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Brokerage rents and intermediation networks

Syngjoo Choi^a , Sanjeev Goyal^{b,c,1}, and Frédéric Moisan^d

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This paper provides experimental evidence on the economic determinants of intermediation networks by considering two pricing rules—respectively, criticality and betweenness—and three group sizes of subjects—10, 50, and 100 subjects. We find that when brokerage benefits accrue only to traders who lie on all paths of intermediation, stable networks involve interconnected cycles, and trading path lengths grow while linking and payoff inequality remain modest as the number of traders grows. By contrast, when brokerage benefits are equally distributed among traders on the shortest paths, stable networks contain a few hubs that provide the vast majority of links, and trading path lengths remain unchanged while linking and payoff inequality explode as the number of traders grows.

brokerage | linking | inequality | intermediation

Intermediation is a salient feature of the modern economy. In some contexts, as in online retail, there exist dominant intermediaries with direct links to vast numbers of buyers and sellers while in other cases, as in tea and coffee supply chains and financial instruments, there exist long paths of intermediation (1–4). The goal of this paper is to examine the economic determinants of these different types of intermediation networks.

Our focus will be on the role of pricing rules that allocate the surplus from trades. The first pricing rule—criticality pricing—assumes that a trader earns rents for a trade between two other traders if it lies on all paths of the network that connects these traders (5–7). This reflects situations where network path lengths do not matter because goods can easily be processed and/or replicated (financial instruments, digital goods). By contrast, in environments where multiple links are a reflection of physical distances or there are significant costs of processing at every node, path lengths are important. To reflect such situations, the second pricing rule—betweenness pricing—presumes that a trader earns rents from a trade between two other traders only if it lies on the shortest path between them. This leads to payoffs that are proportional to betweenness centrality.

The economic theory of network formation helps us in identifying strategically stable networks under these pricing protocols. With criticality pricing, the networks involve (one or more interconnected) cycles; with betweenness pricing, the networks contain prominent hubs (who support a disproportionate share of all links). As a result, under criticality pricing, distances grow but degree and payoff inequality remain modest as the number of traders grows; under betweenness pricing, distances remain unchanged but degree and payoff inequality grow massively as the number of traders grows. This theory also tells us that the selected networks—cycle and star—maximize the sum total of payoffs of the traders. And it suggests that stable networks can exhibit egalitarian earnings (like a cycle) or very unequal earnings (like a star network), depending on the pricing protocol (see Fig. 1 below).

This difference in stable networks is due to subtle variations in linking incentives under the two pricing rules. An individual's linking problem is complicated because the attractiveness of links depends on the overall network. As the number of traders grows, the informational and computational requirements to make correct decisions become progressively more challenging. So it is quite unclear, *a priori*, if actual traders will abide by the incentives that drive the dynamics in the theoretical model. This motivates an experimental investigation of the pricing rules and their impact on networks and the distribution of payoffs.

The work of refs. 8–11 suggests that continuous time experiments offer subjects better prospects for learning and experimentation than discrete time experiments. Our experimental platform builds on this insight. We consider a design with criticality and betweenness pricing rules and with three group sizes (10, 50, and 100). This allows us to systematically examine how incentives matter and how they interact with group size.

The first experimental finding is that pricing rules have strong effects on the macroscopic features of the network. Under the criticality rule, networks with multiple cycles with long path lengths are observed, and they generate modest payoff

Significance

Social, infrastructure, and economic networks offer informational and resource advantages. Economic theory helps us understand how brokerage rent protocols shape incentives for linking and how this in turn gives rise to different network architectures (resp. cycles and long paths versus stars and small worlds) and different distribution of payoffs (resp. equal versus very unequal). A large-scale laboratory experiment offers strong evidence in support of these predictions.

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The authors declare no competing interest.

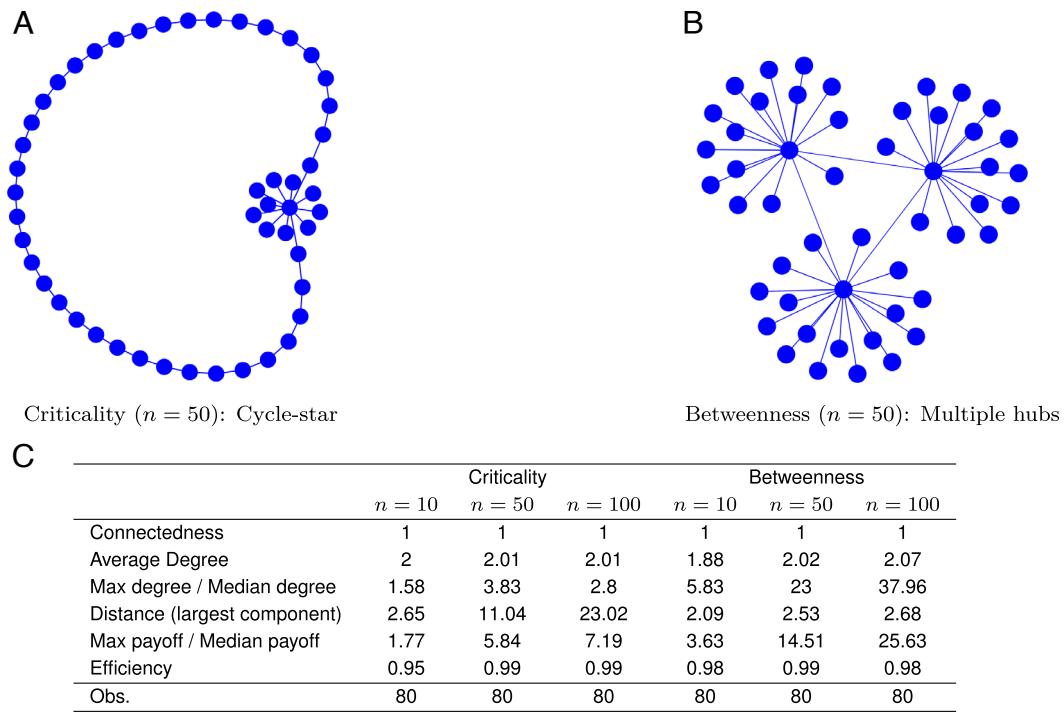
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Network statistics from computer simulations (after 80 runs of myopic best response dynamics)

Fig. 1. Prominent limit networks and statistics from computer simulations. (A) presents a limit network, cycle-star network, emerging in the Criticality & $n = 50$ treatment. (B) shows a limit network with multiple hubs in the Betweenness & $n = 50$ treatment. (C) presents key outcomes of limit networks emerging after 80 runs of myopic best response dynamics in computer simulations in each of the treatments.

inequality across all group sizes. Under betweenness pricing, networks with multiple hubs emerge and they support extreme degree and payoff inequality in large groups. These findings are consistent with the theory.

Our second experimental finding concerns efficiency: Under criticality, subjects create efficient networks very early on and sustain them across time, for all group sizes. Under betweenness, subjects create efficient networks early on and sustain them for the group of 10, but for the 50 and 100 groups the networks are initially inefficient and efficiency grows gradually over time. This initial inefficiency is due to excessive linking activity, which can be explained by substantial noise in individual decision-making. Moreover, such excessive linking is largely caused by a few subjects making many link proposals in an attempt to become hubs (and earn large rents). Other subjects instead reciprocate these link proposals to economize on rents involved in long intermediation chains. These incentives are absent under criticality pricing.

Our paper is a contribution to the study of brokerage and intermediation in networks. There is a long tradition of research on power and exchange in networks; prominent contributions include (7, 12–29). Building on this research, a recent literature in computer science and economics examines how surpluses and market power emerge through the deliberate creation of links in a network formation setting (5, 30–35); for an overview of this research, see ref. 4. Our contributions may be summarized as follows: We offer a model of betweenness pricing and the demonstration of selection of networks under different pricing protocols and best response dynamics and we offer an experimental test of how different brokerage pricing rules shape incentives to form links and create great payoff inequality in networks.

The rest of the paper is organized as follows. In Section 1, we describe the pricing models and formulate our hypotheses. Section 2 describes the design of the experiment. Section 3 presents the main experimental findings. Section 4 provides a discussion on efficiency and individual behavior. Supplementary materials (including theoretical analyses and experimental instructions) are presented in *SI Appendix*.

1. Theory

We consider a game with $N = \{1, 2, \dots, n\}$ individuals, where $n \geq 3$. 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} . Let $N_i(g) = \{j | g_{ij} = 1\}$ denote the nodes with whom node i has a link, i.e., the neighbors of i . Let $\eta_i(g) = |N_i(g)|$ be the number of links or degree of i .

Individuals propose links to each other. The strategy of a player i is a vector of link proposals $s_i = [s_{ij}]_{j \in N \setminus \{i\}}$, with $s_{ij} \in \{0, 1\}$ for any $j \in N \setminus \{i\}$. 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 $s = (s_1, s_2, \dots, s_n)$ induces an undirected network $g(s)$. With a slight abuse of notation, for simplicity, we will write g instead of $g(s)$. 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, \dots, i_n such that $g_{ii_1} = g_{i_1i_2} = g_{i_2i_3} = \dots = g_{i_nj} = 1$. Let $d(i, j; g)$ denote the geodesic distance or length of the shortest path between i and j in network g . $C_i(g)$ is

the set of players with whom i has a path in network g ; it is the component to which i belongs.

Players are traders who can exchange goods and this exchange creates a surplus of V . We assume this exchange is carried out whenever there exists a path between a pair of traders. 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 potential surpluses are 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.

Following (5), we shall say that 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 $t(j, k; g) = |T(j, k; g)|$ denote the number of critical players between j and k . Following (5) and (7), for every strategy profile $s = (s_1, s_2, \dots, s_n)$ the net payoffs to player i are given by:

$$\Pi_i^{crit}(s) = \underbrace{\sum_{j \in C_i(g)} \frac{V}{t(i, j; g) + 2}}_{\text{Access Benefits}} + \underbrace{\sum_{j, k \in C_i(g) \setminus \{i\}} V \frac{I_{i \in T(j, k; g)}}{t(j, k; g) + 2} - \eta_i(g)c}_{\text{Brokerage Rents}} \quad [1]$$

where $I_{i \in T(j, k; g)} \in \{0, 1\}$ stands for the indicator function specifying whether i is critical for j and k in network g . Under criticality pricing, the surplus is equally divided between two traders and all critical intermediaries connecting them. Recall, from ref. 7 that, under posted pricing by traders, the unique outcome is that traders will pay rents to intermediaries only if they are critical, and these rents will be roughly equal to all critical traders. *SI Appendix* illustrates this pricing rule with the help of examples.

In the criticality pricing model, trade can take place along arbitrarily long paths even when shorter paths are available, and that too without any costs. However, in practice, there is likely to be costs of transiting long paths. To take this factor into account, we propose a model of intermediation that emphasizes the role of shortest paths between traders. 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 surplus 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 (*SI Appendix* illustrates this pricing rule with the help of examples). 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. We write $b_{jk}^i(g) \in [0, 1]$ to denote betweenness of player i between j and k . Formally,

$$b_{jk}^i(g) = \frac{\# \text{ shortest paths between } j \text{ and } k \text{ on which } i \text{ lies}}{\# \text{ shortest paths between } j \text{ and } k}.$$

Given a strategy profile $s = (s_1, s_2, \dots, s_n)$, the net payoffs to player i under betweenness pricing are given by:

$$\Pi_i^{btwn}(s) = \underbrace{\sum_{j \in C_i(g)} \frac{V}{n_{ij} + 2}}_{\text{Access Benefits}} + \underbrace{\sum_{j, k \in C_i(g) \setminus \{i\}} V \frac{b_{jk}^i}{n_{jk} + 2} - \eta_i(g)c}_{\text{Brokerage Rents}} \quad [2]$$

The model of betweenness pricing is inspired by a model presented in ref. 30, according to which trade only occurs between directly connected traders or traders that are two links apart. We modify two dimensions of their model—we allow for trading along arbitrary paths and we introduce brokerage rents as being proportional to the length of the shortest paths. It is possible to show that a model of markup pricing by traders located in a network will yield payoffs proportional to betweenness centrality.*

Following (38), a network is said to be pairwise stable if no one can benefit by removing any existing link, and no pair can mutually benefit by adding a nonexisting link with each other. *SI Appendix* provides a formal definition of this concept and a general description of pairwise stable networks. *Fig. S1* presents examples of pairwise stable networks. The figure shows that the theory of pairwise stability is permissive: When $c > V/2$ the empty network and the hub-based networks are stable under both pricing rules. However, the cycle and hybrid cycle-star networks are also stable under criticality pricing but they are not stable under betweenness pricing. These networks vary greatly in their architecture and they also differ greatly on economically relevant dimensions that we now discuss.

The efficiency of a network is measured as the ratio between the sum of individual payoffs and the maximum sum of individual payoffs that can be achieved:

$$E(s) = \frac{\sum_i \Pi_i(s)}{\max_{s'} \sum_i \Pi_i(s')} \quad [3]$$

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

From standard considerations, we know that an efficient network is either empty or minimally connected (5), i.e., either there are no links at all or every pair of traders has a path that connects them in the network. The total payoffs in a minimally connected network are $\frac{Vn(n-1)}{2} - 2(n-1)c$, and they are equal to 0 in the case of an empty network. So an efficient network is minimally connected if $c < \frac{Vn}{4}$, and empty otherwise. A prominent example of a minimally connected network is the star network (with $n-1$ links); as it contains the same number of links, a minimally connected network with multiple hubs is also efficient. We note that a cycle network contains n links and is connected, so it is (approximately) efficient for large n , i.e., $E(\text{cycle})$ is close to 1 for large n .

We define degree inequality as the ratio of the highest degree to the median degree, and we define payoff inequality as the ratio of the highest payoff to the median payoff.

$$I(s) = \frac{\max_i(\Pi_i(s))}{\text{med}_i(\Pi_i(s))} \quad [4]$$

It follows that $I(s) \geq 1$. The outcome is equal if $I(s) = 1$, which is true for a cycle network. On the other hand, in the star

*Here is a sketch of how this can be done. We start from the theory of markup pricing (36, 37) and proceed as follows: Suppose that there is a small cost $c > 0$ to crossing a node and suppose that nodes use markup pricing and markup is fixed and exogenous and given by $m > 0$: so pricing for every node is $c(1+m)$. Suppose trade opportunities arise for every pair of traders; the pairs are designated origin and destination nodes. Suppose the designated pair chooses the cheapest path and if there are multiple cheapest paths, then they pick one at random. Then, intermediation payoffs to node x for trade between two nodes A and B will arise only if x lies on a shortest path between A and B . Moreover, the share of surplus accruing to x will be $b_{AB} \times cm$, where b_{AB} is the betweenness of x for the pair of traders, A and B . By aggregating across all possible pairs of traders, we see that the payoffs of x are proportional to its betweenness centrality in the network. To facilitate comparison with criticality pricing, we would like to allow for general path lengths. To avoid placing restrictions on the value of c , m , and size of surplus, we felt it was simpler to work with the smoother model in which brokerage rents vary with the length of the shortest path. This leads to the formulation used in the paper and reflected in payoffs Eq. 2 above.

network, under both criticality and betweenness pricing, the hub and spoke earn, respectively:

$$V(n-1) \left[\frac{1}{2} + \frac{n-2}{6} \right] - (n-1)c \quad V \left[\frac{1}{2} + \frac{n-2}{3} \right] - c. \quad [5]$$

The median payoff corresponds to the spoke's payoff; the ratio of hub payoffs to the median payoff is unbounded in the number of players.

Our interest is in the role of pricing protocols in determining the architecture and the economic properties of networks. With this goal in mind, we examine the dynamics of linking and show that the limit networks under the two pricing protocols are quite different.

A. Dynamics of Linking and Testable Hypotheses. Building on refs. 39–43, we define the dynamics as follows: Start from an initial random network and suppose that at each point a single individual (picked at random) makes a decision. This individual considers the potential payoffs that can be attained (according to either pricing rule) by adding or deleting a single link with any other player. The individual chooses the option with the highest immediate payoff. In an iteration of the simulation, every individual gets 100 opportunities to make a decision.

In order to ensure that the predicted networks are not an artifact of initial networks, we consider both egalitarian as well as inegalitarian networks and sparse as well as dense networks (we use Erdos–Renyi and Barabasi–Albert models with either low or high link density as initial networks—the details are provided in *SI Appendix*). The model parameters used in the simulations are as follows (the same parameters are used in the experiment): The value of trade between any two traders is given by $V = 10$; there are three group sizes, 10, 50, and 100. The cost of a link is adjusted across group sizes to keep incentives as similar as possible: so $c = 8$ for $n = 10$, $c = 40$ for $n = 50$, and $c = 80$ for $n = 100$.

The simulations yield sharp selection across pricing rules. Under criticality pricing, networks with (one or more dominant) cycles are common; under betweenness pricing, networks with multiple hubs are common (the number of hubs increases with the number of players). We present representative networks in Fig. 1. Fig. 1C presents the average statistics in the resulting network structures at the end of the 80 simulations run for three group sizes, under both pricing rules. Further details of the procedure and statistics corresponding to each initial network can be found in *SI Appendix*, Tables S1–S4.

Fig. 1C tells us that limit networks are connected, i.e., there is a path in the networks between every pair of traders. Distances grow under criticality but remain small under betweenness across group size. Under criticality pricing, degree and payoff inequality remain modest across group sizes; under betweenness pricing, they grow massively with group size. Finally, as the limit networks are connected and have very low average degree, they attain efficiency in all cases. These observations motivate the following testable hypotheses.

Hypothesis A. *Under criticality pricing networks are connected. An increase in group size leads to i) larger average distances and ii) a small change in degree and payoff inequality.*

Hypothesis B. *Under betweenness pricing networks are connected. An increase in group size leads to i) a small change in average distances and ii) a large increase in degree and payoff inequality.*

Hypothesis C. *Networks attain full efficiency under both pricing protocols, for all group sizes.*

2. Materials and Methods

A. Experimental Design. The experiment uses the same parameters as the simulations and consists of 6 treatments: 3 group sizes (10, 50, and 100) and two pricing protocols (criticality, betweenness). In each treatment, 4 independent groups participated in 4 separate sessions; a total of 1,280 subjects took part in the experiment. In each experimental session, a continuous time game is played over 6 min and is referred to as a round: The first minute is a trial period, and the subsequent 5 min of the game are payoff relevant. Every group played six rounds. In a round, at any moment, the subject is shown the entire network of reciprocated links. In addition, every subject is shown all outstanding link proposals—made and received—that involve them. Every subject is also provided full information on the payoffs of everyone. *SI Appendix*, Fig. S10 presents the decision screen observed by subjects. At any instant in the 6-min game, a subject can make or remove a proposal to another subject by simply double-clicking on the corresponding node on the computer screen. Any reciprocated proposal leads to the formation of a link. Nonreciprocated links were represented through different node shapes (see *SI Appendix* for details).

At the end of each round, subjects' earnings are determined based on the network structure observed at a randomly selected moment within the last 5 min. In analyzing the data, we will focus on subjects' behavior and group outcomes from these last 5 rounds. Further details about the procedure are provided in *SI Appendix*.

B. Ethics Approval. The local ethics committee of University of Valencia approved the study (under the heading IBSEN Project Number H1454277593524), and written informed consent was obtained from all participants.

3. Experimental Results

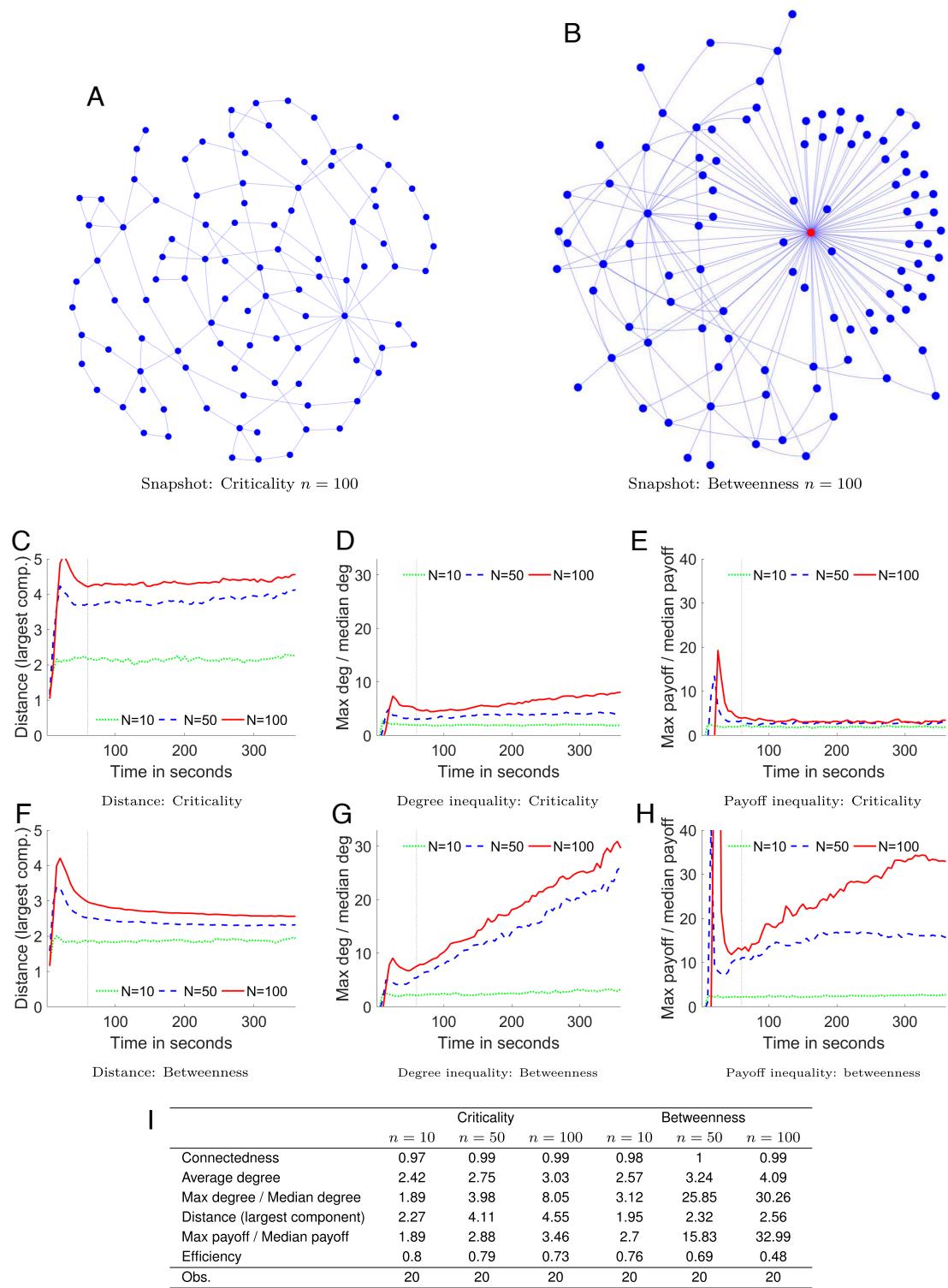
For simplicity, in the empirical analyses, the data are organized on a second-to-second basis. So, every round yields us 360 observations on every subject's choices. Although some information about choice dynamics between two time intervals may be lost, we believe that the second-by-second record is 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 dataset, we run panel regressions for the treatment effects with time-fixed effects and standard errors clustered at the group level and report regression results in *SI Appendix*, Table S7.

Fig. 2 A and B show the snapshots of the criticality and betweenness treatments, respectively, for a large group ($n = 100$) at the end of a representative round of the experiment.[†] These snapshots draw attention to three points: One, under both pricing protocols, subjects create sparse and connected networks; two, we see equal and dispersed networks under criticality pricing and unequal and small distance networks under betweenness pricing; and three, recalling the payoff functions (1) and (2), we can infer that there is little payoff inequality under criticality pricing but great inequality under betweenness pricing. We now analyze the experimental data more systematically.

We begin with a summary of the findings on connectedness: Connectivity is very high and similar across treatments: on average, 98.6% for $n = 10$, 99% for $n = 50$, 98.7% for $n = 100$ under criticality pricing; 97.5% for $n = 10$, 99.4% for $n = 50$, 98.1% for $n = 100$ under betweenness pricing. This is in line with the prediction of connectedness under Hypotheses A and B.

We next turn to the treatment effects on distance, degree, and payoff inequality (Fig. 2). Fig. 2 C and F show that as group size

[†] Behavioral dynamics of the groups that generated the network structures presented in Fig. 2 A and B can be viewed through our interactive tool at the following websites: https://networks.econ.cam.ac.uk/net_formation/animation_brokerage_critical.php (Fig. 2A), and https://networks.econ.cam.ac.uk/net_formation/animation_brokerage_betweenness.php (Fig. 2B).



Network statistics from the experiment (averaged across the last 10 seconds of each round)

Fig. 2. Network structure, dynamics, and statistics. (A) and (B) show the snapshots of the criticality and betweenness treatments for $n = 100$ at the end of a representative game. (C–H) present the dynamics of experimental outcomes—distance, degree inequality, and payoff inequality—in two pricing protocols and for the three group sizes. (I) reports key outcomes of limit networks in the last 10 seconds of each experimental game.

grows, distances grow under criticality pricing but they change only slightly under betweenness pricing. Under criticality pricing, the average distance is around 2 in the small group, around 4 in $n = 50$, and above 4 in $n = 100$. Under betweenness pricing, average distance lies between 2 and 3 in both small

and large groups. Recall from Fig. 1C that the average distance grows sharply with group size under criticality but remains around 2 for all group sizes under betweenness. We attribute the relatively small increase in average distances under criticality to the existence of a few excess links (this is consistent with the

work of ref. 44; a few extra links can lower average distances in a ring network very sharply). The regression analysis in the first column of *SI Appendix*, Table S7 confirms the treatment effects on distance at the 1% significance level.

Fig. 2 D, E, G, and H show that as group size increases, degree and payoff inequality remain modest under criticality pricing but become very large under betweenness pricing. In particular, under criticality pricing, payoff inequality lies between 2 and 3 across all group sizes, while under betweenness pricing, payoff inequality explodes with group size—from around 2 to 16 to 35 as we move up from group sizes of 10 to 50 to 100. The regression analysis in the second and third columns of *SI Appendix*, Table S7 confirms the treatment effects on degree and payoff inequality at the 1% significance level. These findings on network properties and payoff inequality are consistent with Hypotheses A and B (see Fig. 2I for summary statistics that compare with Fig. 1).

Result 1. *The networks are (close to) connected in all cases. Under criticality pricing, average distance grows, while degree and payoff inequality remain modest across group sizes. By contrast, under betweenness pricing, average distance remains small while degree inequality and payoff inequality grow massively as we increase group size.*

We next turn to efficiency. Fig. 3A shows that under criticality, high efficiency—over 70% of the maximum welfare—is attained early and is sustained throughout, for all group sizes. By contrast, under betweenness, Fig. 3C shows that high efficiency—over 60% of the maximum possible welfare—is attained early and is sustained for group size 10; but, for groups of size 50 and 100, efficiency is initially low—around 30% of maximum welfare—and it grows steadily over the course of the experiment. The regression analysis in the fourth column of *SI Appendix*, Table S7 confirms the treatment effects on efficiency at the 1% significance

level. The gradual increase in efficiency observed in large groups under betweenness is broadly consistent (although it is slower) with the simulations on best response dynamics that are presented in *SI Appendix*, Fig. S4.

Result 2. *Under criticality pricing, high efficiency is attained early and is sustained throughout, for all group sizes. Under betweenness pricing, high efficiency is attained early and is sustained for group size 10, but for groups of size 50 and 100 efficiency is low initially and it grows steadily over the course of the experiment.*

We now examine the reasons for the lower efficiency under betweenness pricing.

4. Discussion on Efficiency and Behavior

Efficiency of a network is a function of the connectedness of the network and the number of links in the network—connectedness enhances welfare, additional links once connectedness is attained, however, lower welfare. We have already noted that subjects create (almost) connected networks in all cases. So the differences in efficiency must be due to differences in the number of links. Indeed, Fig. 3 B and D show that under criticality pricing, average degree lies between 2 and 3 and changes only slightly as group size increases. On the other hand, under betweenness pricing, average linking grows substantially as group size grows. The regression analysis in the fifth column of *SI Appendix*, Table S7 confirms the treatment effect on average degree (at the 1% significance level). Thus, pricing protocol and group size interact to push up linking activity. We now examine the reasons for this excessive linking.

Can noisy behavior explain such excessive linking? To address this question, we consider a simple model of myopic best response with noise in *SI Appendix*. We estimate the level of noise in each treatment during the payoff effective period (i.e., the last 5 min)

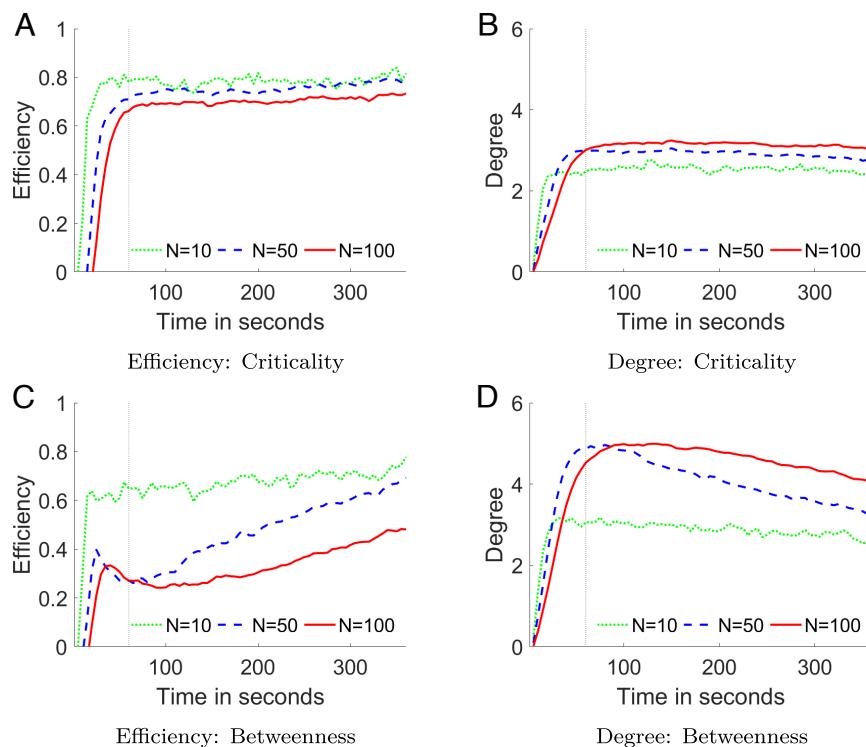


Fig. 3. Efficiency and degree. (A) and (C) present the dynamics of efficiency achieved in Criticality and Betweenness treatments for the three group sizes, respectively. (B) and (D) show the dynamics of average degree per subject in the Criticality and Betweenness treatments for the three group sizes, respectively.

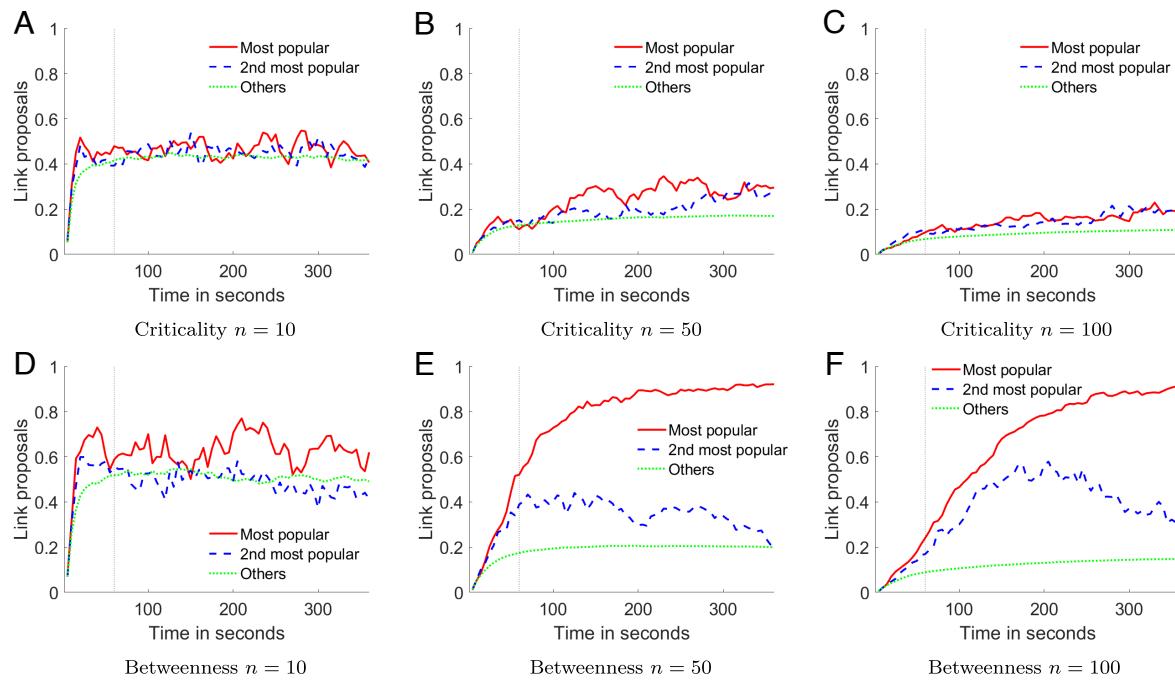


Fig. 4. Link proposals (normalized by $n - 1$). Three types of subjects in terms of the number of links they receive—the most popular individual, the second most popular individual, and all the other individuals. (A–F) show the dynamics of link proposals, normalized by $n - 1$, for the three types of subjects in each treatment.

in *SI Appendix*, Fig. S23, and find that it is very similar for both pricing protocols in the small group ($n = 10$), but in the large groups ($n = 50$ and $n = 100$) subjects exhibit less noise under betweenness pricing. This behavior helps explain the efficiency increase (and the decrease of average degree) observed in Fig. 3. However, this analysis remains silent on the large inefficiency initially produced during the trial period (i.e., the first minute, which is not payoff relevant). To further identify behavioral differences, we then estimate noise during this period in *SI Appendix*, Fig. S30.

We find higher levels of noise across all treatments in the first minute as compared to the last 5 min of the experiment. Since behavior in the first minute is payoff irrelevant, this is intuitive. Perhaps more interestingly, our analysis of the first minute also reveals greater noise under betweenness pricing as compared to criticality pricing, which is in line with the larger excessive linking activity observed under betweenness pricing. This is consistent with the idea that there is a stronger need to reduce trading paths to cut intermediation rents under betweenness. After forming many links at random in the first minute, subjects aim to increase their payoffs by deleting redundant links during the last 5 min of the experiment.

Is excessive linking activity homogeneous in the large groups? To answer this question, we define three types of subjects in terms of the number of links they receive—1) the most popular individual, 2) the 2nd most popular individual, and 3) all the other individuals. Fig. 4 plots the time series of the number of link proposals normalized by $n - 1$ for each type of player. We see that, in the large groups, there is a major difference in this ratio across the two pricing rules. Let us next examine the reason for this difference by examining incentives for links under the two pricing rules.

Under criticality pricing, most subjects form 2 links and no one forms a very large number of links; this keeps the average degree close to 2. Turning to linking incentives, note that, once a cycle is formed, there are no brokerage rents to be earned under

criticality pricing. Matters are quite different under betweenness pricing: In this case, there are brokerage rents to be earned even after a connected network or a cycle is created. This encourages individuals to seek to become hubs. On the other hand, nonhubs reciprocate such proposals because that enables them to shorten paths involved in trading. Both these incentives are greater in big groups. *SI Appendix*, Table S8 elaborates on these points.

The rents to being a hub grow with group size. So we should expect greater competition to become a hub as group size grows. This is indeed what we see: The number of link proposals by the most popular individual is large and grows over time (Fig. 4 E and F). Moreover, an increase in group size also leads to the second most popular subject to propose many links. The second most popular subject withdraws links at a later point in time as group size grows. *SI Appendix*, Fig. S20 shows that the resulting fraction of realized links follow the same patterns as link proposals for the three types of individuals, confirming that subjects indeed respond to incentives. At the start of the experiment, the proposals are reciprocated by other subjects embedded in long paths, who seek to reduce intermediation rent payments. This leads to significant linking in large groups. Linking by traders has positive externalities on other traders, as it reduces their trading path lengths and hence their intermediation rent payments. Over time, this leads to deletion of links and a fall in average degree (while the average distance remains stable) as seen in Figs. 2 and 3.

5. Concluding Remarks

We have studied the influence of pricing—criticality versus betweenness—on intermediation networks. The static theory is permissive—under each of the two pricing rules, there exist many pairwise stable networks and it is ex ante difficult to say whether there is a trade-off between efficiency and inequality. Building on the theoretical literature, we study best response dynamics starting from random initial networks. The analysis reveals a

sharp difference in network outcomes under the two pricing protocols. The experimental findings of this paper are consistent with these dynamics and suggest the following general message: When the incentive to shorten trading paths is present, in large groups purposeful linking will push toward excessive linking and unequal earnings. When there is no pressure toward shortening paths, there will be little excessive linking, and networks will be more dispersed, more efficient, and earnings will be more equal.

We have studied the implications of two prespecified pricing protocols. In view of our findings, it is natural to ask what happens to networks and earning distributions when individuals choose both link proposals and prices? This is an important open question for future research.

Data, Materials, and Software Availability. For the raw data files, and the other for the Matlab scripts for data analyses: <https://github.com/FredMoisan/Brokerage-rents-and-intermediation-networks-PNAS>. All study data are included in the article and/or *SI Appendix*.

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