The Effect of Social Relationships on Market Efficiency*

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Abstract

This paper investigates the impact of social relationships on imperfectly competitive markets. I model social relationships as linear directed altruism in markets with substitutes and complements. The model generates testable predictions, the most important of which being that social relationships among sellers of substitutes increase prices and reduce efficiency. In contrast, social relationships among sellers of complements reduce prices and increase efficiency. I test these predictions in a controlled laboratory network structure among market participants, drawing on real-world friendships. The results confirm the model's key insights. Additional treatments explore the robustness of these findings and the underlying mechanisms. Overall, the results suggest that economists can analyze social relationships in imperfectly competitive markets similarly to how they evaluate other forms of profit internalization, such as common ownership and mergers.

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Social relationships are woven into markets (Granovetter 1985). People selling houses in Amsterdam attend 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 social relationships interact with the market? Do friends conspire and raise prices (Smith 1776, p. 130), or can their cooperation benefit consumers?

Although social relationships shape market efficiency, the specifics of this relationship remain unclear. In fact, many industrial organization (IO) economists regard social relationships as an important impediment to competition that is "beyond the reach of conventional analysis" (Scherer and Ross 1984, p.311).

Three problems may 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 relationships are endogenous and difficult to manipulate: They develop over a long time, and natural experiments that change them are rare.[2] Third, market efficiency is unobservable because we need to know individual preferences to compute the gains from trade. I combine a laboratory experiment with a theoretical model to address these problems.

To address the first issue, I propose a model of social relationships in markets. The model isolates the features of a social network that are likely to affect market efficiency. I assume that the main aspect of a social relationship is that relational partners act more altruistically towards each other. These preferences are called directed altruism (Leider et al. 2009). I integrate directed altruism preferences into a model of imperfect competition with complements and substitutes (building on Economides and Salop 1992). This model suggests that market efficiency in a social network is influenced by whether relationships are between sellers of complements or substitutes.

1. While there are theoretical models of contract enforcement through social networks (Karlan et al. 2009) and enabling exchange (Kranton 1996), economics lacks a model of how social networks affect efficiency within formal market institutions.

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

To address the second issue, I propose a controlled laboratory experiment. In this experiment, I study friendships as a prototypical social relationship. To do so, I invite real-world friends to participate in laboratory markets and assign them different roles. This assignment results in a within-subject design, where the same individual makes choices in different social networks, while everything else is held constant. In some of these networks, the participant's friend sells a complement; in some, they sell a substitute, and in others, they do not participate. This variation allows me to estimate the causal effects of friendship among sellers of substitutes and sellers of complements on market efficiency and prices. I also estimate the equilibrium effect of a friendship between two participants on an unrelated participant's actions using asymmetric social networks. The experiment further tests directed altruism and a likely alternative theory in a market setting.

The experiment also solves the third issue of unobservable preferences. I focus on material efficiency, 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. Therefore, to observe efficiency, one needs to observe values and costs. These quantities are observable because I set and thus observe participants' monetary rewards for the experiment. Consequently, I observe the gains from trade and use them to calculate market efficiency.

The directed altruism model predicts that friendships between sellers of complements decrease prices and that friendships between sellers of substitutes increase prices. The reason is that directed altruism partially internalizes a pricing externality: If a seller increases the price of its good, the demand for a substitute rises and the demand for a complement falls. Sellers attempt to increase the demand for their friend's product, so they adjust their own price accordingly. The incentives here are the same as in the Cournot (1897) result on complement and substitute mergers.

The effect of friendships on prices in turn influences market efficiency. Since the market is imperfectly competitive, prices start above the efficient 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, while 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: Friends could have more accurate beliefs about their friends' actions (familiarity), which would make them act differently.[3] 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.

I test whether a single underlying directed altruism parameter can explain the magnitudes of different treatment effects by estimating a structural model. In addition to this directed altruism parameter, the model includes additional parameters that capture the price levels but not the effect of different social networks. I find that a single parameter can 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 representative participant will pay between 20 and 36 cents (95% CI) for her friend to receive one dollar.

This paper shows that economists 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) and IO: Edgeworth's coefficient of effective sympathy (Edgeworth 1881 p.53, Vives 2020). The coefficient of effective sympathy models the extent to which 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; Ederer and Pellegrino 2022). Mergers between two firms are mostly equivalent to full profit internalization. In the case of friendship, Edgeworth's coefficient is the directed altruism parameter. This paper indicates that friendships replicate a particularly salient feature of mergers. 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 one's product has a negative externality on the seller of a complement (lower demand) and on the demand side (higher prices, less trade). I find that

3. I selected this theory because it was the second most popular among participants in the pilot. Indeed, 60% of participants in the experiment believe in it.

friendships among sellers of complements internalize this externality and raise efficiency. This finding introduces a social network perspective into market design with complements.

This paper contributes to the experimental literature on the effects of social relationships on economic decision-making. Previous experiments have exposed real-world friends (Leider et al. 2009; Leider et al. 2010; Goeree et al. 2010; Ligon and Schechter 2012; Chierchia, Tufano, and Coricelli 2020) and participants sampled from real-world social groups (Gächter, Starmer, and Tufano 2023; Gächter et al. 2022; Finseraas et al. 2019; Baldassarri and Grossman 2013; Goette, Huffman, and Meier 2006) and social networks (Breza and Chandrasekhar 2019; Iacobelli and Singh 2024; Jain 2020; Chandrasekhar, Kinnan, and Larreguy 2018) to a laboratory setting to test the effect of social relationships on cooperation, contract enforcement, and other behaviors. These experiments test the effect of social relationships on cooperation, contract enforcement, and other actions. I add to this literature by using paired friendships as building blocks of social networks in a market setting. This approach allows me to study the interplay between the product network described by complementarity and substitutability and the social network defined by friendships.

1 Theoretical Framework

The experiment features a Bertrand oligopoly with differentiated products, including complements and substitutes. In this section, I outline this setting and apply the linear directed altruism model to derive predictions for the effect of different social networks on prices.

The theory builds on a standard result in the theory of IO: Mergers among sellers of complements increase efficiency, while mergers among sellers of substitutes decrease it (Cournot 1897). My main theoretical contribution is to draw an analogy between mergers and directed altruism. I apply existing theory to the experimental setting.

1.1 Model

Participants play one of four human sellers who sell land to a computerized buyer. Sellers 1 and 2 own land on the left side of a river, and sellers 3 and 4 own land on the right side of a river. Sellers make 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 private valuations that are independent draws from identical uniform distributions θ_ℓ and θ_r for two plots on the left and 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 S for successful sales.

I distinguish between a participant's material utility (m_i) and general utility (U_i). In this section, I assume that the material utility is equal to the expected monetary payoff from the experiment. The general utility (U_i) incorporates altruism between friends. [4]

If a participant sells, her material utility (m_i) is her price plus the subsidy; in all other cases, it is zero. The probability that the buyer 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.

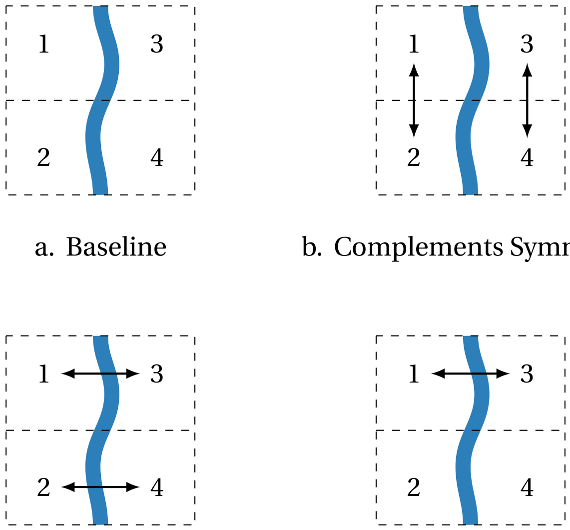
I use the simplest possible model of friendships and cooperation: linear directed altruism with a homogeneous altruism parameter $\mu \in [0, 1]$. The model allows us to define a player's utility in terms of all players' material utility. Define the adjacency matrix $\boldsymbol{M}$. This matrix has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

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

4. I assume that people are not altruistic towards strangers (no baseline altruism). As Appendix M shows, baseline altruism is unlikely to perceptibly affect behavior in this game.

1.2 Predicted Prices for Different Social Networks

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



a. Baseline

b. Complements Symmetric

c. Substitutes Symmetric

d. Substitutes Asymmetric

Figure 1: The experimental market with different social networks. The different plots are separated by the river (in blue) and the dotted line. Bidirectional 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 pair sets an identical price, and similarly, each individual acting alone chooses a uniform price.

Lemma 1 demonstrates that all games with symmetric networks possess unique symmetric Nash equilibria. These symmetric equilibria are interior and in pure strategies.

The lemma imposes a regularity condition ($50 > (1+\mu) \cdot S$). Very high subsidies or directed altruism parameters can lead to participants always charging a (corner solution) price of zero.

The lemma rules that out. [5] The proof of this lemma 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 her price to increase her friend's demand. Conversely, if the friend sells a substitute, the seller increases her price to increase her 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 that in the Baseline network (p_b^*), which exceeds that in the Complement Symmetric network (p_c^*), $p_s^* > p_b^* > p_c^*$.*

A friendship between two sellers of substitutes decreases other players' prices. I formally demonstrate this in Proposition 2. The proof of this proposition is provided in Appendix A). Here, I provide a brief intuition that ignores second-round equilibrium effects.

I compare the Substitutes Asymmetric network (Figure 1, Subfigure d) with the Substitutes Symmetric network (Figure 1, Subfigure c). In both networks, players 1 and 3 are friends. Transitioning from the Substitutes Asymmetric to the Substitutes Symmetric network results in

5. This condition is satisfied if the subsidy paid for a successful sale is not too high. This assumption is satisfied for the parameters in the experiment if people value others' utility at most 1.5 times their own utility. Specifically, I assume that $50 > (1 + \mu) \cdot S$. Given that $0 \leq S \leq 20$ in the experiment, this assumption holds for all $\mu \leq 1.5$.

players 2 and 4 also becoming friends. The following paragraphs analyze the impact of this additional friendship on the prices set by players 1 and 3.

To discuss the equilibrium effects of this friendship, I need to determine which prices are strategic complements and which are strategic substitutes. When one player raises her price, the other player on the same side of the river will lower his price to offset the overall increase in total price. On the other hand, a player selling a substitute experiences less competitive pressure and can raise her price. In essence, the prices of complements are strategic substitutes, while the prices of substitutes are strategic complements.

Since players 2 and 4 sell substitutes, their friendship leads to an upward shift in their best responses. This shift has two opposing effects on the price set by player 1. Player 1's product is a complement to player 4's product and a substitute for player 2's product. Due to strategic substitutability, an increase in player 2's price will decrease player 1's price. Conversely, due to strategic complementarity, an increase in player 4's price will increase player 1's price. The influence of strategic substitutability surpasses that of strategic complementarity because of the higher cross-price elasticity between complements. Therefore, the friendship of players 2 and 4 lowers the price of player 1. Symmetrically, this also reduces the price for player 3.

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 between sellers of substitutes is predicted to decreases the price of the two other players ($p^*_s < p^*_{\text{pair}}$); by an analogous argument, this effect also occurs when the two other players are strangers ($p^*_{isol} < p^*_b$).

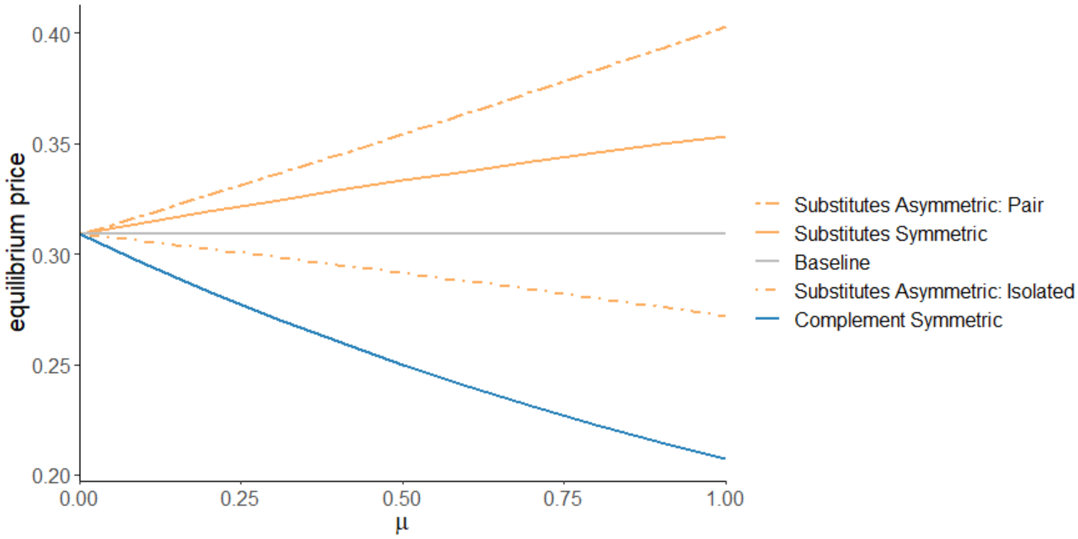


Figure 2: Numerical solutions for the symmetric Nash equilibrium in different treatments. Subsidy is set to zero. The horizontal axis displays the directed altruism parameter.

I display numerical solutions for the symmetric equilibrium in Figure 2. In this figure, the subsidy is set to zero. The x-axis indicates the directed altruism parameter, whereas the y-axis indicates the equilibrium price. Colors indicate the different treatments. Prices are ranked $p_{pair} > p_s > p_b > p_{isol} > p_c$, with the distance increasing in the extent of directed altruism.

1.3 Predicted Relationship between Prices and 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

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

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

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 mechanisms through which friendships internalize externalities, 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 her friend does not cooperate, she can stop being friends and withdraw that utility. This threat can enforce cooperation.

Social collateral theory can predict more substantial effects of friendship when other players' prices are observable. To sanction my friend, I need to observe what she did to me. If my friend believes that she can avoid these sanctions by behaving more altruistically towards me, price transparency should increase altruistic behavior and, in turn, the observed directed altruism parameter. Consequently, in this case, social collateral theory predicts that price transparency raises prices when sellers of substitutes are friends and lowers prices when sellers of complements are friends. One can visualize this prediction as a rightward move along the horizontal axis of figure 2. As opposed to social collateral, intrinsic altruism does not depend on observability and should not increase with price transparency.

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 within-subject design. [6]

6. I preregistered the design, analysis, hypotheses, and sample size (240) at https://osf.io/5ytnz. Analyses that are not preregistered are clearly marked as exploratory in the text.

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) comprehension questions; and (5) an explanation of the treatment conditions.

Then, in the central part of the experiment, (6) participants made decisions in an experimental land market for different treatments. These decisions are interspersed by belief elicitations. Throughout this process, participants did not receive any feedback and were not able to communicate. Finally, after making all of their decisions, (7) participants received feedback, answered some open-ended questions and were paid.

The remainder of this section details how I capture the theoretical market model and social networks in the experiment. I then discuss how the price transparency treatment allows me to investigate the mechanisms underlying directed altruism behavior. The central portion of the section concludes with an overview of the decision screen, which integrates these various design elements. Finally, I summarize the different treatments, relate those to the payment procedures and incentive levels, and include a list of implementation details omitted from the prior discussion.

2.1 Implementing the Land Market in the Experiment

Participants in the experiment participated in laboratory versions of the market from Section 1.1.

I induce all material components of the model through monetary rewards (Smith 1976). Rewards are denoted in the experimental currency unit thaler. 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.

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 decisions from different one-shot games, avoiding repeated game effects.

I asked participants to make choices in slightly varying market environments to increase statistical power. While holding 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 in addition to the price. The subsidy corresponds to the parameter S in Section 1.1.

2.2 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 sellers' (not the friend's) prices. To test these theories, I generated the networks depicted in Figure 1 in Section 1.1, exogenously.

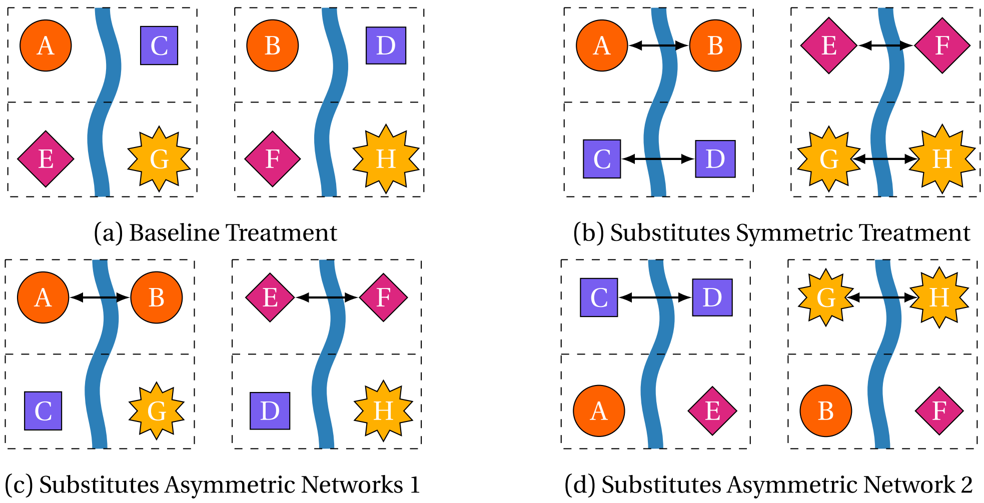
Generating an exogenous social network starts with recruiting pairs of friends to the experiment. I recruited 240 participants, half of them from "anchors" from the database of the BonnEconLab (via hroot (Bock, Baetge, and Nicklisch 2014)). Each anchor had to bring one friend to the experiment, which completed the other half of the sample. To incentivize bringing a friend, I announced, as in Leider et al. (2009), that all participants could earn 5 euro for correctly answering a trivia question about their friend.[7]

I generated different social network treatments by assigning participants to different positions in the experimental market. The following paragraphs discuss these 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 3 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 the theoretical social networks in Figure 1, although the former depicts participants in the experiment and the latter the players in the theoretical game.

7. 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?"

Participants who are friends share shape and color and have consecutive letters assigned to them. Participants are depicted in the spot of the player whose role they have been assigned.



(a) Baseline Treatment

(b) Substitutes Symmetric Treatment

(c) Substitutes Asymmetric Networks 1

(d) Substitutes Asymmetric Network 2

Figure 3: Assignment of friendship pairs to the experimental market for different social network treatments. Each panel depicts the full allocation of participants to markets for one type of round in the experiment with 8 participants. Each colored node represents one participant. Friends are indicated by consecutive letters and a common style of their node.

Panel (a) of Figure 3 illustrates the *Baseline treatment*. I invited 4 pairs of friends and split them into two markets. From each pair, one participant takes part in the market on the left, and the other does so in the market on the right. This assignment results in two markets without 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 assignment results in two friendships among sellers of substitutes in each market. These friendships are indicated by bidirectional 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 (C–D and G–H) across the two markets. In this case, the pairs that were not split up (A–B, and E–F) received the *Substitutes Asymmetric: Pair* treatment. The pairs that were split up received the *Substitutes Asymmetric: Isolated* treatment. I complement this network by its mirror image depicted in

Panel (d).

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.

2.3 Decision Interface

Before making any decisions, participants saw a diagram of the current social network treatment, based on the map of the four plots (see Figure 13 in Appendix E). 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 4. 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 also echos the initial diagram of the social network treatment.

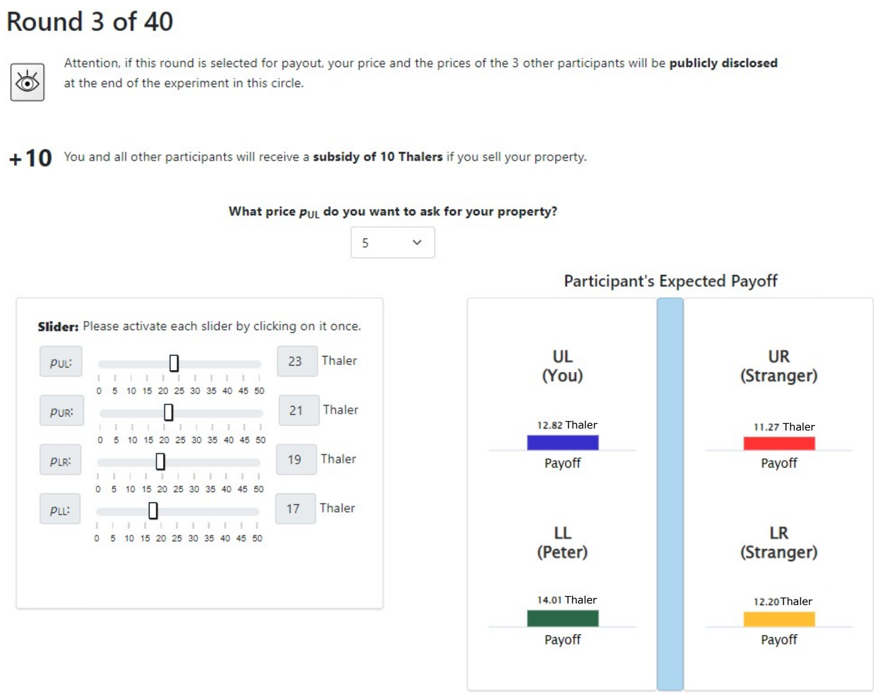


Figure 4: The (translated) decision screen used in the experiment to elicit participant choices for different subsidy levels. This screenshot displays a decision for the public treatment and the Substitutes Asymmetric: Pair treatment. The subsidy is 10.

The decision aid is intended to reduce decision error. It calculates each player's expected payoff from all players' 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.

2.4 Overview of the Experiment and Predictions

Five social network treatments and two price transparency conditions result in a five-by-two factorial design. I omit the private condition for the asymmetric networks. Table 1 summarizes all treatments run in in the experiment and the corresponding predictions.

Table 1: Overview of all social network treatments and the effect of price transparency in these treatments. The effect of price transparency is the change in prices when switching from the private to the public treatment. Treatments are listed in order of decreasing predicted price.

Social Network Treatment	**Price**	**Price Transparency**
Substitutes Asymmetric: Pair	p_{pair}	not tested
Substitutes Symmetric	p_s	$p \uparrow$
Baseline	p_b	no effect
Substitutes Asymmetric: Isolated	p_{isol}	not tested
Complement Symmetric	p_c	$p \downarrow$

The expected level of incentives is determined by the number of treatments and the conversion rate from thalers to euros. Treatments, different subsidies and belief elicitation resulted in 48 decisions that were all equally likely to be selected for payout. If a decision was selected for payout, participants received one euro for every 2 thalers earned in that decision. Therefore, 1 thaler in expectation corresponds to 4.1 cents at the 2022 German price level.

2.5 Implementation Details

I omitted several implementation details from the preceding discussion. For more information on the friendship survey, see the discussion in Section 3.1 and the questionnaire in Appendix B. I elicited beliefs using the binarized scoring rule (Hossain and Okui 2013), following standard practices developed in response to Danz, Vesterlund, and Wilson 2022. I elicited beliefs for all networks but only in the public condition, without a subsidy. For further details on belief elicitation, see Appendix F. For a list of comprehension questions see Appendix C. I take several measures to minimize order effects and minimal group effects (see Appendix D for a detailed description). The experiment was conducted in German and implemented in oTree (Chen, Schonger, and Wickens 2016).

3 Empirical Results

In this section, I estimate the effect of social networks on prices and efficiency and how it varies with price transparency. These results confirm most of 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 compared an estimated structural directed altruism model to the data to test directed altruism theory's quantitative implications.

3.1 Manipulation Checks

I conducted manipulation checks to verify that the participants had close and meaningful friendships and that they understood the experiment.

My primary measure of friendship closeness is 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 additional survey questions as an alternative measure of friendship closeness (see Appendix B for the questionnaire).

The survey's results suggest that participants have meaningful social connections with their friends (see Table 4 in Appendix B). 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, in contrast to the slightly below twenty hours found by Goeree et al. (2010), who find strong effects of friendship on dictator game contributions.

Comprehension questions tested participants' knowledge about the cross-price derivatives of the seller's probability of buying a specific plot of land (demand) (for additional 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.

3.2 Testing Directed Altruism Theory in Markets with Complements and Substitutes

I estimate the effect of substitute friendships as the mean difference in prices between the Substitutes Symmetric and the Baseline treatment. The effect of complement friendships is estimated analogously. Unless otherwise specified, I implement all estimations in this section with an OLS regression with standard errors clustered at the friendship-pair level.[8]

Empirically, complement friendships lower prices, and substitute friendships increase prices. Figure 5 depicts the estimated causal effect of friendships on prices. The horizontal axis shows the social network treatment, and the vertical axis shows the estimated effect on thaler prices. My analysis deviates from the preregistration by presenting coefficient plots with 95% confidence intervals instead of one-sided t-tests. Compared to the baseline, prices are approximately 2 thalers lower in the complement network and approximately 2.5 thalers higher in the substitute network. At the end of this Section, I interpret these magnitudes in terms of their implied directed altruism parameter (μ). A participant's beliefs about others' prices move in the same direction as the corresponding prices (See Figure 14 in Appendix F).

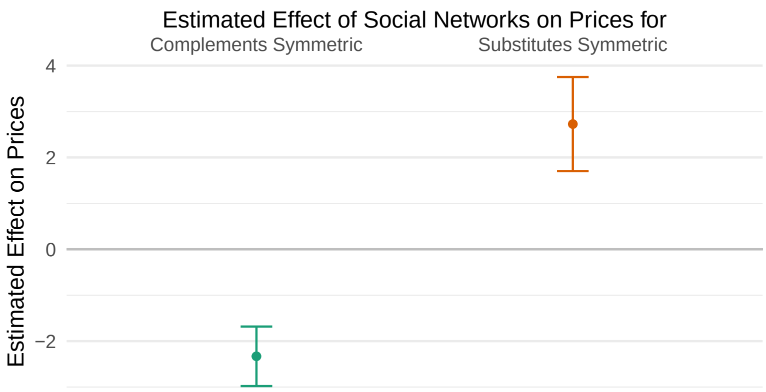
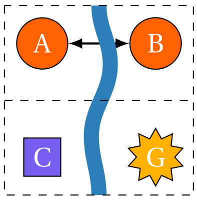


Figure 5: Estimated effects of Complement Symmetric and Substitutes Symmetric networks relative to the Baseline network. Standard errors are clustered at the friendship-pair level. Error bars indicate 95% confidence intervals. Each analysis includes 4800 observations from 240 participants $\times$ 2 networks $\times$ 2 transparency treatments $\times$ 5 subsidy levels.

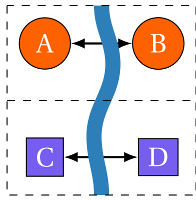
Figure 6 reports the social network treatments used to test for equilibrium spillovers of

8. See Appendix I

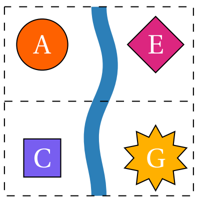
asymmetric friendship. I provide an example for Participant A. I estimate the equilibrium spillover with the change in A's average price when we move from the left to the right column. In each row, participant A's relationship stays the same. However, in the left column, strangers C and G take the two southern spots, whereas in the right column, we replace G with C's friend D. Thus, moving from the left to the right row, A's relationships are balanced, but we introduce a friendship between the two substitutes in the south.



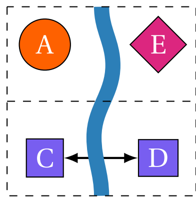
a. Substitutes Asymmetric: Pair



b. Substitutes Symmetric



c. Baseline



d. Substitutes Asymmetric: Isolated

Figure 6: This figure depicts all social network treatments used to test for the equilibrium effects of friendships. The treatment effect estimate of the friendship between C and D on A's price is the average price difference between the networks in the first and second columns.

I report the estimated treatment effects of an asymmetric friendship between sellers of substitutes in Figure 7. As predicted, an asymmetric friendship among sellers of substitutes raises their prices. However, contrary to the prediction, I do not find any evidence for strategic spillovers of that friendship to the other players.

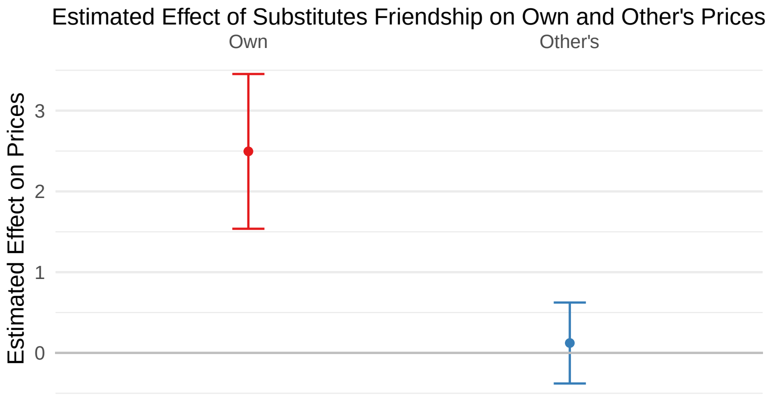


Figure 7: Estimated effects of substitute friendships on own and others' prices in the asymmetric substitutes network. Standard errors are clustered at the friendship-pair level. Error bars indicate 95% confidence intervals. I restrict the analysis to the networks with price transparency since (as preregistered) I did not collect data for asymmetric networks without price transparency. Each analysis includes 4800 observations from 240 participants $\times$ 4 networks $\times$ 1 transparency treatment $\times$ 5 subsidy levels.

I calculate the expected total surplus to investigate the effects of social networks on efficiency. I know the buyer's behavior, because he is played by the computer. Consequently, I can take the expected value over the buyers' actions. I do this for each iteration of the market. Then, I average over all markets. These markets differ in subsidies, transparency conditions, and the players involved. Figure 8 reports the average expected total payoffs by network (social surplus). Table 9 in Appendix N 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 expected total surplus. Since the market is imperfectly competitive (prices are too high), lower prices increase efficiency (ceteris paribus). As shown in Figure 8, markets with the Complements Symmetric network have the highest total surplus, followed by the Baseline. Substitutes Asymmetric, and 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, standard errors clustered at the session level).

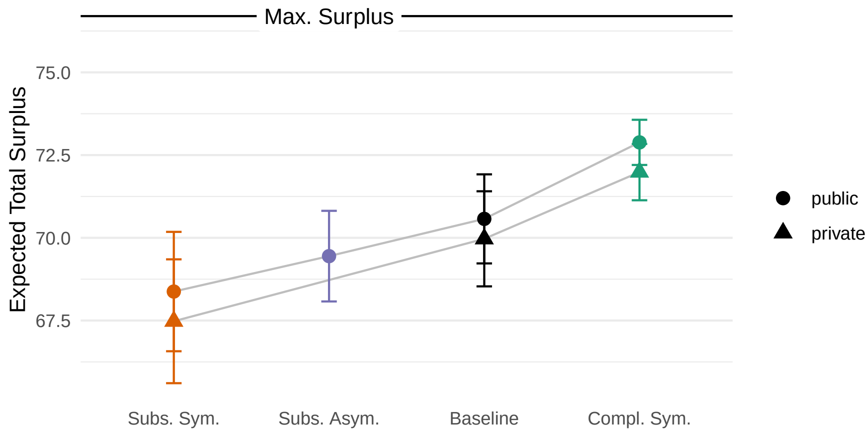


Figure 8: Average expected total surplus for all symmetric social networks. Confidence intervals are 95%. Standard errors are taken from a network-wise linear regression of average prices on a constant, with standard errors clustered by session. Each regression uses 300 observations for 29 sessions. There were 28 sessions with 8 people each and one session with 16 people.

I test the hypothesis that price transparency increases the effects of directed altruism by comparing prices with and without transparency in the Substitutes Symmetric and the Complements Symmetric treatment. Figure 9 shows the difference in prices between the treatments with (public) and without price transparency (private) for the Complements Symmetric, Substitutes Symmetric, and Baseline networks. According to my hypothesis, price transparency should increase the effects of friendship. Therefore, it should raise prices for the Substitutes Symmetric network, lower prices for the Complements Symmetric network, and leave the Baseline network unaffected. Contrary to my hypothesis, price transparency lowers prices in all networks. Figure 15 in Appendix F shows that price transparency affects beliefs like it affects the underlying prices.

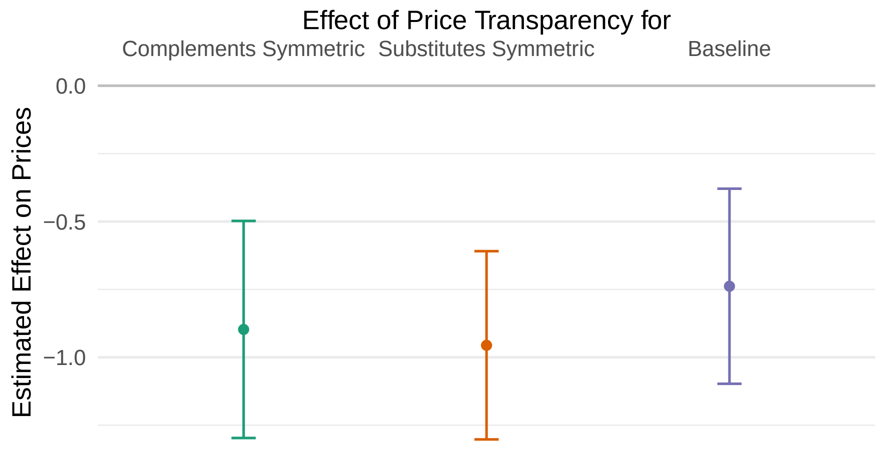


Figure 9: Estimated effects of price transparency on prices in the Complements Symmetric and Substitutes Symmetric treatments. Standard errors are clustered by friendship pair. Error bars indicate 95% confidence intervals. Each regression includes 2400 observations in 120 clusters.

3.3 An Alternative Theory: Friendship and Belief Accuracy

Friends are more familiar with each other, which could lead them to have more accurate beliefs about each other and might affect their behavior in the 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 knew how their friend "ticks", which might affect their behavior. After the experiment, I asked a subset of participants (not preregistered) if they agreed with the following statement "I am a better at predicting what 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 the accuracy of beliefs about 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. To facilitate interpretation, I divide by the maximum possible deviation (50^2) to normalize the values from 0 (lowest deviation/highest accuracy) to 1 (highest deviation/lowest accuracy).[9]

I test whether beliefs are more accurate for friends than strangers by regressing this

9. This normalization merely changes the scale of the coefficients in the subsequent estimation. It has no substantive consequences.

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 1 for beliefs about the prices of other participants, who sell complements to the person who believes, and 0 for beliefs about the prices of participants who sell substitutes. The friendship dummy is 1 if the person having the belief is friends with the person about whom they have the belief. I cluster standard errors at the friendship-pair level for the believers.

Participants' beliefs about friends are not significantly more accurate than those about strangers. Row one of Table 2 reports the result of the preregistered specification. The coefficient of the friendships dummy is nonsignificant and small.

Rows two and three report exploratory (not preregistered) analyses to explore the robustness of this finding. 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 about strangers (better beliefs dummy) do not have significantly more accurate beliefs about their friends than about strangers.

I also tested the behavioral consequences of this theory. If participants know something about their friend's actions, they should adjust their choices based on that knowledge. This adjustment should lead to a correlation between friends' choices. The analysis reported in Appendix H does not find any evidence of such a correlation.

Table 2: Do participants have more accurate beliefs about friends? Regressions of belief accuracy on a friendship dummy an additional controls. All regression controll for treatment dummies and a dummy that indicates if the belief is about a person selling a complement.

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

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

3.4 A Structural Model of Directed Altruism in Markets with Complements and Substitutes

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

To obtain accurate estimates of the directed altruism parameter (μ), I amend the model from Section 1 with joy of winning, decision error, and social image concerns. My data differ in two ways from the risk-neutral Nash Equilibrium predictions outlined in that section. First, prices are uniformly lower than predicted. This pattern is common in auction experiments (John H Kagel 1995; Kagel and Levin 2016). I model this pattern by adding a constant joy of winning (α) to the utility function. Second, price transparency uniformly lowers prices. I model this effect of price transparency (social image concerns) with a "tax" (ρ) on high prices in the public treatment. These two modifications model features of the data that are not the focus of this paper to avoid confounding the estimates of the main parameter.

I denote the subsidy by S, the transparency treatment by O and the social network treatment by D. I write the adjacency matrix as a function of D ($\boldsymbol{M}(D)$) to indicate that it depends on the social network treatment. I let the directed altruism parameter depend on the transparency condition ($\mu(O)$) to capture that social sanctions may intensify altruism between friends.

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

Player 1's material utility is given by

$$m_1(p_1, p_2, p_3, p_4, S, \gamma) = Pr_\ell(p_1, p_2, p_3, p_4)(\alpha + S + p_1). \tag{1}$$

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

$$\underbrace{\begin{bmatrix} U_1(p_1,p_2,p_3,p_4,S,D,O,\gamma) \\ U_2(p_1,p_2,p_3,p_4,S,D,O,\gamma) \\ U_3(p_1,p_2,p_3,p_4,S,D,O,\gamma) \\ U_4(p_1,p_2,p_3,p_4,S,D,O,\gamma) \end{bmatrix}}_{\text{expected utilities}} = \underbrace{\begin{bmatrix} m_1(.) \\ m_2(.) \\ m_3(.) \\ m_4(.) \end{bmatrix}}_{\text{own payoff}} \underbrace{+\mu(O) \cdot \boldsymbol{M}(D) \cdot \begin{bmatrix} m_1(.) \\ m_2(.) \\ m_3(.) \\ m_4(.) \end{bmatrix}}_{\text{altruism term}} \underbrace{-\mathbb{1}(O = public) \cdot \rho \cdot \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix}}_{\text{tax on high prices}}. \tag{2}$$

I model the heterogeneity in participant choices with a quantal response equilibrium (QRE; McKelvey and Palfrey (1995)). QRE generalizes discrete-choice, random-utility models to games. I use the parameterized model Logit-QRE, where best responses take a logit form. The parameter λ captures the relative size of material payoffs and noise. Higher values of λ lower the noise. If incentives decrease, decisions become noisier.

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

$$\sigma_1(p_1,S,D,O,\gamma) = \frac{exp(\lambda\mathbb{E}_{p_2,p_3,p_4}[U_1(p_1,p_2,p_3,p_4,S,D,O,\gamma)])}{\Sigma_{p_1'\in\mathbb{P}} exp(\lambda\mathbb{E}_{p_2,p_3,p_4}[U_1(p_1',p_2,p_3,p_4,S,D,O,\gamma)])} \tag{3}$$

$$\mathbb{E}_{p_2,p_3,p_4}[U_1(p_1,p_2,p_3,p_4,S,D,O,\gamma)] = \tag{4}$$

$$\sum_{p_2\in\mathbb{P}}\sum_{p_3\in\mathbb{P}}\sum_{p_4\in\mathbb{P}} \sigma_2(p_2,S,D,O,\gamma)\sigma_3(p_3,S,D,O,\gamma)\sigma_4(p_4,S,D,O,\gamma)U_1(p_1,p_2,p_3,p_4,S,D,O,\gamma). \tag{5}$$

The probabilities for the other players are analogous.

I estimate the model by quasi-maximum likelihood. Due to computational constraints, I use the Bajari and Hortaçsu (2005) method and substitute the observed choice distributions for the equilibrium beliefs. I adjust the maximum likelihood standard errors for clustering with the Huber–White sandwich estimator as implemented in Zeileis (2006). For more details on the estimation, see Appendix J.

Table 3 lists the estimated parameters with 95% confidence intervals. Directed altruism in the private condition ($\mu(private)$) is between 0.2 and 0.36. This parameter implies that a participant will pay approximately 30 cents to give one dollar to her friend. Directed altruism does not significantly differ between public and private treatments. Social image concerns impose a tax of 4% on prices in the public treatment. This value is small but significant, in line with the small treatment effects of price transparency.

Table 3: Parameter estimates for the QRE-Directed-Altruism model.

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

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

I plot the fitted model alongside the data to determine whether directed altruism can rationalize behavior in the experiment. Figure 10 shows the treatment effects of the symmetric networks compared to the Baseline network. I reproduce the empirical treatment effect estimates from Figure 5 (Main Effect) with yellow triangles labeled “Data.” I conduct the same analysis used to derive 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.

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 difference between the transparency and private conditions. 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.

If friendship is the primary channel behind directed altruism, closer friends will exhibit

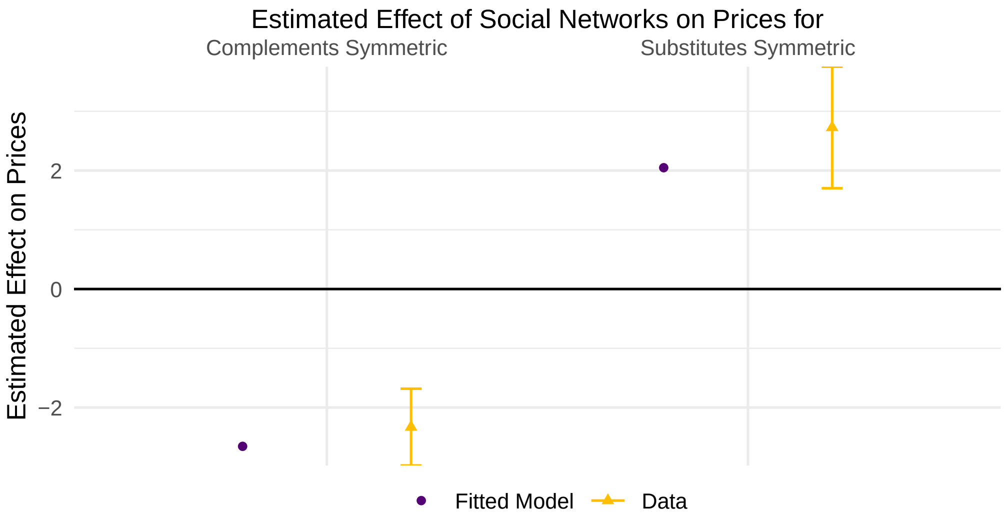


Figure 10: This figure shows the estimated treatment effects predicted by the fitted structural model and the reduced-form treatment effect estimates, along with 95% confidence intervals calculated using standard errors clustered at the friendship-pair level. The estimated treatment effects are drawn from the main analysis, which is reported in Figure 5.

higher directed altruism parameters. To test this, 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. Refer to Appendix K for additional details.

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. Since baseline altruism does not affect a participant's behavior, the underlying parameter is difficult to estimate. Appendix M 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.

4 Discussion

I find two deviations from the predictions developed in Section 1. These deviations suggest avenues for further research and how the basic model could be amended.

I do not find evidence for equilibrium spillovers of friendships between two people on other people's strategies. This lack of equilibrium effects is likely due to biased beliefs and decision errors. I estimate how participants' beliefs change when introducing an asymmetric friendship (see Appendix L). The analysis reveals that participants fail to forecast the effect of a social network link if they do not experience an analogous link themselves. Furthermore, I compare the estimated spillovers of an asymmetric friendship to those predicted by the fitted QRE model. I find that the 95% confidence interval of the estimated spillover narrowly excludes the predicted spillover. Further research should investigate whether experience reduces this underreaction to other people's friendships.

The data and the estimated structural model suggest that price transparency does not increase cooperativeness between friends but reduces prices uniformly. This price reduction could be due to increased social image concerns: Participants care how they appear to their friends and strangers and reduce their prices because high prices seem greedy. This theory aligns with the participants' free text answers to an open question about the topic (See Appendix G).

This broader social image concern is not detectable in previous two-person experiments on friendship, directed altruism, and social collateral (Leider et al. 2009). Leider et al. use transparency in a dictator game to cleanly separate directed altruism and social collateral. My results highlight that in a four-player game, the effects of price transparency are less clear. Therefore, more research is needed in this direction before we can employ price transparency as a policy tool.

5 Conclusion

While the preceding section highlights the boundaries of directed altruism theory, the theory performs well overall. The main prediction of directed altruism theory holds in the data: Complement friendships decrease prices and increase efficiency, while substitute friendships do the opposite. Furthermore, we do not find evidence for the most likely alternative theory of increased belief accuracy. Finally, a simple structural model of directed altruism fits the data well and captures the effects of different symmetric networks in a single, homogeneous directed altruism parameter. Overall, the experimental results recommend the model as the primary candidate for modeling the effect of social relationships on prices.

One setting in which the directed altruism model of social relationships in markets could be beneficial is the interaction between social relationships and firms with common ownership. This experiment indicates that the same preferences can describe friendships in markets as firms with common owners. This similarity suggests a way for shareholders to implement common ownership preferences: Replicate the ownership network in terms of the social network of top managers. 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 she can sell. Real-world firms have a more complex organizational structure. Directed altruism at the level of individual decision-makers is embedded in this structure. To understand the firm-level impact of linear, directed altruism preferences, we must understand the interplay between these preferences and corporate governance. How can individual-level directed altruism translate to firm-level common ownership preferences?

The experiment suggests that markets for the assembly of complements can be more efficient when there are complement friendships. Therefore, markets with complement friendships might need less government intervention.

Furthermore, market designers want to emphasize social networks when there are complement friendships. They can achieve that goal by reducing anonymity and using mechanisms that retain externalities between participants instead of reducing them like Bierbrauer et al. (2017).

One example of markets with complement friendships is land markets with geographic, social networks (Ambrus, Mobius, and Szeidl 2014). 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.

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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

$$\Pr_\ell(p_1, p_2, p_3, p_4) = \int_0^1 \int_0^1 \mathbb{1}(\theta_\ell - p_\ell > \theta_r - p_r)\mathbb{1}(\theta_\ell - p_\ell > 0) f(\theta_r) f(\theta_\ell) d\theta_\ell d\theta_r \tag{6}$$

$$= \begin{cases} (1 - p_\ell) - 0.5(1 - p_r)^2 & \text{if } p_\ell \leq p_r \\ (1 - p_\ell) \cdot p_r + 0.5(1 - p_\ell)^2 & if\ p_r < p_\ell \end{cases}. \tag{7}$$

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 7 into the second-order condition, we obtain

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

and

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

which is true and implies that player 1's utility function is strictly concave in p_1. Since the first-order conditions are linear in the 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:

$$g(p_s,\mu):=\frac{\partial Pr_\ell(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)+\Pr_\ell(p_s,p_s,p_s,p_s)+\mu\frac{\partial \Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S)=0 \tag{8}$$

$$\Leftrightarrow g(p_s,\mu)=-(p_s+S)+(1-2p_s)-0.5(1-2p_s)^2+\mu(1-2p_s)(p_s+S)=0 \tag{9}$$

.

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 first-order condition 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 7 into the second-order condition, we obtain

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

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

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

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 the 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:

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

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

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 first-order condition has an interior solution by the intermediate value theorem. Checking ($\frac{\partial i(p_c,\mu)}{\partial p_c} = -3-\mu-p_c < 0$ 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 Baseline 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:

$$\frac{\partial \Pr_\ell(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S) + \Pr_\ell(p_s,p_s,p_s,p_s) + \mu\frac{\partial \Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S) = 0 \tag{12}$$

$$\frac{\partial \Pr_\ell(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+S) + \Pr_\ell(p_c,p_c,p_c,p_c) + \mu\frac{\partial \Pr_\ell(p_c,p_c,p_c,p_c)}{\partial p_1}(p_c+S) = 0 \tag{13}$$

$$\frac{\partial \Pr_\ell(p_b,p_b,p_b,p_b)}{\partial p_1}(p_b+S) + \Pr_\ell(p_b,p_b,p_b,p_b) = 0. \tag{14}$$

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

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

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

Taking the difference between Equations 12 and 14 and rearranging yields:

$$h(p_b) - h(p_s) = \mu\frac{\partial \Pr_r(p_s,p_s,p_s,p_s)}{\partial p_1}(p_s+S) > 0 \tag{15}$$

$$\leftrightarrow h(p_b) > h(p_s) \Leftrightarrow p_s > p_b. \tag{16}$$

Taking the difference between Equations 13 and 14 and rearranging yields:

$$h(p_b) - h(p_c) = \mu \frac{\partial \Pr_\ell(p_c, p_c, p_c, p_c)}{\partial p_1}(p_c + S) < 0 \tag{17}$$

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

□

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 $p_{isol} := p_1 = p_3$ and $p_{pair} := p_2 = p_4$. 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,

$$p^*_{isol} = BR_{isol}(p^*_{pair}) \tag{19}$$

$$p^*_{pair} = BR_{pair}(p^*_{isol}). \tag{20}$$

Equations 22 and 23 define the the best-response functions BR_{pair} and BR_{isol} as the solution to the player's first order conditions under symmetry. Since players 1 and 3 are friends, their objective function is identical to the objective function in the Substitutes Symmetric case. Players 2 and 4 are strangers, so their objective function is identical to that 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 combines the best responses from the Substitutes Symmetric and Baseline games.

$$
\begin{aligned}
&MU_{pair}(BR_{pair}(x), x) := && (21)\\
&\frac{\partial \Pr_\ell(BR_{pair}(x), x, BR_{pair}(x), x)}{\partial p_1} \cdot (BR_{pair}(x) + S) + \Pr_\ell(BR_{pair}(x), x, BR_{pair}(x), x)\\
&+ \mu \frac{\partial \Pr_r(BR_{pair}(x), x, BR_{pair}(x), x)}{\partial p_1} \cdot (BR_{pair}(x) + S) = 0,\\
&MU_{isol}(y, BR_{isol}(y)) := && (22)\\
&\frac{\partial \Pr_\ell(y, BR_{isol}(y), y, BR_{isol}(y))}{\partial p_2} \cdot (BR_{isol}(y) + S) + \Pr_\ell(y, BR_{isol}(y), y, BR_{isol}(y)) = 0.
\end{aligned}
$$

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

$$
\begin{aligned}
y &= BR_{pair}(x),\\
x &= BR^{-1}_{pair}(y),\\
p^*_s &= x = y.
\end{aligned}
$$

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^{-1}_{pair}. 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 $S < 1$ and $\mu < 1$. For the isolated participants we have,

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

Consequently, both marginal utilities are (globally) once 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, and the best responses, evaluated at symmetry, exist and are once continuously differentiable with derivatives

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

That is, they are decreasing.

Figure 11 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 indicates 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 players 2 and 4 (dotted red line) indicates the Substitutes Asymmetric equilibrium point. 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 Symmetric as a rightward shift of best responses. Define

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

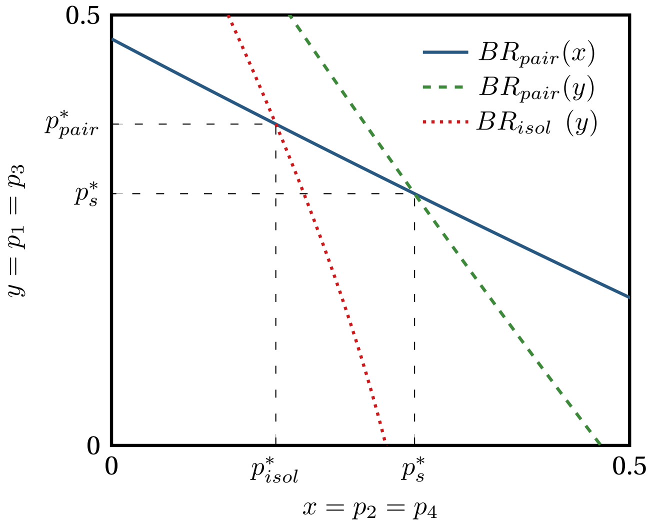


Figure 11: Aggregate best-response functions for the Substitutes Asymmetric (couple and separate) and the Substitutes Symmetric Treatment. Parameters are set at $\mu = 0.8$ and $S = 0.2$.

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 obtain $\frac{\partial h(a,b)}{\partial a} = -1 - a - b < 0$. Therefore, h falls in a.

We use h and Equations 22 and 23 to rewrite the first-order conditions as follows:

$$h(BR_{pair}(y), y) + \mu \frac{\partial Pr_r(BR_{pair}(y), y, BR_{pair}(y), y)}{\partial p_1} \cdot (BR_{pair}(y) + S) = 0 \tag{23}$$

$$h(BR_{isol}(y), y) = 0. \tag{24}$$

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 $BR^{-1}_{isol}(0) > BR_{pair}(0)$, which is the case if

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

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

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

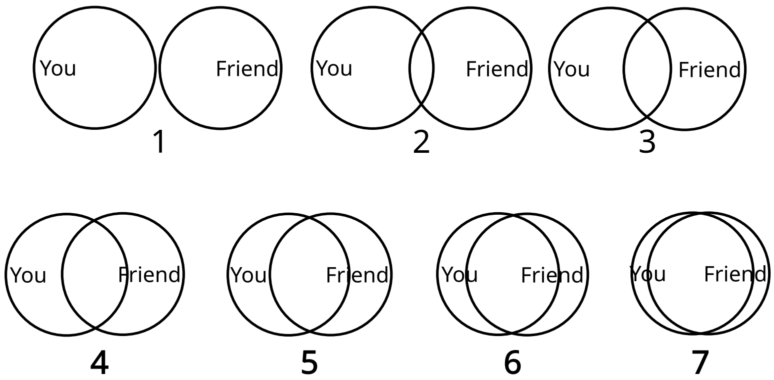
I asked the following survey questions. I present possible answers in square brackets.

- 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][10]

- 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"]

I summarize the answers to the friendship part of the survey in Table 4.

Table 4: Summary of answers to the introductory survey.

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

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

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 12).

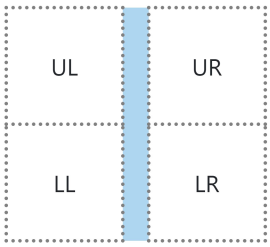


Figure 12: Map that I showed before each batch of comprehension questions.

D Ruling Out Minimal Group and Order Effects

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

To balance minimal group effects, I conducted the experiment using two conditions: a building condition and a bridge condition. The building condition works as described previously. In contrast, 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.[11] I randomized the transparency treatment order and the order of subsidies within each social network treatment.[12] I attempted to balance the bridge and building conditions across treatment orders.[13]

E Explanation of Social Network Treatment

Figure 13: 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.

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

12. 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 forth.

13. I ran 15 sessions in the bridge and 15 sessions 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 preregistration (by accident).

F Beliefs

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 were 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 that 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).

Figures 14 and 15 revisit analyses from Section 3, 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.

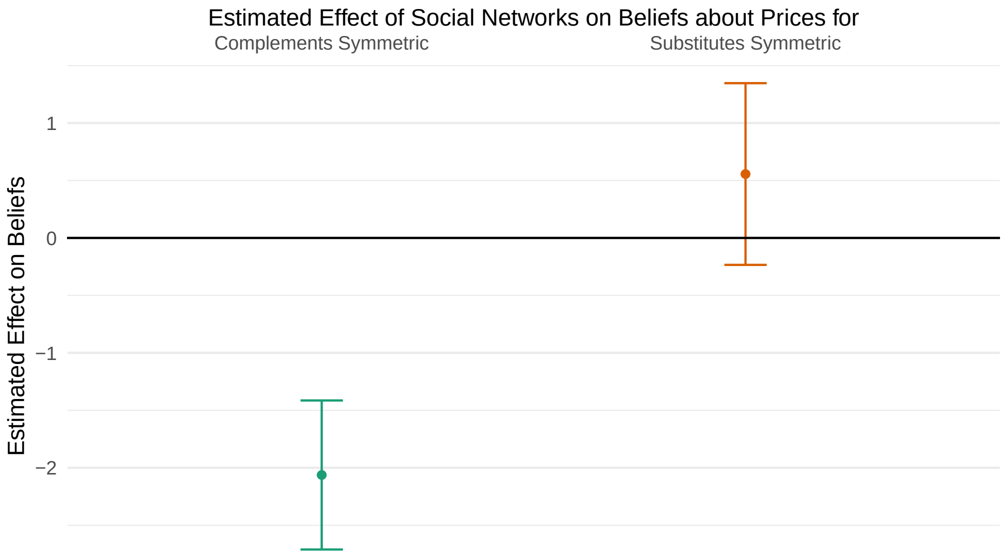


Figure 14: Estimated effect of complement and substitute friendships on beliefs about others' prices. Standard errors are clustered at the friendship-pair level. This figure is analogous to Figure 5.

Figure 15: 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 9.

G Open Question Price Transparency

Figure 16 displays the open question that I asked about the price transparency treatment for the Substitutes Symmetric network. The remainder of this section indicates the answers to this question for the subset of participants that lowered their prices.

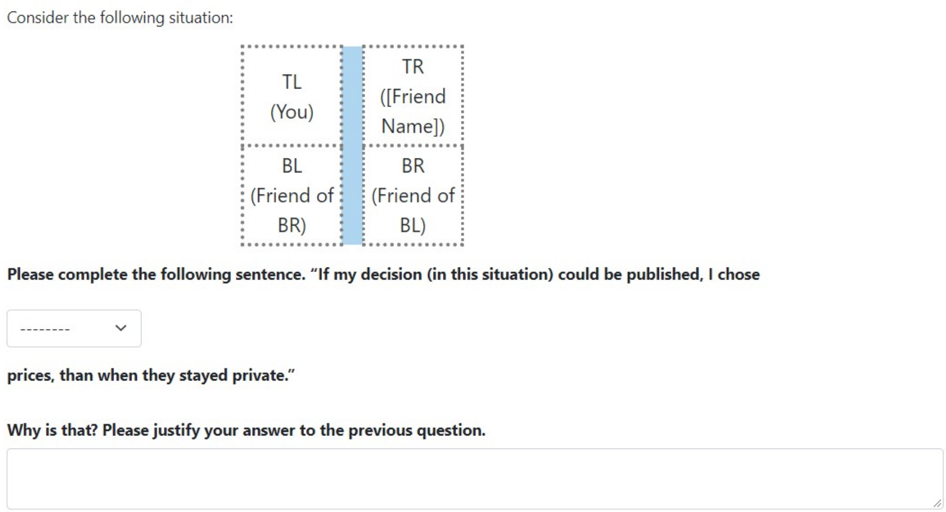


Figure 16: Open question regarding price transparency in the substitutes treatment (translated from German).

“I think in this situation, I could have created 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 do 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 made 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 had 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 at 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 faulted afterwards if a purchase does not take place."

"I didn't want to overestimate my prices when other participants see that. "

H Correlation Between Prices

Suppose that friends have more accurate beliefs about each other's prices than strangers. In that case, their strategies should be positively correlated when selling substitutes and negatively correlated when selling complements. Prices of substitutes are strategic complements, and prices of complements are strategic substitutes. Suppose that my friend sells a substitute and I know he is more likely to ask for a high price than a generic stranger. In that case, because of strategic complementarity, I will ask for a high price as well. The same holds for low prices. This interaction leads to a positive correlation between prices of substitutes. An analogous argument with the opposite sign holds for prices of complements. In equilibrium, the effect might be magnified for substitutes and and attenuated for complements.

I test for the correlation between friends' prices by regressing a person's price on her 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 her answer to the general risk question [14]. I cluster standard errors at the friendship-pair level.

Table 5: Estimated relationship between friends' prices.

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

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

14. This is a nonincentivized question from Falk et al. (2023): "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 with answers on an incentivized lottery choice task (Dohmen et al. 2011) I add a separate dummy for each possible answer to this question.

I Estimation Framework

Treatment effects are estimated as simple differences in means. To estimate clustered standard errors, I use ordinary least squares to regress the price ($p_{i,D,O,S}$) on a treatment indicator (T) and a constant:

$$p_{i,D,O,S} = \alpha + \beta \cdot T + \epsilon_{i,D,O,S}. \tag{25}$$

The treatment indicator (T) and the sample vary across analyses. I index individuals by i, social network treatments by D (Baseline, Substitutes Symmetric, Complements Symmetric, Substitutes Asym. Separate, Substitutes Asym. Couple), the transparency condition by $O = \{public, private\}$, and subsidies by $S \in \{0, 5, 10, 15, 20\}$. Unless specified otherwise, I pool data from both the "public" and "private" treatments and always pool data from different subsidy levels. I cluster standard errors at the friendship-pair level. I implement the estimation with the lfe package (Gaure 2024).

J Structural Estimation Details

I estimate the model by maximum likelihood and introduce some additional notation to state the likelihood function. Observations are indexed by $j \in \{1, ..., N\}$. The price of player 1 in observation j is p_{1j}. Treatments 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 method from structural auction models to avoid this. Equation 3 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 replace $\sigma_2(p_2, S_j, D_j, O_j, \gamma)$ with the empirical frequency that a player plays p_2 when the subsidy is S_j for social network treatment D_j and transparency condition O_j.

I maximize the log-likelihood function,

$$LLH(\gamma) = \Sigma_{j=1}^{N} \log(\sigma_1(p_{1j}, S_j, D_j, O_j, \gamma)), \tag{26}$$

with respect to the parameter vector γ.

K 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 do so less when selling substitutes. In my model, 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 into 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 whether this question had 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.

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 $\times$ Friendship Closeness Index" should be negative and the coefficient

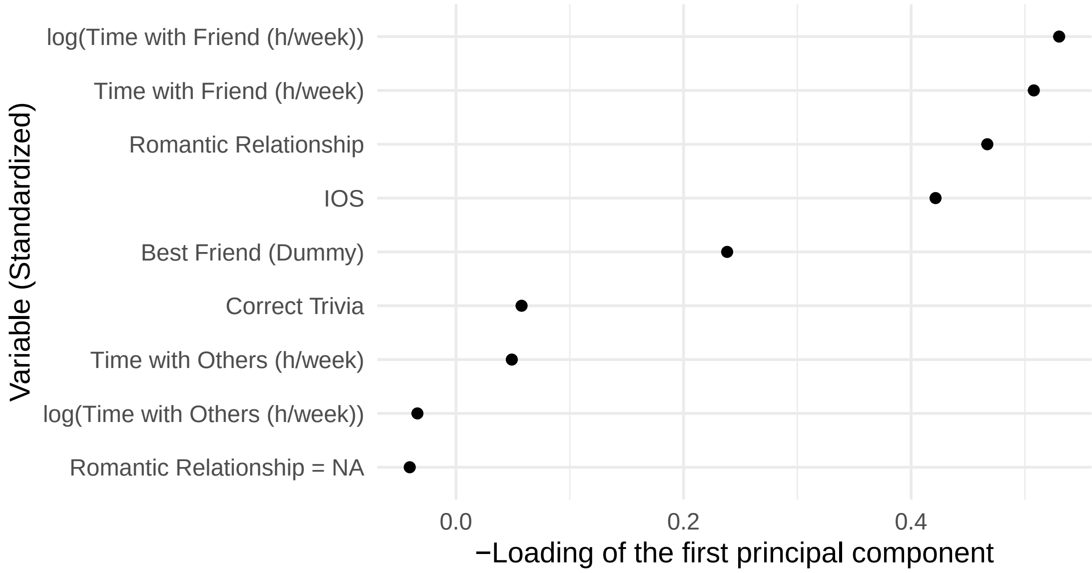


Figure 17: Factor loadings of the first principal components of friendship measures. All factor loadings are multiplied by -1, because I use -1 times the first principal component to measure friendship strength.

of "Substitutes × Friendship Closeness Index" should be positive. These coefficients have the expected sign, but they are not significantly different from zero. This is because I am making a between-subject comparison in an experiment that is powered to detect a within-subject treatment effect. I can increase power by requiring that friendship closeness should act similarly in the Complements and Substitutes networks but in different directions. I do this with the help of a structural model.

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,

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

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

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

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

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

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

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

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

L Mechanisms Behind the Lack of Equilibrium Spillover of Friendships

This section explores two mechanisms behind the lack of equilibrium spillovers of friendships: decision error and biased beliefs. The data are relatively unlikely to be explained purely by decision error and participants have biased beliefs that could explain the lack of equilibrium spillover.

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 6. Then, I calculate the noise best response by plugging them into Equation 3 (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. This results in a predicted spillover effect of -0.4.

QRE-style decision error might explain part, but likely not all, of the lack of equilibrium spillovers of friendship. The predicted treatment effect of -0.4 is narrowly outside of the 95% confidence interval of the observed effect. However this prediction ignores estimation error in the QRE parameters. The actual decision error might be larger than estimated. However that would also imply estimates that are closer to the middle of the strategy space, which is something that we do not observe.

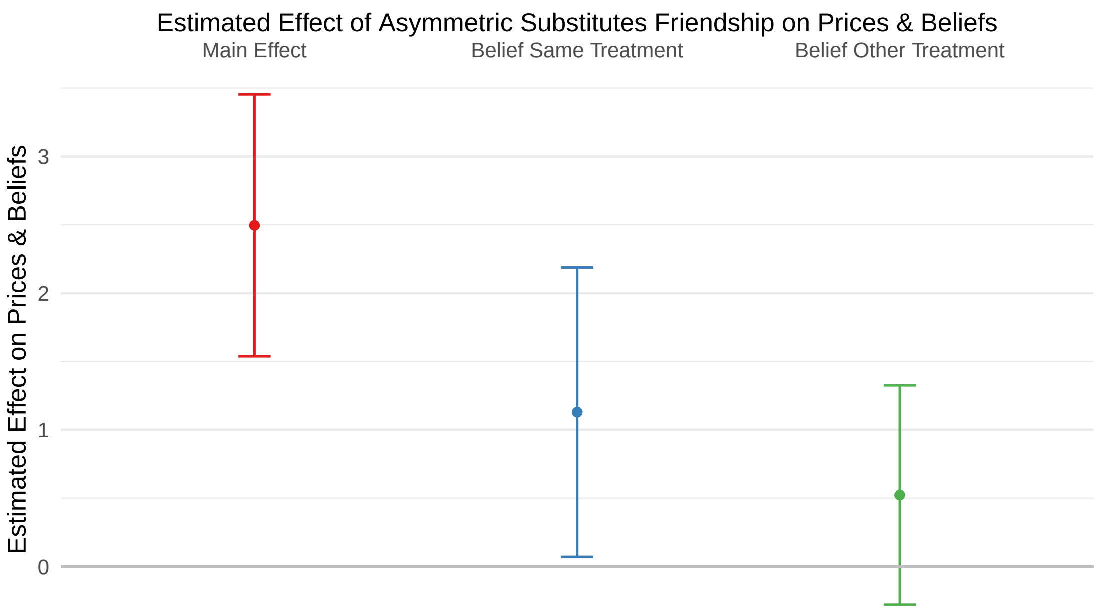


Figure 18: Main effect of an asymmetric link among sellers of substitutes, including corresponding first-order beliefs. Beliefs are categorized by individuals who are treated as well, interacting with a friend posttreatment but not pretreatment, and those who are not.

Having examined decision error under the assumption of correct beliefs, we can also test that assumption. Figure 18 reports the effect of a substitute friendship on friends, the belief of one participant that is affected by the friendship on how it affects the other friendship and the belief of the other two participants about this effect while their treatment status stays the same. People that are affected by the friendship underestimate its effect on others. However, people who are not affected do so even more. These are exactly the people that should exhibit the spillover. Consequently, the lack of spillovers is partly due to biased beliefs. One possible source of bias is that it is easier for participants to forecast the reaction of others to a change when they experience it themselves.

M 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 difficult to disentangle the two.

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

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

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

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

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

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

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

N 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