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BROKERAGE

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Brokerage*

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Abstract

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1 Introduction

Intermediaries are a prominent feature of the modern economy: they are a defining feature of banking, retail, and information services. At a high level, an intermediary may be seen as facilitating valuable exchanges between economic actors. So intermediaries may be seen as lowering costs of exchange or reducing frictions inherent in an economic transaction. The intermediation role has a reinforcing aspect: the more actors use an intermediary, the more attractive it becomes for other actors to use. This economic pressure gives rise to highly visible globally dominant intermediaries, who acquire great market power and earn enormous revenues. The goal of the present paper is to better understand the mechanisms underlying the emergence of such dominant intermediaries.

Networks represent a natural way to reason about the process of intermediation. Trades between two actors can be realized if they have a direct link or if they are indirectly linked through a chain of intermediaries.[1] The key point to bear in mind is that these links are costly to maintain. For concreteness, consider a network with n actors in which all pairs are linked (the complete network). In this setting, every bilateral exchange involves direct trading: there is no intermediation. However, there are $n(n-1)/2$ links formed. By contrast, consider the hub-spoke network: in this setting all the exchanges involving pairs of spokes – i.e., $(n-1)(n-2)/2$ pairs – entail intermediation (and possibly large rents for the hub). This is accompanied by a large saving in costs of links, as the hub-spoke network contains only $n-1$ links.[2] More generally, a network may be sparse and connected without concentration of intermediation power. An instance of such a network is a cycle containing all actors: in this setting, there are only n links and as everyone is symmetrically located, every actor will earn an equal payoff. So the cycle reconciles efficiency and equity. The goal of the paper is to examine circumstances that give rise to hub-spoke networks as against sparse networks with one or more cycles.

The paper considers a network formation model taken from Goyal and Vega-Redondo [2007]: individuals choose to form links with each other and then use the network constructed to engage in exchange. If an actor maintains links with many others, she incurs large linking costs but she will be able to appropriate a fair share of the surplus generated by the exchanges. If on the other hand she maintains few links then her linking costs will be

[1] The links may embody trust relations, reflect communication channels, or simply reflect physical infrastructure (such as train, road or shipping services).

[2] This is the minimum number of links needed to connect n actors.

modest, but she will either not undertake many exchanges (as she has no path connecting her to several traders) or she will conduct her exchange with the help of intermediaries. Over and above this, this environment gives rise to an intermediation incentive: an actor may wish to strategically form links with others with a view to extracting rents by acting as an intermediary for trades between other actors. Goyal and Vega-Redondo [2007] propose that surplus generated by exchange between two traders is split equally between these two traders and the set of 'critical traders': a trader A is critical for traders B and C in a network if she lies on all paths between the pair. With this allocation rule, they show that a wide range of networks can be strategically stable: this includes the hub-spoke network and the cycle network. The complete network is never stable with this allocation rule.

One feature of this surplus allocation rule is that trade can take place along arbitrarily long paths even when shorter paths are available, and that too without any costs. However, if costs are similar, it is easy to see that a small friction arising out of distance would make a large difference in the flow of trade. Following Kleinberg et al. [2008] and Galeotti and Goyal [2014] consider an alternative allocation rule where surplus of a bilateral exchange is distributed equally between the two traders and the intermediaries that lie on the shortest paths between them. This gives rise to intermediation rents in proportion to the betweenness centrality of traders. With this allocation rule, a wide range of networks – such as the hub-spoke network and the complete network – are stable. The cycle, however, is not stable. These observation set the stage for an experimental investigation of intermediation and network formation.

In a real world setting, groups are often very large and individuals choose linking at different points in time. The individual decision problem is complicated because the attractiveness of links depends on the overall structure of links. As group size grows, these informational requirements become more demanding. So it is quite unclear if subjects will follow the predictions of a static model. The work of Friedman and Aprea [2012], and Choi et al. [2019], suggests that continuous time experiments offer subjects more opportunities for choice and for learning and that they may offer better prospects for convergence to equilibrium than discrete time experiments. Our paper builds on this insight.

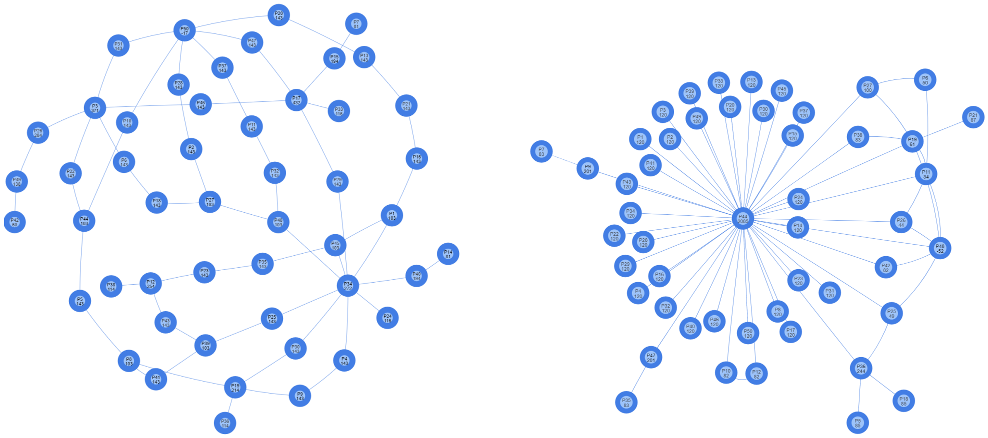
A large-scale continuous-time experiment on network formation generates a great deal of information that is in principle relevant for decision making. To help subjects navigate this environment, we develop a new experimental platform. This platform includes a network visualization tool that uses the Barnes-Hut approximation algorithm (Barnes and Hut [1986]). This algorithm allocates nodes and edges in a two-dimensional space to improve visual clarity of network presentation. This tool for network visualization is integrated with the interactive tool of dynamic choices. This feature allows individuals to form and remove links and change effort levels instantly. The integration enables us to update rapidly evolving networks in real time on the computer screen.

The paper considers a design with three alternative allocation rules for intermediation rents; the two rules discussed above and an additional rule that is close to the betweenness centrality allocation rule but imposes the restriction of trade taking place within a certain distance. Different allocation rules generate different incentives for individual linking activities and result in different predictions on pairwise stable networks. However, the multiplicity of pairwise stable networks makes it difficult to predict the role of allocation rules in the emergence of networks. We use the experiment as a complement to the theory to predict empirically salient outcomes. There are four distinct groups of 50 subjects, each of whom play 6 rounds. In each round, the linking game is played over 6 minutes. The experiment involves groups of 50 subjects in a controlled laboratory environment.

Figures 1a presents snap shot of the network that emerges under criticality. The network is sparse and trades take place along long cycles. The network is connected and sparse: subjects realize almost 90% of all possible surplus. And there exist a few critical nodes with limited power: the payoffs are very equal. In contrast, Figure 1b reveals a very different network that emerges under betweenness allocation rule. We observe a network that closely approximates a hub-spoke structure. The network is sparse and connected: consequently it attains high efficiency. However, the 'hub' earns more than 12 times the median payoff. The analysis of the data reveals that these patterns are robust across the rounds and the groups.

Our experiment shows that differences in the allocation rules give rise to very different networks: linking is quite dispersed under criticality, whereas network centralization is prominent in the other two treatments. As a result, trades take place in longer distance in the criticality treatment. There emerges a main broker in the betweenness treatments who involves in trading for many pairs of traders.

The emergence of different networks has large implications in inequality. Payoffs are equally distributed among subjects in the criticality treatment but are highly unequal in the other two treatments. The individual earning the highest payoff in these treatment turns out to be the main broker in the network who earn a huge amount of intermediation rents. Therefore, the main source of payoff inequality is the unequal distribution of brokerage rents among individuals.



(a) Criticality pricing (b) Betweenness pricing

Figure 1: Network Outcomes (at minute 6)

In order to examine the forces of driving the emergence of different networks across the allocation rules, we look into subjects' myopic incentives that show changes of payoffs from creating or deleting a link from a given network. Under the criticality-based allocation rule, once the network is connected, individuals can benefit by adding new links whenever they have less than 2 links, and by deleting links whenever they have more than 2 links. In other words, they are incentivized to maintain only 2 links, necessary to create cycles and avoid paying rents to intermediaries. They also have no incentive to directly connect with a critical intermediary.

On the other hand, under the betweenness-based allocation rules, subjects' incentives are more subtle. We find that subjects initially form many links as a means to maximize their access to trades (by reducing path lengths with other nodes). Once the network is connected however, they have a strong incentive to form a link with the subject extracting the highest brokerage rent while deleting any links with others. In the meantime, the main broker has an incentive to form new links with others. This allows for the emergence of a hub-spoke structure.

Our paper is a contribution to the study of intermediation. One strand of the existing work examines pricing by intermediaries, their ability to reduce frictions, and thereby extract surpluses. For an early model, see [Rubinstein and Wolinsky, 1987]; for more recent work see [Condorelli et al., 2016],Choi, Galeotti, and Goyal [2017], and Manea

[2018]. Condorelli and Galeotti [2016] provide a survey of this work.[3] Another strand of work examines how market power emerges through the deliberate creation of links in a network formation setting: in addition to Goyal and Vega-Redondo [2007], Kleinberg et al. [2008] and Buskens and Van de Rijt [2008], recent contributions include Farboodi [2014] and Kotowski and Leister [2018]. Dominant intermediaries are a defining feature of the modern economy. The present paper presents robust experimental evidence for the rise of such dominant players and the very large inequality they generate. The strikingly different outcomes under criticality and betweenness based pricing draw attention to the role of economic incentives in explaining how such dominance comes about.

These findings on inequality are intimately related to major themes in the behavioral and experimental economics literature. A prominent strand of work argues for the role of inequality aversion in shaping human behavior in economic interaction. Prominent contributions include [Fehr and Schmidt, 1999, Bolton and Ockenfels, 2000] and [Kosfeld et al., 2009]. In the context of networks, Falk and Kosfeld [2012] and Goeree et al. [2009] argue that inequality aversion explains why experimental subjects do not create the hub-spoke predicted by the theory. In our setting, networks with dominant hubs arise and there is great inequality. How can we reconcile our findings with these earlier findings? We show that, somewhat surprisingly, the large inequality in our experiment is consistent with inequity aversion [Fehr and Schmidt, 1999, Bolton and Ockenfels, 2000]. Indeed, models based on average payoff differences are tolerant to large inequalities between a few wealthy individuals and others in a large population.[4] For example, take a population of n individuals where everyone earns x except for one person earning $10x$. While an inequality averse individual may strongly disapprove of the large disadvantageous payoff difference between themselves and the wealthiest person ($10x - x$ is large), the same individual would be more tolerant of the average inequality in the context of the entire group ($\frac{10x-x}{n-1}$ is small for some large n). In other words, the aversion to isolated inequalities is diluted in large groups and therefore has limited effects on individual incentives.

Furthermore, we note that behavior observed in our experiment is also consistent with

[3] For experiments on trading in networks and on intermediation, see Gale and Kariv [2009], Kariv et al. [2018], Charness et al. [2007] and Choi, Galeotti, and Goyal [2017]. For a survey of experiments on networks, see Choi, Gallo, and Kariv [2016].

[4] According to Fehr and Schmidt [1999], given a group of n individuals and a vector of (monetary) earnings $\pi = (\pi_1, \ldots, \pi_n)$, the utility of person i is determined by: $u_i(\pi) = \pi_i - \frac{\alpha_i}{n-1}\sum_j \max(0, \pi_j - \pi_i) - \frac{\beta_i}{n-1}\sum_j \max(0, \pi_i - \pi_j)$ where α defines i's distaste for disadvantageous inequality, and β defines i's distaste for advantageous inequality such that $0 \leq \beta < 1$ and $\beta_i < \alpha_i$.

the theory of fairness relying on efficiency seeking from Charness and Rabin [2002]. According to this model, individuals weight how much they care about pursing the social welfare by maximizing the aggregate payoffs, versus their own self-interest.[5] In the above example, an individual with such fairness concerns would compare their own payoff x with the aggregate payoff $(n-1)x+10x$. Consequently, by making the aggregate welfare salient to the individuals, a large group size n can encourage efficiency seeking behavior. In our experiment, this type of incentives can promote the emergence of hub spoke structures.

Our paper contributes to the experimental literature on continuous time games. Existing studies are built on a development of an experimental software, called ConG (Pettit, Friedman, Kephart, and Oprea [2014]) and have focused on small group interactions (see e.g., Friedman and Aprea [2012]; Calford and Oprea [2017]). The novelty of our experimental software is that it enables us to study large group interactions. In order to overcome information overload of evolving networks and relax subjects' cognitive bounds in information processing, our software integrates the network visualization tool with the interactive tool of asynchronous choices in real time. This is achieved by adopting an enhanced communication protocol between the server and subjects' computers. It allows us to run both network visualization and asynchronous dynamic choices in real time without communication congestion and lagged responses, even when participants are interacting remotely from different physical locations.[6]

The rest of the paper is organized as follows. In Section 2, we describe the three payoff models and discuss their properties in terms of stability, efficiency and inequality. Section 3 presents details about the large scale network formation experiment used to study the problem of intermediation, after discussing the various challenges associated with it. Section 4 presents the main experimental findings together with their explanations. All proofs and supplementary materials (including experimental instructions) are presented in the Appendix.

[5] According to Charness and Rabin [2002], given a group of n individuals and a vector of (monetary) earnings $\pi = (\pi_1, \ldots, \pi_n)$, the utility of person i is determined by: $u_i(\pi) = (1-\lambda_i)\pi_i + \lambda_i[\delta_i \min(\pi_1, \ldots, \pi_n) + (1-\delta_i)\sum_j \pi_j]$ where $\lambda_i \in [0,1]$ defines how much i cares about pursuing the social welfare versus his own self-interest, and $\delta_i \in (0,1)$ measures the degree of concern for helping the worst-off person versus maximizing the total social surplus. Efficiency seeking therefore assumes $\delta_i = 0$.

[6] Also see our companion paper Choi, Goyal, and Moisan [2019], that uses the same platform to conduct a large scale experiment on the 'law of the few' model of Galeotti and Goyal [2010].

2 Theory

We consider a game with $N = \{1, 2, ..., n\}$ individuals, where $n \geq 3$. Relationships between nodes are conceptualized in terms of binary variables, so that a relationship either exists or does not exist. Denote by $g_{ij} \in \{0, 1\}$ a relationship between two nodes i and j. The variable g_{ij} takes on a value of 1 if there exists a link between i and j and 0, otherwise. Links are undirected, i.e., $g_{ij} = g_{ji}$. The set of nodes taken along with the links between them defines the network; this network is denoted by g and the collection of all possible networks on n nodes is denoted by $\mathcal{G}$. Given a network g, in case $g_{ij} = 0$, $g + g_{ij}$ adds the link $g_{ij} = 1$, while if $g_{ij} = 1$ in g, then $g + g_{ij} = g$. Similarly, if $g_{ij} = 1$ in g, $g - g_{ij}$ deletes the link g_{ij}. Let $N_i(g) = \{j | g_{ij} = 1\}$ denote the nodes with whom node i has a link; this set will be referred to as the *neighbors* of i. Let $\eta_i(g) = |N_i(g)|$ denote the number of connections/neighbors of node i in network g. Furthermore, let $d(i, j; g)$ denote the geodesic distance between players i and j in network g.

Individuals propose links with others. The strategy of a player i is a vector of link proposals $s_i = [s_{ij}]_{j \in N \backslash \{i\}}$, with $s_{ij} \in \{0, 1\}$ for any $j \in N \backslash \{i\}$. The strategy set of player i is denoted by S_i. A link between agents i and j is formed if both propose a link to each other, i.e., $g_{ij} = s_{ij} s_{ji}$. A strategy profile $s = (s_1, s_2, \ldots, s_n)$ induces an undirected network $g(s)$.[7] The network $g(s) = \{g_{ij}\}_{i,j \in N}$ is a formal description of the pairwise links that exist between the players. There exists a path between i and j in a network g if either $g_{ij} = 1$, or if there is a distinct set of players $i_1, \ldots, i_n$ such that $g_{ii_1} = g_{i_1 i_2} = g_{i_2 i_3} = \ldots = g_{i_n j} = 1$. All players with whom i has a path defines the component of i in g, which is denoted by $C_i(g)$.

Suppose that players are traders who can exchange goods and that this exchange creates a surplus of V. This exchange can be carried out only if these traders have a link or if there is a path between them. There is a fixed (marginal) cost c per individual for every link that is established. On the other hand, any proposal that is not reciprocated carries no cost.

The central issue here is how are potential surpluses allocated between the different parties to the trade. In the case where two traders have a link, it is natural that they split the surplus equally, each earning $\frac{V}{2}$. If they are linked indirectly, then the allocation of the surplus depends on the nature of competition between the intermediary agents. One simple idea is to view these paths as being perfect substitutes. Another possibility is that

[7]With a slight abuse of notation, for simplicity, we will write g instead of $g(s)$.

the paths offer differentiated trading mechanisms. We will develop models of intermediation that build on these ideas.

2.1 Models

We start with the notion of paths between traders being perfect substitutes. All traders set prices simultaneously. Trade occurs along the cheapest path (or at a path picked at random in case there are multiple cheapest paths). A trader is said to be *critical* for a pair of traders A and B if she lies on all paths between these traders. Trade between A and B occurs if there is a path on which the sum of prices set by the intermediaries is smaller than or equal to V. Using a combination of theory and experiments, Choi, Galeotti, and Goyal [2017] show that, for any network, this pricing game generates a sharp prediction: the surplus is divided more or less equally between the origin and destination traders and the critical traders, while the non-critical traders earn close to zero. We build on this result to develop a payoff function in the network formation game with intermediation.

Formally, a trader i is said to be critical for trader j and k if i lies on every path between j and k in the network. Denote by $T(j,k;g)$ the set of players who are critical for j and k in network g and let $t(j,k;g) = |T(j,k;g)|$. Following Goyal and Vega-Redondo [2007], we may write the payoffs as follows. For every strategy profile $s = (s_1, s_2, \ldots, s_n)$ the net payoffs to player i are given by:

$$\Pi_i^{crit}(s) = \sum_{j \in C_i(g)} \frac{V}{e(i,j;g)+2} + \sum_{j,k \in N \setminus \{i\}} V \frac{I_{i \in T(j,k;g)}}{t(j,k;g)+2} - \eta_i(g)c \tag{1}$$

where $I_{i \in T(j,k)} \in \{0,1\}$ stands for the indicator function specifying whether i is critical for j and k. This payoff offers a very simple rule for the allocation of trading surpluses. We shall refer to it as the model of criticality based payoffs.

One feature of this payoff model is slightly implausible: trade can take place along arbitrarily long paths even when shorter paths are available, and that too without any costs. However, if costs are similar, it is easy to see that a small friction arising out of distance would make a large difference in the flow of trade. To take this factor into account, we consider a simple alternative model of intermediation that emphasizes the role of shortest paths between traders.

Formally, let $n_{jk} = d(j,k;g) - 1$ denote the number of intermediaries on a shortest path between j and k in network g. Trade between j and k is equally distributed among the source and destination j and k, and among the intermediaries on the shortest path. In the case of multiple shortest paths, one of them is randomly chosen. Therefore, the (ex-ante) expected return for any trader i is in proportion to the shortest paths between j and k that i lies on. Formally, we write $b^i_{jk}(g) \in [0,1]$ to denote *betweenness* of player i between j and k. For every strategy profile $s = (s_1, s_2, \ldots, s_n)$ and the resulting network $g(s)$, the net payoffs to player i are given by:

$$\Pi_i^{btwn}(s) = \sum_{j \in C_i(g)} \frac{V}{d(i,j;g)+2} + \sum_{j,k \in N \setminus \{i\}} V \frac{b^i_{jk}}{d(j,k;g)+2} - \eta_i(g)c \tag{2}$$

We shall refer to this formulation as the model with betweenness based payoffs. Betweenness based payoffs have been proposed as a model for the allocation of surplus in a network by Kleinberg et al. [2008] and Galeotti and Goyal [2014].

The betweenness based pricing system allows for trade on shortest paths of arbitrary length. Kleinberg et al. [2008] also impose the restriction trade only takes if traders are within distance 2. Buskens and Van de Rijt [2008], Burger and Buskens [2009] propose similar restrictions on the distance between traders. This motivates a third model, in which every intermediary on a selected shortest path earns a fixed rent $0 < p \leq V$. Since a trade between j and k generates a finite surplus of V, trade only takes place if the number of intermediaries on a shortest path $n_{jk} \leq \frac{10}{p}$. Traders j and k equally share the remaining part of the surplus, i.e., $V - n_{jk}p \geq 0$. This sets a natural bound to the limits of trade. For every strategy profile $s = (s_1, s_2, \ldots, s_n)$ and the resulting network $g(s)$, we define the net payoffs to player i by:

$$\Pi_i^{dist}(s) = \sum_{j \in C_i(g)} \frac{\max(0, V - pn_{ij})}{2} + p \sum_{j,k \in N} I_{n_{jk} \leq \frac{V}{p}} b^i_{jk}(g) - \eta_i(g)c \tag{3}$$

where $I_{n_{jk} \leq \frac{V}{p}} \in \{0,1\}$ stands for the indicator function specifying whether the trade between j and k is realized in network g. We shall refer to this formulation as distance based payoffs.

2.2 Stability and Welfare

We will study pairwise stable networks. Following Jackson and Wolinsky [1996], a network is pairwise stable if no one can benefit by removing any existing link, and no pair can mutually benefit by adding a non existing link with each other.

Definition 1. *A strategy profile s^* leads to a pairwise stable network $g(s^*)$ if the following conditions hold:*

- *For any $i \in N$ and any $s_i \in S_i$, $\Pi_i(s^*) \geq \Pi_i(s_i, s^*_{-i})$;*
- *For any $i, j \in N$ and any $s \in S$ such that $g_{ij}(s^*) = 0$ and $g(s) = g(s^*) + g_{ij}$, if $\Pi_i(s) > \Pi_i(s^*)$, then $\Pi_j(s) < \Pi_j(s^*)$.*

We now turn to the welfare aspects of networks. The efficiency of an outcome is measured as the ratio between the sum of individual payoffs and the maximum sum of individual payoffs that can be achieved:

$$E(s) = \frac{\sum_i \Pi_i(s)}{\max_{s'} \sum_i \Pi_i(s')} \tag{4}$$

It follows that $E(s) \leq 1$. A network is said to be socially efficient if it maximizes social welfare, i.e., $E(s) = 1$.

Observe that in our setting, the intermediation payoffs cancel out. So surplus arises out of trades realized less the costs of forming links. There is therefore no benefit in having a cycle in a network, as that merely adds to the costs, without any gain in additional trades being realized. So, every component in an efficient network must be minimally connected or a singleton. From Goyal and Vega-Redondo [2007] it follows that an efficient network is either the empty network or the minimally connected network. The total payoffs in the latter case are $\frac{Vn(n-1)}{2} - 2(n-1)c$ and they are equal to 0 in the case of an empty network. So it follows that an efficient network is minimally connected if $c < \frac{Vn}{4}$, and empty otherwise. A prominent example of minimally connected network is the star network (see Figure 2b).

We turn next to inequality: for a survey of inequality measures, see Dasgupta et al. [1973]. As hub-spoke networks arise naturally in our context, we would like to have a measure that captures extremely large payoffs appropriately. We define inequality as the ratio of the largest payoff to the median payoff.

$$I(s) = \frac{\max_i(\Pi_i(s))}{med_i(\Pi_i(s))} \tag{5}$$

It follows that $I(s) \geq 1$. An outcome is said to be equal if $I(s) = 1$. In the appendix, for completeness, we also present other measures of inequality such as the Gini coefficient.

(a) Cycle (b) Star

Figure 2: Cycle and Star networks

Observe that the outcome is equal in the empty network and in a cycle network (see Figure 2a). By contrast, in the star network, under the criticality and betwenness models above, the hub and spoke earn, respectively

$$V(n-1)\left[\frac{1}{2}+\frac{n-2}{6}\right]-(n-1)c \qquad\qquad V\left[\frac{1}{2}+\frac{n-2}{3}\right]-c \tag{6}$$

The ratio of the hub payoff versus the spoke payoff is clearly growing and unbounded in n. More specifically, the ratio of hub payoffs to the median payoff too is unbounded (the median payoff corresponds to the spoke's payoff).

More generally, observe that in all three models, efficiency dictates that a non-empty network must be minimal. In a minimal network, some nodes will necessarily be leaves and will earn zero intermediation rents, while other nodes will be critical and will earn positive intermediation rents. So there is a tension between efficiency and equality. While this is true in general, it is also worth noting that in the criticality and betweenness models, the cycle network is almost perfectly efficient, as it contains only 1 redundant link. With this in mind we now draw attention to a class of networks that combine elements of cycles and/or stars. In particular, networks with multiple local stars are as efficient as the star network, as they similarly are minimally connected (see Figure 3a). However, the inequality they generate can differ and vary with the size of the network and the number of links formed by the main hub. Indeed, in specific settings, the earnings of the main hub can be larger that those of the hub in the star network of the same size. Other networks involving multiple cycles combined with a star, as shown in Figure 3b, offer different interesting features. The multiplicity of cycles has direct consequences on decreasing efficiency as they each add one extra link without generating extra benefits (in the context of criticality and betweenness

(a) Local stars (b) Cycle-star

Figure 3: Hybrid networks

based models). Furthermore, the presence of a star connecting cycles can generate large inequality, which can surpass that of the star network. This is because extra links decrease payoffs earned by non-hub players on cycles, whereas the hub earns large benefits without forming too many links (at least in the criticality based model).

2.3 Analysis

This section examines the incentives for linking in the three models, through a study of pair-wise stable networks. We have been unable to develop a complete characterization of pairwise stable networks. To focus attention on the key dimensions of efficiency and equity, we will pay special attention to the cycle and star networks.

We begin with a result on criticality based payoffs.

Proposition 1. *Suppose payoffs are given by (1). There always exists a pairwise stable network. Pairwise stable networks include the empty network if* $c > \frac{V}{2}$*, the star network if* $\frac{V}{6} < c < \frac{Vn}{3} - \frac{V}{6}$*, and the cycle network if* $c < \sum_{i=1}^{n-2} \frac{Vi}{2(2+i)}$*. The complete network is not stable for* $n \geq 4$*.*

Proofs of all results in this section are presented in the Appendix A.

A general observation is that pairwise stable networks cover a wide range of structures including the star and the cycle. So incentives in this model sustain networks with very small diameter as well as very large diameter. This also means that stability is not incompatible with efficiency or equality. However, the stability of star and cycle does focus attention on the issue of equality.

We turn next to betweenness based payoffs.

Proposition 2. *Suppose payoffs are given by (2). There always exists a pairwise stable network. Pairwise stable networks include the empty network if* $c > \frac{V}{2}$*, the complete network if* $c < \frac{V}{6}$*, and the star network if* $\frac{V}{6} < c < \frac{Vn}{3} - \frac{V}{6}$*. Given values for* c *and* V*, the cycle is not pairwise stable for large* n*.*

This result yields one important insight: betweenness based pricing rules out the cycle network. For large n, a cycle network creates incentives for traders to create bridges that reduce the shortest path length. This bridge cuts down intermediation payment for traders who create the link and also enhances their intermediation rents as they now sit on shortest paths for many other traders.

Finally, we turn to stable networks when pricing is based on distance based payoffs.

Proposition 3. *Suppose payoffs are given by (3). There always exists a pairwise stable network. Pairwise stable networks include the empty network if* $c > \frac{V}{2}$*, the complete network if* $c < \frac{p}{2}$*, and the star network if* $\frac{p}{2} < c < \frac{V}{2} + (n-2)\min(p, \frac{V-p}{2})$*. The cycle is not pairwise stable for large* n *when* $c < \frac{5V^2}{2p} - 4V + 2p$*.*

This result on pairwise stability is similar to the finding for the betweenness based payoffs model. The main difference between those models relates to efficiency: unlike in the previous models, connectivity of a network does not guarantee realization of all trades in the distance based payoffs model. As a result, networks with a large diameter are not efficient.

To summarize, the empty network and star network are pairwise stable in all three models. However, in the criticality model, a cycle network (and hybrid cycle-star networks) are also stable, while they are not stable in the betweenness and distance based payoff models. By contrast, in the latter two models, a complete network is stable, and this is never the case in the criticality based payoffs model. The star is efficient under a wide range of circumstances, but it leads to extreme inequality. By contrast, the cycle (and related networks) are close to being efficient and attain equality. These observations set the stage for our experiments.

2.4 Experimental Setting

We now present details of the theoretical analyses in the context of our experiment with concrete parameter settings. Focusing on a fixed group size $n = 50$, we choose a value $V = 10$ for the surplus generated by a trade, and a cost of linking $c = 40$. In the particular case of the distance based model described by (3), we set the fixed brokerage rent to $p = 3$, which restricts trades to be realized only within a distance 4 (at most 3 intermediaries). In this context, theoretical results in terms of pairwise stability, efficiency, and inequality for some concrete network structures are summarized in Table 1.

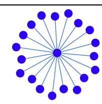
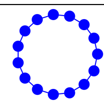
Network		**Payoffs**	**Pairwise stability**	**Efficiency** $E(s)$	**Inequality** $I(s)$
Star		(1)	yes	1	17.6
		(2)	yes	1	17.6
		(3)	yes	1	13.6
Cycle		(1)	yes	0.99	1
		(2)	no	0.99	1
		(3)	no	< 0	1

Table 1: Features of non-empty networks according to experimental setting

3 Experiment

3.1 Challenges and methodology

The goal of this paper is to understand the role of pricing mechanisms in shaping trade and intermediation through network formation in large groups. Experiments in this setting pose at least several challenges to human subjects because of (*i*) the large decision space, (*ii*) the complexity of payoff functions, and (*iii*) the observability of link proposals and network structure. We discuss these challenges and explain how our experimental software and design address each of them. Some of the discussion is taken from our companion paper, Choi, Goyal, and Moisan [2019].

Learning and dynamics. We wish to allow subjects ample opportunities to learn about the environment of decision making, other subjects' behaviors, and how to respond optimally to them. Because of the complexity of payoff functions and decision making, the issue of learning and behavioral convergence is particularly important. To address these issues, we run the experiment in continuous time with near real time updating on the evolution of network structure and link proposals made by and to the subject.[8] Continuous time

[8]More precisely, the network depicted on any subject's screen is updated every 2 seconds or whenever the subject makes a new decision.

experiments can also offer better prospects for convergence than discrete time experiments (see e.g., Friedman and Aprea [2012]).

In our experiment, the game is played in continuous time for 6 minutes during which every subject was free to asynchronously adjust their link proposals. Because subjects face a complex problem of decision making and need some time to figure out the game and coordinate their actions, a trial time of one minute is provided (during which subjects start choosing their actions with no monetary consequence). After the trial period is over, the subsequent 5 minutes are payoff relevant and one second is randomly chosen to determine subjects' earnings in the game. This information is publicly known to subjects (see detailed instructions in the appendix).

Two-sided linking protocol. The intermediation models we consider use the two-sided linking protocol with which a link between two individuals is formed if and only if both individuals consent to form it. This protocol distinguishes between link proposals (i.e., choices made by subjects) and realized links (i.e., link proposals that are reciprocated). Compared to the one-sided linking protocol, the two-sided linking protocol introduces an extra layer of the relationship between any two individuals: the pair is linked, or unlinked with none of them making a link proposal, or unlinked with only one of them making a link proposal to the other. Keeping track of such information in large groups can be a challenge for human subjects.

In order to make it easy for the decision maker to grasp the relation with any individual, we use the visual representation on the status of the linking relationship between the decision maker, denoted by Me, and an individual as shown in Table 2: An individual who neither made a proposal to nor received a proposal from the decision maker is represented with a circle shape; If an individual sent a link proposal to the decision maker who did not reciprocate it, that individual is depicted with a square shape; If an individual receives a link proposal from the decision maker but did not reciprocate it, the individual is represented with a triangle shape; If both an individual and the decision maker make link proposals to each other, the link between them is visualized with the individual being shaped with a circle.

On the other hand, from the decision maker's perspective, information about the relation between any other two individuals is provided in the binary form: the corresponding pair is shown to be either linked or not linked. Therefore, no information about the detail of unlinked individuals is provided to the decision maker.

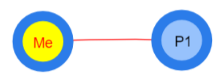
No link / no proposal	⇒	
Sent proposal	⇒	
Received proposal	⇒	
Realized link	⇒	

Table 2: Visualization of proposals and link

Figure 4 illustrates our method of distinguishing these different cases. In the initial network depicted on the left side of Figure 4, the decision maker who is represented with a yellow node identified as "me" does not make any link proposal, but receives link proposals from players P2, P3, and P4; these individuals are triangle shaped. From the network on the left, if the decision maker makes link proposals to P2, P3, P4, and P6, the network changes to the right side of Figure 4. The decision maker then have three realized links with P2, P3, and P4, and one pending link proposal to P6. On the other hand, the decision maker can only see the realized links between any other players (e.g., between P1 and P5); no information is provided about unlinked pairs (e.g., the pair of P5 and P7 may be unlinked because either P5, P7, or both P5 and P7 do not make a link proposal).

Network visualization. Existing studies of network formation in economics have considered small group sizes such as 4 or 8 people in a group and visualized evolving networks with fixed positions of nodes (e.g., Goyal et al. [2017]; van Leeuwen et al. [2018]). When the group size increases, such a representation of networks with fixed positions of nodes makes it very difficult for subjects to perceive network features adequately. For example, consider a group of 20 people with fixed positions of nodes in a circle as depicted in Figure 5a. While the exact nature of the network is hardly perceptible by observing Figure 5a, the same network structure can be represented in a transparent manner in Figure 5b.

For subjects to learn what to do, they must have a good idea of the evolving networks. An appropriate tool for visualizing networks is thus critical in running large-scale experiments in continuous time. This leads us to develop an experimental software including

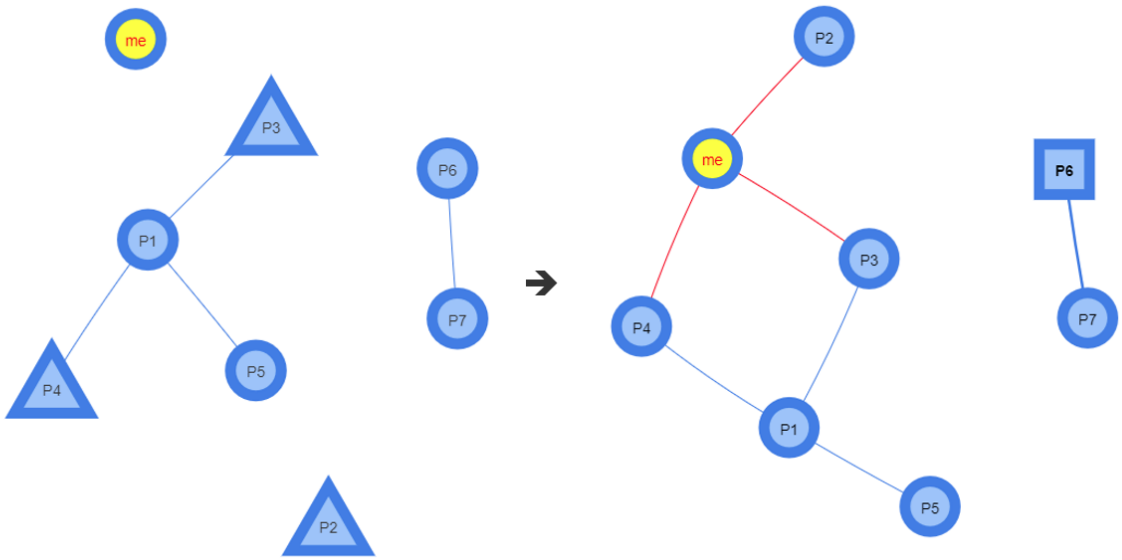
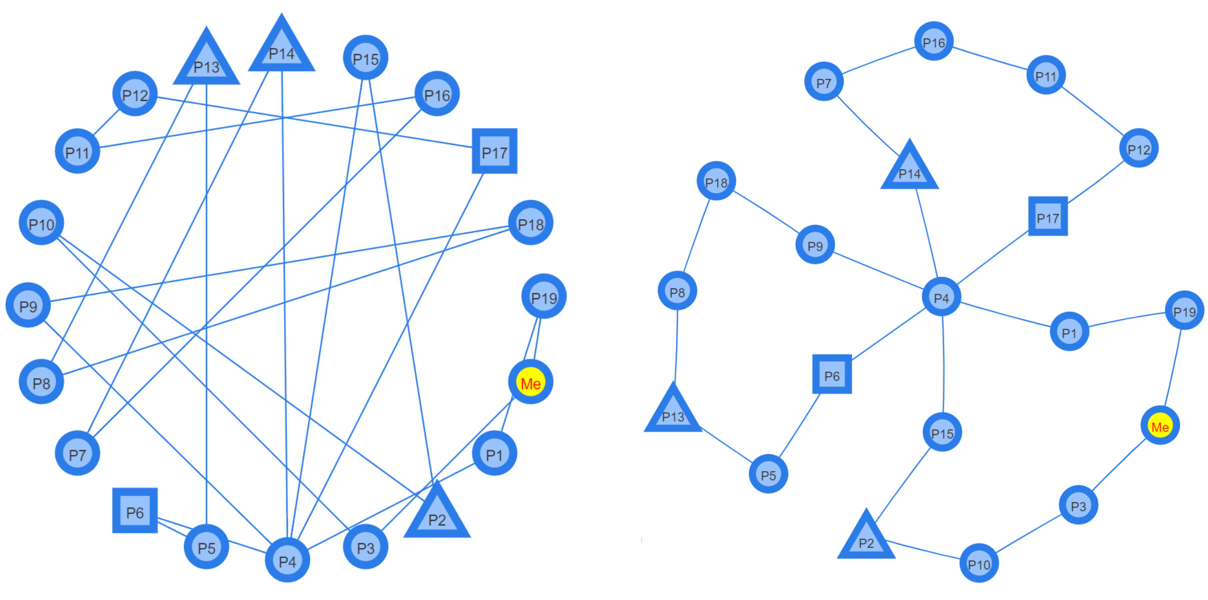


Figure 4: Example of network updates after new choices



(a) Fixed visualization

(b) Adaptive visualization

Figure 5: Examples of network visualization

an interactive network visualization tool that allows the network to automatically reshape itself based on its evolving structure. We use the Barnes-Hut approximation algorithm [Barnes and Hut, 1986] for grouping nodes in a network that are sufficiently nearby and adjust their relative positions on the subject's computer screen. It enables us to apply repulsion forces between nodes so that they are sufficiently separated from one another, attractive forces to nodes that are directly linked with each other, and gravity to all the nodes with respect to a central origin on the screen such that nodes not linked with each other remain within reasonable distance from each other.

The network visualization in Figure 5b was made using this algorithm. In our large-scale experiment, this visualization tool improves graphical clarity of evolving networks and helps subjects distinguish between those who hold an important brokerage position and those who do not (e.g., P4 is the key intermediary in Figure 5b and extract the largest brokerage rents). It is important to emphasize that this tool allows interaction between the subject and the network: while the nodes are subject to the above attraction and repulsion forces, they can also be freely manipulated by the participant through the usual drag-select functionality. The creation and removal of links is also interactive through double-clicking on corresponding nodes. A further detail regarding the specifics of the network visualization tool can be referred to Choi, Goyal, and Moisan [2019].

3.2 Treatments and design details

The experiment varies the pricing mechanism used to determine the cost of intermediation for each realized trade according to the three models described above: Treatment **Criticality** is based on (1), Treatment **Betweenness** is based on (2), and Treatment **Distance** is based on (3). The cost of linking, set to $c = 40$, is paid only when a link is realized, i.e., when both players make a proposal to each other.

At any instant in the 6 minutes game, every subject can make or remove a proposal to another subject by simply double-clicking on the corresponding node in the computer screen. Any reciprocated proposal leads to the formation of a link. Any non reciprocated proposal sent is characterized by the targeted node's shape being a square. Finally, any non reciprocated proposal received is characterized by the source node's shape being a triangle. The default node shape for nodes involving no link or proposal is the circle. Every subject can see every node on the screen, regardless of their position in the network. Some zoom in/out options are also made available for the subject to personalize their visualization of the network.

At any moment of the experiment, each subject is provided with detailed information about their own net payoff resulting from the currently depicted network structure. More precisely, subjects explicitly see the amount of access benefits, brokerage rents, overall cost of linking, and net payoffs. Finally, the subjects are also provided with information about the net payoffs of every other player, which are described in each corresponding node of the network. Further information on the screen is provided in Online Appendix D.

3.3 Experimental procedures

The experiment was conducted in the Laboratory for Research in Experimental and Behavioral Economics (LINEEX) at the University of Valencia. Subjects in the experiment were recruited from online recruitment systems of the laboratory. Each subject participated in only one of the experimental sessions. After subjects read the instructions, the instructions were read aloud by an experimenter to guarantee that they all received the same information. While reading the instructions, the subjects were provided with a step by step interactive tutorial which allowed them to get familiarized with the experimental software and the game. Subjects interacted through computer terminals and the experimental software was programmed using HTML, PHP, Javascript, and SQL. Sample instructions and interactive tutorials are available in Online Appendix C.

There were in total 12 sessions: 4 sessions of 50 subjects for each of the Criticality, Betweenness, and Distance treatments. In each experimental session, 50 subjects were matched to form a group and interacted with the same subjects throughout the experiment. Therefore, there are 4 independent groups for each treatment. A total of 600 subjects participated in the experiment.

The experiment consists of 6 rounds of the continuous-time game, each of which lasted for 6 minutes with the first minute as a trial period and the subsequent 5 minutes as the game with payment consequence. At the end of each round, every subject was informed, using the same computer screen, of a time moment randomly chosen for payment, detailed information on subjects' behavior at the chosen moment including a network structure and all subjects' earnings. While each group of people was fixed in a session, subjects' identification numbers were randomly reassigned at the beginning of every round in order to reduce potential repeated game effects. The first round was a trial round with no payoff relevance and the subsequent 5 rounds were effective for subjects' earnings. In analyzing the data, we will focus on subjects' behavior and group outcomes from the last 5 rounds.

At the beginning of the experiment, each subject was endowed with an initial balance of 400 points and added positive earnings to or subtracted negative earnings from that initial balance. Subjects' total earnings in the experiment amounted to the sum of earnings across the last 5 rounds and the initial endowment. Earnings were calculated in terms of experimental points and then exchanged into euros at the rate of 110 points being equal to 1 euro. Each session lasted on average 90 minutes, and subjects earned on average about 16.4 euros, including a 5 euros show-up fee.

At the end of the experiment, subjects took incentivized tasks to elicit social preferences and risk preferences. They are a modified version of Andreoni and Miller [2002] and Holt and Laury [2002], respectively. In addition, subjects answered a brief version of the Big Five personality inventory test adapted from Rammstedt and John [2007], a comprehension test related to the experimental game, and a debriefing questionnaire including demographic information. More details about them can be found in Online Appendix E.

4 Experimental Results

This section presents our experimental findings on the impact of pricing rules on efficiency, inequality, and network structure. It also discusses how the large effects we observe can be understood in terms of myopic best response by individuals to incentives for link formation, across the different pricing rules.

For simplicity, in all the empirical analyses, the data is organized on a second to second basis. So, every round yields us 360 observations – snapshots of every subject's choices in the group. Although some information about choice dynamics between two time intervals may be lost, we believe that the second by second record is adequate for our purposes. Moreover, unless otherwise stated, all analyses are focused on data from the last 5 payoff relevant minutes of each round of the game. Using this data set, we run linear regressions for treatment effects with standard errors clustered at the group level and report regression results in Appendix B.

4.1 Efficiency

We begin with the analysis of the treatment effects on efficiency. Figure 6 shows the dynamics of efficiency attained. The efficiency measure is relative to the first best network.

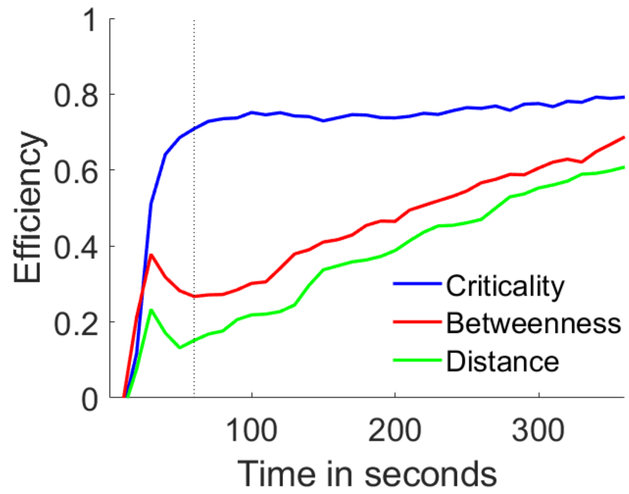


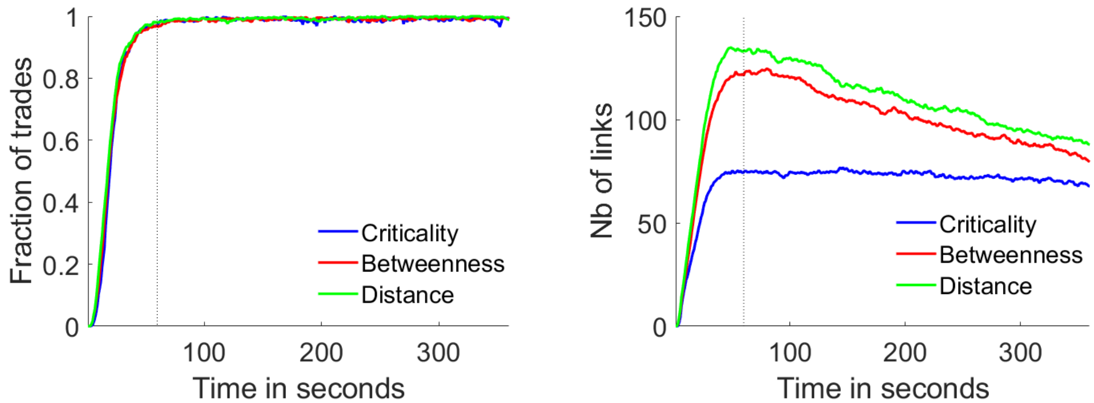
Figure 6: Dynamics of efficiency

The vertical dotted line represents the 60th second from the beginning of the game, after which the play of the game is payoff relevant.

There are substantial differences across treatments: under criticality pricing, subjects attain (an almost constant) 80% efficiency. On the other hand, efficiency in the other two treatments is initially very low — around 28% and 16%, respectively, under betweenness and distance pricing. Efficiency steadily increases over time, eventually reaching 70% and 61%, respectively. The level of efficiency under betweenness and distance pricing is significantly lower than that under criticality pricing, controlling for the time trends. For details on the regression estimates refer to Table 4 in Appendix B.

The effects of pricing rule on efficiency are large. What are the sources for this great difference? There are potentially two reasons for loss in efficiency: breakdown of trade due to missing connections and an excessive number of links. Figure 7 presents data on fraction of realized trades and on the total number of links.

Figure 7a shows that (roughly) 99% of all trades are realized under all pricing rules. Hence, there is little loss of efficiency due to breakdown of trade. Figure 7b shows that the number of links under criticality pricing is (around) 70 and is stable over the last 5 payoff relevant minutes. On the other hand, the number of links is 121 and 133, respectively, at the start and decline to 79 and 88, respectively under betweenness and distance pricing. Controlling for time trends, we observe that the average number of links under criticality



(a) Fraction of realized trades

(b) Total number of links

Figure 7: Sources of inefficiency

pricing is significantly lower than under the other two pricing rules. The regression results are presented in Table 5 in Appendix B. Note that the number of links in an efficient network is 49. We are led to the conclusion that over-linking is the principal source of inefficiency in the experiment. Our analysis of efficiency is summarized as follows.

Result 1 (Efficiency) *(i)The level of efficiency is consistently high under criticality pricing. (ii) Under betweenness and distance pricing, efficiency is initially very low; the main source of inefficiency is over-linking. The number of links decline over time and this leads to rising efficiency.*

4.2 Inequality

We measure inequality as the ratio of the maximum payoff to the median payoff (as defined in equation 5).[9] Figure 8 presents the dynamics of the (average) ratio of the maximum payoff to the median payoff. We observe large and significant differences across pricing rules: the average of the ratio is 2 under criticality pricing, 15 under betweenness pricing and 19 under distance pricing. These differences are stable across time. We run a linear regression with time trends: the inequality measure under criticality pricing is significantly lower than that under the other two pricing rules. These regression results are presented in Table 6 in the Appendix B. It is worth noting that the inequality observed under criticality

[9] An alternative measure based on the Gini coefficient is also provided in the Appendix.

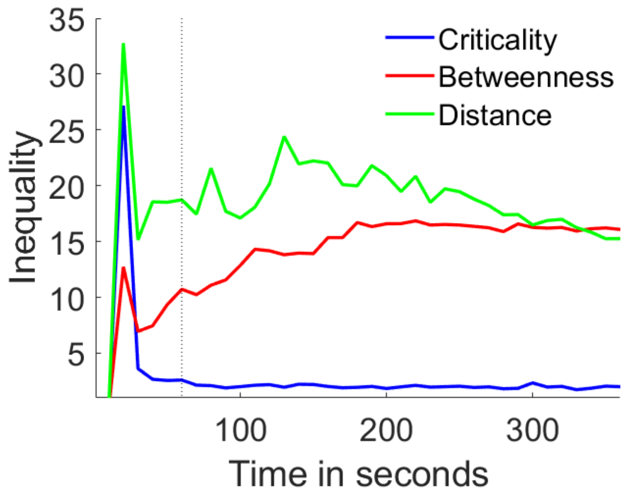


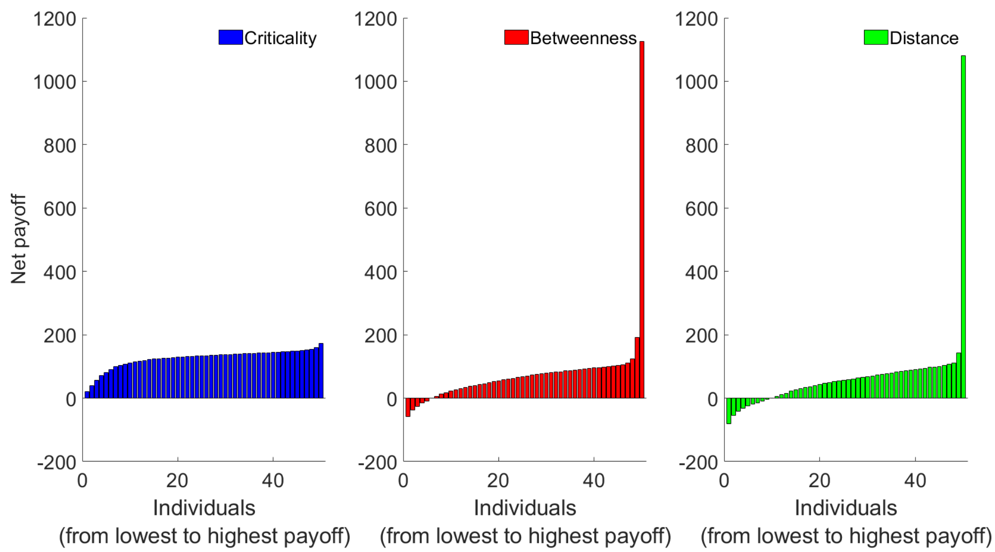
Figure 8: Dynamics of inequality

pricing is closer to the cycle network ($I(s) = 1$), while the inequality observed under the other two pricing rules is closer to the hub-spoke network ($I(s) \approx 14$ and $I(s) \approx 18$ under betweenness and distance pricing respectively).

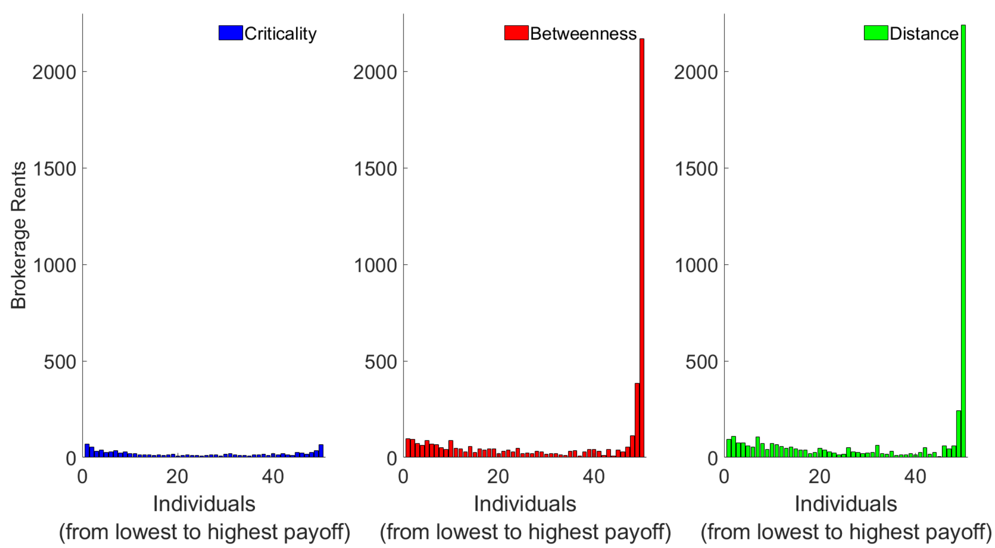
What is the source of such a large inequality in earnings? To address this question, we present the distribution of overall earnings and of brokerage rents. Specifically, we first compute for each round the average payoffs earned by subjects and rank them from the lowest to the highest. We then take, for each rank, an average of payoffs across rounds and groups. Figure 9a presents the bar graphs of the resulting payoffs from the lowest (left) to the highest (right). This reflects the rather large differences in inequality that we have noted already. Figure 9b presents the corresponding bar graph of brokerage rents (using the same ranking system as in Figure 9a).

This figure reveals that under criticality pricing, subjects earn very similar payoffs. In contrast, under the other two pricing rules, there is a single individual who earns much larger payoffs than anybody else. The highest earning individual under betweenness and the distance pricing earns very large brokerage rents; the rest of the subjects earn negligible brokerage rents. We conclude that the main source of earning inequality is the extremely unequal distribution of brokerage rents. Our analysis of inequality is summarized as follows:

Result 2 (Inequality) *(i) The level of inequality is substantially higher in the betweenness and distance treatments than in the criticality treatment. (ii) The unequal dis-*



(a) Distribution of payoffs



(b) Distribution of brokerage rents

Figure 9: Sources of inequality

tribution of brokerage rents is the main source of payoff inequality in the betweenness and distance treatments.

4.3 Network Structure

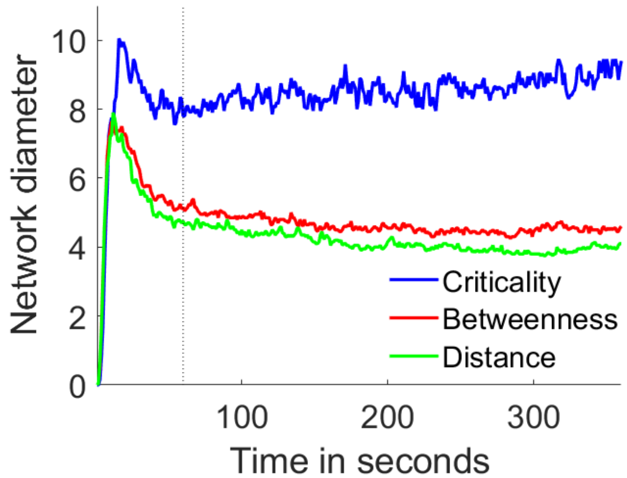
The effects on inequality and efficiency ultimately arise out of different linking patterns. We now turn to a study of network structure under the three pricing rules. Three network measures are presented: diameter of the network (the shortest distance between the two most distant subjects), the distribution of (geodesic) distances between subjects, and the ratio of maximum to minimum number of links of an individual.

Figure 10a presents the dynamics of network diameter. We observe large and statistically significant difference in network diameter under criticality pricing on the one hand and the diameter under the other two treatments: the average network diameter is 8.5 under criticality pricing, 4.6 under betweenness pricing and 4.1 under distance pricing. The differences of network diameter persist over time and are statistically significant. For details of the regression estimates, refer to Table 7 in Appendix B.

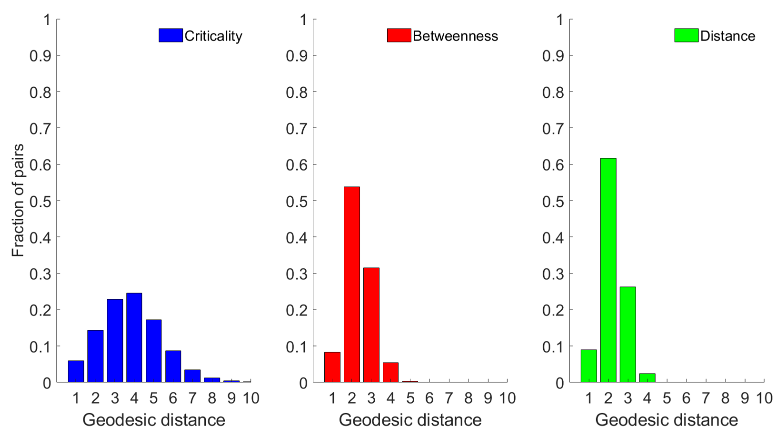
Figure 10b presents the distribution of (geodesic) distances between individual subjects. Less than 10% of pairs are directly linked (i.e., geodesic distance of 1) in all pricing rules: this provides strong evidence for sparseness of the emerging networks. However, 54% and 62% of all pairs of subjects under betweenness and distance pricing have distance 2; this frequency is much lower under criticality pricing at 14%. This difference is reflected in average path length: it is 3.8 under criticality pricing, 2.4 under betweenness pricing, and 2.2 under distance pricing.[10]

Next we examine the extent of network centralization across pricing rules: Table 3 reports the average degree distribution. The striking feature is the great centralization under betweenness and distance pricing: about 2% of individuals – one subject out of 50 – have 25 or more links. However, almost no one has more than 10 links under criticality pricing. Second, the fraction of subjects with only one link under betweenness and distance pricing is more than 3 times higher than that under criticality pricing. On the other hand, the frequency of subjects with two links is more than 2 times higher under criticality pricing as compared to the other two pricing rules. These observations taken together suggest that the concentration of linking to a hub is a prominent feature of networks under betweenness

[10]These findings suggest differences in closeness centrality across pricing regimes. More supporting evidence on closeness is provided in the Appendix (see Figure 16b).



(a) Network diameter



(b) Distribution of pairs across path lengths

Figure 10: Diameter and closeness

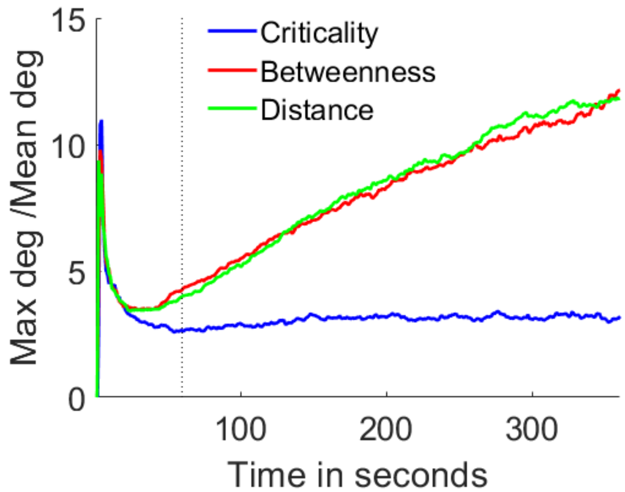


Figure 11: Dynamics of the ratio of max degree to mean degree

and distance pricing while the patterns of linking under criticality pricing is very dispersed.

Table 3: Distribution of Degrees

	Treatment		
Degree	**Criticality**	**Betweenness**	**Distance**
0	0.4%	0.3%	0.3%
1	8%	31%	28%
2	43%	19%	19%
3	24%	13%	13%
$[4, 10)$	23%	29%	30%
$[10, 25)$	0.7%	6%	7%
$[25, 49]$	0%	1.6%	1.8%

To further substantiate the different levels of centralization, we present the ratio of maximum to average degree. Figure 11 presents this ratio. At the start, there is a moderate difference in this ratio across pricing rules: it is around 6 under criticality pricing and 10 under betweenness and distance pricing. The ratio remains stable under criticality pricing but rises steadily over time and reach around 25 in the other two pricing rules.

The final statistic we present pertains to the persistence of centrality: Figure 9 suggests

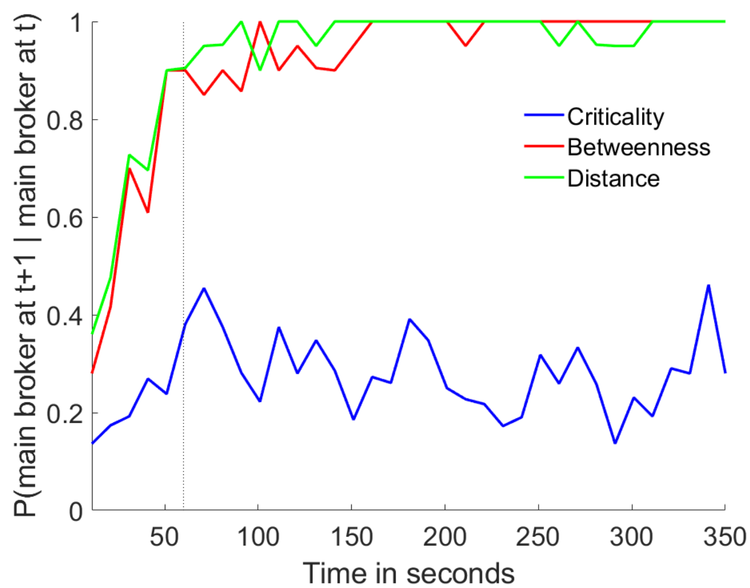


Figure 12: Dynamic stability of the main broker status

that the highest earning subject under betweenness and distance pricing obtained the largest brokerage rents. This subject is also the one who attracted the highest number of links (as shown in Table 3). For every interval of 10 seconds, we define the *main broker* as the subject who earns largest brokerage rents for the longest time within the interval. We study the transition probability of such an individual keeping their status in the next interval of 10 seconds. Figure 12 shows that there is little persistence of main broker under criticality pricing: this trader maintains her status with probability (roughly) 30%. On the other hand, under betweenness and distance pricing, the main broker persists with probability close to 1. Our analysis of network structure is summarized as follows.

Result 3 (Network structure) *(i) The network is dispersed under criticality pricing while network centralization is strong and grows over time under betweenness and distance pricing. (ii) The identity of the main broker is unstable under criticality pricing but very stable under betweenness and distance pricing.*

4.4 Individual Incentives and Behavior

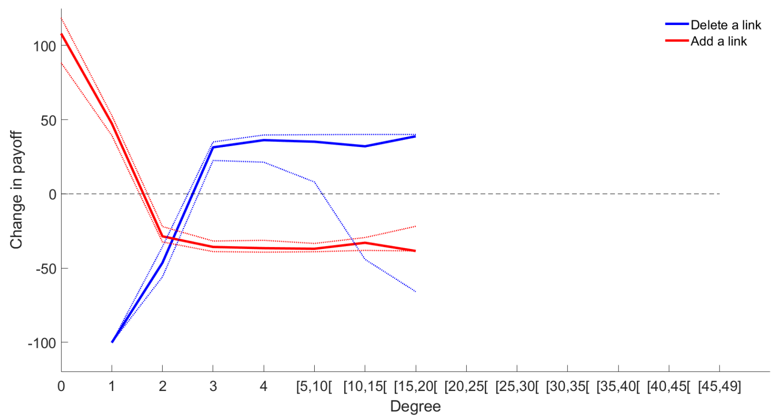
We have observed that pricing rules have large effects on the emerging network structure; the difference is economically significant as efficiency and inequality varies greatly across these networks. The large treatment effects arise due to different linking choices by individuals. In this section, we show that pricing rules give rise to different incentives for forming and deleting links and this helps account for the large treatment effects.

On way to understand incentives is to ask, for any instant of time t, given an actual network and the proposals available, what are the maximum and minimum payoff changes that the individual could obtain by positively responding to a link proposal or by deleting a link. Note that we do have data about what the individual actually does: so we can, for the time t, observe the actual choice of subjects and compute from the impact on their actual earnings.

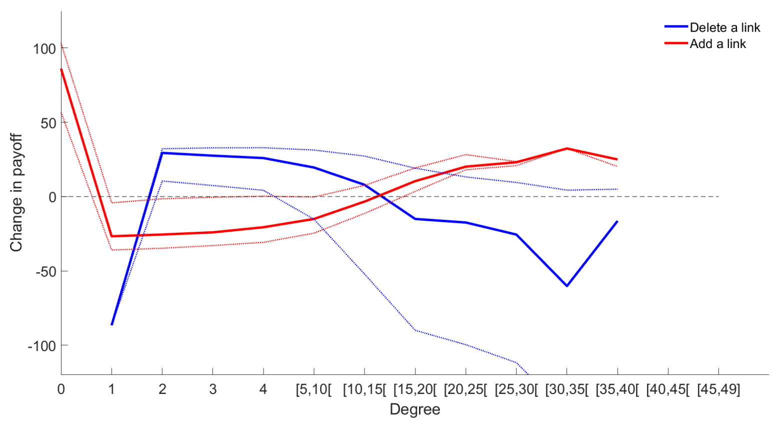
Figure 13 represents the (average) payoff changes arising out of the actual choices by individuals of adding a link (solid red line) and deleting a link (solid blue line) across pricing rules. It also presents the (average) maximum and minimum payoff changes that the individual could potentially obtain (dotted lines for corresponding colors). Due to small sample problems, we pool samples and compute average payoff changes in intervals of 5 consecutive degrees from degree 5.

We note that there is a stark difference in incentives across treatments. Under criticality pricing, subjects face strong incentives for settling on *two* links. The figure reveals that subjects can benefit by adding a link when their degree is either 0 or 1 but cannot benefit by doing so when their degree is 2 or higher. On the other hand, the incentive for deleting a link goes the other way: removal of a link is not profitable when their degree is either 1 or 2, and may be profitable when the degree is 3 or higher. Taking these points together, we find that subjects with degree 2 cannot benefit by a single deviation of either adding or deleting a link. This observation is consistent with the dispersed network whose degree distribution has the mode at degree 2. In contrast, under betweenness and distance pricing, subjects face very different structure of incentives: 'locally' it is unprofitable to form a link beyond *one* link, and it is profitable to add links if they already attracted many links.

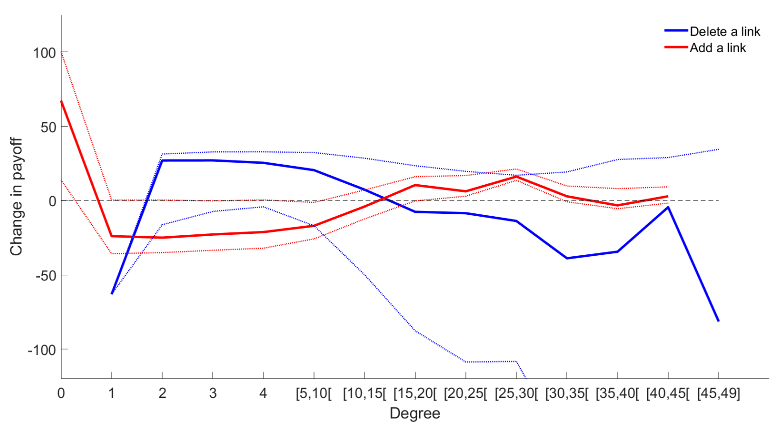
Is subject behavior consistent with these incentives? Figure 14 present the time series of the proportions of subjects with one link and two links, respectively, across pricing rules. In the line with the analysis of incentives, the proportion of subjects with degree 1 increases over time under betweeness and distance pricing rules; it reaches around 50% by the end



(a) Criticality based pricing



(b) Betweenness based pricing



(c) Distance based pricing

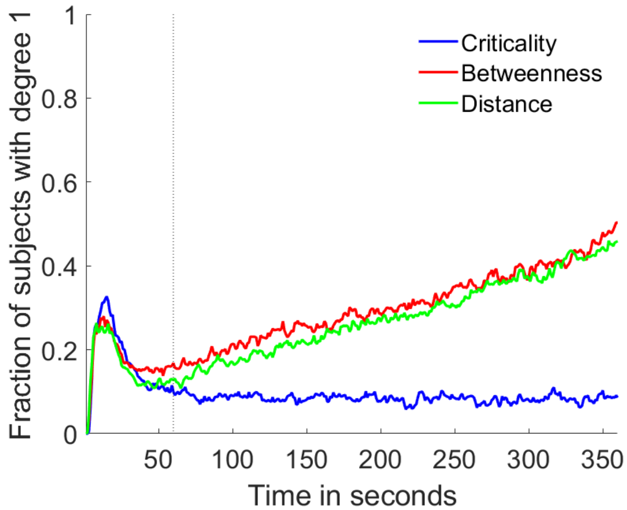
Figure 13: Payoff changes from single actions (add / delete a link)

of the game. Under criticality pricing, this fraction is much lower, always below 10%. Second, under criticality pricing subjects maintain two links increasingly more frequently over time and the frequency of subjects with degree 2 is (roughly) 50% by the end of the game. Under betweenness and distance pricing, the corresponding frequency is (roughly) 20% over time.

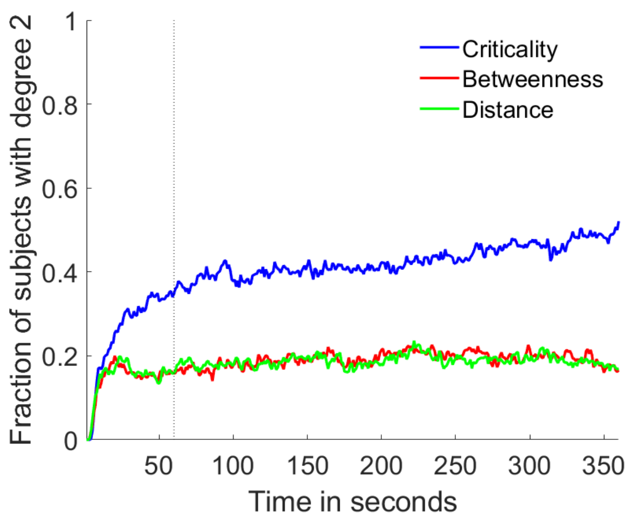
Finally, we examine choices of the individual with the highest degree. Figure 15 presents the time series of the maximum degree over time across treatments. Under betweenness and distance pricing, subjects with the highest degree steadily increase their degree, over time. On the other hand, under criticality pricing, the maximum degree is always below 10.

We summarize our analysis of incentives and individual behavior under pricing rules as follows:

Result 4 (Incentives and behavior) *(i) Under criticality pricing subjects have a (myopic) incentive to maintain two links and tend to do so with high frequency. (ii) Under betweenness and distance pricing, subjects have a (myopic) incentive to either form only one link or become highly connected. Subject behavior is in line with these incentives: the proportion of subjects with degree 1 and the maximum degree both increase over time.*



(a) Proportion of subjects with one link



(b) Proportion of subjects with two links

Figure 14: Time series of proportions of subjects with degree 1 and 2

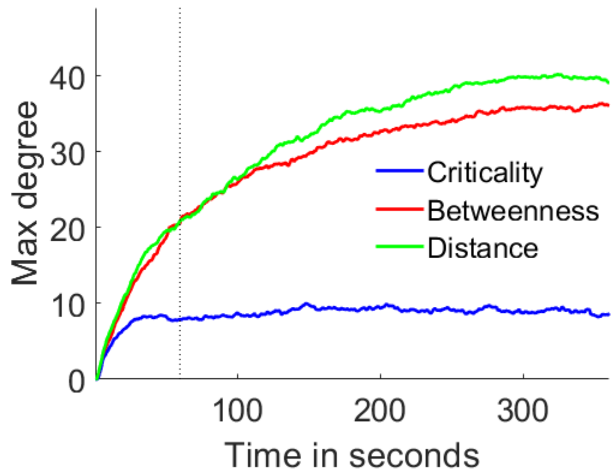


Figure 15: Time series of the maximum degree

5 Conclusion

Providing intermediation services can represent a highly profitable activity in the modern economy. While it facilitates value exchange between users, the presence of dominant intermediaries also widens the wealth inequality gap in the population. Previous work on the economic theory of networks provide some insights into the stability of such outcomes. However, those models are limited in identifying the economic forces that drive the emergence of such powerful intermediaries. This paper provides an experimental investigation of this important question.

We conduct a laboratory experiment with groups of 50 subjects (with homogeneous preferences) who play a link formation game in continuous time. We manipulate the type of pricing rule that allocates the surplus from bilateral trades that are realized between connected pairs of subjects in the network. Across three simple rules, the star network with high efficiency and large inequality is stable. Moreover, the cycle network, which reconciles efficiency and equality, is stable only under one specific pricing rule (criticality).

Our experiment provides clear evidence that different allocation rules have strong effects on the macroscopic features of the network. Under the criticality rule, a network with multiple cycles with long path lengths is observed, thereby generating high efficiency and low payoff inequality. On the other hand, a hub-spoke network emerges under the other pricing rules, thereby increasing efficiency while creating extreme inequalities between the unique intermediary - the hub - and other actors. This observation clearly contrasts with previous experimental studies (generally involving small groups) suggesting that inequality aversion is a powerful barrier to the emergence of extremely unequal outcomes in the lab.

We explain these important treatment effects through the different individual incentives associated with different pricing rules. Under the criticality rule, subjects are incentivized to form two links to prevent others from extracting intermediation rents. Under the other pricing rules, we distinguish between two types of incentives conditional on the individual's degree: subjects with low connectivity benefit by forming a single link with the most central individual; subjects with high connectivity benefit by forming more links to become more dominant. The subjects' effective reaction to those myopic incentives, despite the significant complexity of the decision environment in which they navigate, provides further support for the novel methods associated with our experimental platform to study large scale economic phenomena.

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APPENDIX

A Proofs

A.1 Proof of Proposition 1

Pairwise stability of the Empty network is straightforward.

In the Star network, the hub does not benefit from removing a link if $c < \frac{Vn}{3} - \frac{V}{6}$. Under the same condition, no spoke can benefit from removing a link. No pair of spokes can benefit by adding a link with each other if $c > \frac{V}{6}$. The Star network is therefore pairwise stable if $\frac{V}{6} < c < \frac{Vn}{3} - \frac{V}{6}$.

In the Cycle network, no pair of players can benefit by adding a link because $c > 0$ and it cannot change the access benefit ($= \frac{(n-1)V}{2}$) or the intermediation rent ($= 0$). Given that that the access benefit obtained by a player removing a link is $\sum_{i=1}^{n-1} \frac{V}{i+1}$, such an action is not profitable as long as $c < \frac{V(n-1)}{2} - \sum_{i=1}^{n-1} \frac{V}{i+1} = \sum_{i=1}^{n-2} \frac{Vi}{2(2+i)}$. The Cycle network is therefore pairwise stable if $c < \sum_{i=1}^{n-2} \frac{Vi}{2(2+i)}$.

In the Complete network, if $n = 3$ and $c < \frac{V}{6}$, no one can benefit by removing a link. If $n > 3$ and $c > 0$, then any player can benefit by removing a link because it cannot reduce either access benefit ($= \frac{(n-1)V}{2}$) or intermediation rent ($= 0$). Therefore. the Complete network is not pairwise stable for a sufficiently large n.

Finally, it is easy to see that, for any values of $c > 0$ and $n \geq 3$, there is at least one pairwise stable network among the Empty, Star, and Cycle networks.

A.2 Proof of Proposition 2

Pairwise stability of the empty network is straightforward.

Pairwise stability of the Star network follows the same arguments as in the proof of Proposition 1.

In the Complete network, no player can benefit by removing a link as long as $c < \frac{V}{6}$.

In the Cycle network, it is easy to see that, the gain in benefits (access benefits and brokerage rents) for adding a link between two players sitting at an extreme distance from one another increases with n. As a result, if n is sufficiently large, then such a move becomes profitable for both players. This argument naturally extends to any k-cycle-s-Star network with fixed values of k and s, and a sufficiently large n.

Finally, it directly follows that, for any values of $c > 0$ and $n \geq 3$, there is at least one pairwise stable network among the Empty, Star, and Complete networks.

A.3 Proof of Proposition 3

Pairwise stability of the Empty network is straightforward.

In the Star network, the hub does not benefit from removing a link if $c < \frac{V}{2} + p(n-2)$. Similarly, no spoke can benefit by removing a link as long as $c < \frac{V}{2} + \frac{(n-2)(V-p)}{2}$. No pair of spokes can benefit by adding a link with each other if $c > \frac{p}{2}$. The Star network is therefore pairwise stable if $\frac{p}{2} < c < \frac{V}{2} + (n-2)\min(p, \frac{V-p}{2})$.

In the Complete network, no player can benefit by removing a link as long as $c < \frac{p}{2}$.

In the Cycle network, let x represent the maximum number of intermediaries for a trade to be realized, i.e., $x \leq \frac{V}{p}$. If the group size n is sufficiently large, then adding a link between two players sitting at an extreme distance from one another leads to the following gains in benefit earned by each. The gain in access benefit corresponds to $\frac{V}{2} + xV - \frac{xp(x+1)}{2}$ whereas the gain in brokerage rents corresponds to $2px^2$. The total gain in benefits therefore adds up to $\frac{V}{2} + xV + \frac{px}{2}(3x-1)$. Since adding a link costs c, such a move is profitable for both players if $\frac{V}{2} + xV + \frac{px}{2}(3x-1) > c$. Setting up a conservative value for x such that $x = \frac{V}{p} - 1$, the latter condition becomes $\frac{5V^2}{2p} - 4V + 2p > c$. Therefore, the cycle network is not pairwise stable for a sufficiently large n as long as $c < \frac{5V^2}{2p} - 4V + 2p$.

Finally, it is easy to see that, for any values of $c > 0$ and $n \geq 3$, there is at least one pairwise stable network among the Empty, Star, and Complete networks.

B Additional Tables and Figures

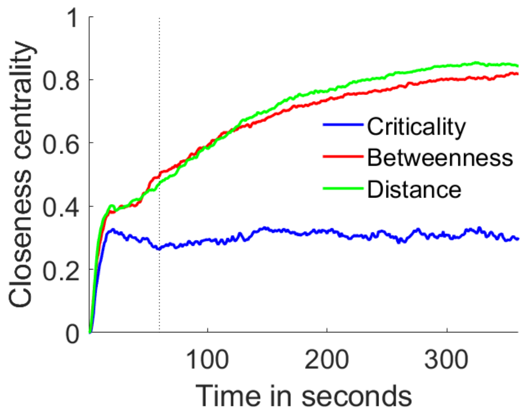
B.1 Network Centrality Measures

We consider two standard measures of network centrality: closeness and degree centrality.

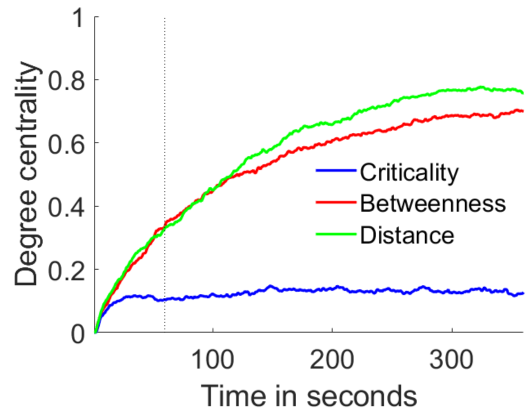
Closeness centrality of a player i in a given network g captures how close i is from all other players. Formally, it is calculated as $C_c(i;g) = \sum_{j \neq i} \frac{n-1}{d(i,j;g)}$. Closeness centrality of a network g with n players, as used in Figure 16a, corresponds to $C_c(g) = \frac{\sum_{i=1}^{n}[C_c^{max}(g) - C_c(i;g)]}{(n-2)(n-1)/(2n-3)}$ where $C_c^{max}(g) = \max_i C_c(i;g)$. Average closeness centrality of networks realized across different treatments in the experiment is depicted in Figure 16a.

Degree centrality of a player i in a given network g captures the fraction of links realized by i. Formally, it corresponds to $C_d(i;g) = \sum_{j \neq i} \frac{\eta_i(g)}{n-1}$. Degree centrality of a network g

with n players, as used in Figure 16b, corresponds to $C_d(g) = \frac{\sum_{i=1}^{n}[C_d^{max}(g) - C_d(i;g)]}{n-2}$ where $C_d^{max}(g) = \max_i C_d(i; g)$. Average closeness centrality of networks realized across different treatments in the experiment is depicted in Figure 16b.



(a) Closeness centrality



(b) Degree centrality

Figure 16: Network Centrality Measures in the Experiment

B.2 Alternative Inequality Measure

Figure 17 depicts an alternative to the inequality measure presented in the main text, based on the well known Lorenz curve and Gini coefficient.

B.3 Explanations of Macroscopic Patterns

During the game, we compute the average payoff change for adding a link by considering all individuals who gained a link by the means of their own single action or that of their counterpart (or both) at any moment t, conditional on their degree at t-1. For each observation, we further compute the minimum and maximum payoff change that could have been obtained by considering all proposals at t-1, from the individual or the counterpart, that could have turned into a link at t. Similarly, we compute the average payoff for deleting a link by considering all individuals who lost a link by the means of their own action or that of their counterpart at any moment t, conditional on their degree at t-1. For each observation, we further compute the minimum and maximum payoff change that could have been obtained by considering all links that could have been deleted by the individual

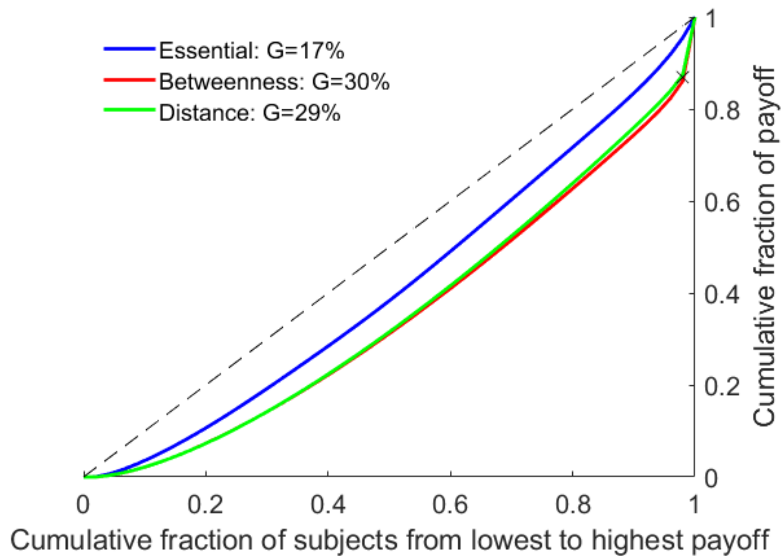
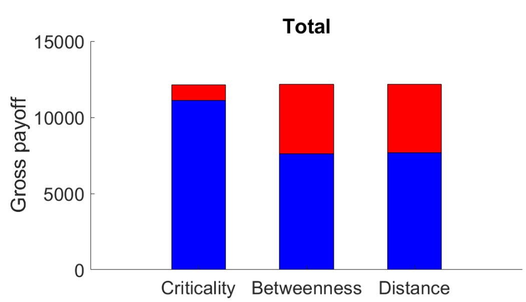
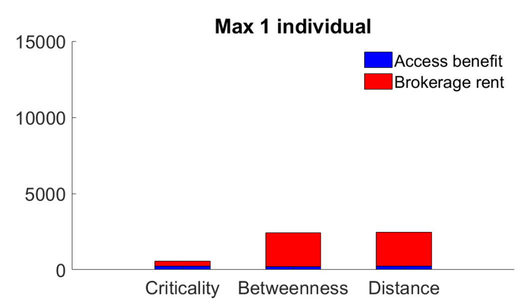


Figure 17: Lorenz curve and Gini Coefficient



(a) Sum of individual benefits



(b) Maximum individual benefits

Figure 18: Distribution of gross payoffs

or the counterpart at t-1. Corresponding results across treatments are presented in Figure 19.

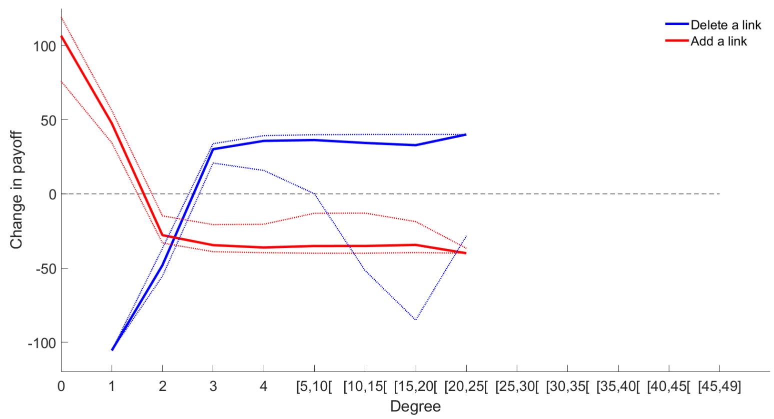
Furthermore, Figure 20 replicates the analysis depicted in Figure 13, across different periods during the game. We see that the corresponding patterns are consistent with the results from Figure 13, indicating that the incentives do not significantly vary over time.

B.4 Regression tables

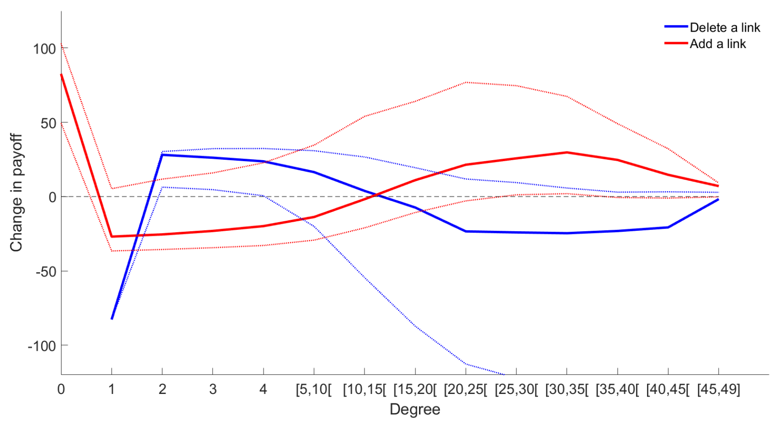
Table 4: Treatment effects on efficiency

	Efficiency
Betwenness	-0.532***
	(0.022)
Distance	-0.641***
	(0.053)
Critical × time	0.000***
	(0.000)
Betweenness × time	0.001***
	(0.000)
Distance × time	0.002***
	(0.000)
Constant	0.716***
	(0.005)
Number of observations	18,000
R-squared	0.681

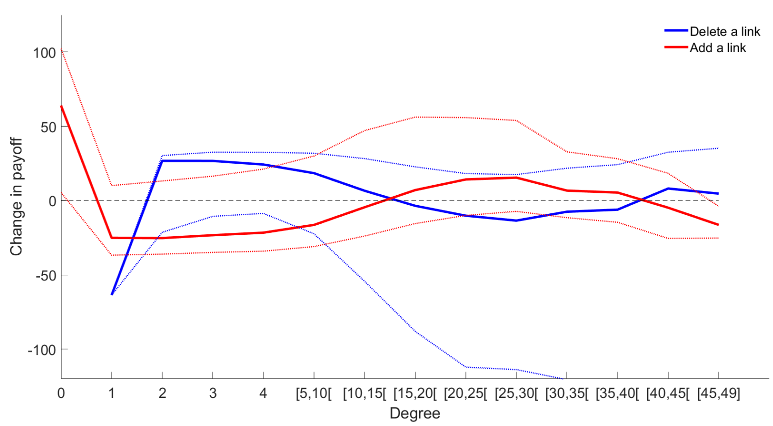
Notes: Robust standard errors, clustered by group, are reported in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.



(a) Criticality based pricing

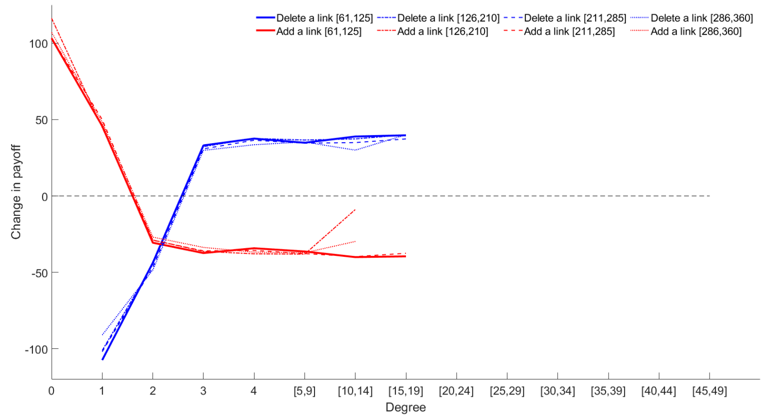


(b) Betweenness based pricing

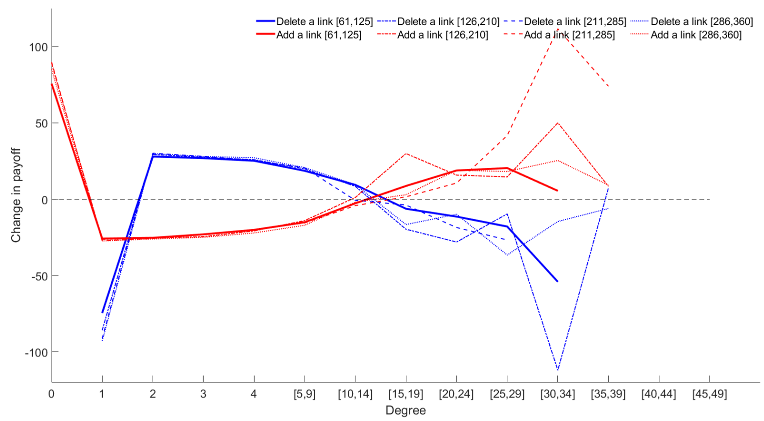


(c) Distance based pricing

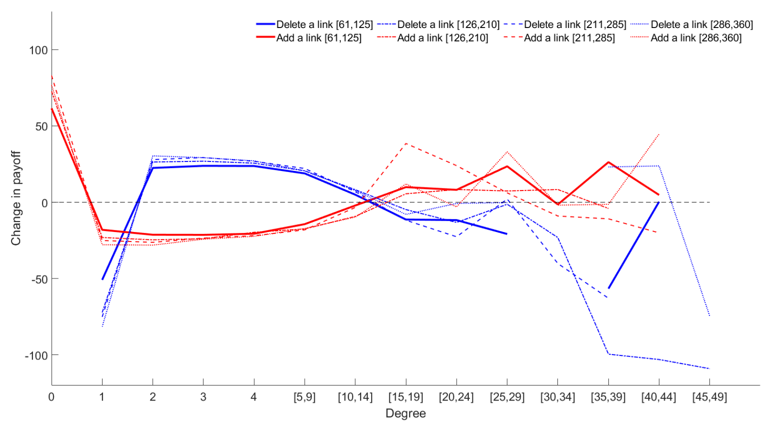
Figure 19: Payoff changes from actions (add / delete a link)



(a) Criticality based pricing



(b) Betweenness based pricing



(c) Distance based pricing

Figure 20: Payoff changes from actions (add / delete a link) across different periods during the game ([61,125], [126,210],[211,285].[286,360])

Table 5: Treatment effects on the number of links

	Nb of links
Betwenness	55.838***
	(2.339)
Distance	66.476***
	(5.446)
Criticality × time	-0.018***
	(0.001)
Betweenness × time	-0.147***
	(0.011)
Distance × time	-0.160***
	(0.018)
Constant	76.791***
	(0.469)
Number of observations	18,000
R-squared	0.683

Notes: Robust standard errors, clustered by group, are reported in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Inequality
Betweenness	9.625***
	(0.874)
Distance	23.062***
	(2.171)
Criticality × time	0.000
	(0.000)
Betweenness × time	0.014***
	(0.002)
Distance × time	-0.028**
	(0.007)
Constant	2.747***
	(0.080)
Number of observations	17,977
R-squared	0.310

Notes: Robust standard errors, clustered by group, are reported in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Treatment effects on inequality

	Network Diameter
Betweenness	-2.948***
	(0.127)
Distance	-3.271***
	(0.145)
Criticality × time	0.003***
	(0.000)
Betweenness × time	-0.002***
	(0.000)
Distance × time	-0.003***
	(0.000)
Constant	7.946***
	(0.125)
Number of observations	18,000
R-squared	0.805

Notes: Robust standard errors, clustered by group, are reported in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Treatment effects on network diameter

C Experimental instructions

[All treatments]
Please read the following instructions carefully. **These instructions are the same for all the participants**. The instructions state everything you need to know in order to participate in the experiment. If you have any questions, please raise your hand. One of the experimenters will answer your question.

In addition to the 5 euro show up fee that you are guaranteed to receive, you can earn money by scoring points during the experiment. The number of points depends on your own choices and the choices of other participants. At the end of the experiment, the total number of points that you have earned will be exchanged at the following exchange rate:

110 points = 1 Euro

The money you earn will be paid out in cash at the end of the experiment. The other participants will not see how much you earned.

In this experiment, you will participate in 6 independent rounds of the same form. The first round is for practice and does not count for your payment. The next 5 rounds will be counted for your payment. At the beginning of the first round, you will be grouped with 49 other participants; so there are 50 participants in all in your group. This group will remain fixed throughout the six rounds.

A round

We now describe in detail the process that will be repeated in each of the six rounds.

At the beginning of a round, you in your computer screen will be identified as the circle of 'Me' and the other participants will be randomly assigned an identification number of the form "Px" where x is a number between 1 and 49, and identified as the circle of "Px". The ID assignment of the other participants will remain unchanged within the round and will be randomly made again at the beginning of the next round (e.g., node P4 does not refer to the same participant across different rounds).

Each round will last 6 (six) minutes. At the very beginning of the round, participants will start with an empty network where no link among them is formed. All participants will then be asked to propose any number of links to any of the other participants to whom they wish to link by double-clicking on their corresponding nodes. Anyone who makes a link proposal to you (while you do not make a link proposal with them) will become **triangle-shaped**. For example, players P2, P3, and P4 make link proposals to you in the left part of Figure 1 (while you do not make any link proposal). Similarly, any link proposal that you make to player who does not make one with you will become **square-shaped**.

A link between two participants will be formed only if both of the participants proposed a link with each other. Anyone who is linked with you, called your neighbour, will become **circle-shaped**.

For example, from the left part of Figure 1, suppose that you make link proposals to each of P2, P3, P4 and P6. Because you also received link proposals from P2, P3, and P4, each of them is now linked to you and becomes circle-shaped. This is shown in the right part of Figure 1. On the other hand, P6 did not make a link proposal to you, and as a result, P6 will become square-shaped on your screen. Those who neither proposed a link to you nor received a link proposal from you will remain circle-shaped (for example, P1, P5, and P7, in the right part of Figure 1). Note that the network depicted in Figure 1 is also shown on your screen as a tutorial for you to test the experimental interface by creating and/or removing link proposals with other (virtual) players.

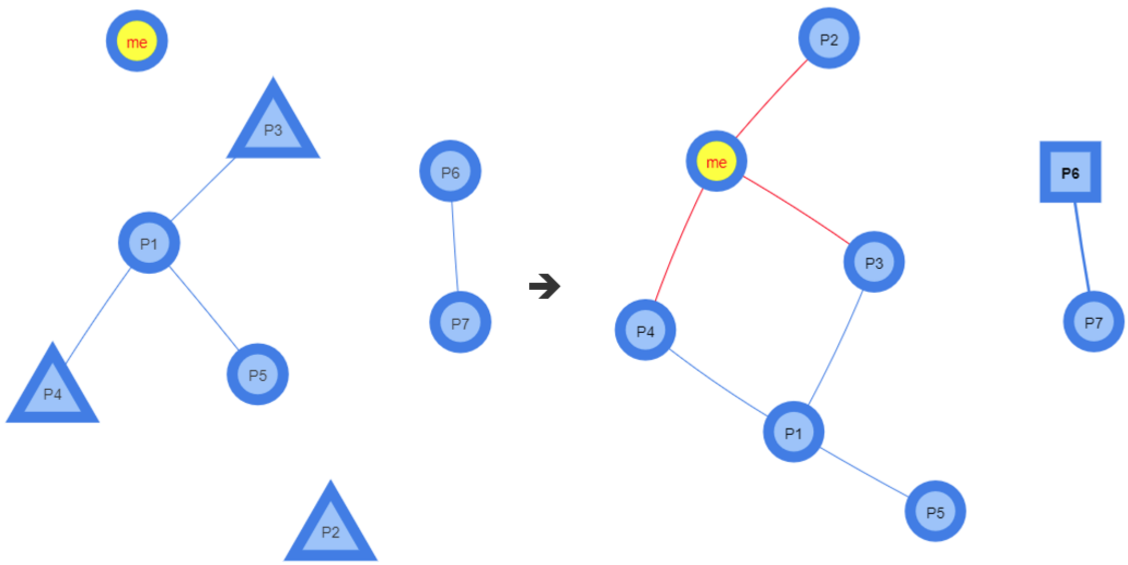


Figure 1

Every participant will be allowed to **add/delete link proposals with other participants** at any moment during the six minutes of the round. If you delete a link proposal to a participant who was linked to you (someone shown circle-shaped in the screen), then that participant will no longer be linked to you and will revert to being triangle-shaped. If you delete a link proposal to a participant who received a link proposal from you but did not propose a link to you (who was shown square-shaped in the screen), that participant will become circle-shaped. For example, starting from the network in the left part of Figure 2, deleting the link proposals to P3 and P6 will result in the network shown on the right part of Figure 2. In these ways, the computer screen will update the network every 2 seconds or whenever you revise your linking decision.

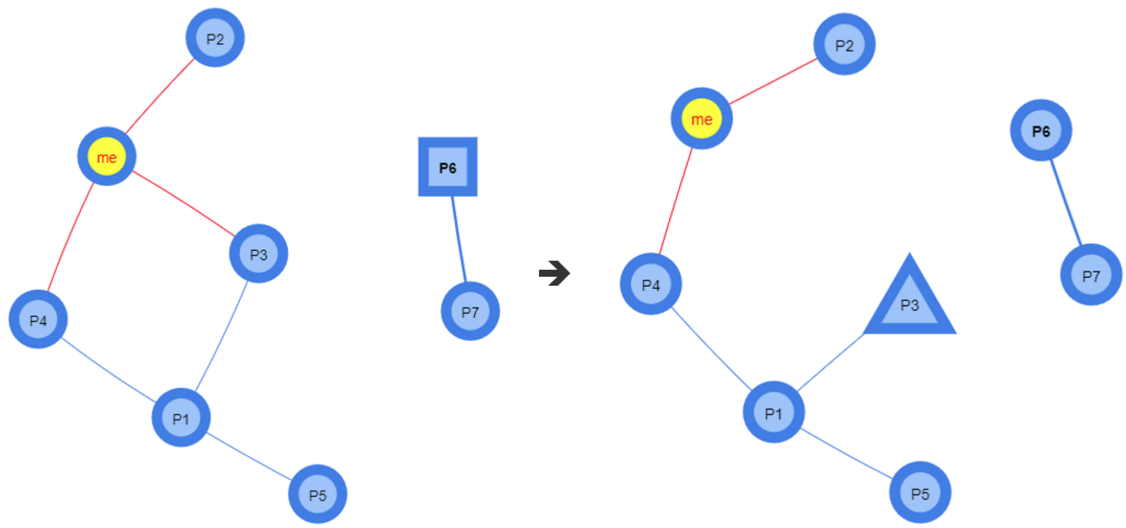


Figure 2

In summary, the shape of each participant on the computer screen indicates your relationship with them.

- **Circle**: they are linked with you or unlinked (no proposal from them or from you)
- **Square**: you propose a link, but they do not reciprocate.
- **Triangle**: they propose a link to you, but you do not reciprocate.

The first minute of each round will be a trial period and only the last 5 minutes will be relevant for your earnings in that round. Your earnings in the round will be based on everyones choice **at a randomly selected moment in the last 5 minutes of the round**. In other words, any decision made before or after that randomly chosen moment will not be used to determine your points. This precise moment will be announced to everyone only at the end of the round, along with the corresponding behavior and earnings.

In order to help you keep track of potential earnings which you and the other participants make during the round, your earnings at each moment will be presented at the top part of the computer screen. In addition, the payoff of each participant from the network is presented inside their corresponding node (rounded to the closest integer, below their identification number).

After participants are informed of their earnings at a randomly chosen moment, the next round will start with the computer randomly assigning IDs of the other participants in your group. This group is the same as in the previous round. However, IDs of other players are likely to be different across different rounds.

Earnings

At the beginning of the experiment, you are given **an initial balance of 400 points**. The first round will be used to familiarize yourself with the experiment and will have no influence on your earnings. Your final earnings at the end of the experiment will consist of the sum of points you earn across the last 5 rounds, plus this initial balance. Note that if your final earnings go below 0, they will be treated as 0.

Your earnings in each round depend on benefits you get from your own connection to the other participants and whether you are critical for the connection between two other participants (brokerage rent), and the cost of linking you pay.

In a network, two participants are said to be **connected** when there exists a path linking them. For example, in the right part of Figure 1, you are connected with the five participants of P1, P2, P3, P4, and P5.

[Treatment Criticality only]
A participant is said to be **critical** for the connection between two other participants if they are connected and the participant lies on ALL paths between them. In the pair between you and P5, P1 is critical because P1 lies on each of the two paths between you and P5.

Every connected pair of two participants creates a value of **10 points**. The pair creating the value of 10 points shares this value equally among themselves and all the critical participants between them.

Your total benefits consist of

(1) The benefits you earn from your own connection to other participants,

(2) The brokerage rents you earn from by being critical for the connection between pairs of other participants.

[Treatment Betweenness only]
Flow of transactions between two participants will be only made through a shortest path between them in the network. This means that only a participant who lies on a shortest path between two other participants can be involved in transactions and earn brokerage rent. For instance, consider the right part of Figure 1: between Me and P5, there are two shortest paths: Me-P4-P1-P5 and Me-P3-P1-P5. Both paths have two participants lying on them, and can be used for trade between Me and P5.

Every connected pair of two participants create a value of **10 points**. This value is divided equally among the connected pair and participants lying on any existing shortest path. If M is the number of participants lying on any shortest path for the pair, then each member of the pair earns **10/(M+2) points**. Other participants lying on any shortest path earns **10/(M+2) points** multiplied by the proportion of the number of shortest paths that she lies on. By way of illustration, consider the right part of Figure 1: there are two shortest paths between Me and P5 with 2 participants lying on each of them (M=2), and therefore participants P3 and P4 who lie on one shortest path each receive 1.25 points $(10/(2+2) \times 1/2)$. However, participant P1 lies on both the shortest paths and receives 2.5 points $(10/(2+2))$.

Your benefits therefore consist of

(1) The benefits you earn from your own connection to other participants,

(2) The brokerage rents you earn for lying on shortest paths between pairs of other participants.

[Treatment Distance only]
Flow of transactions between two participants will be only made through a shortest path between them in the network. This means that only a participant who lies on a shortest path between two other participants can be involved in transactions and earn brokerage

rent. For instance, consider the right part of Figure 1: between Me and P5, there are two shortest paths: Me-P4-P1-P5 and Me-P3-P1-P5. Both of them can be used for trade between Me and P5.

A participant lying on a shortest path for a pair of participants receives **3 points** multiplied by the proportion of the number of shortest paths that she lies on. By way of illustration, consider the right part of Figure 1: there are two shortest paths between Me and P5, and therefore participants P3 and P4 who lie on one shortest path each receive 1.5 points (3/2). However, participant P1 lies on both the shortest paths and receives 3 points.

Every connected pair of two participants have a potential value of **10 points**. This value is realized only if the sum of brokerage rents on a shortest path that need to be paid by the two connected participants is less than or equal to 10. If the sum of brokerage rents exceeds the potential value 10, then the value is not realized: the connected pair and all participants on every shortest path between them earn 0. In case the value is realized, the connected pair earns a surplus that equals the value (10) less the sum of brokerage rents. The surplus is equally divided between the two members of the connected pair.

Your total benefits consist of

(1) The benefits you earn from your own connection to other participants,

(2) The brokerage rents you earn for lying on shortest paths between pairs of other participants.

[All treatments]

On the cost side, you pay **40 points** per link that is created by you. Note that a link proposal made by you will cost you 40 points only if the participant who received your link proposal has also made a link proposal to you. Otherwise, your link proposal does not create a link and costs nothing.

Therefore, your earnings in each round correspond to the network chosen at a random moment from the last five minutes of the experiment.

Earnings = (sum of values you obtain from your connections with others) + (sum of values you obtain from brokerage) (total cost of links created by you)

The top part of the computer screen shows you the earnings that are decomposed into the three parts:

- **Benefits from being connected**
- **Brokerage rents**
- **Costs of linking**

To give you a concrete idea of how each part of earnings is computed, let us take the network on the right part of Figure 1. You are presented as Me.

First, observe that there is no path to two participants - P6 and P7: as you are not connected to them, you obtain no benefit from them.

[Treatment Criticality only]
Second, you are connected to four participants P1, P2, P3 and P4 without any critical participants. You obtain $10/2 = 5$ points from each of these connections. You are also connected to another participant, P5, and there is one critical participant, P4, between you and P5. You obtain $10/3 = 3.3$ points. Therefore, the benefits that you get from your connections are

$$\frac{10}{2} \times 4 + \frac{10}{3} \approx 23.3$$

Third, observe that you are critical between P2 and each of the four participants P1, P3, P4, and P5. So you obtain brokerage rents from these pairs. Specifically, you are the only critical participant in three pairs (P2, P1), (P2, P3), and (P2, P4). In the pair (P2, P5), you and P1 are both critical. The brokerage rents you obtain are

$$\frac{10}{3} \times 3 + \frac{10}{4} = 12.5$$

Recall that your payoff is only affected by the reciprocated links.

[Treatment Betweenness only]
Second, you are connected to three participants P2, P3 and P4 without any intermediary. You obtain $10/2 = 5$ points from each of these connections.

You are connected to participant P1, through two participants P3 and P4, lying on two distinct shortest paths, between you and P1. You and participant P1 each receive $10/(2+1) = 3.3$ points. You are also connected to participant P5 through 3 intermediaries: P3 and P4 lying on only one shortest path, and P1 lying on both shortest paths. You and participant P5 each receive $10/(2+2) = 2.5$ points. Therefore, the benefits that you get from your connections are

$$5 \times 3 + 3.3 + 2.5 \approx 20.8$$

Third, observe that you lie on all shortest paths between P2 and each of the four participants P1, P3, P4, and P5. So you receive brokerage rents from these pairs (P2, P1), (P2, P3), (P2, P4), and (P2, P5). You are the only intermediary for the pairs (P2,P3) and (P2,P4) and therefore earns 3.3 points ($\approx 10/(1+2)$) for each.

Two other intermediaries (P3 and P4) are lying on a shortest path for the pair (P2, P1). Since they each lie on only one of the two existing shortest paths, you earn 2.5 points ($= 10/(2+2)$).

Similarly, there are three other intermediaries lying on a shortest path for the pair (P2, P5): P3 and P4 lie on only one of the two shortest paths, and P1 lies on both of them (as you do). As a result, you earn 2 points ($= 10/(3+2)$).

You also lie on one shortest path out of the two shortest paths between P3 and P4. You therefore receive brokerage rents 1.7 points ($\approx 10/(1+2) \times 1/2$) from this pair. The total brokerage rents you obtain are

$$2 \times 3.3 + 2.5 + 2 + 1.7 \approx 12.8$$

Recall that your payoff is only affected by the reciprocated links.

[Treatment Distance only]
Second, you are connected to three participants P2, P3 and P4 without any intermediary. You obtain $10/2 = 5$ points from each of these connections.

You are connected to participant P1, through two participants P3 and P4, lying on two distinct shortest paths, between you and P1. You and participant P1 each receive $(10 - 3/2 - 3/2)/2 = 3.5$ points.

Finally, you are connected to participant P5 through 3 intermediaries: P3 and P4 lying on only one shortest path, and P5 lying on both shortest paths. You and participant P5 each receive $(10 - 3/2 - 3/2 - 3)/2 = 2$ points. Therefore, the benefits that you get from your connections are

$$5 \times 3 + 3.5 + 2 \approx 20.5$$

Third, observe that you lie on all shortest paths between P2 and each of the four participants P1, P3, P4, and P5. So you receive brokerage rents (3 points) from these pairs (P2, P1), (P2, P3), (P2, P4), and (P2, P5). You also lie on one shortest path out of two shortest paths between P3 and P4. You therefore receive brokerage rents 1.5 points (= 3/2) from this pair. The total brokerage rents you obtain are

$$3 \times 4 + 1.5 \approx 13.5$$

Recall that your payoff is only affected by the reciprocated links.

D Network game interface

The decision making interface used in the experiment is similar across all treatments. More specifically, Figure 21 illustrates a (fictitious) example of a subject's computer screen in Treatment **Criticality**. The top part of the screen depicts information about the timer indicating how much time has lapsed in the current round (the timer turns red when payoffs become effective, i.e., after 1 minute has passed), and a comprehensive description of the subject's own payoff. Information about payoffs include own benefits from own connections, brokerage rents, the cost of linking, and the net earnings. The bottom part of the screen shows detailed information about the network (the subject's node is highlighted in yellow).

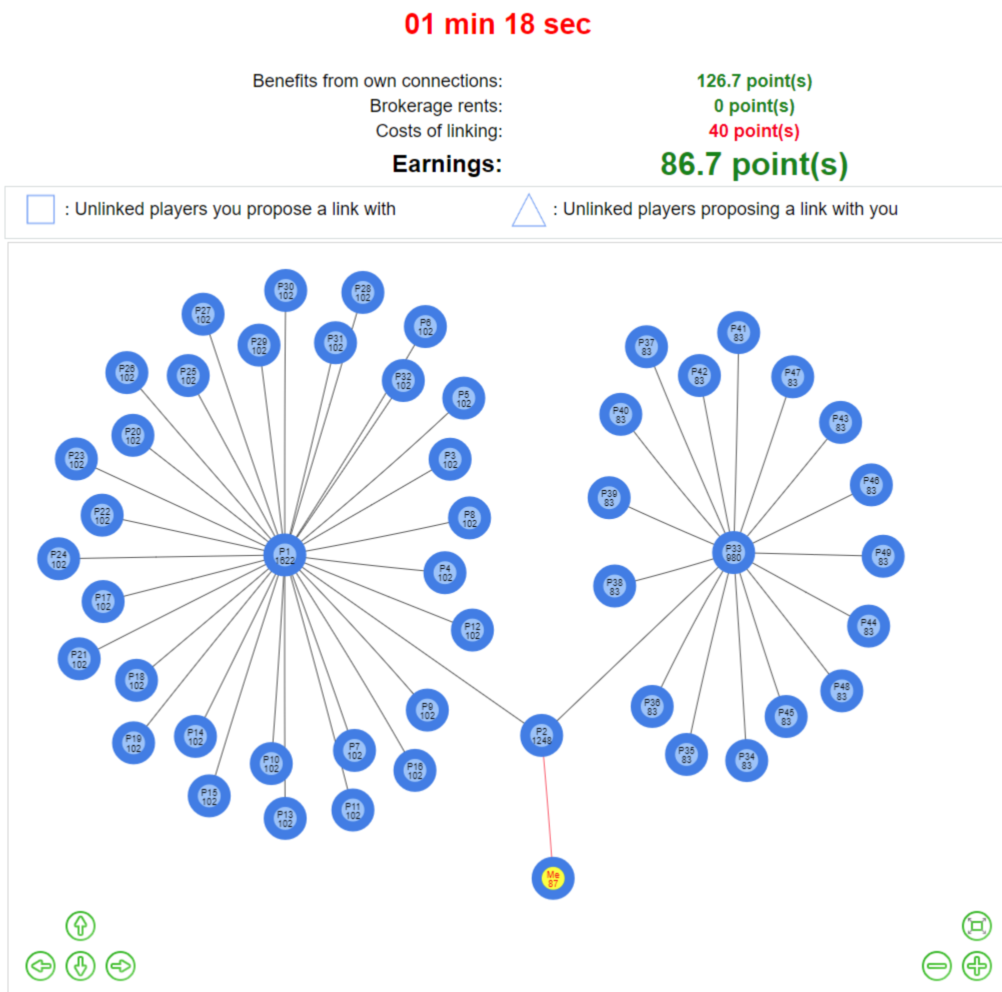


Figure 21: Example of decision screen for Criticality Treatment

E Questionnaires

At the end of the experiment, subjects answered a set of surveys aiming at measuring various types of individual differences. More precisely, incentivized measures of comprehension in network game, social preferences, and risk preferences were used. Finally non incentivized personality measures were used before which subjects filled up a debriefing questionnaire that includes demographics information.

E.1 Comprehension check

In order to assess the subjects' comprehension of the network game played during the experiment, we provided 6 questions, each of which with a unique correct answer. Each correct answer was rewarded with 0.1 euro for the subject.

All the same 6 questions were used across all treatments. In all treatments, the correct answers are "10 pts" to question 1, and "40 pts" to question 2, and "a randomly selected moment in the last 5 mins" to question 3.

The following questions 3, 4, and 5 relate to best response behavior in forming a link in some network. Correct answers are as follows: "P1" in question 4 (all treatments); "P1" (hub of the left hand side star) in question 5 (all treatments); "P18" (only node connecting the left and right component) for Criticality treatment, and "P1" (center of wheel on left hand side) for Betweenness and Distance treatments in question 6.

Part 2/2: Questionnaire

Please answer the following questions. Any correct answer will earn you 0.1 euro.

Question 1: In the previous game, how many points were created by a connected pair?

- 0 pts
- 2 pts
- 4 pts
- 6 pts
- 8 pts
- 10 pts
- more than 10 pts

Question 2: In the previous game, how many points did forming a link cost you?

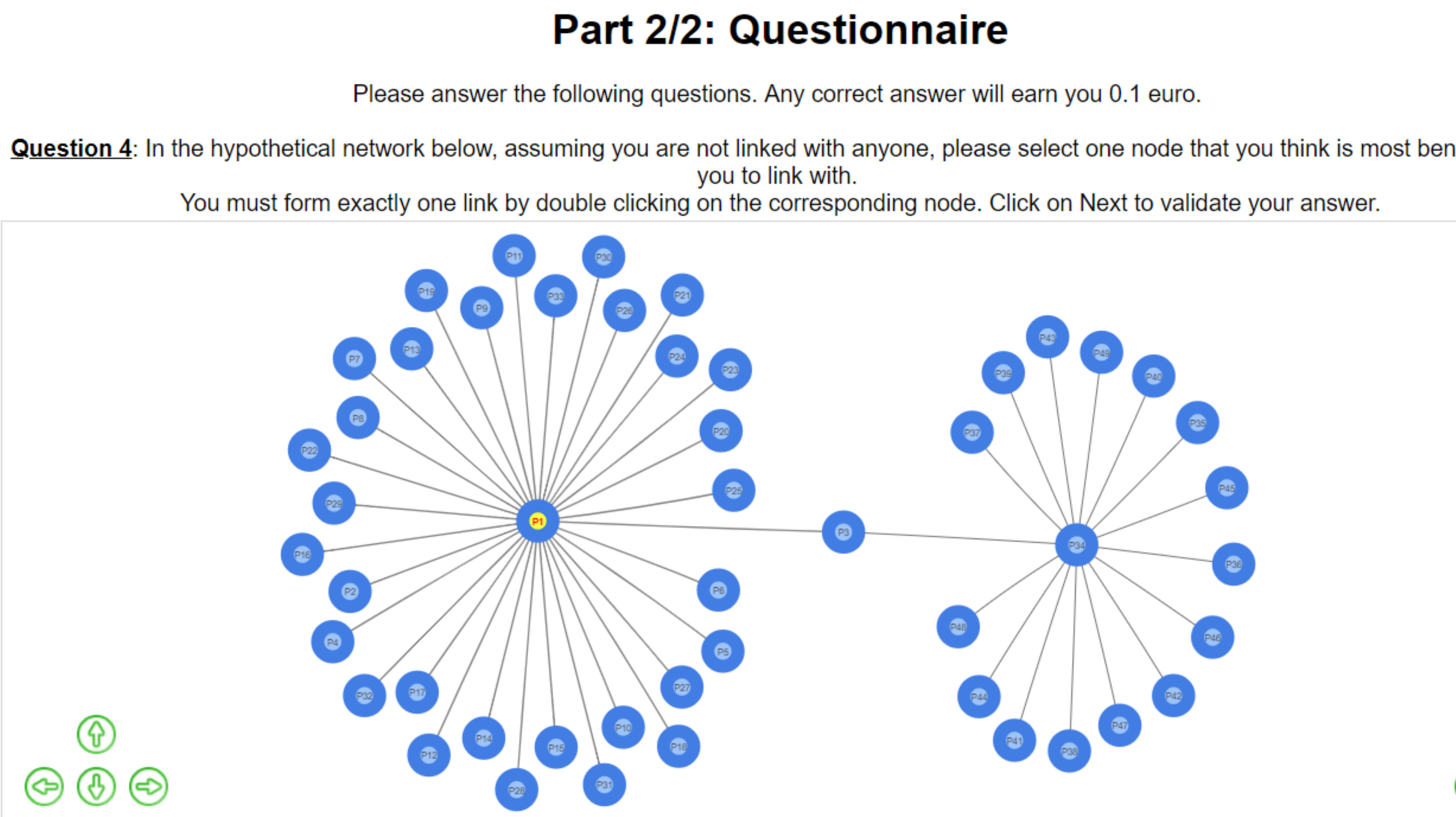
- 0 pt
- 10 pts
- 20 pts
- 30 pts
- 40 pts
- 50 pts
- more than 50 pts

Question 3: In each of the previous games, your earnings were determined by considering everyone's choice at:

- A randomly selected moment in the 6 minutes
- A randomly selected moment in the last 5 minutes
- Every moment of the 6 minutes
- Every moment of the last 5 minutes
- The end of the 6 minutes
- The end of the 1st minute

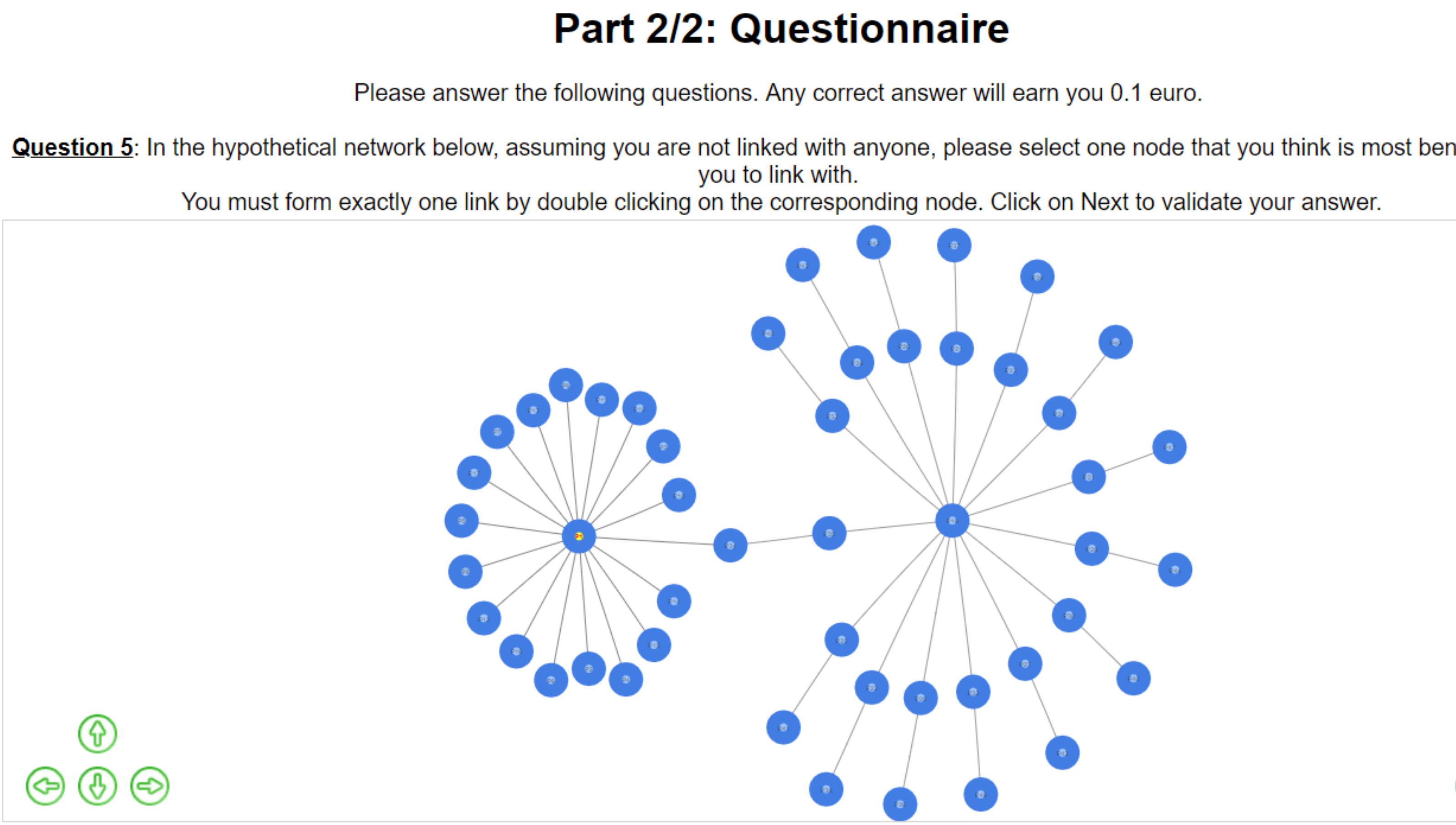
E.2 Social preferences

The social preferences measure was adapted from Andreoni and Miller [2002] and involved a series of five money allocation tasks between the decision maker and some anonymous external participants of another experiment at the LINEEX lab (corresponding payments were therefore made to these external passive participants). The five tasks used in our experiment were represented through sliders as shown in the following figure:



Note however that each question was presented in a different screen, and the order of presentation was randomized for every subject. Furthermore, 50 points were worth 1 euro both the subject, and the other anonymous external participant. Detailed instructions provided to the subjects, as well as a screenshot highlighting one of the above five questions are described below.

<u>Instructions</u>: *You are asked to answer a series of 5 questions, each of which consists of selecting an allocation of points that you most prefer between yourself and an anonymous randomly selected person who is participating to a different experiment in this lab. At the end of the study, we will randomly select your allocation for 1 of the 5 questions to determine the payments for both you and the other person in this part. Your decisions will remain unknown to the other persons you are matched with.*



E.3 Risk preferences

The risk preference measure was adapted from Holt and Laury [2002] and consisted of a series of five binary choices between lotteries, presented as in the figure below.

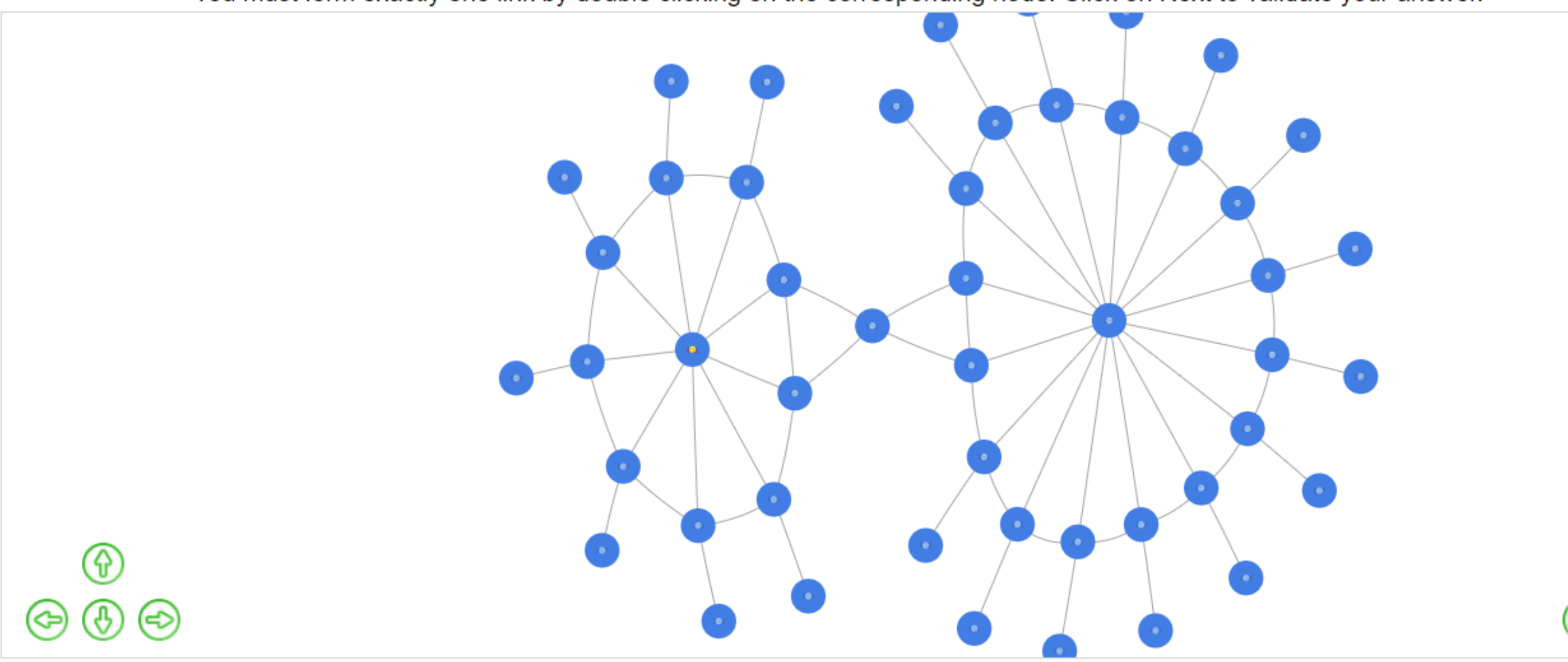
E.4 Personality test

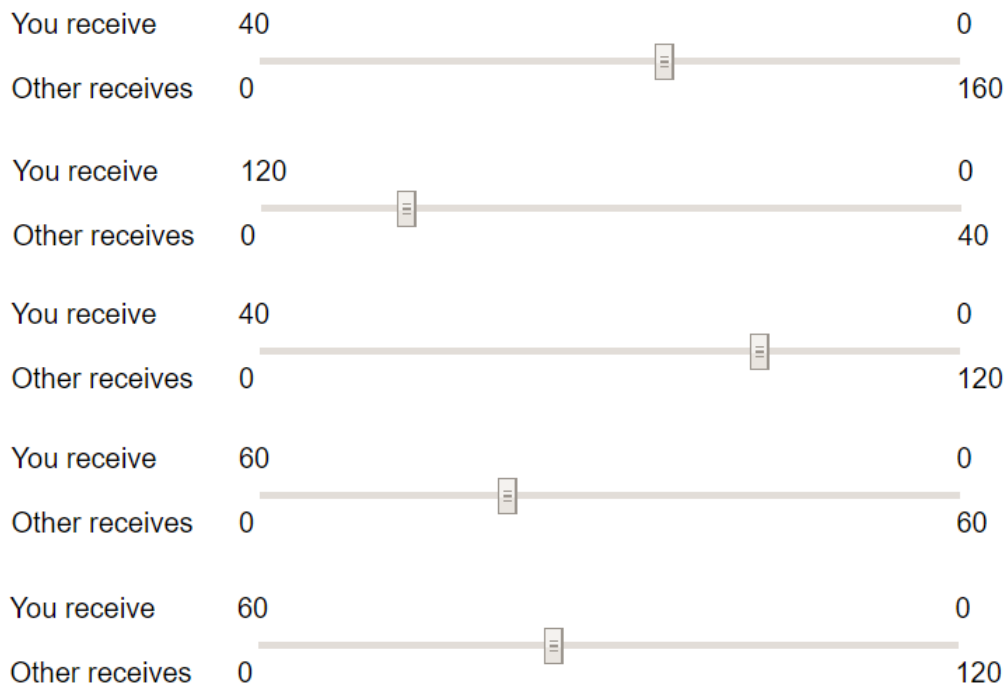
Non incentivized measures were used through a simplified version of the Big Five personality inventory test adapted from Rammstedt and John [2007], as shown below.

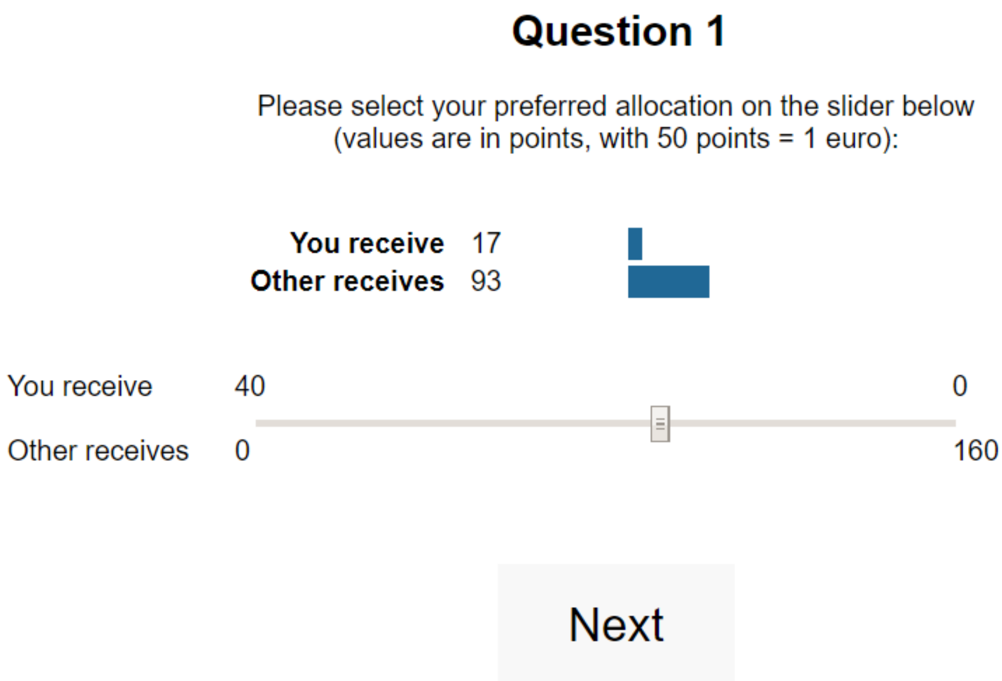
Part 2/2: Questionnaire

Please answer the following questions. Any correct answer will earn you 0.1 euro.

Question 6: In the hypothetical network below, assuming you are not linked with anyone, please select one node that you think is most bene
you to link with.
You must form exactly one link by double clicking on the corresponding node. Click on Next to validate your answer.




You receive 40 0
Other receives 0 160
You receive 120 0
Other receives 0 40
You receive 40 0
Other receives 0 120
You receive 60 0
Other receives 0 60
You receive 60 0
Other receives 0 120


Question 1
Please select your preferred allocation on the slider below
(values are in points, with 50 points = 1 euro):
You receive 17
Other receives 93
You receive 40 0
Other receives 0 160
Next

You are now asked to make 5 independent choices between two lotteries. According to **Lottery A**, you can win 2.00€ with a certain probability **p**, and 1.60€ otherwise. According to **Lottery B**, you can instead win 3.85€ with the same probability **p**, and 0.10€ otherwise. For each of the following 5 choices, which only differ in the value of the probability **p**, please select the lottery that you prefer. At the end of the study, we will randomly select one of your 5 preferred lotteries to determine your payment in this question.

	Lottery A			**Lottery B**
Choice 1:	2.00€ with probability 20/100, 1.60€ with probability 80/100	○	○	3.85€ with probability 20/100, 0.10€ with probability 80/100
Choice 2:	2.00€ with probability 35/100, 1.60€ with probability 65/100	○	○	3.85€ with probability 35/100, 0.10€ with probability 65/100
Choice 3:	2.00€ with probability 50/100, 1.60€ with probability 50/100	○	○	3.85€ with probability 50/100, 0.10€ with probability 50/100
Choice 4:	2.00€ with probability 65/100, 1.60€ with probability 35/100	○	○	3.85€ with probability 65/100, 0.10€ with probability 35/100
Choice 5:	2.00€ with probability 80/100, 1.60€ with probability 20/100	○	○	3.85€ with probability 80/100, 0.10€ with probability 20/100

Next

How well do the following statements describe your personality?

I see myself as someone who...	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
1. ... is reserved					
2. ... is generally trusting					
3. ... tends to be lazy					
4. ... is relaxed, handles stress well					
5. ... has few artistic interests					
6. ... is outgoing, sociable					
7. ... tends to find fault with others					
8. ... does a thorough job					
9. ... gets nervous easily					
10. ... has an active imagination					

Next