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Labor Market Policy Evaluation with ACE

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Abstract

I develop an agent-based computational economics (ACE) model with which I evaluate the aggregate impact of labor market policies. The findings are that government-financed training measures increase the outflow rate from unemployment to employment. Although the overall effect is positive, this effect is achieved by reducing the outflow rate for those who do not receive subsidies. Furthermore, the outflow rate would have been downward-biased had one supposed a matching function that is exogenous to policies.

Keywords: Labor market policy evaluation, agent-based computational model, endogenous matching function, job displacement

JEL Classification: C63, J61, J68

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1 Introduction

The objective of labor market policies is at least twofold: to provide benefits to those people who are unemployed in order to cushion their income loss, and to improve the allocation of workers to job openings in the labor market. The former usually goes under the heading of passive labor market policy whereas measures that follow the second aim are usually referred to as active labor market policies. As table 1 shows, a considerable amount of money is spent on labor market policies in OECD countries each year. The interest in the effectiveness of those policies follows quite naturally.

Nowadays, there is considerable microeconometric evidence on the effects of training measures for individuals, mainly about whether it improves an individual's chance of finding a job, about how it has an impact on wages, and sometimes also about its stabilizing role on lifetime employment and income (see, e.g., Heckman et al., 1999). However, studies based on micro-data cannot tell us what the aggregate effects of those labor market policies look like. As has been proposed by Garfinkel et al. (1992), Calmfors (1994), Schmid et al. (1996), and the OECD (2005), the aggregate impact of labor market policies might be smaller than what evaluations on the individual level suggest because deadweight losses and substitution and displacement effects of labor market policies are not taken into account. This is why studies based on micro-data should be complemented by aggregate impact studies of labor market policies in order to arrive at sound public policy recommendations.

In this article I link individual and aggregate impact studies with an agent-based model of the labor market. In particular, I address three issues: a) I evaluate the aggregate impact of government training subsidies, which, as table 1 reveals, make up a considerable share of active policies; b) quantify how a policy that improves an individual's chances of finding a job harms those who do not receive government transfers; and c) point out that evaluating labor market policies within flow models that depend on matching functions that are exogenous to the labor market policies under investigation may result in biased results.

Following up on the first issue, I intend to add to an existing literature that studies the aggregate impact of training policies an alternative methodology (as suggested by Freeman, 2005, among others for policy evaluation) that complements the use of flow models and the estimation of aggregate matching functions (see, e.g., Mortensen and Pissarides, 1999; Bellmann and Jackman, 1996, respectively). The second topic is, in my estimation, a potentially interesting contribution that agent-based models can make in linking micro- and macro-level evaluations. Micro-evidence is not informative when it comes to judging the macroeconomic consequences of labor market policies. In addition, a mere look at aggregate variables does not allow one to make inferences about to what extent the success of a program of a treated group of individuals comes at a cost for the non-treated. By its very construction, an agent-based labor market model allows the extraction of information on the individual level and the aggregate level. Thus, job displacement effects of labor market policies can be studied. The third result questions the use of matching functions as a key building block in flow models of the labor market. Matching functions relate two stock variables, jobseekers and vacancies, to outflows from unemployment (a flow variable). The properties usually attributed to the matching function are outflows as an increasing and concave function of the inputs to the matching function, and constant returns to scale. Moreover, those properties are usually seen as exogenous to policies. Here I raise the concern that if one takes a micro-foundation of the matching function seriously, namely, that policies target the agents' choices and that the properties are driven by firms' and workers' search decisions, then one should also expect that properties of the matching function change under the auspices of different policies. A failure to take into account that the matching function is endogenous to policies might lead to biased results in aggregate impact studies of labor market policies.[1]

Butters (1977) and Hall (1979) were among the first to provide a micro-foundation of the matching function on the basis of a coordination failure argument exemplified by the so-called urn-ball model. From that point of departure many roads have been taken to add more structure to either the demand side or the supply side of the market, or to introduce models of wage determination in order to study the properties of the endogenous matching function.[2] Agent-based approaches to matching functions were made by Tesfatsion (1998), Richiardi (2004), and Fagiolo et al. (2004). In Neugart (2004) I showed within an agent-based computational economics (ACE) framework what properties for an endogenous matching function arise if there is endogenous vacancy creation, endogenous search intensity, and a wage formation such that heterogenous workers are paid their reservation wages. I also hinted towards the possibility of policies affecting the properties of the matching function, an issue that has been pointed out by Lagos (2000) before.

The model with which I address the three issues is an agent-based computational model of a labor market with different sectors.[3] Firms in those sectors have sector-specific skill requirements. Sectors are hit by exogenous

[1] Examples of evaluations of labor market policies with an exogenous matching function can be found in Mortensen (1994), Pissarides (1998), and Fredriksson and Holmlund (2001), who look at the effects of unemployment benefit systems. Job protection legislation, active labor market policies, and a negative income tax system were analyzed by Pissarides (2001), Mortensen (1996), and Coe and Snower (1997), respectively.

[2] Work in this direction has been done by Cao and Shi (2000), Julien et al. (2000), Burdett et al. (2001), Albrecht et al. (2003), and Smith and Zenou (2003). A comprehensive survey of the matching function is provided by Petrongolo and Pissarides (2001).

[3] For an introduction to agent-based modeling, see, for example, Tesfatsion (2006).

shocks. In such an event firms close down, dismissing their employees. As sectors are differentiated by skill requirements, unemployed workers have to make an upfront investment in their human capital in order to qualify for vacancies opening up in other sectors. The government subsidizes the unemployed workers' human capital investment, which is financed by a tax on the employed.

The findings are that subsidizing training increases the outflow rate from unemployment to employment and reduces the unemployment rate. Furthermore, dividing the group of jobseekers into a treatment and a non-treatment group shows that a higher outflow rate of the treated jobseekers comes at the cost of a lower outflow rate of the non-treated. Finally, had I supposed an exogenous matching function, the aggregate impact of the government policy on the outflow rate from unemployment would have been underestimated.

In the following section I describe the model. Section 3 presents the results, and the last section summarizes my findings.

2 The model

There shall be $numSectors$ sectors in the economy, allocated on a circle (see figure 1). The number of firms in the labor market is $numFirms$, with $numFirms > numSectors$. Firms in sector i have different skill requirements from firms in sector j, with $i \neq j$. Skill differentiation varies with the distance between sectors. Assume $numSectors = 10$; then from the perspective of the sector $i = 0$, sectors numbered 1 and 9 would be closest in terms of the skill requirements of the firms, whereas sectors 2 and 8 would require skills more distinct from what is needed in sectors 1 and 9, and so on. Each firm posts one vacancy. If the firm can fill its vacancy, it produces output.

The returns from production are fully paid out to the workers in terms of a fixed wage *wage*.

Initially firms and workers are randomly allocated to sectors. With probability r sectors are hit by shocks. All firms in the sector hit by a shock close down. Workers in those firms become unemployed. A number of firms equal to the number of closing firms is opening up in local labor markets that were not hit by the current shock.[4] Again, those firms are allocated randomly to the new sectors. Because the number of firms is held constant, aggregate labor demand is constant, too. In other words, the shocks considered are asymmetric.

Firms that have a vacancy on the market and received applications randomly choose one applicant, to whom they make an offer. The worker always accepts the first offer that he gets. The order in which firms are allowed to make offers is random, approximating the simultaneous actions of the firms. Thus, it may happen that a firm that received multiple applications cannot fill the vacancy because all applicants were hired by other firms, or that a vacancy is not filled because no worker applied.

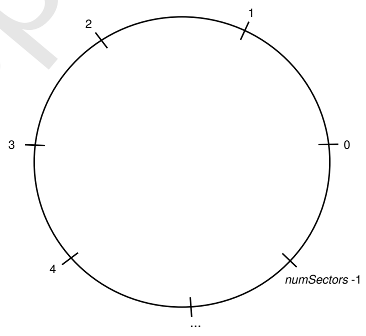

Figure 1: Allocation of sectors in the labor market

The number of workers in the market equals the number of firms. Thus,

[4]Sectors hit by a shock, however, may be populated by firms again in the future.

in principle there could be full employment. Workers are heterogenous in terms of their skill endowments, their initial skills determined by the random allocation to a sector. Unemployed workers can make an upfront human capital investment. If they decide not to invest in their human capital, they can only apply for vacancies that are posted in the sector in which they worked. However, if they make an upfront investment in their human capital of the size of one unit, they would also qualify for vacancies posted in sectors 1 and 9, assuming that they are currently located in $i = 0$ and $numSectors = 10$. A human capital investment of the size of two units would, in addition, qualify the worker for jobs in sectors 2 and 8. The human capital investment is costly. Acquiring skills that qualify the worker for the adjacent two sectors implies costs $humCapInvCost$. An investment in the worker's human capital that would qualify him for the closest additional four sectors incurs costs $2 \cdot humCapInvCost$, and so on. Workers may want to make upfront human capital investments up to the point at which they qualify for all sectors ($0 \leq numHumCapInv \leq numSectors/2$).[5] A worker shall send applications to all firms that have vacancies with skill requirements that match the worker's skills. An unemployed worker who makes an upfront human capital investment, but does not find a job in the current period, will have to invest in his human capital again in order to qualify for job openings outside his past field of work.

Workers learn how much they should invest in their human capital whenever they become unemployed or do not find a job. I model this as a process of individual reinforcement learning.[6] In the initial stage, a worker chooses the amount of human capital investment from the strategy set with equal

[5] I assume that $numSectors$ is an even number.

[6] Another option to model learning on the individual level is genetic algorithms; see McFadzean and Tesfatsion (1999) or Dawid (1999). Brenner (2006) extensively discusses the pros and cons of various learning models.

probabilities. Then, workers keep track of the payoffs that accrued to them after the choice of a distinct human capital investment strategy. As time evolves each worker experiences from market outcomes that some strategies work better than others. The performance measure is the average of payoffs of each strategy accruing in periods in which a worker had to look for a new job (whether successful or not). Let $numHumCapInv$ denote a human capital investment strategy; then an unemployed worker k will choose a strategy $h = numHumCapInv$ with probability

$$p(k,h) = \frac{e^{\lambda \cdot payOffAve(k,h)}}{\sum_{s=0}^{numSectors/2} e^{\lambda \cdot payOffAve(k,s)}}, \tag{1}$$

where $\lambda > 0$ is a learning parameter, reflecting the speed of learning, and $payOffAve(k,h)$ is a worker k's average payoff for a strategy h. A learning mechanism like the one proposed in equation (1) has the characteristic that application strategies that led to relatively high payoffs are more likely to be chosen.[7]

The role of the government is to subsidize training. The government refunds a share of the human capital investment costs to the unemployed workers. Unemployed workers receive a rebate of $rebate = numHumCapInv \cdot humCapInvCost \cdot workerPolicy$, having invested in $numHumCapInv$ units of skills at a cost of $humCapInvCost$, with $workerPolicy$ being the fraction of costs refunded. The government shall finance the policy through a tax on workers' wages. It tries to run a balanced budget. After every period, the government adjusts the tax rate that will be in effect in the following period such that the tax would have balanced the budget in the current period. Figure 2 presents the pseudocode of the model summarizing the main elements

[7] Equation 1 is known as the Gibbs-Boltzmann probability measure.

and the sequence of actions taken by the agents.

3 The results

3.1 Aggregate impact of training policies

I simulate a labor market that consists of 20 sectors, each having different skill requirements; 100 firms, each posting one vacancy; and 100 workers. A local labor market is hit by a shock with probability $r = 0.05$. Productivity and hence wages are normalized to one. Costs for investing in one's human capital shall be 15% of the quarterly wage for one unit of human capital. This implies that in order to acquire the skills most distinct from the current endowment, the worker would have to invest 10 units, given that there are 20 sectors. In this case, human capital investment costs would amount to 150% of the quarterly wage. The learning parameter is $\lambda = 10$.

A single iteration involves the steps summarized in the pseudocode (see figure 2). An iteration is repeated 1000 times, which makes up a run. After each run new initial conditions are set and a new run begins. What is reported are the values of the last iteration of each of the 5000 runs that were conducted.

In figures 3, 4, 5, and 6 the histograms for the number of vacancies posted, the number of jobseekers, outflows from unemployment to employment, and the unemployment rate are plotted. The histograms refer to the case without government training policies. Summing up the observations that are plotted into the histograms yields the number of runs conducted, namely 5000.

On average the unemployment rate is 10.7% (see first row in table 3). The average inflow rate and the quarterly calibration imply an average duration of jobs of five years. The average outflow rate implies an unemployment duration of slightly less than a year.[8] Each vacancy receives on average 2.6 applications, which could be considered too small given casual evidence on employers being inundated with applications, but note that by assumption workers send applications only to vacancies for which they qualify. The sum of human capital investment translates into 5% if measured as a share of total output, or put differently, an unemployed worker on average invests into almost three units of human capital. Tightness shows that on average there are 0.66 vacancies for an unemployed worker. Compared with cross-country evidence this ratio seems to be too high (see OECD, 2001). Overall, however, the properties of the labor market model appear to be reasonable.

Table 3 summarizes the findings of the labor market policy evaluation. Increasing the subsidy for the training costs for the unemployed workers from zero to 50% in steps of 10 percentage points lowers the unemployment rate from 10.7% to 8.2%. The decline in the unemployment rate is driven by an increase in the outflow rate from unemployment to employment given a constant inflow rate from employment to unemployment. As it becomes less costly for the unemployed to invest in training, more training is undertaken. The sum of human capital investments increases from 29.5 units to 49.8 units. Additional training qualifies the unemployed for jobs with skills that are more distinct from those of the jobs they currently hold. Consequently, they will apply for job openings in sectors that are more distant in terms of skills from those sectors in which they currently work. This is reflected in the increase in the average number of applications per unemployed person,

[8] While it might be tempting to compare the outcomes of the model also with flow data on labor markets (see, e.g., Key Indicators of the Labor Market (KILM), International Labour Office Geneva, 2007), one should be aware of the sensitiveness of the simulation results with respect to the calibration time of the underlying model. In the future, less stylized models may investigate perhaps more realistic approaches where firms and workers are more flexible with respect to the timing of their decisions as the labor market unfolds.

as shown in the last column of table 3. Thus, a government subsidizing training reduces unemployment. Unemployment is reduced because lower training costs encourage unemployed workers to invest more in their human capital. As a consequence they qualify for job openings in sectors for which they otherwise would not have been qualified.[9] In short, the training policy reduces frictional unemployment due to skill mismatch.

Quite importantly, this result is not sensitive to the magnitude of the costs for the human capital investment. Increasing *humCapInvCost* reflects again the driving mechanism of the model, frictional unemployment due to a skill mismatch. The results are not shown in the table. However, as the costs for human capital investments increase, unemployment goes up driven by a lower outflow rate from unemployment. The decrease of the outflow rate is caused by a smaller amount of human capital investment that lowers the average applications sent out by a worker.

Whereas we have empirical knowledge on the size of most of our parameters listed in table 2, the choice of the learning parameter is debatable. Reducing the learning parameter to half of the size of the baseline model yields a decrease of the unemployment rate for all government policy parameters. The lower unemployment rates are driven by higher average outflow rates. Behind the higher outflow rates are increased human capital investments and, consequently, a higher average number of applications per person. However, although a less strong feedback mechanism distorts the levels of the endogenous variables, the effects are still small enough to argue that the magnitudes of the endogenous variables are reasonable. Doubling the size of the learning

[9] While the subsidies reduce the costs for training that raises transitions to employment, employment may become less attractive from the perspective of an unemployed worker as the employed finance the training policy. However, this effect is comparably small as the tax on the income of employed persons amounts to 4% on average when the subsidy is 50%.

parameter with respect to the baseline model results in an increase of the unemployment rate for all government policy parameters. The outflow rates are somewhat lower, as are human capital investments and applications per vacancy, but again, and more important, quite considerably increasing the size of the learning parameter with respect to the baseline model, leaves the qualitative results of the baseline simulation unaffected. It is still the case that as the government takes over a higher share of the training costs, the unemployment rate decreases. Thus, with respect to the learning parameter, evaluation results of the training policy appear to be robust. Moreover, for given learning parameters, increasing the number of time steps from 1000 to 2000 does not distort the results shown in table 3 that suggest that the system has converged.

3.2 Endogenous matching function

A matching function relates the two stock variables, vacancies and jobseekers, to the flow variable outflows from unemployment. In policy evaluations this relationship is assumed to be exogenous to the policies under investigation. A policy that is targeted to change the behavior of agents is assumed not to affect the properties of the matching function. For the same inputs the matching function is supposed to deliver the same number of outflows from unemployment. However, what happens if the policy changes the properties of the matching function? Will not taking into account that policies might change the relationship between jobseekers and vacancies on the one hand and outflows from unemployment on the other hand lead to biased results in policy evaluations? If so, one would have a situation in which the policy alters the properties of the matching function, leading to a situation in which for equal inputs, outflows differ.

The agent-based model developed here does not make use of an exogenous matching function, so it becomes possible to shed some light on whether there is an issue of biased evaluation results. Whether policies change the properties of the matching process in the labor market can easily be checked by comparing the outflow rates in the model with a training policy with the outflow rates in the model without a training policy for (almost) equal inputs. The simulation generated 5000 observations for the treatment and each non-treatment case. From those observations I extract triples of jobseekers, vacancies, and outflow rates, where the two inputs to the matching function, jobseekers and vacancies, match between the treatment and the non-treatment case. I say that the inputs match if the absolute deviation of the inputs between the treatment and the non-treatment case is smaller than two. Table 4 illustrates this procedure. After the comparable cases had been extracted, a Wilcoxon-test was applied in order to check for the null hypothesis of equal distributions of outflow rates.

In all five treatments, the average outflow rate is higher than in the non-treatment case where there is no government policy (see table 5). Thus, the policy improves the matching process in the labor market. The shift in the distribution of outflow rates is, moreover, statistically significant. Again, I checked for the robustness of the results when the learning parameter is doubled and reduced to half of the size of the baseline case.[10] A matching function endogenous to labor market policies still seems to be an issue.

3.3 Job displacement effects

The model also can be used to shed light on the relationship between treatment effects on the individual level and the macroeconomic outcome. Al-

[10] Those results are not given in this article.

though a training policy might increase the chances of those jobseekers who receive subsidies, it might do so by reducing the job-finding rates of those who are not covered by the program. Job displacement effects in the sense that the treated jobseekers crowd out other jobseekers who are not benefiting from a labor market policy program might reduce the overall success of a policy. I attempt to quantify the effect within the agent-based model by dividing the workers into equally sized groups, one of treated and one of non-treated workers. If a worker from the treated group becomes unemployed, he will receive government subsidies for his human capital investment. The workers from the non-treated group do not receive transfers. The following experiment was then conducted (see also figure 7): the number of iterations is increased to 2000, whereas all other parameters are identical to the baseline simulation. In the first 1000 iterations, no subsidies are given for jobseekers' human capital investments, neither for the treatment nor for the non-treatment group. The outflow rates at iteration 1000 are noted for both groups. From iteration 1001 to 2000, jobseekers who belong to the treatment group receive a transfer from the government of 50% of their human capital investment costs. Finally, the outflow rates at iteration 2000 for both groups are stored again. The experiment was repeated 5000 times.

Table 6 summarizes the mean values for the outflow rates for the treated and the non-treated group before and after the government policy was implemented. First of all, it can be seen that jobseekers of the treatment and the non-treatment group have equal outflow rates before the policy was introduced. We cannot reject the null hypothesis of equal outflow rates, as shown in the last row of the first column. A comparison of the mean outflow rates for the treatment group before and after the government policy was introduced reveals that on average the policy increases the job-finding rate from 0.257 to 0.374. Testing against the null hypothesis of equal outflow rates, the difference turns out to be strongly statistically significant. Also in economic terms the effect is strong: the outflow rate of the treated group of jobseekers increases by 45%. If there were no substitution effect, the mean values of the outflow rates of the non-treatment group should be equal before and after the policy was introduced. This is, however, not the case. Again, one can clearly reject the null hypothesis of equal outflow rates. The substitution effect is also economically relevant. The outflow rate of the jobseekers who do not receive government subsidies is reduced by 12%.[11] A sensitivity analysis with respect to the choice of the learning parameter does not change the qualitative nature of the results.[12]

What is the interpretation of the job displacement effect? In this model, it is driven by a reduction of the treated jobseekers' human capital investment costs. As the costs are reduced, workers in the treatment group invest more, allowing them to apply for jobs that are more distant in terms of skills from their current human capital resources. In those sectors where the treated workers would not have applied without government transfers, they compete for jobs with workers who did not receive transfers. Those workers might not get a job offer because a treated worker was given that offer. Thus, the job-finding rate of the non-treated group declines.

One may wonder how other policy measures fare with respect to the displacement effect. In an extension to the described model the effect of unemployment benefit policies on the transition probability of an unemployed worker into a job was analyzed. In order not to compare apples with pears the following approach was taken. With the parameters as in the previous

[11] In more technical terms, one would claim that the stable unit treatment value assumption (SUTVA) is violated; see Rubin (1974) for an early discussion of causal effects in experiments.

[12] Again, those tables are not included in this article.

experiment, one can calculate the average budget of the government needed to finance the training policy, and this average budget was taken as exogenous to the unemployment benefit program. Then, the taxes for the employed and the transfers to the unemployed were determined endogenously given the number of unemployed in the economy. One finds that an unemployment benefits policy that has the same budget as the training policy does not affect the transition rates. The reason for this finding is straightforward. Contrary to the training policy, unemployment benefits do not give an incentive to invest in one's human capital. Thus, labor market frictions due to skill mismatch are not reduced.[13]

4 Conclusions

For the purpose of an aggregate impact study of government-sponsored training policies that rank prominently among active labor market policies in OECD countries, I developed an agent-based labor market model with sector-specific skill requirements. In the model, firms are hit by asymmetric shocks, and workers becoming unemployed have to invest in their human capital in order to qualify for job openings. The government steps in and subsidizes the workers' training costs. First, I show that the subsidizing of training increases the outflow rate from unemployment and reduces the unemployment rate on the aggregate level. Second, there is evidence that the matching technology is not exogenous to policies. This has consequences for aggregate impact studies of labor market policies. In my case, not taking into account that policies change the matching properties of the labor market would have led to an underestimation of the impact of the training policy on the outflow rate

[13] More detailed results are available from the author.

from unemployment. Third, I show how an agent-based labor market model can be used to elaborate potential job displacement effects of labor market policy programs, an evaluation exercise that closed-form analytical models are less apt to achieve. An agent-based approach is especially promising here, because information about the program effects on the individual level and the aggregate level is available. Exploiting this property of an agent-based approach, I find that the training policy reduces the job-finding rate of those who do not benefit from the program to an economically significant extent. In other words, although those individuals receiving transfers have a higher probability of leaving unemployment and although the overall impact of the program on outflow rates is positive, there is a crowding-out of non-participants of the program.

In many respects this study employed strong modeling assumptions. However, the approach of evaluating labor market policies with agent-based models allows for a range of extensions that could alleviate some of the assumptions made in this work. For example, one could analyze the role of market power on the side of the firms or workers (c.f. Tesfatsion, 2001) and its impact on labor market performance. Different wage-setting institutions should be analyzed, and although the current study focuses on training policies, it might also be of interest to compare those policies to alternative measures. Various other unemployment benefit schemes or the effectiveness of job protection legislation are only two examples of social policies that deserve further attention. Another unexplored link is the effect of labor market policies on the distribution of firms and employment across sectors, with its repercussions for employment dynamics.

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5 Appendix

The model is programmed in RePast. The code is available from the author (neugart@wz-berlin.de).

Table 1: Labor market policy expenditures in OECD countries in 2002

Country	Total in % of GDP	Active LMP in % of GDP	Training[a] in % of GDP	Training in % of active LMP
Austria	1.78	0.53	0.19	35.8
Belgium	3.65	1.25	0.19	15.2
Czech Republic	0.45	0.17	0.02	11.8
Finland	3.07	1.01	0.27	26.7
France	3.06	1.25	0.21	16.8
Germany	3.31	1.18	0.32	27.1
Hungary	0.90	0.52	0.06	11.5
Italy	1.20	0.57	-	-
Japan	0.76	0.29	-	-
Korea	0.41	0.27	0.04	14.8
Netherlands	3.56	1.85	0.52	28.1
New Zealand	1.52	0.52	0.14	26.9
Norway	1.41	0.87	0.05	5.7
Slovak Republic	0.94	0.46	0.04	8.7
Spain	2.42	0.87	0.12	13.8
Sweden	2.45	1.4	0.28	20.0
Switzerland	1.30	0.53	0.12	22.6
United Kingdom	0.75	0.37	0.01	2.7
United States	0.71	0.14	0.03	21.4

a: Training includes course costs and subsistence allowances for unemployed adults and those at risk. Special training programs for youths and disabled persons are excluded.
Source: OECD labor market statistics, $http://stats.oecd.org$.

Table 2: Parameters

Parameter	Value
Number of Sectors	$numSectors = 20$
Number of Workers	$numWorkers = 100$
Number of Firms	$numFirms = 100$
Probability for Random Shock to Sector	$r = 0.05$
Wage	$wage = 1$
Cost for One Unit of Human Capital	$humCapInvCost = 0.15$
Learning	$\lambda = 10$

```
Create sectors

Create firms and allocate them randomly to sectors

Create workers and allocate them randomly to sectors

for n periods

      Job destruction
      for each sector
            with probability r sector is hit by shock
            workers lose jobs
            firms hit by shock are relocated
      end each sector

      Applying
      for each unemployed worker
            makes upfront human capital investment
            sends applications to all vacancies for which he qualifies
      end each unemployed worker

      Hiring
      for each vacancy
            randomly draw vacancy to be filled
            if workers applied
                  firm randomly selects worker who did not yet receive offer
                  from application list
            else
                  vacancy is not filled
      end each vacancy

      Workers learn
      if worker unemployed or has found job
            for each such worker
                  for each human capital investment strategy
                        calculate average payoffs
                        choose new human capital investment strategy
                  end each human capital investment strategy
            end each such worker
      else
            no individual learning

      Tax adjustment
      Government adjusts tax following balanced budget rule

end n periods
```

Figure 2: Pseudocode

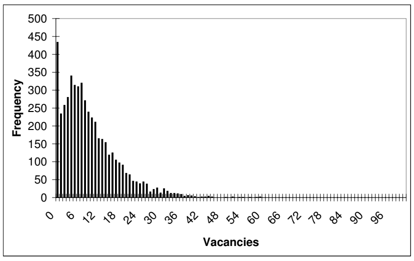

Figure 3: Histogram of the number of vacancies

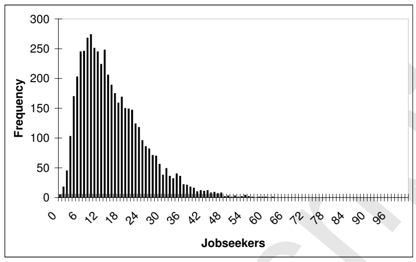

Figure 4: Histogram of the number of jobseekers

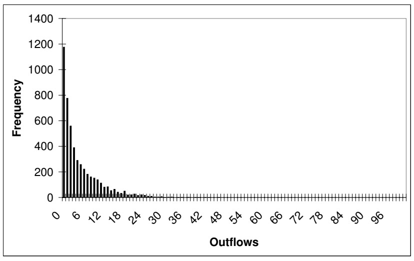

Figure 5: Histogram of outflows

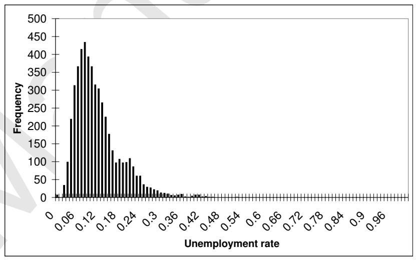

Figure 6: Histogram of unemployment rates

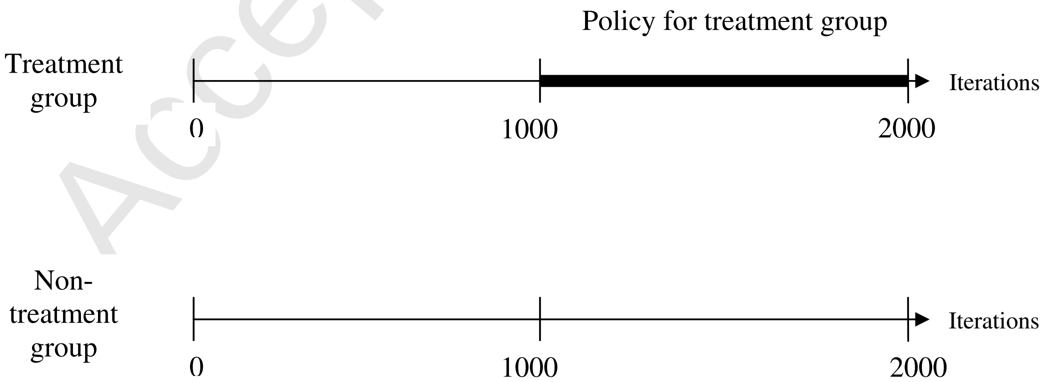

Figure 7: Experiment with respect to job displacement effects

Table 3: Average labor market effects of government-sponsored training

workerPolicy	unRate	inflowRate	outflowRate	humCapInvSum	appliPerVac	tightness	appliAve
Baseline model: $\lambda = 10$							
0	0.107	0.054	0.260	29.5	2.61	0.66	1.63
10	0.101	0.054	0.275	32.5	2.95	0.64	1.78
20	0.094	0.055	0.288	35.9	3.38	0.61	1.93
30	0.091	0.053	0.287	39.8	3.83	0.57	2.01
40	0.087	0.053	0.305	44.4	4.45	0.54	2.22
50	0.082	0.053	0.316	49.8	5.20	0.51	2.45
Sensitivity analysis: $\lambda = 5$							
workerPolicy	unRate	inflowRate	outflowRate	humCapInvSum	appliPerVac	tightness	appliAve
0	0.095	0.054	0.289	35.6	3.33	0.61	1.88
10	0.092	0.054	0.300	38.6	3.70	0.59	2.01
20	0.089	0.055	0.304	41.8	4.10	0.57	2.14
30	0.085	0.053	0.312	44.6	4.47	0.55	2.21
40	0.085	0.055	0.323	49.9	5.17	0.52	2.45
50	0.081	0.055	0.326	53.2	5.68	0.50	2.57
Sensitivity analysis: $\lambda = 20$							
workerPolicy	unRate	inflowRate	outflowRate	humCapInvSum	appliPerVac	tightness	appliAve
0	0.116	0.053	0.229	25.8	2.30	0.66	1.47
10	0.109	0.051	0.240	28.9	2.59	0.64	1.58
20	0.101	0.055	0.260	33.2	3.14	0.61	1.85
30	0.097	0.054	0.273	37.8	3.70	0.57	2.01
40	0.089	0.054	0.289	42.7	4.29	0.53	2.23
50	0.086	0.056	0.303	50.9	5.44	0.50	2.60

Table 4: Outflow rates comparing treatment and non-treatment cases with $workerPolicy = 50$

No.	workerPolicy = 0			workerPolicy = 50		
of observation	jobSearchers	vacSum	outflow rate	jobSearchers	vacSum	outflow rate
1	...	...	...	...	...	...
...	...	...	...	...	...	...
13	5	3	0	6	4	0.17
14	15	7	0.27	14	7	0.50
15	5	5	0.20	4	4	0
16	5	2	0.20	5	1	0.20
17	14	11	0.36	13	11	0.54
18	16	16	0.50	16	16	0.94
...	...	...	...	...	...	...
N	...	...	...	...	...	...

Note: Parameters were set as in baseline model.

Table 5: Endogenous matching function, Wilcoxon-test on equal distributions

	workerPolicy				
	10	20	30	40	50
Δ average outflow rates	0.06	0.07	0.08	0.16	0.17
(p-value)	0.015	0.025	0.003	0.000	0.000
N	177	163	149	161	145

Note: N is the number of observations; p-value refers to two-sided test; parameters were set as in baseline model.

Table 6: Job displacement effect

	Means of outflow rates		
	Before	After	t-test[a] on equal means
Treatment group	0.257	0.374	0.000
Non-treatment group	0.260	0.229	0.000
t-test[a] on equal means	0.308	0.000	

a: Reported are p-values; number of observations $N = 4493$.