

^{6.} I preregistered the design, the analysis, the hypotheses, and the sample size (240) at https://osf.io/5ytnz. Analyses that are not preregistered are clearly marked as exploratory in the text. With a minor deviation, which I discuss later, I stuck to the preregistered design and analysis.

3.1 Social Network Treatments

The experiment uses real friendships to generate exogenous social networks to test the directed altruism predictions, derived in Section 1.1: (1) Friendships among sellers of complements lower prices and increase efficiency, (2) friendships among sellers of substitutes increase prices and lower efficiency and (3) friendships among sellers of substitutes lower other seller's (not the friend's) prices. To test these theories I generate the networks depicted in Figure 1 in Section 1.1, exogenously.

Generating exogenous social network starts with recruiting pairs of friends to the experiment. I recruited 240 participants, half of them from "anchors" from the database of the BonnEconLab (via hroot (Bock, Baetge, and Nicklisch 2014)). Each anchor had to bring one friend to the experiment, which completed the other half of the sample. 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.

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. 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 generated different social network treatments by assigning participants to different positions in the experimental market. The following paragraphs discuss this procedures with three examples: a Baseline network without friendships, the Substitutes Symmetric network with pairwise friendships among sellers of substitutes and the Substitutes Asymmetric treatment where only one pair of sellers of substitutes are friends.

Figure 2 depicts examples for generating different social network treatments. Each panel depicts a stylized version of the experiment consisting of two diagrams of the experimental market. These diagrams resemble those of the theoretical social networks in Figure 1. These

two figures differ in that the former depicts participants in the experiment and the latter depicts the players in the theoretical game. Participants are indicated by colored shapes with a letter in them. Friends share shape and color and have consecutive letters. I assign experimental participants a role in the induced theoretical market. A participant that is assigned the role of a specific player is depicted in the spot of that player.



Figure 2: Assignment of Friendship Pairs to the Experimental Market for Different Social Network Treatments

Panel a of Figure 2 illustrates the Baseline Treatment. I invite 4 pairs of friends and split them into two markets. Out of each pair one participant takes part in the market on the left and one participant takes part in the market on the right. This results in two markets without any social relationships within a market.

Contrast the Baseline treatment with the Substitutes Symmetric treatment in Panel b. In

this case pairs are assigned to the same market on opposite sides of the river. This results in two friendships among sellers of substitutes in each market. These friendships are indicated by bi-directional arrows. Analogously for the Complements Symmetric treatment I assign the pairs on the same side of the market but on the same side of the river.

In the Substitutes Asymmetric Network (Panel c) I assign one friendship pair to each of the two markets on opposite sides of the river and split up the remaining pairs (indicated by the square and start shape) across the two markets. In this case the pairs that were not split up (AB, and EF) receive the Substitutes Asymmetric Pair treatment. The pairs that were split up receive the Substitutes Asymmetric Isolated treatment. I complement this network by its mirror image depicted in Panel d.

3.2 Price Transparency Treatments

I test the predictions of social collateral theory by varying price transparency: In the *public*, treatment prices could be revealed at the end of the experiment, and in the *private* treatment, they always stayed private. In both treatments, there was 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.

3.3 Belief Elicitation

Eliciting participants' beliefs about other participants' strategies helps to identify the mechanism behind the observed treatment effects of social networks. The directed altruism theory I outlined in Section 1 concerns preferences. Alternatively, social relationships could affect participant's beliefs. For example, friends might have more accurate beliefs about each others' actions than strangers. Observing beliefs allows me to test for such effects. Further, it allows me to test if equilibrium beliefs shift consistently with the player's actions, as predicted by the Nash equilibrium model in Section 1.

I elicited each player's beliefs regarding the expected value of other players' prices. Participants had to express distinct beliefs about each other player's price, even if the players where completely symmetric.

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).

3.4 Friendship Survey

I run a survey to check if participants have close and meaningful friendships and collect some control variables for further analysis. I reproduce the complete survey in Appendix B and discuss the friendship questions in the current section.

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.

3.5 Decision Interface

Before making any decisions, participants saw a diagram of the current social network treatment (see Figure 12 in Appendix D). This diagram is based on the 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), instead of indexing them from 1 to 4. I indicated friendships between other players without revealing their names.

After being informed of the current social network treatment participants were usually shown five decision screens for each price transparency treatment. For an example decision screen see Figure 3. The top of the screen conveys information about the transparency treatment and the subsidy amount. Below that, participants could enter a price for their property (indicated by UL on the map) and were provided with a decision aid to simulate the consequences of their decision and others' decisions.

The decision aid aims to reduce decision error. It calculates each player's expected payoff from all player's prices. Participants received one slider for each participant's price, including their own. Bar charts and numbers on each plot indicated the respective participants' expected payoffs. By moving the sliders, participants could simulate how changes in their and others' prices affected everyone's expected payoffs. A map of all plots, the river, and participants' friendships is displayed next to 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.

3.6 Treatment Order

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; followed by (4) an explanation of the treatment conditions.

Then, in the central part of the experiment, (5) participants made decisions in different treatments interspersed by a belief elicitation task. Throughout this process, participants did not receive any feedback and were not able to communicate. Finally, after making all of their

Round 3 of 40

6

Attention, if this round is selected for payout, your price and the prices of the 3 other participants will be **publicly disclosed** at the end of the experiment in this circle.

+10 You and all other participants will receive a subsidy of 10 Thalers if you sell your property.



Figure 3: Screenshot of the decision screen used in the experiment to elicit participant choices for different subsidy levels. This screenshot displays a decision for the public treatment and the Substitutes Asymmetric: Pair treatment. The subsidy is 10.

decisions, (6) participants received feedback, answered some open-ended questions and got paid.

Table 1 presents the combinations of social network and transparency treatments involved in the experiment and specifies which treatments included belief elicitation. I omit the public treatment for the asymmetric networks to avoid overwhelming the participants. Quantal response equilibrium model simulations indicated insufficient power to discern spillovers in asymmetric versions of the Complements network. Therefore, I omit these as well. I elicited beliefs only for the markets in the private network that did not include a subsidy.

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

Table 1: All combinations of treatments and belief elicitation.

3.7 Implementation Details

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). 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 3 in Appendix D.

Payoffs in the experiment use the same numbers as in Section 1.1. In the experiment, participants select prices that are integers ranging from 0 to 50. During the experiment, participants made 48 decisions that were all equally likely to be selected for payout. If a decision was selected for payout, participants get one Euro for every two 2 Thalers earned in that decision.

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.

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. I verify in Section 4.1 with some additional survey questions that the participants' friendships are strong and meaningful social relationships. 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 took steps to address two potential confounds: minimal group effects and order effects.

To balance minimal group effects, I conducted the experiment using a building condition and a bridge condition. The building condition works as described previously. Whereas the bridge condition flips the framing, the seller wants to buy a bridge, adjacent plots on opposite sides of the river are complements, and plots on the same side of the river are substitutes. I run half of all sessions in either condition. If the river induces minimal group effects, this procedure balances them across treatments and rules them out as a confounder.

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 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. These results mostly confirm the predictions derived in Section 1. I continued by investigating 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

^{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.

^{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).

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 on average 33 hours per week with their friends compared to slightly below twenty hours found by Goeree et al. (2010), who find strong effects of friends ship 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

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

Table 2: Summary of answers to the introductory survey.

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:

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

The treatment indicator (T) and the sample vary across analyses. I index individuals by

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

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 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 friend-ships through a parallel comparison for the Complements Symmetric network. Both analyses encompass 4800 observations.¹¹

I preregistered these analyses and the following hypotheses: (1) complement friendships decrease prices, and (2) 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).

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

^{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.



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.

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.

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 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.

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



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.

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 E1.¹³

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"

^{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.

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 expected value of a person's prices maximizes this measure. I divide by the maximum possible deviation (50²), 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.

	Dependent variable:		
		$\frac{(Belief - Price)^2}{50^2}$	
	(1)	(2)	(3)
Friend	0.005 (0.007)	0.005 (0.007)	0.020* (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 R ²	5,757 0.014	5,757 0.015	3,453 0.013

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.

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

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.

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 (Substitutes Symmetric, Complements

Symmetric 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. 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* (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 (*a*) 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,

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

$$\underbrace{\begin{bmatrix} U_{1}(p_{1}, p_{2}, p_{3}, p_{4}, S, D, O, \gamma) \\ U_{2}(p_{1}, p_{2}, p_{3}, p_{4}, S, D, O, \gamma) \\ U_{3}(p_{1}, p_{2}, p_{3}, p_{4}, S, D, O, \gamma) \\ U_{4}(p_{1}, p_{2}, p_{3}, p_{4}, S, D, O, \gamma) \\ \end{array}_{\text{expected utilities}} = \underbrace{\begin{bmatrix} m_{1}(.) \\ m_{2}(.) \\ m_{3}(.) \\ m_{4}(.) \end{bmatrix}}_{\text{own payoff}} + \mu(O) \cdot \boldsymbol{M}(D) \cdot \begin{bmatrix} m_{1}(.) \\ m_{2}(.) \\ m_{3}(.) \\ m_{4}(.) \end{bmatrix}}_{\text{altruism term}} - \mathbb{1}(O = public) \cdot \rho \cdot \begin{bmatrix} p_{1} \\ p_{2} \\ p_{3} \\ p_{4} \end{bmatrix}.$$
(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 bestresponding 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

$$\sigma_{1}(p_{1}, S, D, O, \gamma) = \frac{exp(\lambda \mathbb{E}_{p_{2}, p_{3}, p_{4}}[U_{1}(p_{1}, p_{2}, p_{3}, p_{4}, S, D, O, \gamma)])}{\sum_{p_{1}^{'} \in \mathbb{P}} exp(\lambda \mathbb{E}_{p_{2}, p_{3}, p_{4}}[U_{1}(p_{1}^{'}, p_{2}, p_{3}, p_{4}, S, D, O, \gamma)])}$$
(4)

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

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

(5)

The probabilities for the other players are analogous.

I estimate the model by maximum likelihood and introduce some additional notation to 14. Recall that I use discrete prices ($\mathbb{P} = \{0, 1, ..., 50\}$).

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 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_i , and transparency condition O_i .

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

$$LLH(\gamma) = \sum_{i=1}^{N} \log(\sigma_1(p_{1j}, S_j, D_j, O_j, \gamma)),$$
(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.

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

Parameter	Explanation	Estimate	95% CI
Directed Altruism $\mu(private)$ $\mu(public) - \mu(private)$	private increase public	0.277*** 0.009	(0.193, 0.361) (-0.057, 0.074)
$ \begin{matrix} \rho \\ \alpha \\ \lambda \end{matrix} $	social image concerns constant QRE-parameter	0.037*** 24.600*** 0.250***	(0.013, 0.060) (20.60, 28.60) (0.189, 0.312)

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

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

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 Substitutes Asymmetric treatment to estimate the spillovers and find that they do not significantly differ from zero.

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



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

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 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 Discussion

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.

Participants under-react to other participants' friendships. They expect that friendships among sellers of substitutes increase the friend's prices. However, they do not react to that increase in prices. Cost-proportional errors are unlikely to explain the extent of the underreaction. One possible explanation for participants' under-reaction is a weakness in kardinal reasoning. As Section 1.1 argues, participants trade off two effects. The friendship between two other players raises both players' prices. In this case, one of the players sells a substitute, and the other player sells a complement. Participants should respond to the former by increasing their price and to the latter by decreasing their price. Overall, the second effect dominates. QRE assumes that (ceteris-paribus) trading off two countervailing effects does not affect decision error. If it does, we would expect the observed underreaction that QRE style decision error cannot fully explain.

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 decisionmakers 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 Proofs

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,

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

$$= \begin{cases} (1 - p_{\ell}) - 0.5(1 - p_{r})^{2} & \text{if } p_{\ell} \le p_{r} \\ (1 - p_{\ell}) \cdot p_{r} + 0.5(1 - p_{\ell})^{2} & \text{if } p_{r} < p_{\ell} \end{cases}$$
(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

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

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 . Since the first order conditions are linear in other player's prices, they also hold when the other player is playing a mixed strategy. Therefore all players utility functions are always strictly concave in their own price p_i and their best response solves the first order condition and is deterministic.

Any symmetric equilibrium strategy p_s satisfies the first order condition:

$$g(p_{s},\mu) := \frac{\partial Pr_{\ell}(p_{s},p_{s},p_{s},p_{s},p_{s})}{\partial p_{1}}(p_{s}+S) + Pr_{\ell}(p_{s},p_{s},p_{s},p_{s}) + \mu \frac{\partial Pr_{r}(p_{s},p_{s},p_{s},p_{s},p_{s})}{\partial p_{1}}(p_{s}+S) = 0$$
(10)

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

I use the intermediate value theorem to show that this equation has a solution within the strategy space. 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 smaller than zero. The function *g* has only one critical point at $p_s = \frac{\mu - 2\mu S - 1}{4(\mu + 1)} \leq \frac{\mu - 1}{4(\mu + 1)} \leq 0$. Therefore *g* is decreasing in the strategy space. Consequently, the FOC has a unique 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 of player 1 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

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

, which is true. For $p_r < p_\ell$, we get,

$$(p_1 + S) - 2(1 + p_r - p_\ell) - \mu(p_3 + S) + p_\ell - p_r = p_1 - \mu p_3 + (1 - \mu S) - 2,$$

which is increasing in p_1 , p_2 and S and decreasing in p_3 , p_4 and μ . Therefore if we use S < 0.2, $p_i \in [0, 0.5]$ and $\mu > 0$ we can bound it above by -0.3 < 0. Taken together these conditions imply that player 1's utility function is strictly concave in p_1 . Since the first order conditions are linear in other player's prices, they also hold when the other player is playing a mixed strategy. Therefore all players utility functions are always strictly concave in their own price p_i and their best response solves the first order condition and is deterministic.

Any symmetric equilibrium strategy p_s satisfies the first order condition:

$$i(p_{c},\mu) := \frac{\partial \Pr_{\ell}(p_{c},p_{c},p_{c},p_{c},p_{c})}{\partial p_{1}}(p_{c}+S) + \Pr_{\ell}(p_{c},p_{c},p_{c},p_{c}) + \mu \frac{\partial \Pr_{\ell}(p_{c},p_{c},p_{c},p_{c},p_{c})}{\partial p_{1}}(p_{c}+S) = 0$$
(12)

$$\Leftrightarrow i(p_c, \mu) = (1 - 2p_c) - 0.5(1 - 2p_c)^2 - (1 + \mu)(p_c + S) = 0.$$
(13)

I use the intermediate value theorem to show that this equation has a solution. The function *i* is continuous because it is a composition of continuous functions. I calculate that $i(0, \mu) =$

 $0.5 - (1 + \mu)S$ and $i(0.5, \mu) = -(1 + \mu)(1 + S)$. 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 $(i(0.5, \mu))$ is always larger than zero. Consequently, the FOC has an interior solution by the intermediate value theorem. Checking $\left(\frac{\partial i(p_c,\mu)}{\partial p_c}\right) = -3 - \mu - p_c < 0$, shows that *i* is strictly decreasing and this interior solution is unique. Therefore the Complements Symmetric game has a unique symmetric equilibrium price $0 < p_c < 0.5$.

In conclusion the Substitute Symmetric and Complement Symmetric networks have an interior symmetric equilibrium. This equilibrium is the only equilibrium. Best responses are unique, deterministic and solve the first order conditions. Since both networks nest the Base-line network, for $\mu = 0$, these results 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:

$$\frac{\partial \operatorname{Pr}_{\ell}(p_s, p_s, p_s, p_s, p_s)}{\partial p_1}(p_s + S) + \operatorname{Pr}_{\ell}(p_s, p_s, p_s, p_s) + \mu \frac{\partial \operatorname{Pr}_{r}(p_s, p_s, p_s, p_s)}{\partial p_1}(p_s + S) = 0$$
(14)

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

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

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

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

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:

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

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

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

Proof of Proposition 2. I can express the *Substitutes Asymmetric* equilibrium as the intersection of two best response functions, evaluated at symmetry. I restrict attention to symmetric strategies in the sense that $p_{isol} \coloneqq p_1 = p_3$ and $p_{pair} \coloneqq p_2 = p_4$. I denote the best response for one player that is part of a *pair* of friends by BR_{pair} and the best response for an isolated player by BR_{isol} . The equilibrium then solves,

$$p_{isol}^* = BR_{isol}(p_{pair}^*) \tag{21}$$

$$p_{pair}^* = BR_{pair}(p_{isol}^*). \tag{22}$$

Equations 24 and 25, define the the best response functions BR_{pair} and BR_{isol} as the solution to the player's first order conditions under symmetry. Since player 1 and 3 are friends their objective function is identical to the objective function in the substitutes symmetric case. Player 2 and 4 are strangers so their objective function is identical to the one in the baseline case. Lemma 1, implies that best responses solve the first order conditions. This result also applies in the Substitutes Asymmetric game, because this game combine the best responses from the Substitutes Symmetric and the Baseline games.

$$MU_{pair}(BR_{pair}(x), x) \coloneqq$$

$$\frac{\partial \operatorname{Pr}_{\ell}(BR_{pair}(x), x, BR_{pair}(x), x)}{\partial p_{1}} \cdot (BR_{pair}(x) + S) + \operatorname{Pr}_{\ell}(BR_{pair}(x), x, BR_{pair}(x), x)$$

$$+ \mu \frac{\partial \operatorname{Pr}_{r}(BR_{pair}(x), x, BR_{pair}(x), x)}{\partial p_{1}} \cdot (BR_{pair}(x) + S) = 0,$$

$$MU_{isol}(y, BR_{isol}(y)) \coloneqq$$

$$\frac{\partial \operatorname{Pr}_{\ell}(y, BR_{isol}(y), y, BR_{isol}(y))}{\partial p_{2}} \cdot (BR_{isol}(y) + S) + \operatorname{Pr}_{\ell}(y, BR_{isol}(y), y, BR_{isol}(y)) = 0.$$
(23)

In the *Substitutes Symmetric* game all players have the same utility function as the pair in the Substitutes Asymmetric game. Therefor we can characterize the equilibrium as the intersection of BR_{pair} and its inverse.

$$y = BR_{pair}(x),$$
$$x = BR_{pair}^{-1}(y),$$
$$p_s^* = x = y.$$

This characterization facilitates comparisons between the equilibria of the asymmetric and symmetric networks. Both networks are at the intersection of BR_{pair} with another best response: either BR_{isol} or BR_{pair}^{-1} . To compare these two equilibria we analyze what happens when we change from one to the other.

I proceed by showing that the best responses exist and are decreasing in the symmetric strategy of the other two players. I use the implicit function theorem to prove this claim. Taking the derivative of $MU_{pair}(BR_{pair}(x), x)$ with respect to both its arguments yields, after plugging in functional forms,

$$\begin{aligned} \frac{\partial MU_1(p_{isol}, p_{pair})}{\partial p_{isol}} &= -p_{pair} - p_{isol} - \mu \cdot (p_{pair} + S) < 0\\ \frac{\partial MU_1(p_{isol}, p_{pair})}{\partial p_{pair}} &= -1 - p_{pair} - p_{isol} - \mu(-1 + 2p_{pair} + p_{isol} + S). \end{aligned}$$

Observe that the second expression falls in p_{pair} and p_{isol} . Therefore $\frac{\partial MU_1(p_{isol}, p_{pair})}{\partial p_{pair}} < 0$ if the

condition holds if we set $p_{pair} = p_{isol} = 0$. This is the case if $\mu(1 - S) < 0$, which is true for S < 1and $\mu < 1$. For the isolated participants we have,

$$\frac{\partial M U_2(p_{isol}, p_{pair})}{\partial p_{isol}} = -1 - p_{pair} - p_{isol} < 0$$
$$\frac{\partial M U_2(p_{isol}, p_{pair})}{\partial p_{pair}} = -p_{pair} - p_{isol} < 0.$$

Consequently, both marginal utilities are (globally) one time continuously differentiable and the derivatives with respect to the endogenous variable are (globally)different from zero. Therefore we can apply the implicit function theorem and around each point in the strategy space the best responses, evaluated at symmetry, exist and are one time continuously differentiable with derivatives,

$$\frac{\partial p_{1,coup}(p_{isol})}{\partial p_{isol}} = -\frac{\frac{MU_1(p_{isol},p_{pair})}{\partial p_{isol}}}{\frac{MU_1(p_{isol},p_{pair})}{\partial p_{pair}}} < 0$$
$$\frac{\partial p_{2,sep}(p_{pair})}{\partial p_{pair}} = -\frac{\frac{MU_2(p_{isol},p_{pair})}{\partial p_{pair}}}{\frac{MU_2(p_{isol},p_{pair})}{\partial p_{pair}}} < 0.$$

That is they are decreasing.

Figure 10 illustrates the best responses in both networks. In the figure, p_1 and p_3 align along the x-axis, while p_2 and p_4 align along the y-axis. The solid blue line indicate the best response of players 1 and 3 who are a pair in both networks. The intersection of this line with the best response of isolated player 2 and 4 (dotted red line), indicates the Substitutes Asymmetric equilibrium point. Whereas, the intersection of the solid blue line with the best response of paired up players 2 and 4 indicates the Substitutes Symmetric equilibrium. We need to show that the candidate equilibrium point of Substitutes Asymmetric is inside the strategy space and that Substitutes Symmetric point is downward and to the right of the Substitutes Asymmetric point.

I proceed by showing that the best response of the pair is always above the best response of the couple. That is we can analyze the change from Substitutes Asymmetric to Substitutes



Figure 10: Aggregate best response functions for the Substitutes Asymmetric (couple and separate) and the Substitutes Symmetric Treatment. Parameters are set at $\mu = 0.8$ and S = 0.2.

Symmetric as a rightward shift of best responses. Define,

$$h(a,b) \coloneqq \frac{\partial \operatorname{Pr}_{\ell}(a,b,a,b)}{\partial p_{pair}} \cdot (a+S) + \operatorname{Pr}_{\ell}(a,b,a,b),$$

as the private benefit of an increase in p_{pair} or p_{isol} , keeping the other constant. These two are equal because all players' material utilities are the same. By plugging in the functional form assumptions and taking the derivative of h with respect to its first argument (*a*) we get, $\frac{\partial h(a,b)}{\partial a} = -1 - a - b < 0$. Therefore *h* falls in *a*.

We use h and equations 24 and 25 to rewrite the first order conditions as follows,

$$h(BR_{pair}(y), y) + \mu \frac{\partial Pr_r(BR_{pair}(y), y, BR_{pair}(y), y)}{\partial p_1} \cdot (BR_{pair}(y) + S) = 0$$
(25)

$$h(BR_{isol}(y), y) = 0.$$
 (26)

These two equations imply

$$h(BR_{isol}(y), y) - h(BR_{pair}(y), y) = \mu \frac{\partial Pr_r(BR_{pair}(y), y, BR_{pair}(y), y)}{\partial p_1} \cdot (BR_{par}(y) + S) > 0$$
$$\Leftrightarrow h(BR_{isol}(y), y) > h(BR_{pair}(y), y),$$

and because *h* is falling in its first argument, $BR_{isol}(y) < BR_{pair}(y) \quad \forall y \in [0, 0.5].$

For the Substitutes Asymmetric equilibrium candidate to be interior equilibrium, $BR_{isol}(y)$ and $BR_{pair(x)}$ need to intersect within the strategy space. Since the best responses are continuous we need to show that, within the strategy space $BR_{isol}(y)$ starts out above $BR_{pair(x)}$ and ends up below it. Then because of the intermediate it intersects $BR_{pair(x)}$ and the equilibrium is interior.

The best response of the isolated players $BR_{isol}(y)$ starts out above $BR_{pair(x)}$ if $BR_{isol}^{-1}(0) > BR_{pair}(0)$, which is the case if,

$$\frac{\sqrt{mu^2(s+1)^2 - 2S + 2} + mu(-s) + mu - 1}{2mu + 1} < \sqrt{1 - 2S},$$

which is the case for the bounds we put on μ and *s*.

The intersection of $BR_i sol$ with the x-axis is below BR_pair and within the strategyy space. We know that the Substitutes Symmetric Equilibrium exists and is interior. Further the best response of the isolated player is below the best response of the pair $(BR_{isol}(y) < BR_{pair}(y) \quad \forall y \in [0, 0.5])$. Further $BR_{isol}(0) > 0$, because players want to charge positive prices to get positive profits.

Therefore the Substitutes Asymmetric game has an interior equilibrium.

Since best responses are decreasing, and $BR_{isol}(y) < BR_{pair}(y) \quad \forall y \in [0, 0.5], BR_{isol}(y)$ intersects $BR_{pair}(x)$ to the left and above (p_s^*, p_s^*) . Therefore $p_{pair}^* > p_s^*$ and $p_s^* > p_{isol}^*$.

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 Comprehension Questions

I asked the following comprehension 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 11).



Figure 11: Map that I showed before each batch of comprehension questions.

D Screenshots from The Experiment

Participant Overview

Here you will find an overview of the friendships between all participants in the following rounds. If we reassemble the groups, you will be informed.

UL (You)	UR (Friend of LR)
LL (Peter)	LR (Friend of UR)

Figure 12: 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.

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.

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

^{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.



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 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.

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 a player's risk aversion measured by their answer on the general risk question ¹⁶. I cluster standard errors at 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 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.

^{16.} This is a non-incentivized question from Falk et al. (forthcoming): "Please tell me, in general, how willing or unwilling you are to take risks. [scale of 0 to 10]" I use this question in the German translation from Falk et al. (2018). This question reliably correlates to answers on an incentivized lottery choice task (Dohmen et al. 2011) I add a separate dummy for each possible answers to this question.

	Dependen	t variable:
	Pr	ice
	(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

Table 5: Estimated relationship between friends' prices.

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

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 withinsubject treatment effect. I can increase power by enforcing that friendship closeness should act



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.

similarly in the Complements and Substitutes networks, but in different directions. I do this with the help of a structural model.

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 ,

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

Participants who are not very close to their friends exhibit lower directed altruism. Table 7

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

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

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

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 estimate	es for the QRE-	-Directed-A	ltruism model	l, when the a	altruism param-
eter varies with relationshi	p closeness (n	neasured by	the friendship	o index).	

Parameter	Explanation	Estimate	95% CI
Directed Altruism $\mu(private)$ δ_m δ_h $\mu(public) - \mu(private)$	bottom tercile & private increase medium tercile increase top tercile increase public	0.14*** 0.24*** 0.18*** 0.009	(0.072, 0.21) (0.060, 0.41) (0.062, 0.30) (-0.037, 0.054)
$\begin{array}{c} \rho \\ lpha \\ \lambda \end{array}$	social image concerns constant QRE-parameter	0.037*** 25*** 0.25***	(0.016, 0.058) (21, 28) (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 pricetransparency 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.

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

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

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.

Finally we compare the Baseline game to the Substitutes Asymmetric game. The equilibrium of the Baseline game (p_b, p_b) is the intersection of

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