Referral Hiring, Endogenous Social Networks, and Inequality: An Agent-Based Analysis

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Abstract

The importance of referral hiring which is workers finding employment via social contacts is nowadays an empirically well documented fact. It also has been shown that social networks for finding jobs can create stratification. These analyses are by and large based on exogenous network structures. We go beyond the existing work by building an agent-based model of the labor market where the social network of potential referees is endogenous. Workers invest some of their endowments into building up and fostering their social networks as an insurance device against future job losses. We look into how social networks and inequality respond to increased uncertainty in the labor market. We find that larger variability in firms' labor demand reduces workers' efforts put into social networks leading to lower inequality.

1 Introduction

Nobel laureate James Heckman claims that "A growing body of evidence points to the fact that the world economy is more variable and less predictable today than it was 30 years ago..." (Heckman, 2003, p. 31). On the backdrop of this observation a considerable body of literature emerged trying to explain – mostly comparing the U.S. and European experiences – different patterns

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in labor market performance and inequality based on a combination of higher turbulence and distinct institutions of the welfare state such as employment protection, unemployment benefits or collective wage agreements (see e.g. Blanchard and Wolfers (2000), Bertola et al. (2002), Ljungqvist and Sargent (2008), or Martin and Neugart (2008)).

We draw attention to an insurance device typically not considered in the debates about the welfare state which, however, seems to be an important way in which individuals try to insure themselves against future job or income losses. This is friends or social networks.[1] Job searchers make heavily use of friends to find jobs. Nowadays, starting with the work of Granovetter (1974) there is a huge body of evidence suggesting that referrals play an important role for finding new jobs. In a survey of 24 studies Bewley (1999) concludes that 30 to 60% of jobs are found through friends or relatives. As put by (Montgomery, 1991, p. 1412) it occurs that "...it's not what you know but who you know."[2]

Our contribution builds on these two well documented facts of increased uncertainty and referral hiring by looking at their consequences in terms of efforts spent on maintaining social networks and inequality in the labor market. Thus, we build an agent-based model of the labor market endogenizing the social network. In our model workers eventually adapt the number and

[1]We may also, perhaps more abstractly, refer to number of links instead of using for illustrative reasons the term friends. In the model which we develop friends have a particularly narrow meaning which, however, does not imply that we are not aware of much broader interpretations.

[2]More evidence on job search through friends and relatives can be found in the excellent survey by Ioannides and Loury (2004) or the comparative study by Pellizzari (2004). Recent contributions on the role of social networks and labor market performance using microdata are Cingano and Rosolia (2008) and Hellerstein et al. (2008).

type of friends they want to have as a response to their labor market performance because firms prefer referred applicants over non-referred applicants when hiring new employees. The insight of our approach is that higher job instability holding aggregate labor demand constant yields on average to less friends made and consequently to lower inequality. Intuitively, higher job instability makes friends less valuable as potential referees as by the time they are needed they may search by themselves. Costly maintenance of friendships leads to a reduction of friends. Therefore referral hiring no longer crowds out those unemployed from finding jobs who are not referred. Thus, also stratification of individual labor market performance becomes less prevalent.

One of the earliest contributions linking networks to labor market behavior was made by Boorman (1975). He analyzed to which extent workers should rely on strong ties – a friend giving strong priority to the revelation of job opportunities as opposed to weak ties that require less effort – in order to optimize on the probability of getting a job. He finds that in labor markets where job losses are unlikely weak ties are superior to strong ties. However, this relationship reverses as job losses are very likely. Equally focussing on the role of social networks for the transmission of job opportunities Calvo-Armengol and Jackson (2004) show that employment patterns are positively correlated across time and groups. Moreover, they show that if information about job opportunities spreads through social networks, transition rates into employment for those who are unemployed decrease with the duration of unemployment. In a more general set-up Calvo-Armengol and Jackson (2007) extend the analysis to wage inequality. There, they show by comparing two groups with identical information networks that initial differences in wages and employment status breed long-run differences. The finding originates from the assumptions that expected job offers are non-decreasing in the wages of those workers with whom ties exist, and that the drop-out decision of workers eventually driving inequality is made by comparing wages earned in the labor market and the costs to stay in the labor market. Much in the spirit of Montgomery (1991) who looked into job networks assuming lack of information of firms on workers productivity but assuming correlation in productivity among workers who know each other, Krauth (2004) studies the impact of social networks on employment. Among other things he shows that an individual's likelihood of employment is increasing in the number of his social ties and the employment rate that these group members have. While this model's starting point of why firms recur to referral hiring is equivalent to ours, there is no endogenous network formation. Rather the analysis rests on exogenously varying the network structure. Segregation is also shown to occur in a networked labor market setting by Finneran and Kelly (2003). They look into the dynamics of emerging inequality by arguing that the decision of agents whether to invest into their human capital which would raise their employment chances depends on the costs of becoming skilled and their observation whether there will be referees helping them to get jobs. The major finding is that such a labor market displays critical behavior in the sense that if the density of referrals falls below a threshold individuals end up without jobs. Contrarily to the focus on individual behavior emanating from different types of social networks Tassier and Menczer (2008) explore how the structure of the social network influences the information flows about job openings. By exogenously varying the type of the social network they are particularly interested in analyzing to what degree a random network might be advantageous from an individual's perspective. Two countervailing effects on how groups fare in terms of their labor market performance are explored. More randomness of the network is associated with a higher likelihood of getting the information on vacancies while it by the same time increases the chances that this piece of information gets known to other groups. Given that connections between jobs are non-random, they find that the effect of protecting information dominates and groups with non-random social networks have higher employment rates.

As sketched, the existing literature on referral hiring by and large assumes exogenous networks. Contrarily to these papers, Calvo-Armengol (2004) endogenizes the social network structure in a model of job contacts. Agents are allowed to strategically form mutually beneficial links to other agents. He shows that equilibrium networks exist. In an agent-based simulation, Tassier and Menczer (2001) study endogenous network formation in a labor market with referral hiring where agents choose their effort level to maintain links based on an evolutionary algorithm. They find that there is too excessive (costly) competition for job information causing inefficiencies.

We believe that an agent-based framework particularly suits our purpose of analyzing the effect of higher labor market turbulence on friendships and labor market performance as it is flexible enough to allow for heterogenous workers in an endogenous social network. That an agent-based approach can fruitfully contribute to our understanding of labor markets and the evolution of networks in particular has been documented by various contributions to these fields, see e.g. Pingle and Tesfatsion (2003), Fagiolo et al. (2004), Richiardi (2006), Neugart (2004), Neugart (2008), or Wilhite (2006), and in general may be a step forward to modeling economies as suggested by Kirman (1997).

2 The model

Two types of agents populate our model: firms and workers. The sequence of actions for the workers and firms is summarized in the Pseudocode 1. As a qualitative copy of the actual code of our model which is written in Repast the pseudocode gives an outline along which we will describe the particular assumptions that go into our agent-based model. The code starts by populating the model with firms and workers. Basic characteristics of the workers are their status in the labor market and whom they are friends to. Workers can either be employed which we denote with e or unemployed u. The number of friends which a particular worker i in period t actually has is captured by a variable $z_{i,t} \in \mathbb{N}_0$. There shall be a per time unit cost for each worker to maintain a particular friendship which we denote with c. We assume that a worker i in period t gets payoffs according to

$$\pi_{i,t} = w - cz_{i,t} \tag{1}$$

with $w > 0$ if the worker is employed and $w = 0$ if the worker is unemployed.

A firm is basically characterized by its labor demand and the workers it employs. Labor demand is stochastic. How many workers a firm wants to employ is drawn from a uniform distribution $l \in [\underline{l}, \bar{l}]$.

Pseudocode 1

```
create workers
create firms
for k = 0 to M iterations do
    for all firms h = 1 to F do
        determine vacancies
    end for
    for all workers i = 1 to W do
        send applications to all firms holding vacancies
    end for
    for all firms h = 1 to F do
        if referred workers among applicants then
            fill vacancies with referred workers
        else
            fill vacancies with non-referred workers
        end if
    end for
    for all workers i = 1 to W do
        calculate payoffs
        calculate counterfactual payoffs
        update weights N_t
        update attraction levels A_i^j
        calculate choice probabilities P_i^j
        update number of friends (ẑ_i)
    end for
    for all workers i = 1 to W do
        while workers' actual friends (z_i) > friends wanted (ẑ_i) do
            if friend is employed then
                dissolve friendship with d_e
            else
                dissolve friendship with d_u
            end if
        end while
    end for
    for all workers i = 1 to W do
        while workers' actual friends (z_i) < friends wanted (ẑ_i) do
            draw randomly worker who is not yet a friend
            if worker and drawn worker are employed then
                make friendship with m_e
            else
                make friendship with m_u
            end if
        end while
    end for
    for all firms h = 1 to F do
        firm learns labor demand
        if labor demand l < current workforce then
            dismiss workers
        else
            determine vacancies
        end if
    end for
end for
```

Once workers and firms are created they repeat to interact for k-times. Each iteration starts with firms posting their vacancies. Workers who are unemployed (there is no on-the-job search) apply for vacancies. We assume that a worker i sends applications to all firms that post at least one vacancy. This implicitly assumes that application costs are negligibly small. With job sites becoming more and more popular marginal costs for placing an additional application may indeed be very small justifying such an assumption.[3]

Firms choose among the applicants preferring – if faced with multiple applicants – those who are referred by an incumbent employee. If more than one applicant has a friend working in the firm where he applied, hires among the refereed applicants are random.

We already stated that referral hiring is an empirically well documented fact. From a theoretical point of view, it may be advantageous for firms to apply such a hiring rule for several reasons (see e.g. Montgomery (1991) or Calvo-Armengol and Ioannides (2007)). Firms may make use of referrals because they believe that referees have a better signal about the type of a particular worker than they have themselves. Also, while asymmetric information might be overcome by testing applicants, doing so might be too expensive relative to recurring to referrals. Finally, one may also put forward that using referees posts reputational bonds on the performance of the newly hired. We rather sketch these theoretical reasonings here in addition to the empirical findings in order to justify the behavioral rule which we impose on the firm. However, we abstain from explicitly deriving this rule. Rather we

[3]See Freeman (2002) for how information and computer technologies changed matching employers and employees in labor markets.

focus our modeling efforts on endogenizing the social network.

After firms chose whom to hire workers rethink their friendship strategies. There is a set of strategies $Z_i = \{\hat{z}_i^1, \hat{z}_i^2, ..., \hat{z}_i^n\}$ among which a worker chooses where $\hat{z}$ is the the number of friends he wants to have as opposed to the number of friends z a worker could actually find. We assume that workers learn about how many friends are best for them facing the trade-off that more friends increase the likelihood of being referred when looking for a job but is also costly in terms of maintaining the social ties.

Camerer and Ho (1999) suggested a learning algorithm which they coined experience-weighted attraction (EWA) which among the models that exist to capture learning (see e.g. the survey by Brenner (2006)) has a lot of appeal. Mostly, because it is one of the rare suggestions which come with experimental evidence supporting the algorithm and also allowing to calibrate the parameters following the findings in Ho et al. (2008).

In the EWA learning the particular strategies have attractions which are regularly updated either according to the payoffs they actually provided if chosen or according to a fraction of the payoffs they would have provided if they had been chosen. These attractions are depreciated and normalized each period taking into account an experience measure. Finally, attractions are mapped into probabilities for actual choices. Strategies with higher attractions are chosen more often. Formally there is an experience weight N_t used to weight lagged attractions. In addition, let $A_{i,t}^j$ be worker i's attraction level for strategy $\hat{z}_{i,}^j$ after period t ended. Then the learning mechanism is basically described by the law of motions for the experience variable and the attractions level. The experience level follows according to

$$N_t = \rho N_{t-1} + 1 \tag{2}$$

for $t \geq 0$ and ρ being a discount factor that depreciates the lagged experience weight. N at $t = 0$ is chosen such to reflect the experience collected until the simulation begins. Attractions for a strategy j of a worker i evolve as

$$A_{i,t}^j = \frac{\phi N_{t-1} A_{i,t-1}^j + \{\delta + (1-\delta) I[z_i^j, z_{i,t}]\} \pi_i [z_i^j, z_{-i,t}]}{N_t} \tag{3}$$

with δ being the weight on the hypothetical payoffs that unchosen strategies would have yielded, $I[z_i^j, z_{i,t}]$ as an indicator function being 1 if $z_i^j = z_{i,t}$ and otherwise zero, and ϕ as a discount factor that depreciates previous attractions. Thus, the rule updates attractions as a function of depreciated, experience-lagged attractions plus an additional term capturing either the received or forgone payoffs normalized by the new experience weight. We model forgone payoffs as the average payoffs of all those agents in the population who used a particular strategy z^j in period t.

A logit model translates the attraction levels into choice probabilities for the number of friends $\hat{z}_i^j$ a worker i actually wants to have for the future according to

$$P_{i,t}^j = \frac{e^{\lambda A_{i,t}^j}}{\sum_{k=0}^n e^{\lambda A_{i,t}^k}}. \tag{4}$$

Here, the parameter λ measures the sensitivity of workers' choices with respect to differences in the attraction levels. In the limit case with $\lambda = 0$ all strategies are chosen equally likely, and as λ increases strategies with higher attraction levels are chosen more likely. In compliance with the literature we impose the restrictions $\lambda > 0$, $0 \leq \rho < 1$ and $0 \leq N_0 < 1/(1-\rho)$.

Interpreting the parameters that go into the EWA learning, one may think of δ as the relative weight that is given to a kind of counterfactual reasoning in the sense that a worker thinks of what he would have received had he chosen a different number of friends. The parameter ϕ may simply be interpreted as depreciation of past attractions, and the initial value for N may be thought of as the strength of initial attractions relative to what is incrementally earned as the simulation evolves. The larger N_0 the longer the initial attraction will persist.

Once, the workers have chosen how many friends they want to have they adjust their social network. In case the number of friends with which they want to proceed is smaller than the current number of friends $z_{i,t} > \hat{z}_{i,t}$ friendships are dissolved. Due to the widespread lack of dynamic data there is relatively little evidence on what drives the dissolution as opposed to the knowledge on tie creation in networks. However, summarizing the mostly sociological literature McPherson et al. (2001) conclude that tie dissolution (as well as tie formation) are functions of structural foci including e.g. individuals' status in the labor market. Making use of these findings, we model which friendships will not continue as a stochastic process that is tilted towards dissolving the links with unemployed workers. There is a probability $0 \leq d_e < d_u \leq 1$ with which friendships are dissolved where the subscript denotes the status of a particular friend. Each worker keeps on "testing" his friendships until he at least downsized his social links to the number of friends he wants to have in the future.

For the case that the worker chose to have more friends in the future than he currently has he is trying to find new friends. Matching workers to become friends is done very much in the spirit of a matching algorithm proposed by Currarini et al. (2007). The actual programming code makes use of the idea by creating a list of agents who want to be matched. We randomly draw two agents from that list and match them. This is repeated as many times as there are at least two agents left who want to be matched. As it is the case with dissolving friendships, agents have a preference for making employed friends. That is, after two workers met it is more likely that two employed workers form a friendship than that an unemployed worker establishes a friendship. Formally, we assume that $0 \leq m_u < m_e \leq 1$, where m_e is the likelihood that a social tie is established if two employed workers meet, whereas m_u is the probability that a link is formed if the tuple consists of at least one unemployed worker.

After friendships are adjusted firms labor demand is exogenously determined. Firms that have to downsize dismiss workers randomly until the actual workforce meets their labor demand. Firms that want to increase their labor demand post vacancies, and a new iteration starts.

3 Results

Simulation set-up

We populate our model with 160 workers. For the number of firms F we choose 20 so that the ratio of workers per firm mirrors the average number of

Table 1: Parameters

Number of workers:	$W = 160$
Number of firms:	$F = 20$
Wage:	$w = 1$
Costs for friendship:	$c = 0.1$
Labor demand l:	$\underline{l} = \{4, 5\}$, $\bar{l} = \{7, 8\}$
EWA learning:	$N_0 = 1$, $\delta = 0.3$, $\phi = 0.9$, $\rho = 0$, $\lambda = 1$
Probabilities for making and dissolving friendships:	$d_e = 0.2$, $d_u = 0.8$, $m_e = 0.8$, $m_u = 0.2$

worker per firm usually found in empirical data.[4] The wage is normalized to one, and for the per time-unit costs of maintaining one friendship we choose c such that the endogenously arising fraction of referral hiring is in between the range (30% to 60%) proposed by the empirical evidence cited earlier. On average the firms' labor demand amounts to 6 workers. However, it may vary between 5 and 7 workers, or between 4 and 8 workers per firm. In the latter case labor demand is more volatile. Given that the firms' labor demand is drawn from an identical distribution defined on the interval $[\underline{l}, \bar{l}]$ the standard deviation of aggregate labor demand is two times higher in the more volatile case. Parameters for the learning algorithm are based on the experimental evidence reported in Ho et al. (2008). Finally, the parameters along which friendships are dissolved and made reflect the idea that our agents have a relatively stronger preference for employed friends when they update their friendships.

For each parametrization of our model we replicate 100 runs. Such a run consists of $M = 500$ iterations as described in the pseudocode previously.

[4]See e.g. *http://epp.eurostat.ec.europa.eu/*.

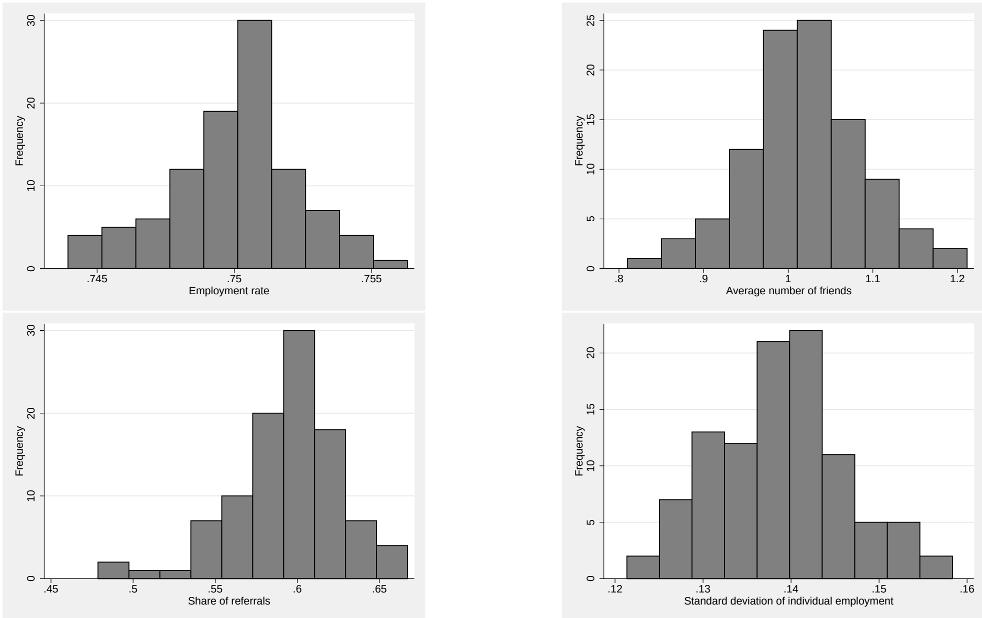
The data which we finally analyze consists for each parametrization of the 100 observations that we get out of the 100 runs. Each of these observations is an average of the last 100 iterations of a single run, i.e. the average over the periods $k = 401$ to 500.

Main findings

In figure 1 we show the distributions of the four main endogenous variables that we are interested in for the baseline case with a low turbulence in labor demand. Starting in the upper left corner we have the distribution of the employment rates (averaged over the last 100 iterations) for the 100 runs we executed. To the right is the distribution of the number of friends (again averaged over the last 100 iterations) for the 100 runs. The histogram for the share of referral hirings is in the lower left corner, again calculated as the previous two variables. Finally, we also show the distribution of the standard deviations of individual employment – our indicator of inequality in the labor market – measured for each individual over the last 100 iterations for the 100 runs.

In table 3 we summarize our main findings. The means in the second column coincide with the distributions shown in figure 1. The second and third column compare the mean values of the various variables for low and high volatility of labor demand. In the last column we report the z-values of a Wilcoxon-Mann-Whitney test on equality of the means. As on average every firm posts six vacancies aggregate labor demand fluctuates around 120 jobs. With a total of 160 workers one gets an employment rate of 0.75. This average employment rate is not affected by a larger volatility in labor

Figure 1: Histograms of the main endogenous variables



demand. What we, however, observe as a response to a larger volatility in labor demand is a decline in the average number of friends each worker has from 1.01 to 0.89, and a drop in the share of referral hirings from 58% to 40%. All this is accompanied by less inequality in the individual incidence of employment as measured by the standard deviation in individual employment rates averaged over the last 100 iteration of each run as described before.

The mechanism that lies behind these findings is the following: as labor demand becomes more volatile jobs go sour more often and more job openings come to the market. Workers that relied on being referred by friends to increase the likelihood of a transition out of unemployment should they loose their jobs realize that in a more volatile environment having friends is less advantageous. This is the case as in a more volatile environment the friend who might have helped with a referral is more likely to be looking for a new

Table 2: Results for endogenous network

	Volatility of labor demand low	Volatility of labor demand high	z-value
Employment rate	0.75	0.75	0.31
Average number of friends	1.01	0.89	0.00
Share of referral hiring	0.58	0.40	0.00
Std. dev. of individual employment	0.14	0.10	0.00

job himself. Thus workers are less inclined to cultivate their costly friendship networks which in addition to less employed friends being available reduces the share of referral hirings. With referral hirings playing a smaller role for transitions from unemployment to employment those who were crowded out from finding jobs by referrals in a less turbulent market suffer to a smaller extent. Their job finding probability increases which explains the reduction in the inequality of the incidence of individual employment.

The interpretation of our findings can be traced by various experiments which we are going to show now. In order to learn about the effect that the number of friends has on the outcomes we ran a battery of exercises where we switched off the feature of an endogenously determined number of friends that a worker wants to have. More specifically we split our workforce into two equally sized parts. Initially each worker no matter which group he belonged to wanted to have one friend. After 250 iterations we exogenously increased for one group of workers – the treatment group – the number of friends these workers wanted to have to two. What we were particularly interested in was the effect of an exogenous change in the number of friends on the employment chances in comparison of the treatment and non-treatment groups. And in addition, how this exogenous change in friendships affected the share of referrals. By way of a difference-in-difference approach these effects were analyzed, i.e. we measured the group specific employment rates and referral shares for the treatment and non-treatment group before and after the policy change, respectively. Figure 2 illustrates the experiment.

By means of taking differences in the employment rates before and after the exogenous change in the number of friends for each group, and between these differences we can shed light on the effect that more friends may have on the labor market performance of one group, potentially at the expense of other workers who do not have so many friends. As the upper part of

Figure 2: Increasing friendships exogenously

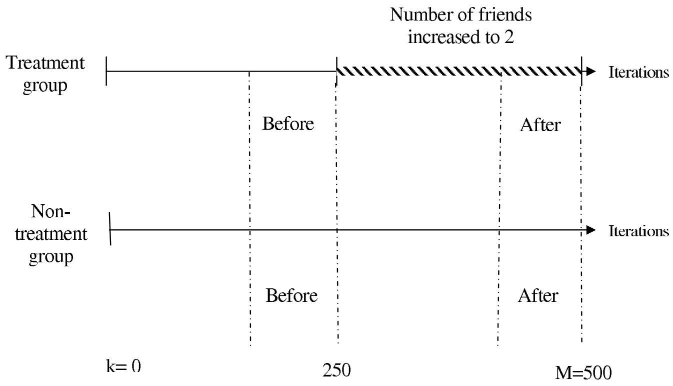


table 3 shows exogenously increasing the number of friends from one to two raises the average employment rate for the group with more friends (the treatment-group) by six percentage points in the low volatility case. By the same magnitude the employment rate for the non-treatment group falls. For higher volatility in labor demand the effect is somewhat smaller. Now, having one more friend yields an average increase in the employment rate of four percentage points. In both scenarios, the better labor market performance of the treated group comes at the cost of crowding-out those from finding employment who have only one friend who may act as a referee. Clearly, the joined effects measured by the difference in differences for the treatment and non-treatment group are also positive. Thus, this part of the experiment supports the interpretation of crowding-out being a systemic feature which eventually leads to inequality in individual employment histories also in the model with endogenous friends.

For the same type of experiment the lower part of table 3 shows what happens to the share of referral hirings. Several findings stand out. First of all the "before" share of referrals is much higher in the low volatility scenario. This is compatible with what we already learned from table 3 where referrals decline as the number of friendships endogenously adjusted downwards in a response to a more volatile labor demand. Secondly, also after the number of friends was exogenously increased the share of referral hirings is higher in the low volatility case as compared to the high volatility. These two results indicate that referral hirings do indeed increase as an individual has more friends, and given friends it is relevant for a referral to occur that these friends have a stable employment performance. Thirdly, the exogenous change in the number of friends has a larger effect on the share of referral hirings for the treatment group in the high volatility case. The change here is 22 percentage points as opposed to 18 percentage points. Thus, on the backdrop of the endogenous network, a downward adjustment in the number of friends has a larger effect on the incidence of referrals in a more volatile environment. And finally, we observe also for the non-treatment group an increase in the share of referral hirings which is due to the crowding out effect. Less unemployed

Table 3: Effect of exogenous number of friends on labor market performance

	Employment rates					
	Low volatility			High volatility		
	Before	After	p-value	Before	After	p-value
Treatment group	0.75	0.81	0.00	0.75	0.79	0.00
Non-treatment group	0.75	0.69	0.00	0.75	0.70	0.00
Diff-in-diff			0.00			0.00
	Share of referral hirings					
	Low volatility			High volatility		
	Before	After	p-value	Before	After	p-value
Treatment group	0.70	0.88	0.00	0.52	0.74	0.00
Non-treatment group	0.70	0.76	0.00	0.51	0.57	0.00
Diff-in-diff			0.00			0.00

find jobs with the absolute number of referrals roughly being constant.[5]

Thus, the exercise holding the number of friends in the network constant corroborates the interpretation that a more volatile labor demand reduces the average number of friends leading to fewer referrals and less crowding out followed by lower inequality in terms of the individual incidence of unemployment.

Robustness

This is also true for our robustness checks. Particularly, we replicated our main results by varying all parameters shown in table 3 ceteris paribus.

[5]Note that the share of referral hirings in our experiment with an exogenously given friend is higher than in table 3 even though the average number of friends is roughly the same. The reason is that an average number of friends equal to one in a framework where friends are endogenous implies that some workers do not have friends at all while others may have two or more. Those who do not have friends will not get referrals and those who have more than one friend might have more friends than they need to get a referral. Thus on average the share of referrals will be lower as compared to the experiment where all workers have one friend.

Changing the costs c for maintaining a friendship by $\pm 20\%$ does not affect our qualitative results. Quantitatively we can observe that higher costs result in fewer friends made and consequently less referrals. The parameters δ, ϕ, and λ were increased and decreased by 0.1 respectively. We tried $N_0 = \{0, 2\}$ and $\rho = \{0.1, 0.2\}$. All these changes to the parameters related to the EWA learning corroborate our qualitative findings. Perhaps, worth to remark is the fact that the number of friends reacts rather sensitively to a change in ϕ. However, we are less concerned here, as we deliberately calibrated the learning mechanism based on experimental findings as sketched earlier. Our results are also confirmed if we change the probabilities for making and dissolving friendships, or the upper bound of friends out of which individuals choose initially.

As an additional robustness check we varied the actual implementation code of our model. In particular we tried various algorithms related to how friendships are dissolved. For instance, we tried a model where agents have a memory variable on which friend was helpful in the past making it less likely that this particular link would be dissolved. Such changes to a particular modeling choice did not alter the main gist of our argument, either.

Summing up, all these findings strongly hint towards a robust mechanism from a more volatile labor market towards adjustments in the network of friendships and finally less segregation in terms of unemployment histories.[6]

[6] Tables that summarize the robustness checks are available upon request.

4 Conclusions

We developed an agent-based model of the labor market with referral hiring. Distinguishing ourselves from existing work we endogenized friendships a worker may want to have in order to improve his chances for finding a job should he become unemployed in the future. We were particularly interested in the consequences of a more volatile labor demand, which we believe has become a common feature of most economies during the last decades, on referral hiring and consequently inequality in the labor market. Perhaps counter-intuitively, we find that a more volatile labor demand reduces the number of friends a worker wants to have in order to "insure" against relatively long-lasting unemployment spells. In a more volatile environment, workers are to a smaller degree willing to cultivate their costly network of friendships as it is more likely to occur that their friends will also be searching for a job when they are needed as referees. Consequently, referral hiring decreases as a response to a more volatile demand for labor. As job creation based on someone referring someone becomes less important, less unemployed are crowded out from exiting unemployed. Thus, the individual incidence of unemployment is more equally distributed. Inequality declines.

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