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Do co-worker networks increase or decrease productivity differences? An agent-based model

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ABSTRACT

Do labor mobility, and co-worker networks contribute to convergence or divergence between regions? Based on the previous literature, labor mobility contributes to knowledge transfer between firms. Therefore, mobility may contribute to decreasing productivity differences, while limited mobility to sustaining higher differences. The effect of co-worker networks, however, can be twofold in this process. They transmit information about potential jobs, which may enhance mobility of workers, even between regions, and this enhanced mobility may contribute to levelling differences. But if mobility between regions involves movement costs, co-worker networks may concentrate locally that may contribute to persistence of regional differences. In this paper we build an agent-based model of labor mobility across firms and regions with knowledge spillovers that reflects key empirical observations on labor markets. We analyze the impact of network information provided about potential employers in this model and find that it contributes to increasing inter-regional mobility, and subsequently to decreasing regional differences. We also find that density of co-worker networks, and also their regional concentration decrease, if network information is available.

JEL codes: C63, D85, J61, R12

Keywords: labor mobility; co-worker networks; regional inequality; knowledge spillovers; agent-based simulation

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A munkatársi kapcsolathálók csökkentik vagy növelik a termelékenységkülönbségeket? Egy ágensalapú szimuláció

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ÖSSZEFOGLALÓ

A munkaerő mobilitása és a munkatársi hálózatok vajon a régiók közötti konvergenciához járulnak hozzá, vagy inkább a divergenciához? A korábbi szakirodalom alapján a munkaerő mobilitása a cégek közötti tudástranszfer egy csatornája. Ezért a mobilitás a termelékenységi különbségek csökkenését okozhatja, míg ennek korlátozott volta a különbségek fenntartásához járulhat hozzá. A munkatársi hálózatok hatása azonban kettős lehet ebben a folyamatban. Ezek információkat továbbítanak a potenciális munkahelyekről, amelyek fokozhatják a munkavállalók mobilitását – régiók között is – és ez a fokozott mobilitás hozzájárulhat a különbségek kiegyenlítődéséhez. De ha a régiók közötti mobilitás költségekkel jár, a munkatársi hálózatok helyben koncentrálódhatnak, ami a regionális különbségek fennmaradásához járulhat hozzá. Ebben a tanulmányban egy ágensalapú szimulációs modellt építünk a cégek és régiók közötti munkaerő-mobilitás vizsgálatára tudástranszfer feltételezése mellett, amely tükrözi a munkaerőpiacokkal kapcsolatos legfontosabb empirikus megfigyeléseket. Ebben a modellben vizsgáljuk a potenciális munkáltatókról szolgáltatott hálózati információk hatását, és megállapítjuk, hogy ez hozzájárul a régiók közötti mobilitás növeléséhez, és így a regionális különbségek csökkenéséhez. Az tapasztaljuk továbbá, hogy a munkatársi hálózatok sűrűsége és regionális koncentrációja csökken, ha a hálózat információt közvetít a munkavállalók számára.

JEL: C63, D85, J61, R12

Kulcsszavak: munkaerő-mobilitás, munkatársi kapcsolathálók, regionális különbségek, ágensalapú szimuláció

Introduction

Worker mobility is a major source of transferring knowledge between firms; as firms utilize the incoming personnel's knowledge and skills they acquired through their careers (Almeida and Kogut 1999; Zucker, Darby, and Torero 2002; Palomeras and Melero 2010; Maliranta, Mohnen, and Rouvinen 2009). A direct evidence for this knowledge spillover is that hiring workers from better performing firms increases the recipient firms' productivity (Balsvik 2011; Stoyanov and Zubanov 2012; Goñi Pacchioni and Pardo 2018; Csáfordi et al. 2020). In addition, increased wages of workers at the recipient firm after hiring personnel from high-performing competitors indicate the within-firm diffusion of the new knowledge (Poole 2013).

These knowledge spillovers through labor mobility have implications on productivity differences within sectors or regions as well. Knowledge transfers between firms may decrease productivity differences, while constraints to knowledge transfers can explain why productivity differences sustain. An example of sustaining productivity differences was observed in the U.S. manufacturing sectors where, the productivity of p90 firms is twice the productivity of p10 firms on average, and it is even higher in some sectors (Syverson 2004b). In India and China even higher differences were observed (Hsieh and Klenow 2009). Previous studies concentrated on the (lack of) market competition when explaining these differences (Syverson 2004a; 2011), or competition advantages due to export activities (Melitz 2003), however, the role of labor mobility was not examined with this relation.

Regarding regional analysis, high mobility between related industries, and increased density of coworker networks are shown to contribute to higher growth of regions (Boschma, Eriksson, and Lindgren 2014; Lengyel and Eriksson 2017; Eriksson and Lengyel 2019). Different mechanisms were proposed explaining this finding. First, high mobility can contribute to agglomeration externalities. Second, dense coworker networks also induce better employer-employee matching. In addition, network density can be an indicator of social capital and trust, which supports learning from contacts (Boschma, Eriksson, and Lindgren 2014; Lengyel and Eriksson 2017; Eriksson and Lengyel 2019).

Furthermore, knowledge transfer via labor mobility may also contribute to catch-up of laggard regions to more developed ones. Skills of migrants returning from more developed regions may boost the productivity of a local sector (Hausmann and Nedelkoska 2018; Diodato, Hausmann, and Neffke 2020), which was shown when external shocks, such as the economic crisis, or a change in immigration policy forced many migrants return home.

Why, however, would migrants move (back) to lower-developed regions in the absence of such shocks? Unrealized expectations on return to skills (e.g. low wage and unemployment) can be one reason (De la Roca 2017), but potential returns of accumulated human capital together with lower price level can be another one (Dustmann and Weiss 2007; Dustmann, Fadlon, and Weiss 2011).

Our first aim therefore is to connect these studies by creating a model of voluntary labor mobility, with which we can assess, how labor mobility levels up within- and between-region productivity differences, and how obstacles to labor mobility contribute to preserving these differences. Our second aim is to examine the role of coworker networks. Though we have empirical observations about regional growth and coworker networks (Boschma, Eriksson, and Lindgren 2014; Lengyel and Eriksson 2017; Eriksson and Lengyel 2019), we know less about the mechanisms, *how* they contribute to catching-up of regions. Further, while the role of obstacles in labor mobility in sustaining regional differences is a relatively straightforward prediction, the role of coworker networks in this picture is less trivial.

Networks of former coworkers do not only serve as transmitters of knowledge between firms but they also convey information about employees and employers. As the labor market is characterized by imperfect or asymmetric information, this influences labor mobility different ways (Ioannides and Datcher Loury 2004). First, networks may transmit information about job vacancies to unemployed persons. This predicts that employment probability is correlated across social networks, and that network size increases the chance of employment (Calvo-Armengol and Jackson 2004). In this regard it was also shown that increased employment rate across former coworkers strongly increases workers' re-employment probability after unemployment (Glitz 2017).

Second, information available by former coworkers decreases uncertainty of employers about the "quality" of candidates (Montgomery 1991). This model has the consequence that having former coworkers at a company increases starting wages. Existence of such wage-gain was shown empirically, together with that this comes from two sources. First that using network information firms can select workers with better unobserved skills, and second that networks enable workers to choose from higher productivity (and thus higher paying) firms (Hensvik and Skans 2016; Boza and Ilyés 2020). Another consequence is that employers are more likely to hire workers to whom their current workers have connections to (Eliason et al. 2019).

A third approach assumes that workers' networks transmit information about the employer-employee fit (Simon and Warner 1992; Dustmann et al. 2016; Glitz and Vejlin 2020). They assume, based on the matching model of (Jovanovic 1979) that each worker has a potential (productivity), which is firm-specific. That is, different workplaces require workers with different skills, and if they match, that makes the worker productive, however, being successful at one firm does not necessary mean that the same worker will be successful at a different one. This matching factor is assumed to be unknown to the workers and firms a priori, and being revealed to them over time with employment, or by network information. Supporting empirical evidence of this model includes that referred workers have higher initial wages, and lower turnover than non-referred ones, and that this wage difference gradually decline with tenure (Simon and Warner 1992; Glitz and Vejlin 2020). A further consequence is that information on matching makes those employers more attractive, where former coworkers are present, thus there is a tendency for workers to follow each other across firms (Glitz and Vejlin 2020).

Therefore, with regard to the regional impacts of more extended coworker information networks, an increased mobility between regions can be expected at the first instance, as networks may provide information on firms at different regions, thus initial mobility can be amplified. This increased mobility, due to knowledge spillovers, therefore expected to decrease regional differences.

However, it is a widely observed property of (labor) mobility that it is negatively related to distance, as mobility over long distances include different material and non-material costs (e.g.) (Greenwood 1997). This implies that coworker networks also tend to cluster locally (Lőrincz et al. 2020). It is therefore also possible, that more extensive network information increases this tendency of local concentration of coworker networks, thus coworker networks may not contribute to decreasing regional differences at all, or may even amplify them.

Accordingly, we extend model of labor mobility and productivity spillovers by adding the information role of co-worker networks. Utilizing this, we study the relation between mobility and productivity differences within and between regions, and the specific role of co-worker information in this relationship.

Method

An analytical model of voluntary labor mobility with heterogeneous workers and firms is itself a rather complicated exercise (a well-known example is (Burdett and Mortensen 1998), and there are also nice examples for modelling labor mobility together with network information (Dustmann et al. 2016), however, we believe that putting together an analytical model of voluntary labor mobility with heterogeneous workers and firms with network information *and* productivity spillovers would be extremely difficult. Therefore, to study the relationship between these phenomena we turn to the technique of agent-based modelling. Agent-based models originate from equation-based models in natural sciences, which is widely applicable to problems in socio-economic sciences (Helbing 2012). They assume independent, adaptive and autonomous actors that follow simple rules, which is congruent with the foundations of economics and microsociology. Key assets of these models, which we utilize are that they can serve as experiments for social sciences, and study complex, emergent outcomes of systems that are not directly derivable form the individual actions (Macy and Willer 2002), or from what one could derive from a mean-field mathematical model. For our purpose of studying labor mobility these are important features, as real experiments are constrained by ethical considerations, and even the possibility of empirical analysis is limited to partial relationships when external shocks can be utilized, due to the endogeneous relationships between our variables (e.g. between mobility and productivity differences).

When creating the model, we build on general assumptions of existing models in labor economics to maintain comparability, and take into consideration the generalizability of our assumptions. Empirically, we set parameters according to existing studies where observations are available, and test our predictions on different parameter settings, considering those parameters, where no such hooks exist. We use the Netlogo program for the simulations. The code for the simulations is included in the Supplementary materials.

Initial setting

To start, we initially distribute the $N_W$workers cross the N_F firms. We generate an initial heterogeneity in the firms' productivity according to uniform distribution: *A=U{0,1}*. This represent heterogeneity of firms' capabilities, may be associated to "managerial talent", correspondingly to the model of (Lucas Jr 1978).

We assume that a fixed, β share of this is paid to the worker as wage, thus the wage of each worker at firm j is $W = \beta A_j$. In addition, each worker i has a firm-specific non-wage utility, μ_{ij} which is also drawn from a uniform distribution, μ_{ij}=*U{-0.5,0.5}*. This adds the heterogeneity in worker's preferences to the model. Therefore, workers maximize across firms their total utility, $W_j + \mu_{ij}$.

An important property of this setting is that workers are homogenous in the sense that they do not differ in their productivity (skills). The reason for this choice is that heterogeneity of workers in the skills would complicate the model by the sorting of workers to firms or regions, which is an interesting question, but it is beyond the aims of this study. In this sense, our approach is different from (Lise, Meghir, and Robin 2016) and (Lopes de Melo 2018), and similar to (Pissarides 1994; Nagypál 2007).

With respect to the parameter β, we can interpret it as the bargaining power of the workers, similarly to the model of (Nagypál 2007), however, in our case it is exogenous and constant, and not specific to the worker-firm relation. Practically, we can manipulate the weight of the non-wage utility compared to wage by this parameter. We set this parameter to $\beta = 0.5$ level throughout the simulation, however, this does not influence the conclusions of the model.

Our workers represent overlapping generations: They are active for 40 periods; thus one period corresponds to one year on the labor market. Afterwards they retire, and new workers replace them. We start the model with heterogeneous initial experience to avoid periodic fluctuations.

In the model we assume imperfect information, where workers are uncertain about their firm-specific fit (non-wage utility, μ_{ij}) at their prospective workplaces, therefore, they choose based on $W_j + E(\mu_{ij})$, where $E(\mu_{ij})$ is the average value in the population. However, once employed, this true μ_{ij} parameter about their current employment is revealed for them. In a later stage we will introduce network information that reveals the true μ_{ij} parameter for the potential workers. Thus, in this respect we follow the network information models of (Simon and Warner 1992) and (Dustmann et al. 2016).

Similarly to the above literature, we introduce labor mobility by assuming that jobs are destructed at an exogenous rate, δ. Workers, whose jobs were destructed have to choose a new job. (Note that the model would be highly similar if we did not assume job destruction, but that people at different points of their life change their preferences about jobs). In addition, workers with existing jobs may also change workplaces. Both groups are given an opportunity to choose among available offers, which arrive at a rate λ. We set the job destruction parameter to $\delta = 0.1$, as it directly influences the mobility rate, and we would like these parameters to be around the empirically observable range (job separation and hire rates are 8-16% in the U.S in the recent decades (Azzopardi et al. 2020)). The parameter of the arrival rate allows the model to reflect real-world decisions better, compared to the perfect information assumption. We set the arrival rate parameter to $\lambda = 0.1$ levels through the simulations, however, it does not influence the conclusions of the model.

Labor mobility and knowledge spillovers

The specialty of our model is that we add knowledge transfers to the labor mobility model. We assume that if workers move, the new firm may utilize some of their experience, creating a productivity spillover. We specify this the following way. The movement of a worker from firm a to firm b yields:

$$\begin{cases} A'_b = A_b + \dfrac{(A_a - A_b)\theta}{N_b} \quad if\ A_a > A_b \\ A'_b = A_b \quad if\ A_a \leq A_b, \\ and\ A'_a = A_a, \end{cases} \tag{1}$$

where A' is the changed productivity parameter, $\theta < 1$ is a parameter representing the transferability of knowledge, and N_b is the number of workers at firm b. This specification is identical to (Stoyanov and Zubanov 2012) and (Csáfordi et al. 2020), assuming that the weight of new knowledge brought by a single worker decreases by the number of incumbent workers, and also corresponds to their empirical findings that negative productivity difference do not make a change. We set the spillover parameter to $\theta = 0.3$, corresponding to the empirical estimates of these studies.

Turning back to the decision on mobility, we assume that this productivity spillover is incorporated in the wage offer, so firms offer wages to workers based on their previous careers and their subsequent future productivity. We also assume that mobility of workers are costly, therefore workers leave their workplace only if their benefit exceeds a switching cost parameter, SC. Therefore, the worker i switches from firm a to firm b if:

$$\begin{cases} E(\mu_{ib}) + \beta\left(A_b + \frac{(A_a - A_b)\theta}{N_b}\right) > \mu_{ia} + \beta A_a + SC \ if \ A_a > A_b \\ E(\mu_{ib}) + \beta A_b > \mu_{ia} + \beta A_a + SC \ if \ A_a \leq A_b \end{cases} \quad (2)$$

If productivity of a recipient firm was increased due to the experience of the incoming workers, we assume that this firm also increases the wages of its incumbent worker accordingly, from $W = \beta A_j$ to $W' = \beta A'_j$, so there will be no wage differentials within the firm between the workers (who are assumed to be similar in skills). This positive externality of the new knowledge on the wage of incumbent workers is in line with the results of (Poole 2013).

We implement labor mobility in two steps. First, those workers look for a job, whose jobs were destructed. They choose from available offers according to Equation (2). As the subsequent productivity spillovers influence the optimal choice of those workers too, whose jobs were not destructed, next we re-consider their workplace choice allowing voluntary mobility. In the model the extent of mobility is influenced by the job destruction and the switching cost parameters, of which we fixed the first, and manipulate only the switching costs.

This setting nicely reproduces the key empirical observation in labor economics that larger pay higher wages (Oi and Idson 1999). This correlation in the model follows from the assumption that firms are heterogeneous in their capabilities (productivity), and more productive firms pay higher wages, therefore they are more likely to attract more workers, similarly to (Lucas Jr 1978), however, in our setting not the decreasing marginal returns in the production function, but the heterogeneity in workers' non-wage utility prevents the highest capability firm from taking over the whole labor market.

Equilibrium in the basic model

In this setting the following dynamics can be observed. If a worker moves from a less productive firm to a more productive one, the productivity difference between them do not change. However, if a worker moves from a productive firm to a less productive one, the difference in productivities decreases. Therefore, productivity differences will continuously decrease, unless there is no mobility in the system. However, in the reality we experience persistent mobility *and* productivity differences, so it would be a nice property of the model to reflect this phenomenon. Therefore, we must introduce a force of divergence of productivities to the model, which will be innovation.

We borrow the idea from the "escape competition" model of (Aghion and Griffith 2008), and assume that more productive firms are more likely to successfully develop a productivity-enhancing innovation. (However, we assume that others do not imitate the innovators, but learn through labor mobility).

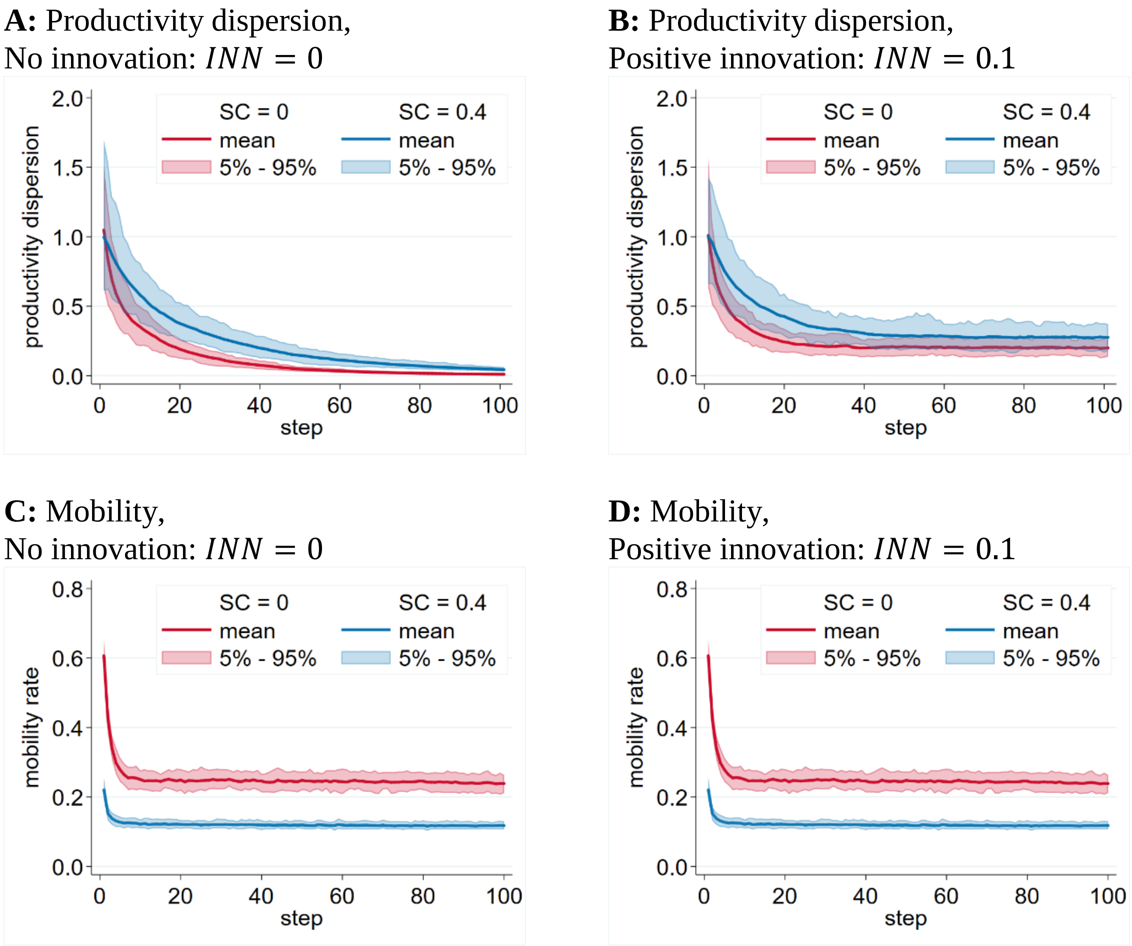
In our system in each round one firm innovates, which is costless, and increases its productivity by the parameter INN. The likelihood of each firm to become the successful innovator is proportional to their productivity, thus

$$pr(innovator = a) = \frac{A_a}{\sum_j A_j}. \tag{3}$$

Furthermore, as a final adjustment, we deflate the productivities by the change of the average productivity of all firms in each round. This is necessary, because otherwise the productivity would grow continuously in the system, which would result in higher and higher wages, therefore the weight of the non-wage element in the workers' choice would slowly but continuously vanish.

After including innovation to the model, it produces the persistent mobility and productivity dispersion over a reasonable set of parameters, for the contentment of the authors. After an initial adjustment, the simulations stabilize on an equilibrium level of mobility and productivity dispersion (Figure 1, Panel B, D). It is also visible, that if we increase switching costs, this equilibrium level of productivity dispersion decreases and the level of mobility increases. On the other hand, without innovation the productivities of the firms converge, thus the productivity dispersion vanishes, even if switching costs are present (Figure 1, Panel A).

Figure 1. Productivity dispersion and mobility with and without innovation



Productivity dispersion is measured by the interquartile range divided by the median, following (Syverson 2004b). **Parameters:** $N_p = 300\, persons, N_f = 30\, firms,\ \beta = 0.5, \delta = 0.1,\ \lambda = 0.1, \theta = 0.3$

Intuitively, the presence of a stable level of productivity dispersion originates from the following two factors. First, if a firm gets more productive, it attracts more workers, and grows bigger, on the expense of the others, which become smaller. However, these small firms benefit more if they can gain a worker from the more productive one, as the mobile worker's knowledge disperses easier in a small community. This is represented by the inclusion of the number of the recipient firm's workers (N_b**)** in the denominator in the spillover formula of Equation (1).

Additionally, as the firm grows bigger, the chance increases, that a randomly selected worker, whose job is destructed, will be drawn from that firm.

One can expect, however, that if mobility costs increase over a certain threshold, the chance increases that a firm can escape from its competitors in a distance, where the productivity spillovers and the difference in non-wage utility cannot compensate the wage differentials any more, therefore it slowly overtakes the whole labor market. The emergence of this phenomenon is examined in Figure 2 with respect to mobility cost and innovation rate. Panel A suggests that on the reasonable range of parameters ($SC \in [0,1]$, $INN \in [0,1]$) firms are not able to escape from their competitors, as labor mobility transfers the new innovation to competitors. Still, if innovation rate increases, the highest productivity firm tends to have some advance in productivity. If innovation rate is high and the cost of mobility is low, these firms gain significant share of workers, however, they do not overtake the whole market (Figure 2 panel B). Firms escaping the competition by innovation only happens, if we increase mobility cost to very high level ($SC > 3$), and if innovation rate is also high. In this case those firms that are initially lucky with the innovation benefit from its cumulative nature (that innovation happens with higher probability at firms having already high productivity). The yellow area on Figure 2A represents that one firm escaped from the competition[1]. In the range of switching costs of $3 < SC < 8.5$ these firms tend to take over the whole labor market, which happens the following way. In the beginning of the simulation productivity levels are relatively even and the very high switching cost prohibit any labor mobility. Due to the high innovation rate, a lucky firm tends to increase its productivity, and start go gain significant advantage. After getting so high productivity advantage that the wage difference exceeds the switching cost, workers from the laggard firms can move to the high productivity one, but the switching costs prohibit the mobility in the adverse direction. In some of the simulations it is not one, but two firms escape from the competition, and a duopoly emerges, indicated by the green dots on

[1] As the mean productivity in the beginning is 0.5, and the average productivity over the simulations is normalized to this level, the highest productivity value of 15 indicates that one firm of the 30 ones has productivity 15, and all others have 0.

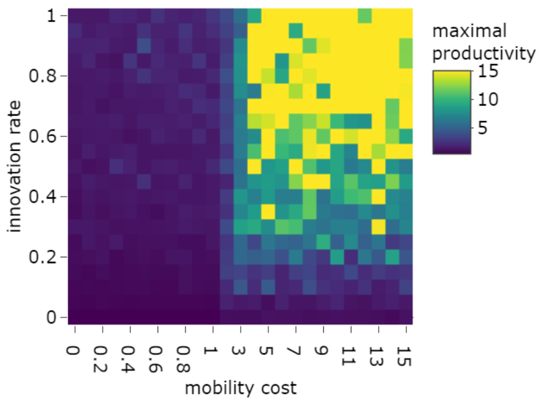
Figure 2 A-B. If we however increase the switching cost to even higher level (SC>8.5 in the 30-firm setting), it prohibits all mobility, even between a firm with a maximum and minimum productivity level. Therefore, a firm typically escapes the competition by innovation, but it cannot overtake the labor market, as mobility is zero (Figure 2 C)

It can be observed that the innovation adds additional motivation for mobility. If a firm innovates, its productivity increases together with the wages offered by it, which creates a motivation to join the firm, which opens up opportunity for new mobility. Therefore, low switching costs and increasing the innovation rate both increases mobility (Figure 2 C).

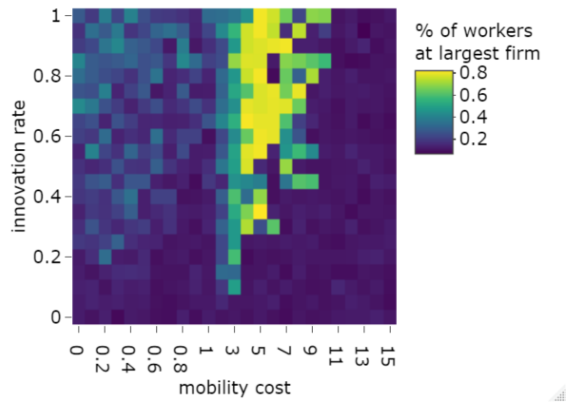
Examination of the workers over their life-cycle reveals that their mobility rate is the highest in the beginning of their career, when their firm-specific non-wage utility increase. Later they find their ideal jobs, and their non-wage utility stabilizes, and mobility settles on a lower level (Figure 2 D). This corresponds to the empirical observations of labor economics literature (Farber 1999).

Figure 2. Equilibria over different ranges of mobility cost and innovation rate.

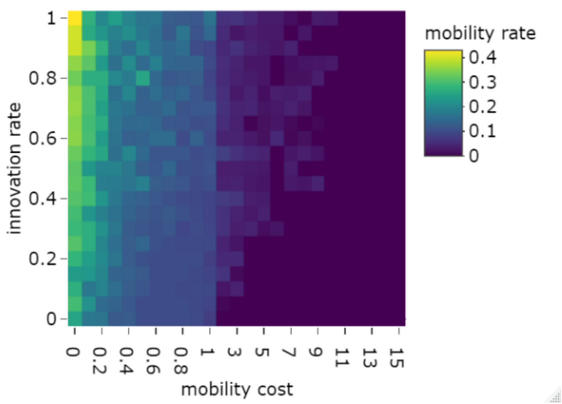
A: The effect of the mobility cost and innovation rate on maximal productivity



B: The effect of the mobility cost and innovation rate on the size of largest firm



C: The effect of the mobility cost and innovation rate on yearly mobility rate



D: Mobility and non-wage utility by workers' experience

Notes. A-C: Each dot represents one simulation at the 1000th step (Higher number of steps was necessary to study the equilibria due to the inclusion of extreme values). **D:** Each line represents the average of 10 simulations at the 100th step **Parameters:** $N_p = 300\ persons, N_f = 30\ firms,\ \beta = 0.5, \delta = 0.1,\ \lambda = 0.1, \theta = 0.3$

The analysis above indicates that the dynamics of the model is stable over a wide range of the parameters ($SC \in [0,1]$, $INN\ \in [0,1]$), so our analysis do not concentrate on an extreme setting.

The effect of network information

We examine the effect of coworker networks by adding the following assumptions:

1) Workers have no initial information about their non-wage utility parameter at prospective employers if none of their former coworkers work there, but
2) if they have a former coworker at a firm, their true parameter is revealed for them initially.

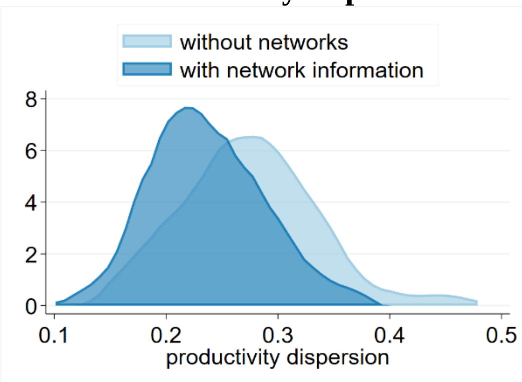
This information may influence mobility both positively and negatively. Information on a bad personal match may distain workers to move to a specific firm, but information a good match may propagate mobility.

To get an idea about the effect of information, consider a special case when compensating differentials at the current workplace, and a prospective workplace are independent and uniform distributions [0,a], and disregard the expected wages and the limitation on available options. In this case the job mobility rate with no information is $(0.5a - SC)a$, as workers expect 0.5 compensating differentials if they have no information. With full information it is $\frac{(a-SC)^2}{2}$ that is always higher than the previous term, thus the information increases mobility. Intuitively this is due to the fact that though networks can provide good and bad news, information on one good potential workplace is enough to motivate mobility.

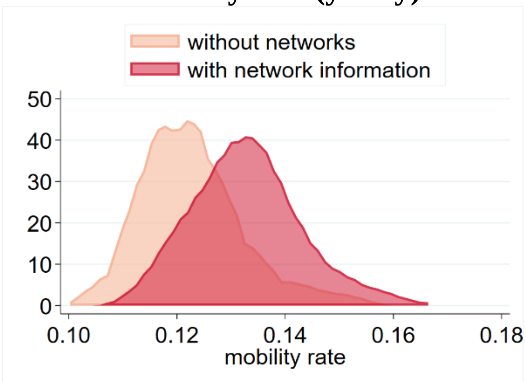
We can also observe this phenomenon in the simulations, which show that network information increases the chance that mobility (Figure 3, Panel B). It is also visible, that by increased mobility the productivity dispersion decreases (Panel A). In the figure we visualize the results of 100 simulations (at the 100^{th} step, which is sufficient to reach the stable range after the initial adjustment based on results shown in Figure 1).

Figure 3. Productivity dispersion and mobility with and without network information

Panel A: Productivity dispersion



Panel B: Mobility rate (yearly)



Notes. Each distribution represents 100 simulations at the 100th steps**. Parameters:** $N_p = 300\, persons, N_f = 30\, firms,\ \beta = 0.5, \delta = 0.1,\ \lambda = 0.1, \theta = 0.3, SC = 0.4$

Regional analysis

Our key interest in this study is the effect of labor mobility on regional differences. To study this, we introduce regions, trying to keep the model as simple as possible.

We create two regions, and distribute the firms between them randomly. We assume that the cost of mobility for workers consist of two parts: they bear a general switching cost (SC), if they change workplace, but if they choose a firm in the other region, the cost of moving (MC) adds to this. This modifies the condition under which worker i moves from a more productive firm a to a less productive firm b the following way:

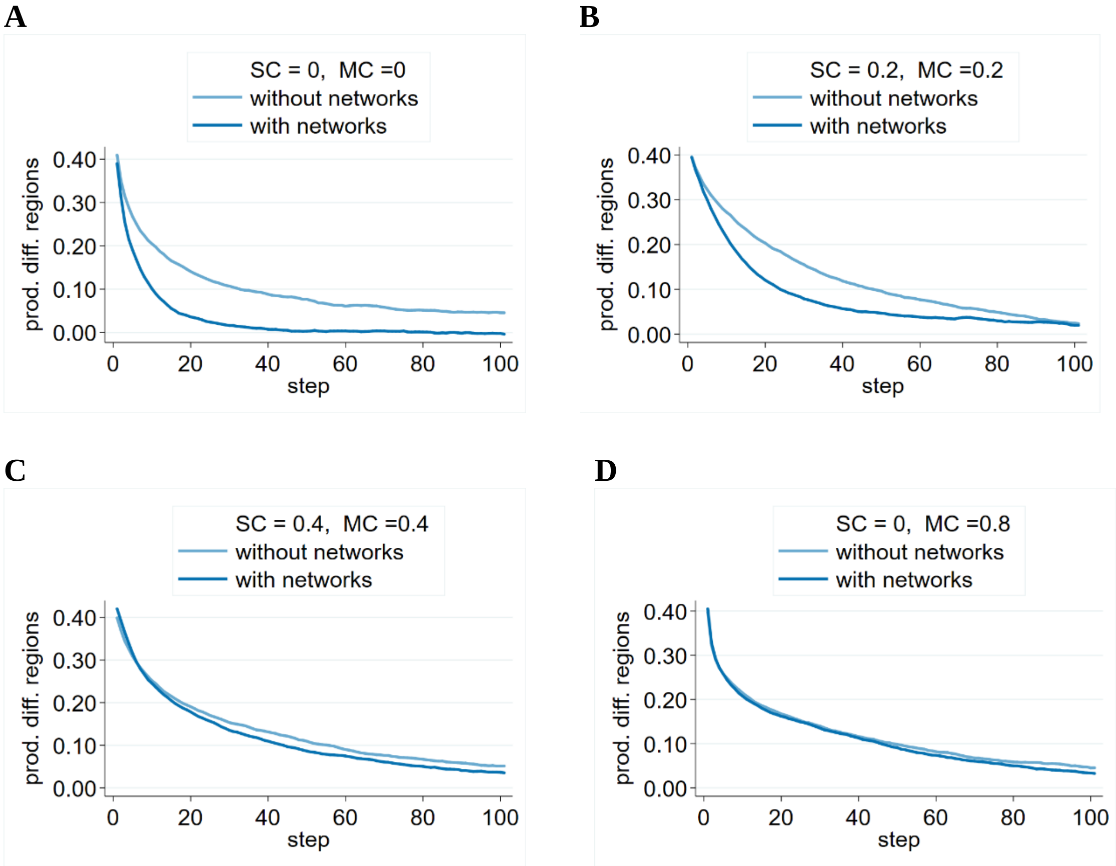
$$\begin{cases} \mu_{ib} + \beta\left(A_b + \frac{(A_a - A_b)\theta}{N_b}\right) > \mu_{ia} + \beta A_a + SC & \text{if firm } a \text{ and } b \text{ are located in the same region} \\ \mu_{ib} + \beta\left(A_b + \frac{(A_a - A_b)\theta}{N_b}\right) > \mu_{ia} + \beta A_a + SC + MC & \text{if they are located in different regions.} \end{cases}$$

(4)

Our question is, whether labor mobility contributes to convergence of the regions, and that how networks contribute to this. Therefore, we start with regions with different average productivity levels, so one can also think of Region 1 as being in a more developed center, and Region 2 as a representative for the less developed periphery. In the simulations we examine a scenario with significant (40%) initial average productivity differences between them.

Simulations indicate rapidly decreasing productivity differences between the regions, and in our simulations they reach an economically insignificant level. It is also visible that the balancing of the average productivity is quicker in the network information scenario (Figure 4), but the effect of network information depends on the level of the moving costs. If the moving costs are zero (Figure 4 A), or they are moderate (Figure 4 B), regional differences level up much quicker, if network information is present, compared to the no network scenario. In case if high moving costs are coupled by significant switching costs (Figure 4 C), or if they are very high (Figure 4 D), the advantage of network information is negligible. Still, we do not see any example even if moving costs are very high for network information to sustain regional differences.

Figure 4. Productivity differences between regions with and without network information over different switching cost and moving cost parameters

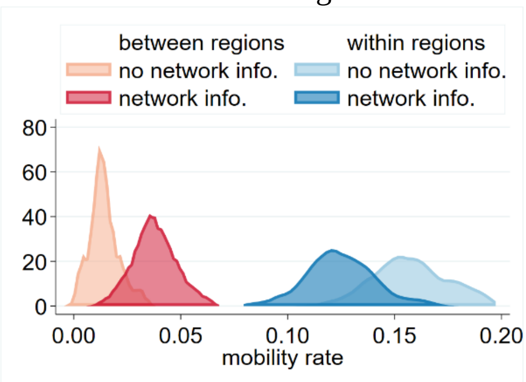


Notes. Averages over 100 simulations. **Parameters:** $N_p = 300\, persons, N_f = 30\, firms,\ \beta = 0.5, \delta = 0.1,\ \lambda = 0.1, \theta = 0.3$

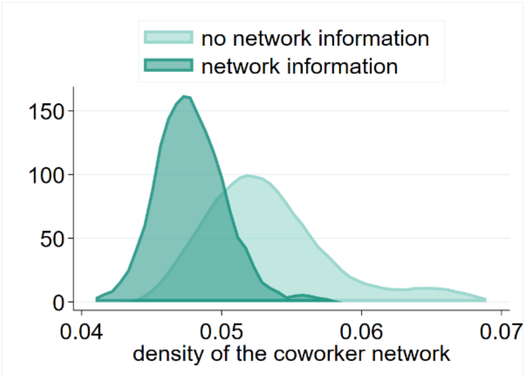
We have seen that network information increases mobility, and this remains true in our two-region model as well. However, our regional analysis reveals an interesting feature that network information actually decreases labor mobility within the region, but increases it between them (Figure 5 A). These tendencies are also reflected in the network structure of coworker networks. The modularity of the coworker network by regions indicates, the extent to which the coworker networks concentrate within regions. Figure 5, C points out, that this tendency is weaker in the network information scenario, corresponding to the higher rate of interregional mobility. On the other hand, the overall density of the network is decreased in the network information scenario (Figure 5, Panel B) despite the overall higher mobility rate. This represents that in the no information scenario movement of the workers is more random, while with network information they are more likely to follow each other across firms, thus they expand their coworker networks less during their life-cycles.

Figure 5. Characteristics of regional labor mobility and co-worker networks with and without network information

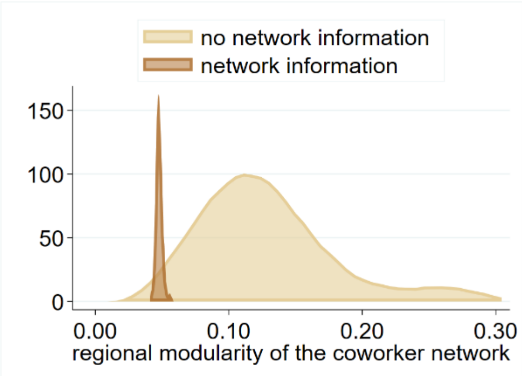
Panel A: Mobility
between and within the regions



Panel B: Density
of the coworker networks



Panel C: Regional modularity
of the coworker networks



Notes. Each distribution represents 100 simulations at the 100th steps**. Parameters:**

$N_p = 300\, persons, N_f = 30\, firms,\ \beta = 0.5, \delta = 0.1,\ \lambda = 0.1, \theta = 0.3$

Conclusions

Previous studies have shown empirical evidence for labor mobility resulting in knowledge transfer observed in productivity of firms (Stoyanov and Zubanov 2012; Csáfordi et al. 2020). On the regional level, it was also observed that dense coworker networks are associated with regional growth (Lengyel and Eriksson 2017; Eriksson and Lengyel 2019; Boschma, Eriksson, and Lindgren 2014) and that distant ties in co-worker networks provide access to new skills for firms (Lőrincz et al. 2020). It was also observed that labor mobility from developed countries to less developed regions induced by external shocks contribute to development of local industries (Hausmann and Nedelkoska 2018; Diodato, Hausmann, and Neffke 2020). Our model provides a missing piece between these findings suggesting that the micro-mechanism of voluntary labor mobility of workers is sufficient for the catch-up of the less developed regions, even without external shocks. This implies that easing labor mobility between regions may have positive impact even for less developed (peripheral) regions (or countries), as they can exploit the knowledge transfer from (return) migration.

The model also provides new non-trivial insights to how micro-mechanisms of labor mobility influence the structure of coworker networks, and to the understanding of the empirical consequences of these. It shows that the feature of coworker networks that they provide information about potential fit of workers to jobs, that induces the tendency of workers to follow each other across firms (Glitz and Vejlin 2020) is manifested by decreased density of coworker networks. Moreover, the model suggests that even in the presence of limited interregional mobility (movement costs), the such network information is associated with higher interregional mobility and subsequently to decreased regional differences. However, we found that the high cost of mobility limits the effect of network information on speeding up regional convergence. These features may promote further empirical analysis of the consequences of different coworker network structures.

With regard to the modelling assumptions, we have made the important choice of assuming workers to be homogenous in the sense that we did not distinguish between low-skilled and high-skilled workers. About modelling network information, we chose a corresponding model that networks provide information about the employer-employee fit. However, the alternative approach is apparent that workers are heterogeneous, and networks provide information about their “quality”, following the model of (Montgomery 1991). This opens up a different research direction about the impact of networks in the selection of high-skilled workers to developed regions, or big cities, which is observed in labor economics (e.g. (Borjas, Bronars, and Trejo 1992; Roca and Puga 2017), and has severe consequences on the development of urban-rural inequalities (Autor 2020).

References

Aghion, Philippe, and Rachel Griffith. 2008. “Competition and Growth: Reconciling Theory and Evidence.” http://eprints.ucl.ac.uk/16507/.

Almeida, Paul, and Bruce Kogut. 1999. “Localization of Knowledge and the Mobility of Engineers in Regional Networks.” *Management Science* 45 (7): 905–17.

Autor, David. 2020. “The Faltering Escalator of Urban Opportunity.” *Securing Our Economic Future, Melissa S Kearney and Amy Ganz (Eds.)*, 108–36.

Azzopardi, Damien, Fozan Fareed, Mikkel Hermansen, Patrick Lenain, and Douglas Sutherland. 2020. “The Decline in Labour Mobility in the United States: Insights from New Administrative Data.”

Balsvik, Ragnhild. 2011. “Is Labor Mobility a Channel for Spillovers from Multinationals? Evidence from Norwegian Manufacturing.” *The Review of Economics and Statistics* 93 (1): 285–97.

Borjas, George J., Stephen G. Bronars, and Stephen J. Trejo. 1992. “Self-Selection and Internal Migration in the United States.” *Journal of Urban Economics* 32 (2): 159–85.

Boschma, Ron, Rikard H. Eriksson, and Urban Lindgren. 2014. “Labour Market Externalities and Regional Growth in Sweden: The Importance of Labour Mobility between Skill-Related Industries.” *Regional Studies* 48 (10): 1669–90.

Boza, István, and Virág Ilyés. 2020. “Decomposition of Co-Worker Wage Gains.” *IZA Journal of Labor Economics* 9 (1).

Burdett, Kenneth, and Dale T. Mortensen. 1998. “Wage Differentials, Employer Size, and Unemployment.” *International Economic Review*, 257–73.

Calvo-Armengol, Antoni, and Matthew O. Jackson. 2004. “The Effects of Social Networks on Employment and Inequality.” *The American Economic Review* 94 (3): 426–54.

Csáfordi, Zsolt, László L\Horincz, Balázs Lengyel, and Károly Miklós Kiss. 2020. “Productivity Spillovers through Labor Flows: Productivity Gap, Multinational Experience and Industry Relatedness.” *The Journal of Technology Transfer* 45 (1): 86–121.

De la Roca, Jorge. 2017. “Selection in Initial and Return Migration: Evidence from Moves across Spanish Cities.” *Journal of Urban Economics* 100: 33–53.

Diodato, Dario, Ricardo Hausmann, and Frank Neffke. 2020. “The Impact of Return Migration from the US on Employment and Wages in Mexican Cities.” Utrecht University, Department of Human Geography and Spatial Planning ….

Dustmann, Christian, Itzhak Fadlon, and Yoram Weiss. 2011. “Return Migration, Human Capital Accumulation and the Brain Drain.” *Journal of Development Economics* 95 (1): 58–67.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker. 2016. “Referral-Based Job Search Networks.” *The Review of Economic Studies* 83 (2): 514–46.

Dustmann, Christian, and Yoram Weiss. 2007. “Return Migration: Theory and Empirical Evidence from the UK.” *British Journal of Industrial Relations* 45 (2): 236–56.

Eliason, Marcus, Lena Hensvik, Francis Kramarz, and Oskar Nordstrom Skans. 2019. “Social Connections and the Sorting of Workers to Firms.”

Eriksson, Rikard H., and Balázs Lengyel. 2019. “Co-Worker Networks and Agglomeration Externalities.” *Economic Geography* 95 (1): 65–89.

Farber, Henry S. 1999. “Mobility and Stability: The Dynamics of Job Change in Labor Markets.” *Handbook of Labor Economics* 3: 2439–83.

Glitz, Albrecht. 2017. “Coworker Networks in the Labour Market.” *Labour Economics* 44: 218–30.

Glitz, Albrecht, and Rune Vejlin. 2020. “Learning through Coworker Referrals.” *Review of Economic Dynamics*.

Goñi Pacchioni, Edwin A., and Francisco Pardo. 2018. *Workers’ Mobility, Technical Transfer, and Firms’ Performance in Peru*. Inter-American Development Bank.

Greenwood, Michael J. 1997. "Internal Migration in Developed Countries." *Handbook of Population and Family Economics* 1: 647–720.

Hausmann, Ricardo, and Ljubica Nedelkoska. 2018. "Welcome Home in a Crisis: Effects of Return Migration on the Non-Migrants' Wages and Employment." *European Economic Review* 101: 101–32.

Helbing, Dirk. 2012. "Agent-Based Modeling." In *Social Self-Organization*, 25–70. Springer.

Hensvik, Lena, and Oskar Nordström Skans. 2016. "Social Networks, Employee Selection, and Labor Market Outcomes." *Journal of Labor Economics* 34 (4): 825–67.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics* 124 (4): 1403–48.

Ioannides, Yannis M., and Linda Datcher Loury. 2004. "Job Information Networks, Neighborhood Effects, and Inequality." *Journal of Economic Literature* 42 (4): 1056–93. https://doi.org/10.1257/0022051043004595.

Jovanovic, Boyan. 1979. "Job Matching and the Theory of Turnover." *The Journal of Political Economy*, 972–90.

Lengyel, Balázs, and Rikard H. Eriksson. 2017. "Co-Worker Networks, Labour Mobility and Productivity Growth in Regions." *Journal of Economic Geography* 17 (3): 635–60. https://doi.org/10.1093/jeg/lbw027.

Lise, Jeremy, Costas Meghir, and Jean-Marc Robin. 2016. "Matching, Sorting and Wages." *Review of Economic Dynamics*, Special Issue in Honor of Dale Mortensen, 19: 63–87. https://doi.org/10.1016/j.red.2015.11.004.

Lopes de Melo, Rafael. 2018. "Firm Wage Differentials and Labor Market Sorting: Reconciling Theory and Evidence." *Journal of Political Economy* 126 (1): 000–000.

Lőrincz, László, Guilherme Kenji Chihaya, Anikó Hannák, Dávid Takács, Balázs Lengyel, and Rikard Eriksson. 2020. "Global Connections and the Structure of Skills in Local Co-Worker Networks." *Applied Network Science* 5 (1): 1–20.

Lucas Jr, Robert E. 1978. "On the Size Distribution of Business Firms." *The Bell Journal of Economics*, 508–23.

Macy, Michael W., and Robert Willer. 2002. "From Factors to Factors: Computational Sociology and Agent-Based Modeling." *Annual Review of Sociology* 28 (1): 143–66.

Maliranta, Mika, Pierre Mohnen, and Petri Rouvinen. 2009. "Is Inter-Firm Labor Mobility a Channel of Knowledge Spillovers? Evidence from a Linked Employer–Employee Panel." *Industrial and Corporate Change* 18 (6): 1161–91.

Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71 (6): 1695–1725.

Montgomery, James D. 1991. "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis." *The American Economic Review* 81 (5): 1408–18.

Nagypál, Éva. 2007. "Labor-Market Fluctuations and on-the-Job Search."

Oi, Walter Y., and Todd L. Idson. 1999. "Firm Size and Wages." *Handbook of Labor Economics* 3: 2165–2214.

Palomeras, Neus, and Eduardo Melero. 2010. "Markets for Inventors: Learning-by-Hiring as a Driver of Mobility." *Management Science* 56 (5): 881–95.

Pissarides, Christopher A. 1994. "Search Unemployment with On-the-Job Search." *The Review of Economic Studies* 61 (3): 457–75.

Poole, Jennifer P. 2013. "Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility." *Review of Economics and Statistics* 95 (2): 393–406.

Roca, Jorge De La, and Diego Puga. 2017. "Learning by Working in Big Cities." *The Review of Economic Studies* 84 (1): 106–42.

Simon, Curtis J., and John T. Warner. 1992. "Matchmaker, Matchmaker: The Effect of Old Boy Networks on Job Match Quality, Earnings, and Tenure." *Journal of Labor Economics* 10 (3): 306–30.

Stoyanov, Andrey, and Nikolay Zubanov. 2012. "Productivity Spillovers across Firms through Worker Mobility." *American Economic Journal: Applied Economics*, 168–98.
Syverson, Chad. 2004a. "Market Structure and Productivity: A Concrete Example." *Journal of Political Economy* 112 (6): 1181–1222.
———. 2004b. "Product Substitutability and Productivity Dispersion." *The Review of Economics and Statistics* 86 (2): 534–50.
———. 2011. "What Determines Productivity?" *Journal of Economic Literature* 49 (2): 326–65.
Zucker, Lynne G., Michael R. Darby, and Maximo Torero. 2002. "Labor Mobility from Academe to Commerce." *Journal of Labor Economics* 20 (3): 629–60.