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ABSTRACT

The Welfare Effects of Mandatory Reemployment Programs: Combining a Structural Model and Experimental Data*

This paper estimates a structural model of job search which accounts for utility costs and benefits linked to mandatory reemployment programs. The estimation uses data from a randomized experiment which generates exogenous variation in the threat of program participation. I use the compensating variation (CV) as a measure of the impact of the experimental treatment on worker welfare, the welfare costs. I find that participants would be willing to give up 1.5–1.7 weeks of UI on average to avoid participation in the program, although the program has a positive effect on the job finding rate. Welfare costs vary across workers and are found to be larger for workers with weaker employment prospects. Overall, the analysis shows that the welfare costs are substantial and therefore necessary to take into account when evaluating the case for mandatory reemployment programs.

JEL Classification: C9, I3, J64, J65, J68

Keywords: unemployment, job search, activation, active labor market program

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1 Introduction

A key objective in the design of an unemployment insurance (UI) system is to balance costs from disincentive effects against benefits such as the value of the insurance scheme for recipients. Another center of attention is on policies to further promote employment via a focus on the job search process or the skills of the unemployed. Many UI systems worldwide use mandatory reemployment programs (MEP) where participation is a condition for remaining eligible for UI to try to achieve some of these objectives. MEP include activation programs as well as e.g. caseworker meetings at the job center.[1] While empirical work on this type of programs has found some positive impacts on e.g. job finding after program participation, it has also documented threat effects, that is, impacts arising prior to actual participation and caused solely by the threat of future participation; see Black et al. (2003); Hall et al. (2021); Geerdsen (2006). This suggests that while these programs may involve benefits from training and learning, they may also trigger utility costs due to e.g. a loss of leisure. Utility costs increase the incentive for (potential) future participants to find employment and thus avoid MEP. In this case MEP promote employment by reducing the benefits of the UI system, i.e. the value of the insurance scheme for recipients via welfare costs which arise although the unemployed may never participate in MEP. Such (welfare) costs thus reduce the social benefit of MEP, and a key question for the design of UI systems is therefore the size and relative importance of such costs.

To shed light on this question, this paper estimates a structural model of job search which takes into account that (future) program participation may influence individual decision making. The paper centers around two questions: what are the individual utility and welfare costs of these programs, and who bears the costs and benefits, if any?

I use a randomized experiment that generates exogenous variation in the threat of future program participation to identify the utility costs and benefits of MEP. The randomized experiment was conducted in Denmark in 2008, and the intervention involved either caseworker meetings or participation in an activation program for UI recipients in the treatment group. Importantly, participation in the treatment was a requirement for benefit eligibility. The intervention lead to a large and immediate increase in job finding (see also Maibom et al. (2017)). However, as argued above, these differences in initial job finding are not sufficient for assessing the social benefit of the intervention which would also require

[1] MEP type programs also include e.g. classroom training, job training, job search assistance as well as temporary (public) work arrangements, see e.g. Heckman et al. (1999); Card et al. (2010). In the U.S. MEP are an important part of the WPRS and RESEA; see US Department of Labor (2000). In the EU, MEP are a key element in the mutual responsibilities approach; see EUCommission (2018). Lastly, note that MEP could also be referred to as active labor market programs in settings where participation is required for continued benefit eligibility.

quantifying the impact of the experimental treatment on worker welfare, i.e. the welfare costs.

Overall, the experiment is an opportunity to compare similar unemployed across different environments, while the structure of the model generates a mapping from data moments to structural parameters such as utility costs and benefits. The dynamic job search model is set up to represent the incentives of the unemployed in the experiment.[2] The agents are risk-averse, and while unemployed they decide how much to search and whether to accept a job offer if one arrives. Participation in MEP is mandatory while unemployed. It triggers utility costs, but may also increase the return to search. As in Moffitt (1983), utility costs could be both monetary and non-monetary. The model includes several dimensions of observed and unobserved heterogeneity to allow for differences in the incentive to and the likelihood of finding employment. This heterogeneity later translates into dispersion in the welfare costs of the experimental treatment.

In the model the treatment group is suddenly introduced to a new series of future events (the experiment), including a higher probability of future participation in MEP. The estimation procedure controls for endogenous eligibility for randomization and program participation, as well as the details/timing of the treatment protocol. This implies that rich model predictions can be contrasted to data for each period from the beginning of the experiment and thus leverage identification of the utility costs of MEP further.

The estimates of the model imply that utility costs associated with program participation are sizable. Based on model counterfactuals, I find that more than 70 percent of the experimental impacts are accounted for by changes in decisions about search intensity only. Threat effects are therefore an important driver of the impacts of the experiment. Further, the response to treatment is dynamic. Since the threat of future program participation changes during the different experimental stages, individuals search more in the early stages of the experiment compared to the later stages. These results outline the behavioral changes, as interpreted through the model, which leads to the experimental impact such as the differences in job finding. They also implicitly illustrate how the model generates ample opportunity to analyze how the impacts of MEP generalize outside the specific setting of the experiment.

To evaluate the welfare costs of the intervention, I calculate the distribution of the compensating variation (CV). The CV is the monetary compensation which makes individuals indifferent to being assigned to the treatment group or not. I find that the average CV corresponds to around 1.5-1.7 weeks of UI. Comparing

[2]Methodologically the model is in accordance with a novel framework developed in Ferrall (2004, 2012) (see also Todd and Wolpin (2006); Attanasio et al. (2012); Lise et al. (2004)). I formulate the job search model in a similar framework and extend the model solution in Ferrall (2012) by adding an inner Markov chain which is included to discipline the evolution and identification of unobserved heterogeneity.

the welfare costs (CV) and operating costs of MEP to the gains from increased job finding, I calculate the average social benefit of the intervention. In the case of meetings, the social benefits fall by 50% after incorporating the CV, and in the case of activation it removes the social benefits completely.[3]

I construct different model counterfactuals where I change the duration of the threat stage, i.e. the period in which treated individuals know of future program participation but can still escape it by finding employment. The results show that both employment impacts as well as welfare costs increase when the threat of future MEP is more intense. These results therefore illustrate the potential danger of focusing too narrowly on employment impacts, which is the primary focus of the large empirical literature focused on the effects of MEP type programs, see e.g. Heckman et al. (1999); Card et al. (2010, 2018) for reviews. My analysis shows that welfare costs are quantitatively important and thus crucial to take account of in the design of a UI system with MEP. Ignoring their existence implies that we put excessive weight on the efficiency of UI systems, i.e. the speed of job finding, while overall welfare may be deteriorated. My analysis is the first empirically-based quantitative assessment of this overall relationship for MEP.

I also analyze heterogeneity in the welfare costs and benefits of MEP. For individuals with good employment prospects and only modest job search prior to the experiment, the welfare costs are low, and the response in terms of increased job finding is large. On the contrary the welfare costs are larger, and the increase in job finding smaller, for individuals with low returns to job search. The dispersion in welfare costs illustrates a classic screening paradox. While MEP may be successful in terms of promoting faster job finding for some groups at low welfare costs, it is disproportionately more costly for the people in greater need of insurance in the first place. These results link back to theoretical work on the role of screening through e.g. workfare type programs (see e.g. Besley and Coate (1992); Nichols et al. (1982)).[4] My results imply that key insights from this previous literature are empirically relevant in the job search context. However, I also show that the job search process further magnifies welfare costs and thereby identify some of the key trade-offs which arise when MEP are used in UI.

[3]Note that the (welfare) analysis focuses on whether the experimental treatment was a useful intervention in its current scale and form. In this sense, the paper is a first intermediate step towards solving for an optimal level of MEP, as chosen by e.g. a social planner in a setting where MEP are rolled out to all workers, and where e.g. equilibrium effects or effects on alternative (unmodeled) margins such as e.g. employment separations should be incorporated into the analysis. I discuss this further in the final section of the paper.

[4]The theoretical literature on the effects of workfare in a static setting has shown that while workfare, i.e. MEP type interventions which only involve utility costs and no benefits, can improve the targeting of transfers through screening, the overall welfare implications are unclear. A key insight is that the welfare costs of workfare primarily affect the actual participants, while individuals with better alternatives are less affected.

The paper proceeds as follows. The next section provides some background including an introduction to the randomized experiment and the available data. The following section describes key features of the data, the model and the estimation. Finally, the last sections contain the results and a conclusion.

2 Background and the experiment

2.1 UI and MEP in Denmark

There are two types of benefits for unemployed workers in Denmark; UI benefits and social assistance. Approximately 80% of the labor force are members of a UI fund and therefore potentially eligible for UI benefits. The remaining 20% may receive means-tested social assistance. UI benefits are essentially a flat rate due to a cap on payments that is binding for 80-90% of workers. UI benefits are subject to taxes as other earnings, and the benefit duration in the period under study is four years.

The Danish UI system is referred to as an example of the flexicurity model where MEP are a crucial component; see Andersen and Svarer (2007). UI recipients receive generous benefits when eligible, but also have an obligation to take action to return to employment, including adequate job search and participation in MEP. The use of MEP is among the most intensive in the OECD with more than EUR 1.6 billion spent on such programs; see Ministry of Employment Expert Panel (2014). In the Danish setting, failure to show up (without prior warning) to a mandatory meeting/activation program at the job center means that the payment of UI stops, or that a sanction is issued.[5][6]

MEP in Denmark primarily consist of contact (meetings at the job center) and activation; see Maibom et al. (2017). At inflow into unemployment, a UI eligible individual has to register at the local job center, upload a suitable resume and engage in job search to receive UI. After registering, the unemployed individual must attend a quarterly meeting with a caseworker and participate in an activation program after nine months of unemployment (six months if under the age of

[5]See Law on UI Eligibility Executive Order No. 808, § 17. Svarer (2011) reports that the size of sanctions related to failure to meet eligibility criteria (e.g. participating in a meeting) ranges from a loss of benefits for two to three days to three weeks. In severe cases, benefits can be removed until new eligibility through employment has been established.

[6]Note that the role of sanctions in job search and in connection with job center activities is the subject of a related literature; see e.g. Fredriksson and Holmlund (2006); Boone et al. (2007). The sanctioning rate was very low in the Danish labor market at the time of the experiment, and the intention of the experiment was to counsel, not monitor; see Maibom et al. (2017). I therefore focus on the "direct" utility costs and benefit aspects of MEP. See also Van Den Berg and Van Der Klaauw (2006); van den Berg and van der Klaauw (2019) who use a randomized experiment and analyze counseling and monitoring programs both theoretically and empirically. They do not consider the existence of utility costs beyond the direct cost of searching.

30) and, subsequently, every 26 weeks. In the experiment outlined below, these labor market policies apply to both controls and treated. Treated individuals are further obliged to participate in additional activities which I describe next.

2.2 Experiment

The experiment was conducted in different regions in Denmark in 2008. Each region was assigned their own treatment and control group. The target population of the experiment was UI-eligible individuals who became unemployed in the period of February to July in 2008 (immigrants are excluded from the sample as special rules may apply). Assignment to the treatment and control groups was based on the date of birth. Individuals born 1^{st} to 15^{th} were assigned to the control groups, while those born from the 16^{th} to 31^{st} were assigned to the treatment groups. The unemployed workers were not given any information about the selection criteria. Maibom et al. (2017) present an evaluation of the experiment and find no deviations from random assignment, and I therefore treat it as such.

The treatment was different across regions and consists of either an intensification of individual meetings (henceforth the meetings region, MR) or early activation (henceforth the activation region, AR).[7] At inflow into the experiment, treated individuals received a letter explaining the new guidelines and requirements that would apply to them. The information letter marks the start of the treatment since the worker may react to this information.

Table 1 presents an overview of the additional activities in the treatment group. In the MR, the treatment group had to participate in individual meetings every other week with a caseworker for the first 13 weeks of the experiment. The meetings lasted around 30 minutes, in addition to preparation, waiting time and transportation time. The stated intention of the meetings was to counsel the unemployed and discuss job opportunities and productive job search, not to monitor them. The high frequency of the meetings created possibilities to follow the unemployed more closely, likely increasing the perceived intensity of the intervention substantially from the point of view of the unemployed.[8] In the AR, the

[7] Denmark has consisted of five regions since 2007. They are primarily responsible for the health care sector and serve as administrative entities at a level between municipalities and the central government. The AR consists of the Central Jutland region which includes the second largest city in Denmark. The MR consists of Region Zealand and the Capital Region which includes the capital city in Denmark. The AR is the smallest of the two regions. According to the official statistics from the Ministry of Employment, there were 16,492 UI recipients in the AR in March 2008. The treatment share is thus less than 5% when we consider the local labor market as the region. These numbers only include individuals receiving UI benefits (not social assistance and the like) and thus only represent a smaller portion of job seekers.

[8] It is, for instance, well known that the unemployed often consider these interactions with the job center or public employment service as burdensome and even costly. See e.g. OECD (2001) for some cross-country experiences and Ministry of Employment Expert Panel (2014) for

treatment group was required to participate in activation programs for at least 25 hours per week from the 14^{th} until the 26^{th} week of the experiment. The activation programs were primarily intended to assess and (slightly) upgrade skills, i.e. shorter educational and training programs (see Maibom et al. (2017)). This category of programs is the most commonly used activation instrument in Denmark. Since these programs are typically shorter in duration (4-8 weeks), the experimental treatment would in practice often involve two consecutive programs.

Overall, the experiment can be divided into three stages of varying duration as outlined in Table 1: i) a threat (TH) stage, which begins with the information letter and stops when treatment begins equaling $1-2$ weeks in MR and 13 weeks in the AR; ii) a treatment (T) stage; and iii) a post-treatment (PT) stage, which marks the end of the experiment. Note that the individual incentives change as individuals progress through the experiment; for instance, if the unemployed consider program participation as costly, they may increase their search effort as the T stage approaches. Similarly the incentive to leave unemployment declines as the PT stage approaches and a decline in the intensity of MEP is near. The job search model accounts for the fact that incentives change as individuals progress through the experiment, permitting an accurate representation of the incentives faced by unemployed workers and, thus, a credible estimation of the key decision parameters.

Table 1: Content of the experiment

	Meetings Region		Activation Region	
Treatment stages	Treatment	Weeks	Treatment	Weeks
Announcement	Information letter	0	Information letter	0
Threat stage	Waiting Period	1	Waiting Period	1-13
Treatment stage	Individual meetings	1-13	Activation program	14-26
Post-treatment stage		14-		27-

Note: This table presents the additional activities in the treatment group across the two different regions and the weeks in which they occur counting since the start of the experiment. The post-treatment stage marks the end of the experiment where individuals in the treatment group face the same obligations as in the control group (see also Section 2.1).

Denmark. An interesting study in this respect is Behncke et al. (2010) who study the effects of caseworker interactions (meetings). They find that caseworkers, who place less weight on a harmonic and co-operative collaboration with clients, increase job finding for the unemployed job seekers. This effect is not driven by an increased use of sanctions or further ALMP measures. A possible explanation is that a less-cooperative caseworker makes the utility costs of meetings and other interactions higher.

2.3 Data and definitions

The primary data used in the analysis is extracted from administrative registers and merged by the National Labor Market Authority into an event history data set. Appendix B provides details about measurements and data sources.[9] The final sample has 3099 individuals who are followed for 100 weeks. Table 2 shows the average characteristics of the treated and control groups in each region and the p-value associated with a test of equality of means between the respective treatment and control groups. In general, the sample is balanced in terms of past earnings, demographics and employment history. The characteristics in Table 2 show that, while the experiment targeted newly unemployed workers, the starting point of 20-30% of the participants was something other than regular employment such as education, part-time unemployment or sick leave. These individuals may already have exhausted many job possibilities, and reduced form impacts should be interpreted with this in mind. The estimated structural model explicitly takes this selection into account and can be used to analyze the sensitivity of the raw impacts along this dimension through different model counterfactuals. Along the same lines, the estimated model can be used to analyze how the experimental impacts (e.g. the changes in employment) change, as we change the initial distribution across states or change some of the structural parameters which define the economic environment. In this sense, the model allows us to examine the external validity of the experimental intervention in several different dimensions.

3 Empirical results

This section briefly analyzes the impacts of the experiment and illustrates key features of the data. The data is divided into subgroups depending on the individuals' educational level, based on three categories: low (primary school only), medium (vocational education) and high (further education).

Figure 1 shows the evolution in employment rates from inflow into the experiment and onward, separately for education, region and treatment groups. Across all groups, the employment rate increases rapidly within the first 20 weeks of the experiment and then stabilizes. After 30 weeks, the employment rate in the control groups is around 65-70% (and slowly increasing) for individuals with a higher education, and it is around 60% (40%) and stable or slightly

[9] In the model individuals are either unemployed or employed. In the analysis below individuals who are not receiving public benefits are therefore treated as employed which means that the definition of employment is slightly different from the definition used in Maibom et al. (2017). See (online) Appendix B for further details and robustness checks. The analysis uses wages and UI after imputed taxes, assuming a tax rate of 37.5% for all workers. This corresponds to the average tax rate for individuals on UI in 2008 as reported in Maibom et al. (2017).

decreasing for individuals with a medium (low) level of education. There are also some regional differences across control groups in the level of employment and in the speed of initial job finding, with the largest regional difference found for low educated workers. As a supplement, Figure 4 in (online) Appendix B shows the hazard rate out of unemployment for the control groups. The hazard rate is declining and is roughly half of the initial level after 20-25 weeks in unemployment, again underlining the very rapid initial increase in employment.

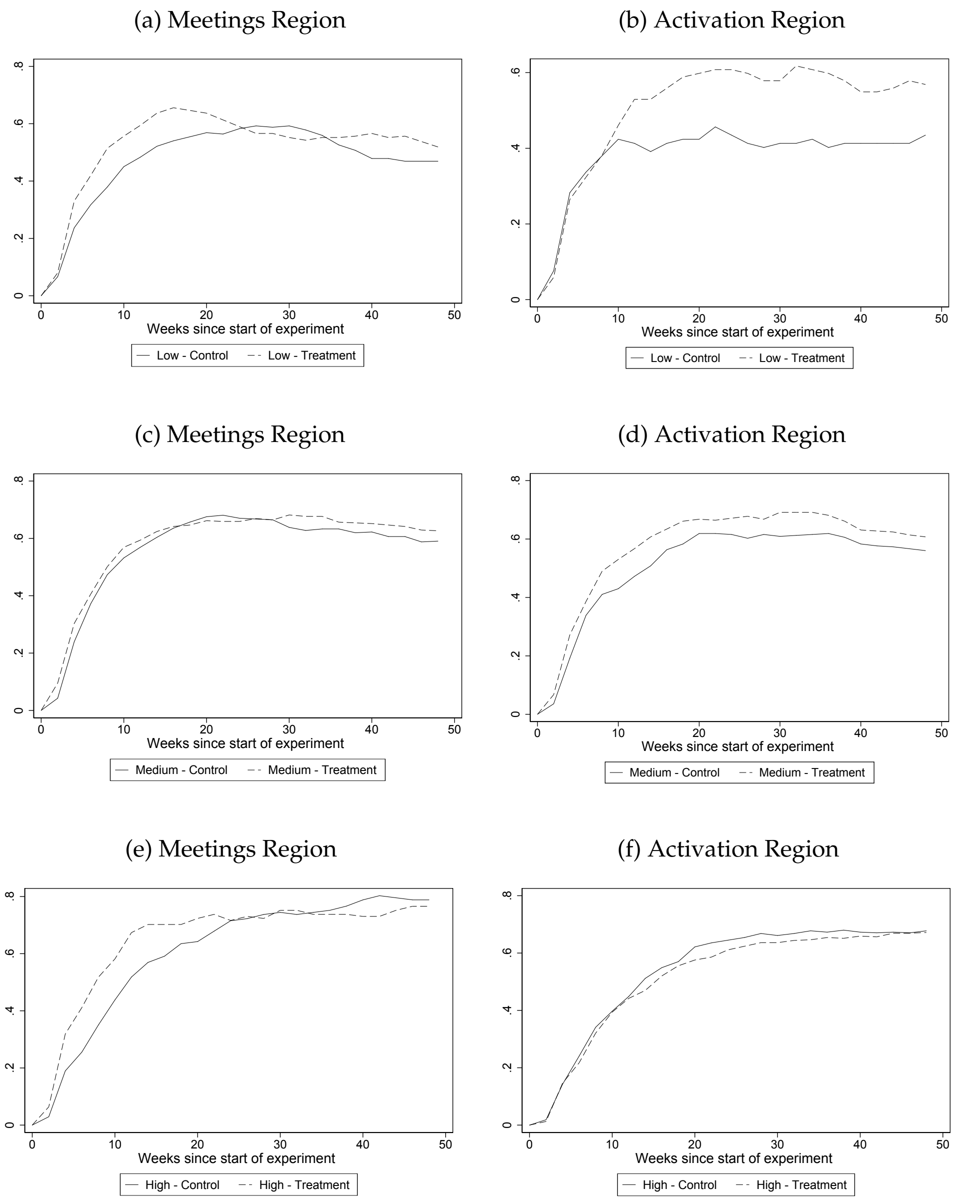
The difference in employment rates between treatment and control groups in Figure 1 illustrates the impact of the experiment. During the first 20-30 weeks, individuals in the treatment groups are employed to a larger extent (with one exception).[10] To substantiate this further, Table 12 in Appendix B shows the result of a regression of employment status on treatment status for different regions and time periods. The estimates reveal statistically significant differences in the employment rate already after 2 to 4 weeks in the experiment in MR. At this point, unemployed individuals may have participated in 1 or 2 meetings which is why the results indicate either a very productive first meeting or the presence of threat effects. In the AR, the results are more mixed after four weeks, but here treated individuals only start participation in activation after 13 weeks (see Table 1). Re-running the regression 10 or 14 weeks into the experiment, and thus closer to program participation, shows statistically significant differences in employment between the treatment and control groups. This illustrates that the link to the experimental design is important for measuring and understanding impacts. Note further, that the fact that the employment effects arise this early, and also prior to program participation, indicates that the *threat* of MEP affects behavior.

For the subset of workers who find employment, I find small differences between treatment and control groups in their wages and the type of future employment. For instance, the unconditional difference in hourly wages between treated and controls who find employment is generally very small and statistically insignificant.[11] Note however, that the results on post unemployment outcomes are likely flawed by selection as treatment status is no longer exogenous, and results should therefore be interpreted with great caution. The structural

[10] Note that the difference in employment levels in Figure 1 is large initially, but then decreases over time in most cases as the control group catches up. Obviously the initial (persistent) differences in weekly employment rates lead to accumulated impacts over time. For an analysis of the accumulated impact, see Maibom et al. (2017).

[11] See Table 16 in Appendix B for results from a regression of wages on treatment status for individuals with sufficient employment within the 100-week data window. The difference between treated and controls is only statistically significant for medium-educated workers in MR and amounts to around €0.5 on average per hour. To put this in perspective, the average hourly wage of an unemployed that began a new job in 2008 was around €23.5 per hour. Furthermore, I also show in Table 15 that there are no statistically significant differences across treatment and control groups with respect to the fraction of individuals working in part-time positions.

Figure 1: Employment rate across education and treatment groups



Note: This figure plots the employment rate for treatment and control groups in the Meetings Region (left panel) and Activation Region (right panel). Results are reported separately for different education levels (low, medium, high). For regression versions (and thus standard errors), see Table 12 and Appendix B.2. For data definitions, see Appendix B.1.

model takes this selection into account and can be used to analyze the extent to which individuals change their preference over job types. Nevertheless, the finding that there seems to be little difference in wages (and earnings) between the treatment and control groups is similar to what Gautier et al. (2018) report from an earlier Danish experiment, and Hall et al. (2021) also report very similar findings from a Swedish activation program.

Lastly, three other data patterns are worth highlighting as they illustrate the importance of within-group (unobserved) heterogeneity in the data. First, the distribution of wages within educational groups has a standard deviation of around 20-25% of the mean, suggesting that within these groups there is substantial heterogeneity. Second, wages change during employment, and the level and the growth rate of wages also differ across education groups. Third, the hazard rate out of subsequent employment is (modestly) declining with the duration in employment, especially for low educated workers. Furthermore, there are level differences across education groups. See (online) Appendix B Table 18 and Figure 5 for illustrations of these data patterns. In the model I will be using these changes as a way to discipline unobserved individual heterogeneity (or skills) and the transition of state variables.

While the previous statistics are only indicative, they do suggest that the value of employment varies across different types of individuals in the sample. Overall, such heterogeneity should lead to additional heterogeneity in the welfare costs of the experimental intervention and is therefore important to capture in the remaining analysis. This calls for a model with rich heterogeneity in the incentives and opportunities that individuals face in unemployment. The model needs to incorporate heterogeneity in wages and jobs across individuals, and the model should be able to match the findings of very limited wage effects but sizable employment effects from the experiment.

Table 2: Sample descriptives at inflow

		Meetings Region			Activation Region		
Variable Type	Variable	Treatment	Control	P-value	Treatment	Control	P-value
Demographics	Age	39.18	39.12	0.91	35.64	35.34	0.53
	Fraction below age 30	0.21	0.23	0.18	0.38	0.35	0.23
	Fraction above age 45	0.27	0.29	0.39	0.20	0.17	0.17
	Fraction Males	0.52	0.55	0.25	0.47	0.48	0.57
	Education length (years)	11.73	11.68	0.79	13.63	13.78	0.26
State before start of experiment	Employed	0.80	0.77	0.18	0.68	0.68	0.83
	Education	0.04	0.03	0.30	0.21	0.21	0.74
	Other public support*	0.12	0.12	0.89	0.06	0.07	0.77
Latest employment	Earnings in 2007 (DKK)	283900	273900	0.22	234400	232800	0.87
	Hourly Wage in 2007 (DKK)	192	188	0.35	158	156	0.28
	Health sector	0.15	0.16	0.97	0.18	0.21	0.19
	Education sector	0.06	0.06	0.055	0.12	0.14	0.24
	Retail sector	0.20	0.23	0.21	0.22	0.21	0.38
	Manufacturing sector	0.12	0.11	0.83	0.08	0.08	0.96
Employment history	Weeks in Empl in 2007**	40.35	39.70	0.48	28.70	29.58	0.44
	Weeks in Empl in 2006	37.82	39.05	0.20	26.69	26.13	0.63
	Weeks in Empl in 2005	36.41	36.88	0.64	25.02	23.49	0.18
Observations		752	724		796	827	

Note: This table presents the average characteristics of the treated and control groups in each region and the p-value associated with a test of equality of means between the respective treatment and control groups. *Other public support includes states like part-time unemployment, sickness benefits, leave, training. **This statistic shows the average number of weeks an individual was employed in the year prior to the start of the experiment.

4 Model

This section presents the job search model. First, I give a broad summary of the main elements of the model, and then I present the different components of the model in more detail. Lastly I discuss the key channels through which MEP affect unemployed individuals. In the next section I discuss how the model is solved and estimated.

Overview of the job search model

The job search model is a 'discrete choices discrete states' dynamic program where risk averse individuals maximize the sum of expected discounted utility over an infinite horizon. The model includes search frictions, and individuals are either unemployed or employed. While unemployed, they decide how much to search and whether to accept a job offer if one arrives. Jobs differ in their wage level and in their risk of future termination and thus reentry into unemployment. Search is random, so the unemployed cannot influence the type of job offers they receive, but they can affect the probability of getting an offer. The probability of getting a job offer depends on the level of search intensity and the return to search which varies across states in the model. While employed, the individuals (stochastically) accumulate skills which translate into wage gains and a lower risk of future unemployment.

While unemployed, the individuals are forced into MEP at certain points in time, and the only way to avoid it is by becoming employed. Participation in MEP in a given period may increase the return to search but may also trigger utility costs.[12]

The model focuses on the role of MEP on the intensive margin in job search and job finding. Employment separations are not a part of the choice set, and I do not allow the selection into unemployment to directly depend on the existence and intensity of MEP. The primary reason for treating this margin as exogenous is that the experiment is unexpected at entry into unemployment.[13]

In addition to the economic environment sketched above, I add a finitely lived experiment where individuals in the treatment group enter a sequence of treatment stages, one of which involves a higher intensity of MEP. The experiment is unexpected for individuals in the treatment group. The announcement of the

[12] The key distinction compared to related papers concerning more classical training programs, e.g. Adda et al. (2007) and Albrecht et al. (2009), is that program participation in my setting is mandatory and involves utility costs. Mandatory program participation implies that we may see individuals participate in MEP even though the current period costs exceed the benefits.

[13] Further, there is no data available on the cause of entry into unemployment (fired, voluntary quit, etc.). Note that it is perfectly plausible that behavior on the extensive margin and the intensive margin is driven by the same utility costs. However, obviously predictions along the extensive margin require quantification of the decision parameters related to this decision.

experiment and the duration of the threat stage and the following sequence of events follow the timing outlined in Table 1. When the experiment ends, treated individuals simply reenter the otherwise stationary and ergodic environment.

The key objects in the model are the utility function, the wage function and a set of transition functions which in combination govern the evolution of state variables over time. Key transition functions are the return to search, the probability of receiving a job offer, the probability of losing employment and the transition of individual time-varying heterogeneity. I let α represent a given action/choice of the individual. I let θ represent the state, i.e. θ is the collection of variables that summarizes all information about the past and present, which may influence current decisions and the transition of states in the forward-looking optimization problem. I discuss the different variables contained in θ in the next section.

Solving the dynamic program involves solving for value functions and an ergodic distribution across θ. The ergodic distribution determines the initial distribution across states. The transition functions of state variables and the policy function (i.e. the choice probabilities in a particular state) then determine how the distribution of θ evolves across time. The policy function is smoothed ex post using a logistic kernel. I return to the exact specification of transition functions and the solution of the dynamic program further below, but first I focus on the different dimensions of heterogeneity in the model.

Heterogeneity and the state space

The model includes several dimensions of heterogeneity which influence the incentive to and the likelihood of successful job search, thereby generating heterogeneity in the welfare costs of MEP. An important trade-off is keeping the state space, θ, manageable in size while including the dimensions of heterogeneity required to provide a good and realistic analysis of the impacts of the experiment and MEP. A further motivation for adding layers of heterogeneity is to enable the model to generate predictions which are rich enough to fit the moments from the micro data including both unemployment and employment dynamics. I illustrate the model's inability to fit the micro data in absence of some of the key layers of heterogeneity in more detail when I discuss the fit of the model in Section 6.

In Table 3, I provide an overview of the elements of the action space, α, and the state space, θ, including the grid size and grid values of the different states and actions. As already explained α consists of two choice variables: a choice of search intensity, sc, which involves choosing among 6 different levels, and a choice of whether to accept a given job offer or not, wc. θ can be partitioned into a set of variables describing the general environment for the control and treatment groups, $\theta_{\text{enviroment}}$, and into a set of variables tracing which stages of the experiment individuals in the treatment group are in, $\theta_{\text{experiment}}$.

$\theta_{\text{enviroment}}$ consists of a time-invariant and a time-varying part. Time-invariant state variables are tg, eg, rg and pg. The state variable tg marks the treatment status, eg marks the education group, and rg the region. Further, individuals differ in how they discount the future – the "patience" groups, pg. Patience group membership is unobserved by the econometrician. The existence of more impatient types may explain why some of the large experimental impacts that evolve prior to and in the early periods of the treatment do not materialize much earlier; see Section 3 on the AR. I allow for two patience groups, $pg \in \{0, 1\}$, in the empirical implementation: An impatient type who prefers lower levels of search leading to longer unemployment durations and lower skills, and a more patient type who values future employment higher and thus likely searches more. In the estimation I allow the distribution of types (as represented by probabilities $\tau_{patient}$ and $\tau_{impatient}$) to differ across educational and regional groups, but the actual discount rate is fixed throughout the analysis, see (online) Appendix Section C.3.3 for the specific parameterization in the model.

Time-varying state variables are m, a, e, d, j and s. The state variables m and a are indicator variables of whether the individual is currently in MEP in meetings or activation. The state variable e marks current employment status. d holds the duration of the current unemployment spell and affects the return to search creating structural duration dependence in unemployment. Generally duration dependence in the return to search and dynamic selection among the remaining unemployed are different channels through which the model can accommodate the large changes in employment rates and the decreasing hazard rate out of unemployment, which are found in the data.

The state variable j represents a draw of a job type and does not change during employment. j affects both the wage and the expected duration of the job. Jobs with a lower j have a lower wage and a higher probability of dissolving. This dual impact makes it more "costly" to accept jobs with a low j. This channel has the potential of reconciling the relatively large threat effects, see Geerdsen (2006); Black et al. (2003); Hall et al. (2021), with potentially smaller effects on post-unemployment outcomes. Heterogeneity in both wages and layoff rates across jobs is in accordance with for instance Bagger and Lentz (2019).

The state variable s represents skills or human capital which affects wages and the expected duration of a job. The value of s may change while employed, reflecting skill improvements through learning on the job similar to e.g. Ljungqvist and Sargent (1998). Overall, the state variables j and s represent two different sources of heterogeneity in jobs/earnings: j is related to the search process while s may be portable across jobs and may also change within a job.

$\theta_{\text{experiment}}$ consists of two state variables, ts and ds, which govern the progression of the experiment. They are only directly relevant for individuals in the treatment group since for the control group, the experiment does not change anything. The state variable *ts* marks the stage of the experiment which the individual is currently in: Threat (TH), Treatment (T) or Post-Treatment (PT). The state variable *ts* counts the time spent in the current stage.

At the start of the experiment unemployed individuals are assigned to either the control or treatment groups. Individuals in the control group directly enter the PT stage which is the environment without (or after) the experiment. Individuals in the treatment group instead enter the TH stage, and their future now differs from what was expected in the previous period. After some time in the TH stage, individuals in the treatment group enter the T stage where they participate in MEP if they are still unemployed. Finally they enter the PT stage, and the environment is identical to that of the control group. Note that, due to the design of the experiment, the distribution across states θ is identical in control and treatment groups at inflow into the experiment, but hereafter the distribution over states θ is potentially different due to the behavioral response to the experimental intervention.

Table 3: Elements of the action and state space

Action variable	Symbol	Grid size	Grid values
Search activity choice	sc	6	$\{0, \frac{1}{5}, ..., \frac{5}{5}\}$
Work choice (accept a job offer if present)	wc	2	$\{0, 1\}$

State variable	Symbol	Grid size	Grid values
Education group	eg	3	$\{0, 1, 2\}$
Region group	rg	2	$\{0, 1\}$
Treatment group	tg	2	$\{0, 1\}$
Time preference (patience) group	pg	2	$\{0, 1\}$
Meetings status	m	2	$\{0, 1\}$
Activation status	a	2	$\{0, 1\}$
Employment status	e	2	$\{0, 1\}$
Unemployment duration	d	10	$\{0, \frac{1}{9}, ..., \frac{9}{9}\}$
Job type/offer	j	6	$\{0, \frac{1}{6}, ..., \frac{5}{6}\}$
Skill level	s	6	$\{0, \frac{1}{5}, ..., \frac{5}{5}\}$
Treatment stage	ts	3	$\{0, 1, 2\}$
Duration in treatment stage	ds	6	$\{0, 1, .., 5\}$

Note: This table presents the different elements of the state space θ and the action space α. Table 19 in (online) Appendix C.3.1 provides additional details.

Utility, utility costs and wages

Utility costs are summarized by $C(\alpha, \theta)$. Utility costs are composed of costs due to search activity, working and costs triggered by participation in MEP:

$$C(\alpha, \theta) = \xi \cdot sc + \kappa^{eg} \cdot wc + \phi_m^{eg} \cdot m + \phi_a^{eg} \cdot a \tag{1}$$

κ^{eg} represents education-specific costs of working. ξ is the marginal cost of searching which is assumed constant across individuals. Note that while the search costs are fixed, the return to job search and the value of employment generally vary across states θ.

The utility costs associated with participation in MEP, ϕ^{eg}, vary by education and type of program as the programs differ in content and scope. ϕ^{eg} may arise from both stigma or disutility associated with participation, loss of leisure and/or direct participation costs (e.g. transportation). In this sense, utility costs could combine several policy-invariant parameters. The specification here is therefore more general than analyzing MEP through its effect via the time or income constraint in terms of e.g. reduced leisure or transportation costs. The point is that individuals may simply value one hour at the job center differently than one hour at work or at home.

The overall utility of a given individual in (α, θ) is determined by a standard CARA utility function which depends on income, $Y(\alpha, \theta)$, and utility costs, $C(\alpha, \theta)$:

$$U(\alpha, \theta) = -e^{-\gamma(Y(\alpha,\theta) - C(\alpha,\theta))} \tag{2}$$

where $\gamma > 0$. The income is determined as the wage $W(\alpha, \theta)$ when employed and UI benefits when unemployed. The UI benefits are a fixed amount, and duration is unlimited.[14] Wages vary over the type of jobs, I return to the specific wage function further below.

The formulation in equation (2) ensures that utility costs, $C(\alpha, \theta)$, are easily interpretable in a monetary metric which is attractive for the purpose of this paper. The CARA specification allows for interactions between participation in MEP and α, and the utility function introduces a wedge between direct utility costs and the overall utility, $U(\alpha, \theta)$. All else equal, including a fixed utility cost of MEP, the observed increase in job finding due to threat effects would generally increase as we increase γ. Similarly lock-in effects, i.e. decreases in job finding during program participation, can arise because the utility loss of searching is higher when the current state is already costly due to participation in MEP.

[14] Note that the specification implies that the utility costs of MEP in a given period can be directly offset by a corresponding change in UI benefits. This would however require UI benefits to change with participation in MEP as well as across education groups. Further, utility costs are only indirectly informative on welfare costs, since MEP may be avoided and utility costs never realized.

The model does not allow agents to smooth utility through savings and asset accumulation, although they would generally prefer to do so due to the CARA specification. Adding a savings choice to the model would require additional data on consumption or savings which is unavailable, and it would also imply a large increase in computational complexity, as the model is already high dimensional and focused on incorporating the experimental stages while simultaneously including several layers of heterogeneity to study the welfare costs. Further, analyzing the impact of MEP and their relation to savings decisions would require explicitly distinguishing monetary and non-monetary costs of MEP, which are simply treated as a composite index in the model. The fact that UI benefits are high and that the experiment is unexpected at inflow into unemployment with a relatively short threat stage should imply that any response on the savings margin in anticipation of future program participation is most likely small. Further, the extent to which agents change their savings decisions to be able to buffer future variation in utility due to potentially non-pecuniary costs such as utility costs of MEP is not well established.

The wage associated with a given job type j is determined by the wage function $W(\alpha, \theta)$:

$$W(\alpha, \theta) = \exp\left(\mu + \sigma^{eg} j + \eta \cdot s\right) \tag{3}$$

for $j > 0$. μ is a constant and represents the deterministic part of wages, η measures the return to skills s, and σ^{eg} measures the importance of a particular draw of job type, j.[15] σ^{eg} leads to education specific wage offers, and it allows the within-group variance on wages (both wage offers and accepted wages) to be different across education groups.

Transition functions: Unemployment dynamics

At inflow into unemployment, individuals have no job offers, $j = 0$. Hereafter, a job offer arrives each period with probability $T_{job}(\alpha, \theta)$.[16] This probability is calculated as the product of search intensity, sc, and the return to search (the part in [] below) which includes benefits from participation in MEP:

$$T_{job}(\alpha, \theta) = sc \cdot \left[\pi^{rg}_{job,d} \cdot (1-d) + \pi^{eg}_{job} + \pi^{eg}_{job,m} \cdot m + \pi^{eg}_{job,a} \cdot a\right] \tag{4}$$

The benefits from participation in MEP are $\pi^{eg}_{job,m}$ and $\pi^{eg}_{job,a}$ where the notation π^{eg} again denotes that the parameters are education-specific. The increase

[15] To generate a non-uniform wage distribution, I map values of j into respective quantiles of the normal cdf to generate a more natural wage distribution of wage offers (log-normal wage distribution). This also ensures that the wage dispersion does not depend on the overall grid size of j. See Appendix C Section C.3.2 for the exact empirical implementation.

[16] I generally refer to all transition functions as $T_i(\alpha, \theta)$ and to the parameters affecting transition functions as $\pi_{i,c}$ where i marks the type of transition and c marks the dependence on a state variable if any.

in the return to search due to MEP arise if program participation makes job search better, for instance it may improve job search skills (e.g. likelihood of success from applications) or open up further job possibilities through e.g. smaller changes/clarifications of the skill set of the unemployed. Note that the increase in the return to search is not persistent. However, repeated participation in MEP, as for the treatment group in the experiment, would imply that the return to search is higher over several periods.

Besides direct benefits from participation in MEP, the return to search consists of a regional-specific duration dependent term, $\pi^{rg}_{job,d} \cdot (1-d)$, and an education-specific part, π^{eg}_{job}, which can be interpreted as the return to search for a long-term unemployed (i.e. when $d = 1$, see Table 3).

Duration dependence in the return to search would, for example, arise if employers use duration in unemployment as a selection/screening criteria (see e.g. Kroft et al. (2013); Wolpin (1987)) or in an environment with stock-flow matching (see Coles and Petrongolo (2008); Ebrahimy and Shimer (2010)). From the perspective of the worker, these explanations imply that the return to search decreases over time in unemployment. The model does not take a stand on the specific mechanism. In this sense, the partial equilibrium approach is advantageous here as duration dependence can simply appear as a 'reduced form' object instead of an equilibrium outcome.

As I show later, the inclusion of duration dependence is important to fit both the short-term and long-term dynamics of the hazard rate out of unemployment. In the empirical implementation, the duration dependent term, $\pi^{rg}_{job,d} \cdot (1-d)$, allows the return to search to decrease (linearly) with duration in unemployment until 20 weeks of unemployment. The 20 weeks cutoff was chosen since around this point, the employment level stabilizes in the data. This is also close to the 26 weeks used in some definitions of long-term unemployment, see Kroft et al. (2013) although in other definitions, e.g. by OECD or ILO, the cutoff is around 52 weeks. Choosing a later cutoff point would not change my results substantially but would increase the state space and, consequently, the computation time quite heavily.

Lastly, the paper works under the assumption that the role of equilibrium and congestion effects are of limited importance in creating the experimental impacts documented above (see Lise et al. (2015) for similar arguments). Equation (4) makes this explicit as the individual return to search does not depend on search behavior of other individuals in the market. Instead, the analysis focuses directly on the identification of utility costs and individual incentives around the experiment by directly including and controlling for these differential treatment stages in estimation.[17]

[17] Gautier et al. (2018) consider equilibrium effects in an earlier Danish experiment. The experiment was conducted in two remote regions of Denmark, whereas the experiment analyzed in this

Transition functions: Employment dynamics

While employed, skills s may increase from period to period with an education-specific probability, $\pi^{eg}_{up,s}$. When separated from a job, skills are lost with probability $\pi_{dw,s}$. The loss of skills means that acquired skills have become obsolete in the market; as a result, future wages will be lower because there are no skills/experience from the previous job that are transferable into a new job. The evolution of skills across time is important as it directly affects the value of employment through the stability and wages in future jobs.

Although the level of skills is generally unobserved by the econometrician, the estimation exploits that changes in skills are the only source of wage growth in employment. The skill loss term is only indirectly identified through subsequent unemployment dynamics and accepted wages out of unemployment. I therefore only allow for educational differences in $\pi^{eg}_{up,s}$ and not in $\pi_{dw,s}$. Note that by assumption participation in MEP does not affect skills s in the model. This assumption is supported by the content of the experimental treatment, i.e. shorter-term training and skill assessment (Section 2.2), and the lack of wage gains from the experimental treatment as discussed in Section 3.

Jobs may also terminate, and the probability of a layoff, $T_{lj}(\alpha, \theta)$, depends on the skill level, s, and the job type j. The higher the level of skills or the job type, the lower the risk of becoming unemployed:

$$T_{lj}(\alpha, \theta) = \pi^{rg}_{lj} \cdot \left[\pi_{lj,j}(1 - j) + \pi^{eg}_{lj,s}(1 - s)\right] \tag{5}$$

where I allow the dependence on s to be education specific and allow for differences in layoff rates across regions through the scale factor π^{rg}_{lj}. The reference region is set to be the MR region, hence $\pi^{MR}_{lj} = 1$.

As explained above the dependence of $T_{lj}(\alpha, \theta)$ on j makes individuals less willing to accept lower job types in exchange for faster job finding. The dependence on s and the within-job evolution of skills generate duration dependence in jobs which may capture the decreasing hazard rate out of employment as found in the data and the high turnover for some jobs especially for low educated workers.

The dynamic program

Individuals maximize the sum of expected discounted utility over an infinite horizon. A time period in the model is 2 weeks, and the environment is stationary and ergodic (as in Ferrall (2004, 2012)). I let $A(\theta)$ contain the set of possible

paper is conducted in the two largest Danish regions where the number of jobs to apply to within a reasonable commuting zone is much larger, see also footnote 7.

choices in a given state θ. The value associated with being in state θ and making choice α, $v(\alpha,\theta)$, is given by:

$$\forall\alpha \in A(\theta), \quad v(\alpha,\theta) \begin{aligned}[t] &= U(\alpha,\theta) + \delta^{pg} E\left[V(\theta')\right] \\ &= U(\alpha,\theta) + \delta^{pg} \sum_{\theta'} P\left\{\theta'|\theta,\alpha\right\} V(\theta') \end{aligned} \tag{6}$$

where $U()$ is a utility function, and $P\{\theta'|\theta,\alpha\}$ governs the mapping from θ into future states θ' which depend on transition functions and the optimal choices of the individual. The value function, $V(\theta)$, can now be determined as:

$$V(\theta) = \max_{\alpha} v(\alpha,\theta) \tag{7}$$

In a next step, choice probabilities are smoothed using a logistic kernel:

$$\begin{aligned} \tilde{v}(\alpha,\theta) &= \exp\left\{\rho\left[v(\alpha,\theta) - V(\theta)\right]\right\} \\ P\{\alpha|\theta\} &= \frac{\tilde{v}(\alpha,\theta)}{\sum_{\alpha}\tilde{v}(\alpha,\theta)} \end{aligned} \tag{8}$$

where $\rho > 0$ determines the importance of smoothing and $P\{\alpha|\theta\}$ is the policy function. This is similar to e.g. Eckstein and Wolpin (1999); Ferrall (2012). If the value associated with a non-optimal choice is close to the value of an optimal choice, the probability of either choice will be similar due to smoothing. On the contrary, actions which are far from optimal are very unlikely. As ρ increases, the probability that agents make unexpected or non-optimal choices further decreases.

While the expression of choice probabilities in equation (8) looks similar to the random utility approach (see Rust (1987)), smoothing here is *ex post*, while in the random utility approach smoothing arises *ex ante* through a continuous taste-shifter in the utility function. Smoothing ex post only adds one additional parameter to the estimation problem and is attractive in this setting where *sc* is unobserved in the data. ρ thus governs choice smoothing on all margins and levels of search intensity. Note that the model also has discrete unobserved dimensions of heterogeneity (taste-shifters) such as, e.g., skills and job offers that affect agents and lead to different choices for observational similar agents.

The role of MEP

Through the lenses of the model, MEP may change behavior before, during and after program participation. Threat effects arise when the unemployed search more intensively prior to potential participation in order to avoid it. During participation, lock-in effects may arise since the utility loss associated with job search is higher due to the CARA utility function and utility costs related to participation. Participation in MEP may also directly increase the return to search.

Lastly, MEP may also influence the type of jobs individuals have out of unemployment. This happens if individuals change decisions about the type of job offers they accept in response to (a threat of) participation in MEP.

Note that in accordance with the institutional setup (see Section 2.1), both the control group and the treatment group participate in MEP, but the intensity of MEP is much higher in the treatment group. The control group faces a constant probability of entering MEP each period in unemployment. In addition to this the treatment group participates in MEP in all periods of the T stage with probability 1. The rate of MEP participation in the control group is set to match the empirical participation rate as documented in Maibom et al. (2017). See (online) Appendix Section C.3.3 for the specific parameterization.

Overall, the model delivers a series of predictions in dimensions that are important for analyzing the impact of MEP. These dimensions are: the duration in unemployment, the speed and timing of job finding, the wage and subsequent dynamics in jobs. The experimental impacts, i.e. differences in all the former dimensions between treatment and control groups, deliver further predictions which are informative on the role of MEP. All these predictions are shaped by the incentives and value of different alternatives for individuals in the experiment.

The quantitative size of these responses generally depends on the state θ. Although the direct utility costs in equation (1) are constant within education groups, a threat of MEP will still lead to differential policies in equation (8) within a given education group. This is because the value of the alternative differs across θ either in how costly it is to secure/find employment, or in the attractiveness of being employed. In this sense, MEP interact with the fundamental heterogeneity of the model and create heterogeneity in the impact of MEP and in the welfare costs.[18] Due to $\theta_{experiment}$, the predictions of the model can be directly contrasted with the time series of data moments and used as a way to discipline the parameters of the model. Thereby the incentives and value of different alternatives for potential participants can be credibly quantified, and the overall impact of MEP – including the overall social benefits – can be appropriately analyzed.

[18] The related theoretical literature on the effects of workfare in a static setting (e.g. Besley and Coate (1992); Kreiner and Tranæs (2005)) also focuses on heterogeneity in the value of the alternatives (earnings ability or cost of working). Nichols et al. (1982) argue that the case for workfare is strengthened when utility costs vary such that individuals with higher valued alternatives are further induced to stop claiming benefits (see also Cuff (2000)). Allowing for further heterogeneity in utility costs of MEP in this paper would require additional data (and ideally also a larger sample). Further, as I show below (Section 7.2), differences in welfare costs are further magnified due to the job search process. Thus, even with further heterogeneity in utility costs, welfare costs are still disproportionately affecting states where the cost of leaving unemployment is large.

5 Solution and estimation

I now explain the solution and estimation of the model as well as identification of some of the central structural parameters. Estimation does not require simulation of the model, as the time series of moments is solved for iterating on a Markov chain from an initial ergodic distribution over observable and unobservable states. The estimation exploits variation in moments within and across experimental stages, treatment status, regions and educational groups.

5.1 Model solution, initial conditions and estimation

The solution procedure consists of a series of steps which are similar to Ferrall (2012) (with one exception). Below I provide a brief overview and in (online) Appendix C, I provide extensive additional details and a step-by-step overview.

As a first step I solve for the objects $V(\theta)$, $P(\alpha|\theta)$ in equations (7) and (8). I then determine how the distribution of states evolves from one period to the next. This state-to-state transition function, $P(\theta'|\theta)$, is then used to calculate the ergodic distribution across states $\Omega^*(\theta)$. Based on $\Omega^*(\theta)$ and $P(\theta'|\theta)$, I then determine the initial distribution across states, $\Omega(\theta|t=0)$, where $t=0$ denotes the start of the experiment. In doing so, I also take into account that participants who had been unemployed for a while prior to the start of the experiment are not a random sample of workers from the ergodic distribution since they had to remain unemployed for some time to enter the experiment.

The characteristics in Table 2 show that the starting point of 20-30% of the participants was some kind of public benefits. While this type of endogenous eligibility to the experiment does not threaten the internal validity of the experiment, reduced form impacts should be interpreted with this in mind. The model takes this into account by modeling this selection process explicitly and thereby solves this initial conditions problem (see e.g. Aguirregabiria and Mira (2010)). If we do not take into account that this group is likely negatively selected in terms of the value of finding employment due to e.g. lower skills or impatience, we misrepresent the incentive to escape MEP which affects the size of utility costs and the subsequent welfare costs.

The next step is to solve for $\Omega(\theta|t)$, the distribution across states for each time period t since the beginning of the experiment, by iterating on the Markov chain, starting from $\Omega(\theta|t=0)$ and using $P(\theta'|\theta)$. Model predictions are solved separately by education, region, treatment status and initial unemployment duration groups. Note that the ergodic distribution, and the stationary environment conditional on state variables including $\theta_{experiment}$, enables estimation of the parameters from the infinite horizon decision problem using data over a finite estimation period which covers the different experimental stages.

I also add a new step to the model solution compared to Ferrall (2012). In particular I introduce an inner Markov chain determining the object $\Omega^{RED}(\theta|t, t+k)$. This object holds the distribution across states for remaining employed individuals at $t+k$, who started employment in period t and thus incorporate the dynamic selection that occurs in employment over time due to differences in skills and job type. This object enables model predictions describing within job dynamics to be added to the set of moments without increasing the state space.

The parameters of the model are estimated using the generalized method of moments. The estimation proceeds as follows: for a set of parameters, the model is solved, and $\Omega(\theta|t)$ is determined. $\Omega(\theta|t)$ is then mapped into model predictions and used to form a time series of moments which is compared to data. The distance between model predictions and data is minimized by changing the parameters of the model until a minimum is found. In Appendix C, I provide further details on the solution of the model, the estimation process and the calculation of standard errors. For an overview of the parameters to be estimated, see Table 21 and 22 in (online) Appendix C.3.4. Further, Table 20 in (online) Appendix C.3.3 presents the parameters which are fixed prior to estimation.

5.2 Identification and the experiment

The moments used in estimation capture employment, unemployment and wage dynamics, which are informative about the structural parameters. In total, I estimate 43 parameters using information from 156 moments (13 moments, 2 regions, 3 education groups and 2 treatment status groups) observed over 35 two-week periods, resulting in 5460 potential predictions. Broadly speaking, the parameters in the model are identified by the restrictions generated through the model in how moments vary over time, within and across education and region groups. These restrictions are both behavioral and functional form restrictions. For instance, regional or education-specific parameters are identified from the restrictions in how education enters the model and by using differences in moments across these groups in the data. Below, I discuss how each chosen moment is informative about different parameters. Data from the control group alone is informative about most parameters, but the experiment is particularly important in order to distinguish between competing utility cost (and benefit) structures.

The experiment generates the opportunity to observe identical agents in different settings and to use the observed differences in data moments in combination with the job search model to analyze the way that the treatment affects individuals. Contrasting moments from the treatment group with the control group allows us to keep other time-varying confounders such as duration dependence and differences in skills fixed; in this sense, the experiment serves as an exclusion restriction, see Wolpin (2013, 1987); Todd and Wolpin (2020). Differences in for instance employment rates between treatment and control groups are mapped into differences in individual decisions. These differences are then informative about the effect of future MEP participation on individual decision making.[19] Differences in individual behavior in the TH, T and PT stages can be used to distinguish between ϕ_a^{eg} and $\pi_{job,a}^{eg}$ – the two different explanations for why MEP increase job finding.

I lastly provide some heuristic arguments motivating the choice of the different moments. See Table 7 in Appendix A for a full list of the chosen moments including means and standard deviations (see also Table 23 in (online) Appendix C.3.5 for additional details about e.g. the time periods used). Mean accepted wages and wages squared (moments #2, #3, #9 and #10 in Table 7) discipline the parameters of the wage function. Wages squared are included to ensure that the model does not only match the average level and evolution of wages, but also the dispersion within periods. Wages squared and average accepted wages for workers transiting from unemployment in a given period are informative of the importance of j, the job type component in wages. Differences across education groups link to the educational specific parameters affecting wage offers.

The (un)employment rate and the share of workers leaving unemployment in a given period (moments #6, #7 and #8) link to parameters determining the overall level of, and dynamics in, unemployment such as the costs of working and searching (equation 1). Average unemployment duration and duration squared (Moments #4 and #5) are included in the set of moments to discipline the predictions regarding the distribution of unemployment durations among individuals and overall unemployment dynamics. These moments are included since they are directly informative about the parameters governing the return to search (equation 4), and because the distribution across states θ changes due to dynamic selection in unemployment.

Since changes in skills, s, are the only source of wage growth in employment, adding moments characterizing employment dynamics and wage changes are informative on the importance and distribution of skills. The interaction of employment duration and wages (moments #12 and #13) disciplines the parameters governing the evolution and level of skills. The share of workers losing their job and the average employment duration (moments #1 and #11) are informative on the employment dynamics and the parameters governing the layoff process. Again differences in moments across education and region groups link to the

[19] Intuitively, using data from both the control and treatment groups in the estimation separates the costs and benefits of MEP from the other features of the environment such as the return to and the cost of job search. Using only data on the control group would challenge the ability to distinguish environments with low costs of MEP and high returns to search, resulting in smaller adjustments in search activity, from other environments where: the costs of MEP are high, the return to search is low, and adjustments in search activity are large. Across these environments, the overall observed response to MEP such as job finding, may be quite similar, but the welfare implications are very different.

importance of regional and education-specific parameters. Further by using the whole time series of moments, both short- and longer-term dynamics are disciplined.

6 Model fit and mechanisms

This section presents the fit of the model. I then present the model estimates and the behavioral changes or mechanisms underlying the experimental impacts. In the next section, I calculate the welfare costs and discuss the implications for usage of MEP.

6.1 Model fit

As discussed in the previous section, the model delivers a wide range of predictions which are disciplined through estimation. In this subsection I illustrate the fit of the model and discuss how the predicted time series of moments aligns with data across the different combinations of education, region and treatment status groups.

Tables 7 and 8 (Tables 9 and 10) in Appendix A present the fit for the treatment (control) group in the MR and AR. Each table reports the means and standard deviations of the time series of moments in the data and the estimated model within education groups. The tables also contain the correlation of the time series for the data and model as well as the relative deviations compared to the levels in the data. Overall these tables show that the model, broadly speaking, succeeds in matching both the level and variability across the various moments. This generally holds across both education and regions, as well as for treatment and control groups. For the vast majority of moments, the correlation is above 0.9, and the relative deviation is less than $10-15$ percent. Moments of particular interest are of course moments related to employment status and speed of job finding, such as e.g. the employment rate (#7) where the correlation is always above 0.9, and the relative deviation is never above 7 percent.

There are also some exceptions where the model fit is less accurate as reflected by either a lower correlation or a higher relative deviation.[20] The fit is perhaps

[20]This primarily concern moments related to inflow or outflows from employment (#1, #5, #8 and #9), such as e.g. the (unconditional) share of job separations and the average wage for hires in a given time period. It is not surprising that the fit is less accurate in these dimensions. First, prediction errors to some extent compound. For example, fitting the share of separations out of employment would require simultaneously fitting both the employment rate, the distribution of employment durations as well as the job destruction process. Second, some of these transitions happen at a very low frequency in the data, hence even small deviations are large in relative terms. For example, with job separations the correlation varies from $0.6-0.9$ across demographic groups, but the average deviations are relatively large (up to 60 percent).

slightly better in the AR compared to the MR, especially for moments related to job separations (#1), wages (#2, #3) and employment (#7). The difference in fit across regions is not surprising given the regional differences in the data and the implicit constraints of the estimation, where the same set of parameters, with a few exceptions, has to fit the data in both regions simultaneously. A similar comment applies to the few cases where the fit performs differently across education groups.

It is, of course, crucial for the analysis below that the model not only captures the overall level and variability in the moments, but also the actual time profiles. To illustrate this further, I plot the time series of the employment rate in the treatment groups for the model and data in panels a) and b) of figure 2. The figure shows that the model captures the high initial outflow from unemployment and, thus, rapidly increasing employment levels in addition to a stable employment rate in the longer run. It also fits job finding rates in the longer run (see also moment #8), suggesting that the main predictions in terms of in and outflow to and from employment are well explained. The long-run employment rates in the MR are slightly overestimated, but this holds in both the treatment and control groups.

Panels c)-f) in figure 2 show the difference between employment rates in the treatment and control groups in the short and long run. As argued previously, the timing and size of experimental impacts are key to identifying utility costs (and benefits) of MEP and, hence, an important statistic for the model to fit. The figures show that in both regions and across educational levels, the model is able to capture both the timing and magnitude of the impacts, especially during the first 20 weeks of the experiment.

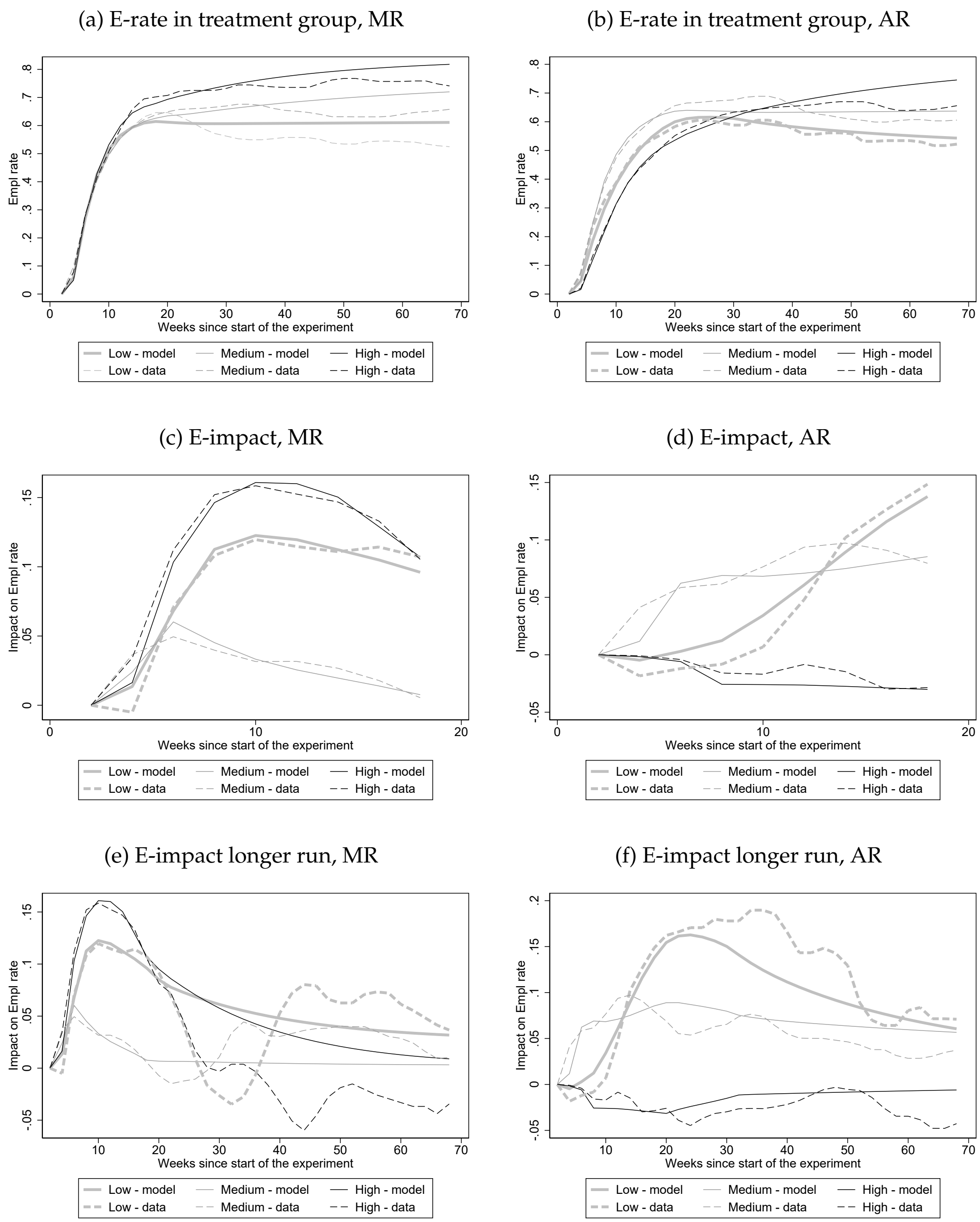
In total, it appears that the model fits the data along key dimensions that are important for analyzing the impact of MEP. This means that the incentives and value of different alternatives for potential participants can be credibly quantified, and the overall impact of MEP – including the overall social benefits and heterogeneity in costs – can be appropriately analyzed.

6.2 Model Estimates

Table 4 presents the estimated parameters and standard errors. The table also reports the p-values from pairwise tests of parameter equality across education groups.

The estimates of the model imply a strong return to education: high educated individuals have a higher return to search, lower work costs and are paid more while employed. In addition, high educated workers keep their jobs longer and have a higher level of skills on average. Low educated workers, in contrast, lose their jobs faster and have lower skills and, thus, a lower return to employment. The estimates also reveal differences across the MR and AR. For instance, dura-

Figure 2: Employment rates across time, region and education groups



Note: Panels (a) and (b) plot the employment rates for the treatment group in the model and data. Panels (c)-(f) plot the difference in employment rates in the treatment and control groups. See Appendix A for further evidence on model fit and employment rates in the control group. MR: meetings region. AR: activation region. Results are reported separately for different education levels (low, medium, high).

tion dependence in the return to search is more pronounced in the AR,[21] where the probability of a layoff is also smaller. The distribution of patience types also differs. These structural differences are likely to lead to regional-specific impacts of a specific intervention and therefore suggest that a comparison of the raw (reduced form) impacts across regions should be carried out with caution.

For low educated workers, the estimates of the immediate benefits of MEP, $\pi_{job,a}$ and $\pi_{job,m}$, imply an increase of around 5 percentage points in the probability of a job offer for an individual searching at the median search intensity ($sc = 0.5$). For other education levels, the estimates are both statistically insignificant and quantitatively small.

On the contrary, the estimates of the utility costs of MEP, ϕ_m and ϕ_a, are sizable; for instance, low educated unemployed would be willing to give up close to 80(50)% of their UI in a given period to avoid activation (meetings). While these estimates are large, it is reassuring that they are below the expected loss in benefits if individuals simply did not show up for MEP activities (see footnote 5). For low and medium educated workers, ϕ_a is only 15-20% lower than the work cost, κ. It is reasonable that ϕ_a is similar in magnitude to the work cost since activation is almost as time-consuming as full-time employment. Meetings on the other hand are less time-consuming, and the sizable estimates of ϕ_m may imply that for instance stigma is an important component of utility costs here.

ϕ_m and ϕ_a are generally decreasing with the education level: ϕ_m is around 30% lower for high educated compared to low educated, but lower for medium educated compared to high educated. The model infers this from the fact that the employment impacts for medium educated workers are smaller and less immediate than for high educated workers in the MR. For activation, low and medium educated workers incur substantial utility costs, whereas high educated workers do not incur utility costs.[22]

The educational differences in utility costs may reflect educational differences in the content of activation and meetings. It is reasonable to expect the content of activation for low educated/unskilled unemployed individuals to be more intense and focused on elementary training, whereas high educated individuals may participate in less intense training or courses they consider less costly, such

[21] To illustrate the importance of duration dependence in the return to search, Figure 11 Appendix D.3 shows the fit of the model with estimates as in Table 4, but now without duration dependence in the return to search. This specification is not able to generate the spike initially in outflow rates followed by lower rates in the longer run. I discuss some of the other features of the model such as the return to search, the wage and expected duration of jobs in further detail in Appendix D.

[22] The estimate of ϕ_a for high educated is actually negative (suggesting utility gains from participation), but quantitatively small and statistically insignificant. The model infers this limited role of utility costs from the absence of threat effects and the small difference in employment rates between the control and treatment group for high educated workers in the AR, see figure 1 and Table 12.

as personal development or job training. It is, however, beyond the scope of this paper to rationalize these differences in utility costs further. Note that utility costs and benefits are not the appropriate metric if we want to understand how potential participants were affected by the threat of MEP. Doing that requires determining the welfare costs which is the aim of the next section.

I now provide some evidence on the behavioral changes underlying the treatment impacts documented in figure 2. This evidence is a useful input to the discussion about the drivers of the welfare costs and the social benefits of MEP in the next sections.

In figure 3 I illustrate the search policy, i.e. the probability distribution over different levels of search activity as determined by the policy function defined in equation (8), in a particular realization of θ in the AR. The left panel compares the search policy in the treatment group to the control group at inflow into unemployment. The right panel illustrates how the search policy of the treatment group changes as individuals progress through the different experimental stages. Overall, the figure illustrates the primary behavioral change underlying the experimental impact: individuals in the treatment group simply search more. Further, the response to treatment is dynamic, for instance, individuals search more in the threat stage (TH) than after treatment (PT). The dynamic response also materialize within treatment stages, for instance, search intensity in the TH stage increases as individuals approach the T stage, i.e. the more intense the threat of MEP becomes.

Another way to illustrate the quantitative importance of changes in job search more directly is to replace the policies in the treatment group in states θ where the individual has no job offers($j = 0$) with the choices of the corresponding control group. In this counterfactual, the impacts are generally much smaller than the impacts arising under the benchmark. This illustrates that a key driver of the experimental impacts are changes in job search decisions, and less so changes in decisions about whether to accept a given job offer. Overall, this decomposition suggests that across region and education groups (with one exception), more than 70 percent of the average experimental impacts during the first 30 weeks arise directly from changes in job search decisions only. See Figure 12 in Appendix D.4 for an illustration and for further discussion of the treatment mechanisms across regions and also with respect to decisions about accepting a particular job offer.

Implicitly the above results also illustrate the advantage of the explicit inclusion of the experiment into the model and estimation. By inclusion of the experiment by $\theta_{experiment}$, model predictions can be directly contrasted to data moments while the time until treatment is controlled for. Thereby model predictions are disciplined through estimation, which lends credibility to the model estimates and predictions. This increases the reliability of the CV and allows us to analyze

Table 4: Estimated parameters and standard errors:

Parameter	Model	Note	Low	Medium	High	Equality Test
ξ	Utility	Search cost	0.342^{**} (0.040)	-	-	-
κ^{eg}	Utility	Work cost	0.631^{**} (0.061)	0.607^{**} (0.094)	0.477 (0.031)	$[0.86, 0.02, 0.20]$
ϕ_m^{eg}	Utility	Utility cost of meetings	0.338^{**} (0.150)	0.141 (0.266)	0.237^{**} (0.090)	$[0.56, 0.60, 0.74]$
ϕ_a^{eg}	Utility	Utility cost of activation	0.526^{**} (0.104)	0.498^{**} (0.249)	-0.041 (0.085)	$[0.93, 0.00, 0.05]$
γ	Utility	Curvature utility	1.582^{**} (0.265)	-	-	-
$\tau_{patient}^{MR}$	Types	Fraction of patient types, MR	0.824^{**} (0.069)	0.999^{**} (0.007)	0.975^{**} (0.027)	$[0.01, 0.02, 0.33]$
$\tau_{patient}^{AR}$	-	Fraction of patient typestype, AR	0.497^{**} (0.066)	0.673^{**} (0.100)	0.565^{**} (0.179)	$[0.13, 0.72, 0.56]$
μ	Wages	Wage constant	-0.419^{**} (0.022)	-	-	-
σ^{eg}	Wages	Search sensitive	0.000 (0.029)	0.031 (0.022)	0.056^{**} (0.016)	$[0.35, 0.02, 0.31]$
η	Wages	Return to skills	0.869^{**} (0.029)	-	-	-
ρ	Smoothing	Smoothing kernel	45.075^{**} (11.416)	-	-	-
$\pi_{job,d}^{MR}$	Job offers	Duration dependence, MR	0.242^{**} (0.020)	-	-	-
$\pi_{job,d}^{AR}$	-	Duration dependence, AR	0.326^{**} (0.025)	-	-	-
π_{job}^{eg}	Job offers	Long term job offer	0.101^{**} (0.018)	0.035^{**} (0.012)	0.258^{**} (0.020)	$[0.00, 0.00, 0.00]$
$\pi_{job,m}^{eg}$	Job offers	Productive effect (meeting)	0.082 (0.068)	-0.007 (0.037)	0.013 (0.042)	$[0.19, 0.44, 0.74]$
$\pi_{job,a}^{eg}$	Job offers	Productive effect (activation)	0.099^{**} (0.033)	0.019 (0.068)	0.030 (0.115)	$[0.35, 0.62, 0.93]$
$\pi_{lj,s}^{eg}$	Layoff process	Impact from s	0.025^{**} (0.008)	0.005 (0.004)	0.000 (0.003)	$[0.07, 0.00, 0.33]$
$\pi_{lj,j}$	Layoff process	Impact of job type j	0.059^{**} (0.006)	-	-	-
π_{lj}^{AR}	Layoff process	Regional effect, AR	0.652^{**} (0.091)	-	-	-
$\pi_{up,s}^{eg}$	Skills evolution	Appreciation of s	0.026^{**} (0.005)	0.022^{**} (0.004)	0.020^{**} (0.000)	$[0.61, 0.27, 0.71]$
$\pi_{dw,s}$	Skills evolution	Loss of s	0.142^{**} (0.028)	-	-	-

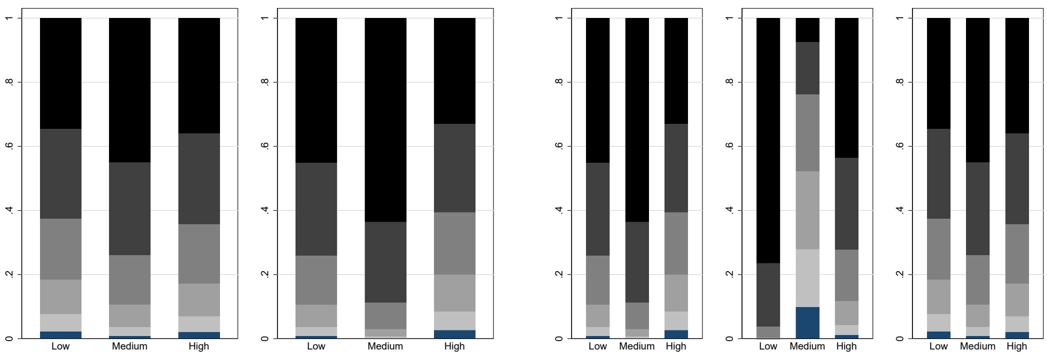
Note: This table shows the estimated parameters including standard errors in (). Low, medium, high refer to the different education levels. Parameters which are not education-specific are reported in column “Low”. The last column “Equality test” contains the p-values from a t-test of the null of equality of parameters across education groups. The tests are pairwise and in the order: (Low, Medium), (Low, High) and (Medium, High). MR: meetings region. AR: activation region. *(**) denotes significance at the 10% (5%) level.

the role of MEP under other counterfactuals, such as e.g. a longer threat stage.

Figure 3: Search levels and job decisions – AR

(a) Search - Control (left) vs. Treatment

(b) Search in TH (left), T (middle) and PT stages



Note: Panel (a) plots the search policy, i.e. the probability distribution (determined by the policy function in equation 8) over different levels of search activity sc for patient individuals in the Activation Region (AR) at inflow into unemployment (the first period in the TH stage). Panel (b) shows the search policy across different experimental stages ts in the treatment group. Within each panel, the left (right) figure is for control (treatment) individuals in state θ. Dark bar colors reflect higher search intensity, blue color indicates no search ($sc = 0$). Keep in mind that high educated workers have no utility costs from participation in activation. See Appendix D.4 for figures from an alternative realizations of θ.

7 Compensating variation

This section quantifies how the experiment, and thus the threat of MEP, affects individuals in the treatment group. I calculate the CV and use it as the measure of the change in worker welfare, i.e. the welfare costs of the experimental intervention. I illustrate how the CV varies across states in the model, and I discuss the implications for appropriate usage of MEP. Finally, I contrast the CV and operating costs of MEP to the gains in terms of increased job finding.

7.1 Results

The CV is the (hypothetical) monetary compensation which makes a given individual indifferent to being in the treatment or the control group. The compensation is paid for each period in the TH and T stage.

By design, the CV quantifies the influence of the threat of MEP although the utility costs may never be realized, as individuals secure employment prior to participation. The CV implicitly contrasts utility costs, benefits and the probability of future program participation against the value of the alternatives. The CV will vary as a function of the initial state at entry into the experiment, θ_{init}.

In practice, $CV(\theta_{init})$ is solved separately for each θ_{init} as a minimization problem where the objective is the difference in value functions between the treatment and control groups for a given compensation scheme. Subsequently, I calculate the average CV by accumulating payments over periods and weighting $CV(\theta_{init})$ with the initial distribution across states $\Omega(\theta|t=0)$.[23]

Table 5 presents the average CV in € per participant and also expressed in terms of weeks of UI in parenthesis. Note that the representation of the CV in terms of weeks of UI is only for expositional purposes to better illustrate the size of the CV (see also footnote 14). The average CV amounts to €554 (494) in the MR (AR) or around 1.72 (1.52) weeks of UI per unemployed participant in the treatment group. The educational differences in the CV reflect differences in the utility costs of MEP, differences in the incentive to work and differences in the return to search.[24] Differences in the CV across patience groups are driven by differences in how the utility loss of job search is valued relative to its return. Impatient workers discount the future more heavily, and hence the gain from future employment is smaller leading to a higher CV. Keep in mind that the CV also varies across θ_{init}. With a few exceptions, the standard deviation of the CV within education, region and patience groups is around 10-30% of the mean. See Table 27 in Appendix D.5 for the (probability weighted) mean and standard deviation on the CV.

Differences in the CV across regions MR and AR in Table 5 are driven by differences in the content of MEP, but also in the timing of treatment. One driver of these patterns is the differences in the intensity of the threat of MEP. In the MR, the TH stage is only 1-2 weeks, whereas in the AR it is longer, see Table 1. For instance the CV is higher for patient low educated workers in the MR compared to the AR, although the direct utility costs of meetings are actually lower than activation. Similar reasoning applies when we compare the CV across different

[23]Since the utility function is non-linear, solving $CV(\theta_{init})$ for a given θ_{init} implies that the contraction mapping should be resolved for each guess of compensation. See Appendix Section C.4 for additional details on the calculation. Further, as a part of the individuals in the model are "impatient" (see Section C.3.3), I have also tested compensation schemes that involve payments in only the TH or T stage. The difference in the total compensation between these schemes is small and does not affect the results, see Appendix D.5 Table 25 for an illustration. Lastly, the average CV is also affected by education and regional differences in the distribution across states at the start of the experiment. Appendix D.5 Table 25 shows the average CV for a common benchmark distribution and also shows that this does not drive the results reported below.

[24]The negative CV estimates for high educated workers in activation arise because the estimate of ϕ_{ap} is negative (see Table 4). At face value the CV suggests that high educated workers would be willing to pay a total of 0.3 weeks of UI benefits in order to secure participation in the experiment with activation. However, keep in mind that ϕ_{ap} is both statistically insignificant and quantitatively small, and this conclusion should therefore be cautioned (see footnote 22).

realizations of θ_{init} in the next section - as the risk of future participation in MEP increases, for instance because the likelihood of leaving unemployment is small, the CV also increases.

Note that while a shorter threat stage would likely increase the CV, it actually also increases the impact on job finding, and thereby both benefits and welfare costs vary with the duration of the TH stage. See Table 26 in Appendix D.5 for an illustration where I calculate the CV and employment impacts across different counterfactuals where the duration of the TH stage changes.

Table 5: Average compensating variation across regions and workers

		Meetings Region	Activation Region
Low educated	Patient	431€ (1.34)	291€ (0.90)
Low educated	Impatient	1471€ (4.56)	2217€ (6.87)
Medium educated	Patient	454€ (1.41)	559€ (1.73)
Medium educated	Impatient	710€ (2.20)	2166€ (6.72)
High educated	Patient	739€ (2.29)	-88€ (-0.27)
High educated	Impatient	1207€ (3.74)	-101€ (-0.31)
Average across all workers		**554€ (1.72)**	**494€ (1.52)**

Note: This table reports the average CV, and in parenthesis the CV is expressed in terms of weeks of UI. The CV is defined in equation 17 and weighted with the initial distribution across states at inflow into the experiment. The compensation scheme is a payment for each period in the TH and T stage. See also (online) Appendix C.4 and D.5 for details on how to calculate the CV and additional results.

7.2 Heterogeneity in the CV and implications

The results in the previous section represent the first empirically-based quantification of the welfare costs of MEP in the literature. The counterfactual in this exercise is the environment of the control group, i.e. a world where MEP exist, but where the threat is much less intense. The results suggest that MEP promotes employment by reducing the benefits of UI, i.e. the individual valuation of UI. Furthermore, the results suggest that the welfare costs vary with the design of the intervention and across realizations of θ_{init}. Understanding the sources of this variation is an important step towards identifying who bears the largest costs and to understand how these results may generalize to other settings, targeting for instance other types of unemployed.[25]

[25] Note that since the CV is a function of the whole economic environment, it generally changes if we change the structural parameters in Table 4 or make other changes to the economic environment such as e.g. changes in the timing of MEP or the type of unemployment targeted. Knowledge on the underlying drivers of the heterogeneity in the CV is therefore useful to think about how the findings extrapolate outside the current intervention.

Analyzing the dispersion in the CV across different states θ_{init} reveals that the CV is particularly high in two groups of states. The first group consists of states where the return to search (equation (4) and thus employment prospects are low. For this group, escaping future program participation requires a large increase in search activity which is costly and thus demands compensation. The second group consists of states where the utility loss of additional job search is high. This would for instance include individuals who in absence of the experimental intervention are already searching intensively for employment. The new threat of MEP induces them to search even harder, but this is increasingly costly given equation (2).

In contrast, individuals with lower CVs are individuals who, in absence of the threat of MEP, search less intensively for employment, although they would be able to find employment rather quickly. While MEP may be an efficient screening device in terms of promoting faster job finding for this group of individuals, other individuals thus bear the costs of this strategy. In Table 28 Appendix D.5 these differential patterns in the CV are illustrated (and further discussed) by comparing the CV across two key dimensions of heterogeneity in θ_{init}: d, the duration of unemployment; and s, the level of skills.

It may be particularly problematic that individuals with weaker employment prospects are among the highest CVs, since they also have the greatest need of (longer-term) UI in the first place. Nevertheless this is perhaps not too surprising. A key insight in previous theoretical work on (static) workfare (see also footnote 4 and 18) is that the welfare costs of workfare are heterogeneous and higher for individuals with weaker alternatives, whereas individuals with other good alternatives are less affected. My estimates, from a dynamic setting and focused on choices on the intensive margin in job search and for MEP type interventions, offer a similar type of insight.

However, in moving from utility costs to welfare costs, my analysis illustrates that additional costs arise due to the job search process and the uncertainty about future employment. First, welfare costs are magnified because individuals cannot easily control whether they end up in MEP or not due to search frictions.[26] Second, the job search process in itself works as an intensifier of the threat of MEP for individuals with weaker employment prospects compared to individuals with better prospects, creating larger differences in welfare costs even when the direct utility costs are similar.

A classic result in the theoretical literature is that screening has lower welfare costs when the utility costs are lowest for those who really need the transfers

[26]These individuals could stop claiming benefits, but this would be more costly than participation in MEP. Note that welfare costs and MEP type interventions could of course be avoided if search effort/intensity was observed by the job center and used to assess benefit eligibility. This is of course not the case, as the problem of unobserved search effort is one of the reasons why MEP (and more generally disincentive effects of UI) exist in the first place.

(see Nichols et al. (1982)). My results suggest that even in a hypothetical scenario where direct utility costs are lower for individuals with weaker prospects, in moving from utility costs to welfare costs, the job search process would tend to wash out such differences and potentially reverse them. As a result welfare costs may still end up being substantially larger for individuals with weaker employment prospects. This happens because of the differences in the probability of future participation in MEP and the value of alternatives. The job search process thereby adds an additional layer of complications for screening through workfare or MEP.

In summary, the previous two subsections have illustrated that welfare costs are quantitatively important and that their size and distribution depend on, for example, the type of individuals targeted and the intensity of (the threat of) MEP. Average welfare costs can be compared to benefits from e.g. increased job finding, in order to determine whether a given MEP type intervention has social benefits. This is the goal of the final part of the analysis.

7.3 Assessing the social benefit of the intervention

I assess the social benefit of the experimental intervention in a partial welfare analysis where the costs of MEP are compared to its benefits. The model estimates are particularly informative about two components in this assessment: the CV and the cost of working. In addition to these costs I include MEP operating costs, i.e. expenditures associated with running the programs at the job center obtained from Maibom et al. (2017).

I assume that benefits are represented by the value of increased production, which I define as the difference between workers' income and costs. Thereby, I assume that workers are paid the value of their marginal product and that there are no equilibrium effects nor changes in the types of jobs individuals in the treatment group have. As the model does not include taxes directly, their role is not considered below, and I therefore implicitly assume that the excess burden (or distortions) of raising public funds for running the MEP programs is 0%. This assumption also implies that any saved income transfers from the experiment, due to e.g. increased job finding, are not included in the calculation below, as they only represent a potential redistribution of income with no distortions (an alternative assumption is that any saved income transfers are used for alternative government consumption which does not have any benefits).

Distortions from raising public funds would increase the operating costs of the experiment (element b in Table 6), but also add additional benefits from the experiment due to saved income transfers and thus a smaller need for public funds (see Maibom et al. (2017) for an illustration).[27] For further details about

[27] The use and size of the "marginal costs of providing public funds" are generally debated in the

the different components, see Appendix Section *D*.6. Note further that this assessment does not take into account that the experiment in itself generated important knowledge which would of course add additional social benefits from the experiment itself.

Table 6 shows the components in the analysis and the result. The counterfactual in this exercise represents the status quo, i.e. the environment of the control group where MEP are much less prevalent (see Section 2.1). The value of increased production is €1706 (1279) per participant in the MR (AR). This benefit comes at a total cost of €1175 (1330), where the operating costs are only a smaller part of the total costs ($b + c + d$ in Table 6).

Table 6 clearly illustrates that a more traditional cost-benefit analysis, which would typically not include the welfare costs (CV), would severely overstate the social benefits. In fact, the social benefits fall by around 50% to €531 per participant in the MR and remove the social benefits completely in the AR once the welfare costs are incorporated.

Obviously, the results in Table 6 are local in nature, and the results would likely change if, for instance, the intervention was introduced as a permanent policy applying to all unemployed job seekers, or if the type of individuals targeted changed in some other way. At least two dimensions are worth highlighting.

First, the importance of equilibrium congestion effects will likely increase if we consider the effect of larger interventions. This concern may be further amplified by the above results showing that the impacts of the experiment primarily arise due to changes in search intensity. Increasing search intensity likely increases congestion in a larger intervention which may then reduce the overall employment gains, thus further decreasing the social benefit of MEP.[28]

Second, the social benefits may also change because of heterogeneity in the CV. As shown above, the CV is particularly large in states where it is costly to escape future treatment. Therefore, intensifying MEP for e.g. weaker unemployed will likely increase the welfare costs and may simultaneously decrease the employment gains. To illustrate these effects further, Table 6 also reports the resulting CV if the intervention was re-targeted for individuals with lower employment prospects (here longer durations of unemployment). Assuming that employment gains would not change, the estimated social benefits in the MR are

literature, see e.g. Kleven and Kreiner (2006); Auerbach and Hines (2002). An alternative approach would be focusing on the "marginal value of public funds" of the intervention as outlined in Finkelstein and Hendren (2020). The key components in this calculation are the willingness to pay for the policy (the CV) and the net costs (i.e. including cost savings from the behavioral response to the intervention). These components are available in Table 6 and from Maibom et al. (2017).

[28] A counteracting force would arise if firms respond to the increase in search activity by posting more vacancies. The results in Lise et al. (2004) and Gautier et al. (2018) would suggest that the congestion channel is dominating at least in settings where MEP are already used (see also Crépon et al. (2013)).See also the comments in footnote 17.

further decreased by 50% driven by the increasing CV; this further illustrates the importance of the experimental design and the individuals targeted.

Table 6: Welfare analysis of the experimental intervention

	Meetings Region	Activation Region
Benefits		
Value of increased production[a]	1706	1279
Costs		
Operating costs (program costs)[b]	47	440
Costs from increase in production[c]	574	396
Welfare costs (CV)[d]	554	494
Welfare costs (CV) for LTU workers[e]	796	723
Social benefit ($a - b - c - d$)	**531**	**-51**
Social benefit LTU only $(a - b - c - e)$	**289**	**-280**

Note: This table gives the results of a welfare assessment of the experimental intervention. The unit is € per participant. The CV (defined in equation 17) is weighted with the initial distribution across states at inflow into the experiment. The time frame is a year. For further details of the different components, see (online) Appendix D.6. LTU (long-term unemployed) workers are workers with more than 12 weeks of unemployment.

8 Conclusion

Many UI systems worldwide use mandatory reemployment programs (MEP) as a condition for remaining eligible for UI. MEP may have components that involve training and learning, and it may trigger utility costs. Given such utility costs, future participants may try to avoid participation by finding employment, and MEP thereby screen workers out of UI. Both of these aspects (training and screening) have been found to be empirically relevant, and sorting out their relative importance and quantifying the size of potential utility costs are crucial as screening through MEP reduces the disincentive effects of UI by reducing the benefits of UI, i.e. the expected utility of the worker in unemployment. Lack of knowledge on the relative importance (and size) of utility costs implies that we risk favoring regimes with too high (or low) levels of MEP.

This paper develops a job search model with discrete choices capturing key behavioral channels which can be affected by a threat of, and potentially participation in, MEP. The aim of the analysis is to quantify the individual utility and welfare costs of MEP and analyze how welfare costs are distributed over the workforce.

The context of the study is a randomized experiment conducted in Denmark in 2008 which involved an increase in the intensity of MEP and led to a large increase in employment in the early stages of the experiment. The experiment generates exogenous variation in the threat of MEP which aids in identifying the key structural parameters. The model allows for a direct and realistic representation of the individual incentives in the experiment including how they evolve over time prior to, during and after participation in MEP. During estimation, the structural parameters are disciplined using the experimental design and the timing of treatment which generates exogenous variation in the threat of MEP, enabling a separation of potential program benefits and utility costs in the model.

I use the compensating variation (CV) as a measure of the impact of the experimental treatment on worker welfare, the welfare costs. The CV is the monetary compensation that makes individuals indifferent to being or not being at risk of participation in MEP. The estimates suggest that the welfare costs associated with MEP are substantial: they correspond to around 1.5-1.7 weeks of UI on average. A partial welfare analysis illustrates that incorporating the welfare costs lowers the overall social benefits of the experiment substantially. In one region, the social benefits fall by 50% after incorporating the CV, and in the other region it removes the social benefits completely.

In addition, the paper documents heterogeneity in the welfare costs of MEP. The dispersion in the welfare costs illustrates a classic screening paradox. While MEP may be successful in terms of promoting faster job finding for some groups of individuals with better alternatives, it is disproportionately more costly for the people for whom UI is highly important in the first case. This latter group includes individuals with low returns to job search and individuals for whom it is otherwise costly to find employment. These results therefore illustrate that the overall attractiveness of MEP in UI depends crucially on the specific design. Important design elements include the type of individuals who are targeted as well as the overall intensity of the threat of MEP.

Overall, this paper complements a large empirical literature focused on evaluating the impacts of MEP-type interventions by providing estimates on the utility and welfare costs. The results suggest that ignoring the existence of utility costs implies that we put excessive weight on the efficiency of UI systems, i.e. the speed of job finding, while overall welfare may be deteriorated. My analysis is the first empirically-based quantitative assessment of this overall relationship.

References

Adda, J., Costa Dias, M., Meghir, C., and Sianesi, B. (2007). Labour market programmes and labour market outcomes: a study of the Swedish active labour market interventions. Technical report, Working Paper, IFAU-Institute for Labour Market Policy Evaluation.

Aguirregabiria, V. and Mira, P. (2010). Dynamic discrete choice structural models: A survey. *Journal of Econometrics*, 156(1):38–67.

Albrecht, J., van den Berg, G. J., and Vroman, S. (2009). The aggregate labor market effects of the Swedish Knowledge Lift program. *Review of Economic Dynamics*, 12(1):129–146.

Andersen, T. M. and Svarer, M. (2007). Flexicurity - Labour market performance in Denmark. *CESifo Economic Studies*.

Attanasio, O. P., Meghir, C., and Santiago, A. (2012). Education choices in Mexico: Using a structural model and a randomized experiment to evaluate PROGRESA. *Review of Economic Studies*, 79(1):37–66.

Auerbach, A. J. and Hines, J. J. (2002). Taxation and economic efficiency. *Handbook of Public Economics*, 3:1347–1421.

Bagger, J. and Lentz, R. (2019). An Empirical Model of Wage Dispersion with Sorting. *Review of Economic Studies*, 86(1):153–190.

Behncke, S., Frölich, M., and Lechner, M. (2010). Unemployed and their caseworkers: Should they be friends or foes? *Journal of the Royal Statistical Society. Series A: Statistics in Society*, 173(1):67–92.

Besley, T. and Coate, S. (1992). Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty- Alleviation Programs. *American Economic Review*.

Black, D. A., Smith, J. A., Berger, M. C., and Noel, B. J. (2003). Is the threat of reemployment services more effective than the services themselves? Evidence from random assignment in the UI system. *American Economic Review*.

Boone, J., Fredriksson, P., Holmlund, B., and van Ours, J. C. (2007). Optimal unemployment insurance with monitoring and sanctions. *Economic Journal*, 117(518):399–421.

Cameron, A. C. and Trivedi, P. K. (2008). *Microeconometrics - Methods and Applications*. Cambridge University Press.

Card, D., Kluve, J., and Weber, A. (2010). Active Labour Market Policy Evaluations: A Meta-Analysis. *The Economic Journal*, 120(November):F452–F477.

Card, D., Kluve, J., and Weber, A. (2018). What works? A meta analysis of recent active labor market program evaluations. *Journal of the European Economic Association*, 16(3):894–931.

Coles, M. and Petrongolo, B. (2008). A test between stock-flow matching and the random matching function approach. *International Economic Review*, 49(4):1113–1141.

Crépon, B., Duflo, E., Gurgand, M., Rathelot, R., and Zamora, P. (2013). Do labor market policies have displacement effects? Evidence from a clustered randomized experiment. *Quarterly Journal of Economics*, 128(2):531–580.

Cuff, K. (2000). Optimality of workfare with heterogeneous preferences. *Canadian Journal of Economics*, 33(1):149–174.

Ebrahimy, E. and Shimer, R. (2010). Stock-flow matching. *Journal of Economic Theory*, 145(4):1325–1353.

Eckstein, Z. and Wolpin, K. I. (1999). Estimating the effect of racial discrimination on first job wage offers. *Review of Economics and Statistics*, 81(3):384–392.

Eisenhauer, P., Heckman, J. J., and Mosso, S. (2015). Estimation of dynamic discrete choice models by maximum likelihood and the simulated method of moments. *International Economic Review*, 56(2):331–357.

EUCommission (2018). Fact Sheet: Active Labour Market Policies. *EU commission*.

Ferrall, C. (2004). *Estimation and Inference in Social Experiments I . Introduction*. Queen's University, Institute for Economic Research.

Ferrall, C. (2012). Explaining and forecasting results of the self-sufficiency project. *Review of Economic Studies*, 79(4):1495–1526.

Finkelstein, A. and Hendren, N. (2020). Welfare analysis meets causal inference. *Journal of Economic Perspectives*, 34(4):146–167.

Fredriksson, P. and Holmlund, B. (2006). Improving incentives in unemployment insurance: A review of recent research. *Journal of Economic Surveys*, 20(3):357–386.

Gautier, P., Muller, P., van der Klaauw, B., Rosholm, M., and Svarer, M. (2018). Estimating equilibrium effects of job search assistance. *Journal of Labor Economics*, 36(4):1073–1125.

Geerdsen, L. P. (2006). Is there a threat effect of labour market programmes? A study of ALMP in the Danish UI system. *Economic Journal*, 116(513):738–750.

Hall, C., Kotakorpi, K., Liljeberg, L., and Pirttilä, J. (2021). Screening through Activation? Differential Effects of a Youth Activation Program. *Forthcomming in Journal of Human Resources*.

Heckman, J. J., Lalonde, R. J., and Smith, J. A. (1999). Chapter 31 The economics and econometrics of active labor market programs. In *Handbook of Labor Economics*, volume 3 PART, pages 1865–2097.

Judd, K. L. (1998). *Numerical Methods in Economics*. MIT press.

Kleven, H. J. and Kreiner, C. T. (2006). The marginal cost of public funds: Hours of work versus labor force participation. *Journal of Public Economics*, 90(10-11):1955–1973.

Kreiner, C. T. and Tranæs, T. (2005). Optimal workfare with voluntary and involuntary unemployment. *Scandinavian Journal of Economics*, 107(3):459–474.

Kroft, K., Lange, F., and Notowidigdo, M. J. (2013). Duration dependence and labor market conditions: Evidence from a field experiment. *Quarterly Journal of Economics*, 128(3).

Lise, J., Seitz, S., and Smith, J. (2004). Equilibrium Policy Experiments and the Evaluation of Social Programs. Working Paper 758, National Bureau of Economic Research.

Lise, J., Seitz, S., and Smith, J. (2015). Evaluating search and matching models using experimental data. *IZA Journal of Labor Economics*, 4(1).

Ljungqvist, L. and Sargent, T. J. (1998). The European unemployment dilemma. *Journal of Political Economy*, 106(3):514–550.

Maibom, J., Rosholm, M., and Svarer, M. (2017). Experimental Evidence on the Effects of Early Meetings and Activation. *Scandinavian Journal of Economics*.

Ministry of Employment Expert Panel (2014). Veje Til Job - en arbejdsmarkedsindsats med mening. Technical report, Ministry of Employment.

Moffitt, R. (1983). American Economic Association An Economic Model of Welfare Stigma. *Source: The American Economic Review*, 73(5):1023–1035.

Nichols, A., Zeckhauser, R., and Zeckhauser, R. (1982). Targeting Transfers through Restrictions on Recipients. *American Economic Review*, 72(2):372–77.

OECD (2001). *Labour Market Policies and the Public Employment Service*. OECD.

Rust, J. (1986). Structural estimation of markov decision processes. In Engle, R. F. and McFadden, D., editors, *Handbook of Econometrics*, volume 4 of *Handbook of Econometrics*, chapter 51, pages 3081–3143. Elsevier.

Rust, J. (1987). Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica*, 55(5):999.

Svarer, M. (2011). The effect of sanctions on exit from unemployment: Evidence from Denmark. *Economica*.

Todd, P. E. and Wolpin, K. I. (2006). Assessing the impact of a school subsidy program in mexico: Using a social experiment to validate a dynamic behavioral model of child schooling and fertility. *American Economic Review*, 96(5):1384–1417.

Todd, P. E. and Wolpin, K. I. (2020). The Best of Both Worlds: Combining RCTs with Structural Modeling. *Working Paper*.

US Department of Labor (2000). Worker Profiling and Reemployment Services. *Doleta*.

Van Den Berg, G. J. and Van Der Klaauw, B. (2006). Counseling and monitoring of unemployed workers: Theory and evidence from a controlled social experiment. *International Economic Review*, 47(3):895–936.

van den Berg, G. J. and van der Klaauw, B. (2019). Structural Empirical Evaluation of Job Search Monitoring. *International Economic Review*, 60(2):879–903.

Wolpin, K. I. (1987). Estimating a Structural Search Model: The Transition from School to Work. *Econometrica*, 55(4):801.

Wolpin, K. I. (2013). *The Limits of Inference Without Theory*. Tjalling C. Koopmans Memorial Lectures. The MIT Press.

Appendix

A Model fit graphs

Tables 7, 8, 10 and 9 list the chosen moments including means and standard deviations in the data (in blue) and in the model (in red). Note that these moments are population moments, i.e. #1 in Table 7 reports the population share of individuals who lost their jobs transitioning into the current period, i.e. not conditional on being employed in the previous period. The time series is 35 periods long (a period is 2 weeks in the data), but see also Table 23 in (online) Appendix C.3.5 for additional details. The tables also contain the correlation of the time series of moments for the data and model for each group and the relative deviation of the moment in the model to the data.

Table 7: Included time series of moments – Treatment group, MR

Education group		Low						Medium						High					
Treatment group		Data		Model		Stats		Data		Model		Stats		Data		Model		Stats	
#	Moment	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev
1	Inflow into U	0.015	*0.009*	0.024	*0.007*	0.63	0.55	0.012	*0.005*	0.018	*0.006*	0.63	0.55	0.011	*0.006*	0.011	*0.004*	0.63	0.55
2	Wages^2	0.528	*0.136*	0.568	*0.154*	0.94	0.05	0.596	*0.154*	0.641	*0.187*	0.94	0.05	0.756	*0.215*	0.841	*0.258*	0.94	0.05
3	Wages	0.542	*0.100*	0.573	*0.114*	0.91	0.04	0.610	*0.115*	0.636	*0.141*	0.91	0.04	0.727	*0.155*	0.759	*0.181*	0.91	0.04
4	UE dur^2	0.243	*0.062*	0.207	*0.038*	0.92	0.13	0.192	*0.043*	0.173	*0.036*	0.92	0.13	0.145	*0.013*	0.137	*0.032*	0.92	0.13
5	E-inflow*Udur	0.009	*0.004*	0.008	*0.003*	0.69	0.01	0.010	*0.004*	0.010	*0.002*	0.69	0.01	0.011	*0.008*	0.011	*0.004*	0.69	0.01
6	U rate + inflow	0.450	*0.103*	0.402	*0.116*	0.94	0.08	0.379	*0.119*	0.348	*0.139*	0.94	0.08	0.303	*0.146*	0.278	*0.165*	0.94	0.08
7	E rate	0.519	*0.135*	0.557	*0.145*	0.97	0.05	0.589	*0.155*	0.613	*0.170*	0.97	0.05	0.665	*0.185*	0.687	*0.199*	0.97	0.05
8	Inflow into E	0.031	*0.048*	0.042	*0.041*	0.98	0.32	0.032	*0.042*	0.039	*0.039*	0.98	0.32	0.033	*0.047*	0.035	*0.044*	0.98	0.32
9	Inflow wages	0.030	*0.046*	0.037	*0.036*	0.97	0.22	0.032	*0.041*	0.037	*0.035*	0.97	0.22	0.034	*0.048*	0.036	*0.042*	0.97	0.22
10	Wages / #7	0.869	*0.338*	0.863	*0.353*	0.99	0.01	0.862	*0.335*	0.870	*0.356*	0.99	0.01	0.915	*0.354*	0.926	*0.378*	0.99	0.01
11	EDur	0.615	*0.370*	0.563	*0.336*	0.99	0.12	0.729	*0.470*	0.677	*0.435*	0.99	0.12	0.860	*0.589*	0.850	*0.579*	0.99	0.12
12	Wages*Edur	0.612	*0.370*	0.570	*0.354*	0.99	0.10	*0.718*	*0.464*	0.678	*0.447*	0.99	0.10	0.907	*0.631*	0.907	*0.632*	0.99	0.10
13	Wages*Edur^2	1.138	*1.032*	0.989	*0.888*	0.99	0.18	1.358	*1.273*	1.210	*1.133*	0.99	0.18	1.751	*1.732*	1.700	*1.665*	0.99	0.18

Note: This table contains the mean and standard deviations on the time series of moments in the data and model for the treatment group in the Meetings Region (MR), see also Table 23 for the specific mapping into the model's state variables and action variables. U=unemployment, E=employment, dur=Duration. Results are reported separately for different education levels (low, medium, high). Moments in the model are solved using equation 15, see also Section 5.1. The data window is 70 weeks, and a time period is 2 weeks.

Table 8: Included time series of moments – Treatment group, AR

Education group		Low						Medium						High					
Treatment group		Data		Model		Stats		Data		Model		Stats		Data		Model		Stats	
#	Moment	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev
1	Inflow into U	0.014	*0.007*	0.014	*0.005*	0.735	0.055	0.012	*0.006*	0.011	*0.004*	0.795	0.086	0.010	*0.005*	0.005	*0.002*	0.877	0.520
2	Wages^2	0.476	*0.133*	0.517	*0.149*	0.984	0.087	0.576	*0.158*	0.588	*0.159*	0.965	0.020	0.587	*0.202*	0.579	*0.211*	0.984	0.013
3	Wages	0.508	*0.106*	0.519	*0.118*	0.988	0.023	0.589	*0.123*	0.582	*0.120*	0.960	0.013	0.585	*0.169*	0.580	*0.181*	0.980	0.010
4	UE dur^2	0.259	*0.042*	0.268	*0.043*	0.987	0.037	0.198	*0.058*	0.224	*0.063*	0.919	0.127	0.214	*0.061*	0.224	*0.074*	0.944	0.047
5	E-inflow*Udur	0.010	*0.007*	0.006	*0.006*	0.710	0.384	0.010	*0.005*	0.005	*0.003*	0.545	0.501	0.012	*0.006*	0.010	*0.004*	0.890	0.185
6	U rate + inflow	0.464	*0.111*	0.458	*0.125*	0.991	0.014	0.396	*0.126*	0.399	*0.125*	0.971	0.007	0.423	*0.163*	0.405	*0.183*	0.980	0.043
7	E rate	0.506	*0.139*	0.514	*0.150*	0.995	0.016	0.574	*0.158*	0.573	*0.157*	0.982	0.001	0.547	*0.185*	0.571	*0.204*	0.985	0.043
8	Inflow into E	0.030	*0.037*	0.030	*0.032*	0.922	0.002	0.031	*0.039*	0.029	*0.041*	0.982	0.044	0.030	*0.027*	0.026	*0.027*	0.973	0.104
9	Inflow wages	0.028	*0.033*	0.027	*0.028*	0.936	0.020	0.029	*0.039*	0.027	*0.037*	0.988	0.069	0.029	*0.027*	0.025	*0.024*	0.977	0.157
10	Wages / #7	0.842	*0.326*	0.848	*0.347*	0.982	0.007	0.858	*0.334*	0.849	*0.347*	0.985	0.011	0.903	*0.350*	0.857	*0.350*	0.982	0.051
11	EDur	0.602	*0.370*	0.594	*0.382*	0.996	0.013	0.715	*0.455*	0.720	*0.471*	0.999	0.006	0.659	*0.471*	0.727	*0.547*	0.998	0.104
12	Wages*Edur	0.575	*0.355*	0.589	*0.390*	0.992	0.025	0.704	*0.452*	0.712	*0.474*	0.998	0.011	*0.678*	*0.492*	0.720	*0.549*	0.998	0.061
13	Wages*Edur^2	1.057	*0.936*	1.077	*1.021*	0.995	0.019	1.323	*1.234*	1.361	*1.300*	1.000	0.028	1.241	*1.254*	1.357	*1.415*	0.999	0.093

Note: This table contains the mean and standard deviations on the time series of moments in the data and model for the treatment group in the Activation Region (AR), see also Table 23 for the specific mapping into the model's state variables and action variables. U=unemployment, E=employment, dur=Duration. Results are reported separately for different education levels (low, medium, high). Moments in the model are solved using equation 15, see also Section 5.1. The data window is 70 weeks, and a time period is 2 weeks.

Table 9: Included time series of moments - control group, MR

Meetings region		Low						Medium						High					
Treatment group		Data		Model		Stats		Data		Model		Stats		Data		Model		Stats	
#	Data Moment	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev
1	Inflow into U	0.015	*0.008*	0.021	*0.007*	0.713	0.423	0.014	*0.007*	0.018	*0.006*	0.663	0.295	0.010	*0.005*	0.011	*0.003*	0.819	0.098
2	Wages^2	0.442	*0.121*	0.485	*0.144*	0.814	0.097	0.603	*0.166*	0.587	*0.184*	0.906	0.026	0.714	*0.248*	0.841	*0.284*	0.988	0.111
3	Wages	0.473	*0.100*	0.504	*0.116*	0.797	0.067	0.604	*0.128*	0.606	*0.148*	0.902	0.004	0.699	*0.202*	0.759	*0.211*	0.987	0.012
4	UE dur^2	0.273	*0.062*	0.253	*0.046*	0.682	0.071	0.203	*0.044*	0.181	*0.034*	0.276	0.107	0.159	*0.047*	0.137	*0.057*	0.956	0.156
5	E-inflow*Udur	0.012	*0.007*	0.009	*0.003*	0.780	0.207	0.011	*0.006*	0.010	*0.003*	0.678	0.093	0.015	*0.011*	0.011	*0.005*	0.818	0.110
6	U rate + inflow	0.503	*0.107*	0.462	*0.119*	0.867	0.082	0.401	*0.129*	0.359	*0.150*	0.938	0.106	0.322	*0.193*	0.278	*0.192*	0.990	0.040
7	E rate	0.467	*0.131*	0.500	*0.141*	0.917	0.070	0.566	*0.158*	0.603	*0.177*	0.963	0.065	0.646	*0.219*	0.687	*0.216*	0.993	0.020
8	Inflow into E	0.030	*0.032*	0.039	*0.029*	0.961	0.278	0.033	*0.037*	0.039	*0.037*	0.977	0.177	0.033	*0.032*	0.035	*0.029*	0.967	0.005
9	Inflow wages	0.029	*0.032*	0.034	*0.025*	0.973	0.178	0.033	*0.039*	0.035	*0.031*	0.987	0.069	0.033	*0.032*	0.036	*0.028*	0.976	0.029
10	Wages / #7	0.843	*0.327*	0.847	*0.346*	0.982	0.005	0.890	*0.345*	0.844	*0.345*	0.984	0.052	0.913	*0.353*	0.926	*0.385*	0.984	0.033
11	EDur	0.522	*0.314*	0.490	*0.305*	0.997	0.061	0.671	*0.433*	0.663	*0.434*	0.999	0.012	0.805	*0.588*	0.850	*0.562*	1.000	0.043
12	Wages*Edur	0.494	*0.294*	0.484	*0.312*	0.994	0.020	*0.680*	*0.439*	0.642	*0.432*	0.999	0.057	0.843	*0.621*	0.907	*0.616*	0.999	0.016
13	Wages*Edur^2	0.884	*0.784*	0.820	*0.752*	0.999	0.073	1.257	*1.189*	1.138	*1.079*	1.000	0.095	1.577	*1.605*	1.700	*1.553*	1.000	0.033

Note: This table contains the mean and standard deviations on the time series of moments in the data and model for the control group in the Meetings Region (MR), see also Table 23 for the specific mapping into the model's state variables and action variables. U=unemployment, E=employment, dur=Duration. Results are reported separately for different education levels (low, medium, high). Moments in the model are solved using equation 15, see also Section 5.1. The data window is 70 weeks, and a time period is 2 weeks.

Table 10: Included time series of moments - control group, AR

Meetings region		Low						Medium						High					
Treatment group		Data		Model		Stats		Data		Model		Stats		Data		Model		Stats	
#	Data Moment	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev	Mean	S.D	Mean	S.D	Corr	%-dev
1	Inflow into U	0.016	*0.007*	0.011	*0.004*	0.595	0.321	0.013	*0.006*	0.009	*0.003*	0.780	0.296	0.010	*0.004*	0.005	*0.002*	0.834	0.487
2	Wages^2	0.353	*0.085*	0.480	*0.135*	0.954	0.358	0.514	*0.148*	0.522	*0.148*	0.974	0.015	0.616	*0.213*	0.603	*0.214*	0.988	0.022
3	Wages	0.394	*0.063*	0.452	*0.096*	0.929	0.147	0.534	*0.122*	0.516	*0.115*	0.966	0.033	0.612	*0.176*	0.597	*0.179*	0.984	0.025
4	UE dur^2	0.322	*0.099*	0.340	*0.097*	0.979	0.053	0.229	*0.062*	0.275	*0.081*	0.947	0.198	0.199	*0.050*	0.215	*0.065*	0.942	0.078
5	E-inflow*Udur	0.010	*0.005*	0.005	*0.002*	0.225	0.526	0.011	*0.006*	0.005	*0.003*	0.612	0.544	0.012	*0.006*	0.010	*0.004*	0.869	0.194
6	U rate + inflow	0.572	*0.069*	0.552	*0.093*	0.943	0.034	0.451	*0.128*	0.467	*0.118*	0.970	0.036	0.399	*0.169*	0.389	*0.180*	0.985	0.025
7	E rate	0.398	*0.096*	0.423	*0.115*	0.970	0.062	0.519	*0.152*	0.507	*0.144*	0.981	0.024	0.571	*0.192*	0.584	*0.203*	0.989	0.023
8	Inflow into E	0.030	*0.035*	0.025	*0.027*	0.946	0.173	0.030	*0.033*	0.026	*0.034*	0.960	0.125	0.030	*0.028*	0.027	*0.029*	0.967	0.104
9	Inflow wages	0.027	*0.033*	0.024	*0.025*	0.940	0.128	0.029	*0.032*	0.024	*0.031*	0.956	0.158	0.030	*0.027*	0.025	*0.027*	0.972	0.141
10	Wages / #7	0.822	*0.323*	0.896	*0.366*	0.979	0.090	0.861	*0.334*	0.851	*0.348*	0.984	0.012	0.905	*0.351*	0.861	*0.352*	0.983	0.048
11	EDur	0.410	*0.251*	0.488	*0.315*	0.999	0.191	0.604	*0.393*	0.631	*0.420*	0.999	0.045	0.691	*0.495*	0.750	*0.558*	0.999	0.086
12	Wages*Edur	0.386	*0.236*	0.514	*0.342*	0.998	0.331	*0.584*	*0.380*	0.625	*0.423*	0.998	0.070	0.714	*0.517*	0.747	*0.563*	0.999	0.046
13	Wages*Edur^2	0.674	*0.600*	0.950	*0.900*	0.999	0.409	1.051	*0.989*	1.188	*1.145*	1.000	0.130	1.313	*1.322*	1.416	*1.467*	1.000	0.079

Note: This table contains the mean and standard deviations on the time series of moments in the data and model for the control group in the Activation Region (AR), see also Table 23 for the specific mapping into the model's state variables and action variables. U=unemployment, E=employment, dur=Duration. Results are reported separately for different education levels (low, medium, high). Moments in the model are solved using equation 15, see also Section 5.1. The data window is 70 weeks, and a time period is 2 weeks.

Online Appendices

This appendix consists of three different sections. In Section B I discuss additional details and results related to the experiment and the empirical analysis in Section 3 in the paper. Section C is devoted to details regarding the solution of the model and the estimation process. Finally, Section D focuses on the estimated model and provides details regarding the model fit and the implications.

B Further details and tables for the experiment

This appendix presents further details and results about the data and various sample definitions. It complements Section 3 in the main text. First, I explain the data sources, definitions and construction of the sample in more detail. Second, I describe the analysis sample, and lastly, I report the results from the different regressions which are discussed in the main text.

B.1 Data and definitions

The data used in the analysis is extracted from administrative registers merged by the National Labor Market Authority into an event history data set, which records and governs the payments of public income transfers, records participation in MEP, and has information on periods of employment. The data includes detailed weekly information on: labor market status (employment, unemployment, in education, on leave, etc.) for a 100 week data window. Labor market status is calculated based on information from the register on payments of public income transfers. This data is subsequently merged with two other datasets BFL and IDA[29] in order to obtain further information, in particular monthly earnings (BFL), monthly hours (BFL) and the education level of workers (IDA). I calculate monthly hourly wages as earnings divided by registered hours. The wage distribution is trimmed at the 10th and 90th percentile (within education and treatment status groups) to avoid noise or outliers to affect the results.

The raw sample (excluding immigrants) consists of 3385 individuals who are either assigned to treatment or control groups. To have a more homogeneous sample, I disregard workers below the age of 22 and above the age of 58. The age restrictions are introduced to justify not modelleling alternatives such as retirement and entry into education in relation to unemployment in the model.

[29]IDA: Integrated Database for Labor Market Research. IDA is a matched employer-employee panel containing socioeconomic information on the entire Danish population. BFL: Employment Statistics for Employees. BFL contains monthly data on jobs, paid hours of work and earnings. Both data sets are available through servers at Statistics Denmark (see dst.dk).

The final sample has 3099 individuals who are followed for 100 weeks. The data is divided into subgroups depending on the educational level of the individual. There are 3 educational levels: low (individuals with only primary education and less than 12 years of education in total), medium (individuals with vocational education and 12-14 years of education), high (individuals with further education and above 14 years of education). Table 11 shows the division into subgroups defined by region, treatment status and education levels.

The final data identifies individuals in any public support schemes at a given point in time.[30] This group is the data equivalent of the unemployed in the job search model. As is typical for work based on administrative (high-frequency) register data of income transfers and earnings, there is a small residual 'self-sufficient' group where there is no information on neither wages nor public support in a given week.

This residual group may contain self-employed, black-sector workers and workers out of the labor force (including e.g. expats, housewifes), but it also contains individuals who have recently started working but where no payment has been recorded yet. In the analysis, individuals transitioning to this self-sufficiency state are therefore treated as individuals transitioning into employment, as this group is effectively individuals who have opted out of any public support scheme. For these workers I impute wages as the average wage within region, education and treatment status bins. Note that, as a result, the definition of employment is slightly different from the definition used in Maibom et al. (2017), as the model and the analysis in this paper focus on the decision of whether to stay in public transfers or not.

Lastly, note that in the final data I treat entry into (publicly subsidized) education as entry into any other public support scheme. In the data, less than 4% of workers transit from unemployment into some kind of education benefit after the experiment has started, and there are no statistically significant differences across treatment and control. Finally see Table 2 for statistics prior to the experiment, these were discussed in Section 2.3.

B.2 Data descriptives

Table 12 shows the result of a regression of employment status on treatment status for different regions and time periods. These results are discussed in section

[30] Due to very fast job finding and inaccuracies in determining the exact starting date of employment spells, there are individuals in the final data set who are never recorded with a full week of unemployment benefits. In the analysis, I treat these individuals as unemployed for the first week and then randomly terminate their unemployment spell within the next 2 weeks to smooth their job-finding rates and avoid a spike in the first week. To further deal with inaccuracies in explicit starting dates of employment and benefits, I require subsequent employment or unemployment spells, besides the initial spell which is left unrestricted, to be of at least two weeks of duration to be counted.

Table 11: Number of observations in different subgroups

Region	Meetings Region			Activation Region		
Education Groups	Low	Medium	High	Low	Medium	High
Control	211	376	137	102	298	396
Treatment	212	399	141	92	307	428

3 of the paper. Table 13 shows the results from the same regressions as in Table 12, now using the stricter employment criterion as in Maibom et al. (2017) (see also section 2.3). The effects are very similar, and the main findings remain although some of the effects are smaller in magnitude which suggests that a part of the response to treatment goes through self-sufficiency or self-employment and then later on to employment. In Table 14 I show that there are no statistically significant long-term effects from the experiment on self-sufficiency, and in Table 15 I show that there are no statistically significant differences with respect to the fraction of individuals working in part-time positions.

Table 16 presents the results from regressing a treatment status indicator on wages for the subset of individuals who have at least 5 months of employment (and thus 5 months of earnings) within the 100 weeks data window.[31] Keep in mind that since treatment status is no longer exogenous in post-unemployment periods, the results should be interpreted with great caution, see the discussion in Section 3.

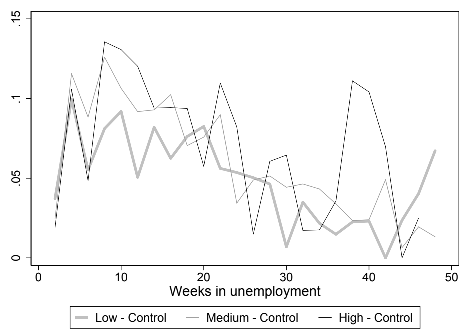
Lastly, I present three different dimensions of variation in the data which are linked to specific features of the model. First, Figure 4 shows the bi-weekly hazard rate out of unemployment for the control groups. In the model, duration dependence in the return to search (see equation 4) and dynamic selection among the unemployed are channels through which this pattern can arise. Second, Table 18 illustrates how the average hourly wage increases as a function of duration in employment. The level and the growth rate of wages also differ across education groups. In the model this is used as a way to discipline the evolution of unobserved (and timevarying) skills s. Third and lastly, Figure 5 shows the bi-weekly hazard rate out of employment spells formed after the start of the experiment for the control group. Data is pooled across regions to increase the number of observations and thus exits to unemployment. While noisy, it is clear from the figure that the hazard rate is (modestly) declining with the duration of time in employment, especially for low educated workers. The model captures this pattern by allowing the expected duration of a job to depend on the job offer

[31] As monthly hourly wages are calculated as earnings divided by registered hours, this cutoff was chosen to have a stable measure of hourly wages. Results are, however, not sensitive to this choice, see Table 17 for the same regressions, but now for individuals with at least 2 months of employment.

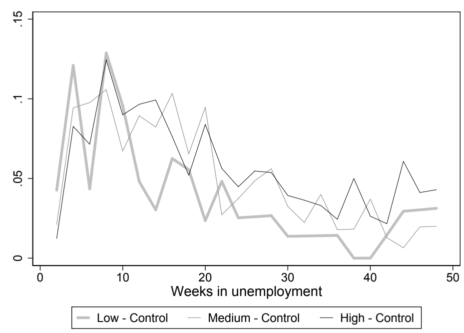
j and the level of skills s. See also the discussion in section 4.

Figure 4: Hazard rate out of unemployment for individuals in the control group

(a) Meetings region



(b) Activation region



Note: This figure plots the bi-weekly hazard rate out of unemployment as obtained via the Kaplan-Meier estimator. I include all spells which start during the first 40 weeks of the experiment. Results are reported separately from the two regions and for different education levels (low, medium, high).

Figure 5: Hazard rate out of employment

Note: This figure reports the bi-weekly hazard rate out of employment as obtained via the Kaplan-Meier estimator. The sample is the control groups from both regions. Results are reported separately for different education levels (low, medium, high).

Table 12: Employment effects of the experiment

	Meetings Region				Activation Region			
After 2 weeks	Low	Medium	High	Equality Test	Low	Medium	High	Equality Test
Treatment indicator	0.014	0.053*	0.035*	[0.21, 0.55, 0.55]	-0.017	0.031+	-0.006	[0.23, 0.77, 0.07]
	(0.025)	*(0.018)*	*(0.025)*		*(0.036)*	*(0.018)*	*(0.009)*	
After 4 weeks								
Treatment indicator	0.093*	0.064*	0.129*	[0.59, 0.64, 0.35]	-0.018	0.080*	0.004	[0.18, 0.75, 0.07]
	(0.044)	*(0.032)*	*(0.052)*		*(0.065)*	*(0.034)*	*(0.025)*	
After 10 weeks								
Treatment indicator	0.106*	0.037	0.144*	[0.26, 0.62, 0.12]	0.037	0.100*	-0.003	[0.45, 0.62, 0.05]
	(0.049)	*(0.036)*	*(0.059)*		*(0.072)*	*(0.041)*	*(0.034)*	
After 14 weeks								
Treatment indicator	0.115*	0.020	0.133*	[0.11, 0.81, 0.10]	0.138+	0.099*	-0.042	[0.63, 0.02, 0.01]
	(0.048)	*(0.035)*	*(0.058)*		*(0.071)*	*(0.040)*	*(0.035)*	
After 20 weeks								
Treatment indicator	0.068	-0.014	0.081	[0.16, 0.86, 0.16]	0.174*	0.049	-0.046	[0.12, 0.01, 0.07]
	(0.048)	*(0.034)*	*(0.056)*		*(0.071)*	*(0.039)*	*(0.034)*	
Observations	423	775	278		194	605	824	

Note: This table reports results from separate OLS regressions after 2, 4, 10, 14 and 20 weeks since the start of the experiment. The dependent variable is current employment status. Huber/White standard errors are reported in parentheses, + $p < 0.10$, * $p < 0.05$. Results are reported separately for the meetings and activation region and for different education levels (low, medium, high). The column "Equality test" report the p-values from a t-test of the null of equality of the estimates across the education groups. The tests are pairwise and in the order: (Low, Medium), (Low, High) and (Medium, High).

Table 13: Replicating Table 12 using an alternative employment criterion

	Meetings Region			Activation Region		
After 4 weeks	Low	Medium	High	Low	Medium	High
Treatment indicator	0.070+	0.029	0.081+	0.030	0.078*	0.016
	(0.040)	*(0.031)*	*(0.047)*	*(0.059)*	*(0.032)*	*(0.022)*
After 14 weeks						
Treatment indicator	0.102*	0.015	0.084	0.094	0.072+	-0.027
	(0.048)	*(0.036)*	*(0.059)*	*(0.070)*	*(0.041)*	*(0.035)*
Observations	423	775	278	194	605	824

Note: This table reports results from separate OLS regressions after 4 and 14 weeks since the start of the experiment. The dependent variable is employment status, i.e. not counting individuals in self-sufficiency; see Section B.1 and footnote 9. In Table 14 I additionally show that there is no statistically significant long-term impact on individuals in self-sufficiency: Huber/White standard errors are reported in parentheses, + $p < 0.10$, * $p < 0.05$. Results are reported separately for the meetings and activation region and for different education levels (low, medium, high).

Table 14: Fraction in self-support

	Meetings Region			Activation Region		
After 10 weeks	Low	Medium	High	Low	Medium	High
Treatment indicator	0.009	-0.003	0.027	0.010	0.025*	-0.015
	(0.026)	*(0.016)*	*(0.026)*	*(0.044)*	*(0.017)*	*(0.012)*
Constant	0.071*	0.051*	0.037*	0.098*	0.036*	0.037*
	(0.018)	*(0.011)*	*(0.016)*	*(0.031)*	*(0.011)*	*(0.001)*
After 20 weeks						
Treatment indicator	0.004	-0.001	0.020	0.021	0.020	0.002
	(0.025)	*(0.017)*	*(0.027)*	*(0.043)*	*(0.017)*	*(0.012)*
Constant	0.066*	0.059*	0.044*	0.087*	0.033*	0.021*
	(0.017)	*(0.012)*	*(0.018)*	*(0.030)*	*(0.010)*	*(0.008)*
Observations	423	775	278	194	605	824

Note: This table reports results from separate OLS regressions after 10 and 20 weeks since the start of the experiment. The dependent variable is an indicator of self-sufficiency (i.e. neither receiving public income support or registered earnings); see Section B.1 and footnote 9. Huber/White standard errors are reported in parentheses, + $p < 0.10$, * $p < 0.05$. Results are reported separately for the meetings and activation region and for different education levels (low, medium, high).

Table 15: Fraction in part-time positions

	Meetings Region			Activation Region		
After 10 weeks	Low	Medium	High	Low	Medium	High
Treatment indicator	0.056+	0.001	-0.004	-0.023	0.011	0.002
	(0.033)	*(0.025)*	*(0.040)*	*(0.044)*	*(0.030)*	*(0.022)*
Constant	0.104*	0.138*	0.124*	0.130*	0.150*	0.114*
	(0.021)	*(0.018)*	*(0.028)*	*(0.035)*	*(0.020)*	*(0.015)*
After 20 weeks						
Treatment indicator	-0.024	0.015	0.026	0.019	-0.012	-0.02
	(0.033)	*(0.025)*	*(0.036)*	*(0.047)*	*(0.029)*	*(0.023)*
Constant	0.147*	0.130*	0.088*	0.109*	0.156*	0.129*
	(0.024)	*(0.017)*	*(0.024)*	*(0.033)*	*(0.021)*	*(0.016)*
Observations	423	775	278	194	605	824

Note: This table reports results from separate OLS regressions after 10 and 20 weeks since the start of the experiment. The dependent variable is an indicator for part-time work (i.e. reported hours less than 35 hours per week); see Section B.1. Huber/White standard errors are reported in parentheses, + $p < 0.10$, * $p < 0.05$. Results are reported separately for the meetings and activation region and for different education levels (low, medium, high).

Table 16: Wage effects of the experiment

	Meetings Region			Activation Region		
	Low	Medium	High	Low	Medium	High
Treatment indicator	2.332	-3.907*	0.447	3.515	-1.287	-0.0359
	(2.451)	*(1.762)*	*(2.694)*	*(3.560)*	*(2.032)*	*(1.443)*
Constant	94.29*	100.1*	101.7*	90.18*	96.50*	100.9*
	(1.722)	*(1.252)*	*(1.773)*	*(2.649)*	*(1.385)*	*(0.967)*
N	303	612	250	126	475	754

Note: This table reports results from separate OLS regressions for individuals with at least 20 weeks of employment within the first 100 weeks in the meetings and activation region and for different education levels (low, medium, high). The dependent variable is the hourly wage in DKK (2008); see Section B.1. Huber/White standard errors, + $p < 0.10$, * $p < 0.05$.

Table 17: Wage effects of the experiment (including shorter spells)

	Meetings Region			Activation Region		
	Low	Medium	High	Low	Medium	High
Treatment indicator	-1.364	-2.002*	0.290	4.172	-0.275	-0.328
	(2.244)	*(1.714)*	*(2.745)*	*(3.046)*	*(1.946)*	*(1.471)*
Constant	94.29*	98.84*	101.2*	89.58*	96.53*	100.6*
	(1.722)	*(1.224)*	*(1.896)*	*(2.183)*	*(1.364)*	*(1.006)*
N	334	664	260	142	502	733

Note: This table shows results from separate OLS regressions for individuals with at least 10 weeks of employment within the first 100 weeks in the meetings and activation region and for different education levels (low, medium, high). The dependent variable is the hourly wage in DKK (2008); see Section 2.3. Huber/White standard errors are reported in parentheses, + $p < 0.10$, * $p < 0.05$

Table 18: Wage growth while employed

	(1)	(2)	(3)	(4)
Employment duration	20 weeks	40 weeks	60 weeks	80 weeks
Low Education	0.011*	0.022*	0.026*	0.034*
	(0.005)	*(0.006)*	*(0.007)*	*(0.009)*
Medium Education	0.009	0.025*	0.027*	0.023*
	(0.003)	*(0.004)*	*(0.005)*	*(0.006)*
High Education	0.024*	0.0401*	0.052*	0.071*
	(0.003)	*(0.004)*	*(0.005)*	*(0.006)*
N	2098	1766	1416	938

Note: This table shows results from separate OLS regressions for employed workers after 20, 40, 60, 80 weeks in employment and for different education levels (low, medium, high). The dependent variable is the difference in LogWages between current and entry wages. Data is pooled across regions and treatment/control groups. Results should be interpreted cautiously as there is obviously dynamic selection out of employment. Huber/White standard errors are reported in parentheses, + $p < 0.10$, * $p < 0.05$

C Solution and estimation of the model

In this appendix, I provide additional details about the solution and estimation of the model. In Section C.1 I explain how to solve the model, and in Section C.2 I show how to construct model predictions and move towards estimation. In Section C.3 I provide details regarding the estimation. I present the parameters (and values) which are set prior to estimation, and I then present the parameters which are estimated and provide details on the moments which are used in estimation. Overall, these three sections complement Section 5.1 in the main text. Finally in Section D.5 I explain how to calculate the compensating variation. The section complements the discussion in section 7 of the main text.

C.1 Model solution

I solve the model in a series of steps presented in Section 5.1.

1. Solve for $V(\theta)$ in (7) using the contraction mapping properties. I use the method of successive approximations and error bounds suggested by McQuad and Porteus (see Rust (1986)). Ferrall (2004) presents conditions under which $V(\theta)$ is a contraction mapping, these conditions are satisfied in the model. The convergence criteria in the contraction mapping is 10^{-7}, and the objective is the square root of the sum of squares.

2. Calculate the policy function $P(\alpha|\theta)$ as given in (8).

3. Use the transition function for state variables $P(\theta'|\theta, \alpha)$ and the policy function $P(\alpha|\theta)$ to solve for how the distribution over states evolves from one period to the next unconditional on choices $P(\theta'|\theta)$.

$$P\left(\theta'|\theta\right) = \sum_{\alpha} P\left(\alpha|\theta\right) P\left(\theta'|\alpha, \theta\right) \tag{9}$$

   The state-to-state transition function allows us to track the evolution of the state space from some t to some $t+k$ exploiting that the model is Markovian (i.e. solving for the distribution of states at $t+k$ requires sequentially iterating on the Markov chain k times). Given an initial distribution over states, the distribution of states at a given point in time can thereby be solved for. The remaining challenge is to specify an initial distribution across states. This is further complicated by the fact that some state variables are unobserved, and therefore an initial distribution over states is also unobservable. As explained in the main text, this problem is solved by sampling from the ergodic distribution across states.

4. Use the state-to-state transition matrix $P(\theta'|\theta)$ to solve for the ergodic distribution across states $\Omega^*(\theta)$.

$$P_{ergodic}(\theta) = \sum_{\theta'} P(\theta'|\theta) P_{ergodic}(\theta) \quad (10)$$

The ergodic distribution specifies how individuals are distributed across states in the economy in steady state. From this distribution the inflow into unemployment can be determined. The ergodic distribution is found by solving for the fixed point in equation (10), see also Judd (1998). Ferrall (2004) presents conditions for the existence of the ergodic distribution, these conditions are satisfied in the model (see also Table 22). The convergence criteria in the fixed point problem is 10^{-5}, and the objective is the square root of the sum of squares.

5. Use $\Omega^*(\theta)$ and the $P(\theta'|\theta)$ and sample an initial distribution across states $\Omega(\theta|t=0)$ which matches the data on observables (e.g. unemployment duration).

6. Solve for $\Omega(\theta|t)$ by iterating on the Markov chain starting from $\Omega(\theta|t=0)$ and using $P(\theta'|\theta)$. Formally:

$$\Omega(\theta|t) = P(\theta'|\theta)^t \, \Omega(\theta|t=0) \quad (11)$$

7. For each t determine the distribution across a reduced set of states $\Omega^{RED}(\theta|t, t+k)$ for workers satisfying certain spell requirements between t and $t+k$.

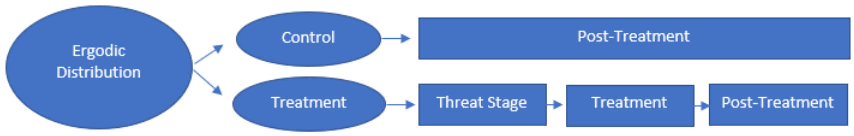
$$\Omega^{RED}(\theta|t, t+k) = P^{RED}(\theta'|\theta)^k \, \omega_t^{INFLOW}(\theta) \quad (12)$$

where $\omega_t^{INFLOW}(\theta)$ denotes the inflow into employment in period t. $P^{RED}(\theta'|\theta)^k$ is a transition matrix which has non-zero entries for transitions which implies that the individual stays employed. $\Omega^{RED}(\theta|t, t+k)$ gives the fraction of individuals who have been employed for k periods at time $t+k$ and the distribution across state variables θ.

Generally speaking, tracing the distribution of skills and other state variables across different employment durations requires either a) adding duration in employment as a state variable, b) simulating the model and directly computing moments or c) doing further calculations. I follow c). The inner chain calculates the distribution of e.g. employment duration over time, although employment duration is not a state variable in the model. A recent paper by Eisenhauer et al. (2015) documents that the simulation error that exists in models exploiting simulated moments can affect the estimates in non-trivial ways.

Lastly, in Figure 6 I illustrate the timing of the model. Workers entering the experiment are sampled from the unemployment inflow (or stock) in the ergodic distribution and then go through a series of treatment stages, see Section 4. See also Table 1 for the content of the different stages in the experiment.

Figure 6: Timing in the model



Note: This figure illustrates the timing in the dynamic job search model.

C.2 Constructing model predictions

To calculate the predictions of the model, I first define the expected value of a certain outcome conditional on a position in the state space θ:

$$E\left(M|\theta\right) = \sum_{\alpha} P\left(\alpha|\theta\right) M\left(\alpha,\theta\right) \tag{13}$$

where $M\left(\alpha,\theta\right)$ is a given outcome which may vary as a function of both choices α and the position in the state space θ. Examples of outcomes are "accepting a job of type θ" and "the duration of the current unemployment spell", see also Table 23. To generate model predictions at time t, $E\left(M|\theta\right)$ is weighted by $\Omega\left(\theta|t\right)$. Keep in mind that t counts time since the start of the experiment. These predictions are determined separately for the time invariant states: patience pg, education eg, region rg, treatment groups tg and for different initial unemployment durations at the start of the experiment $cu_{t=0}$.[32] Repeating this calculation for each t results in a series of moments within these subgroups:

$$E\left[M_M|t,eg,rg,tg,pg,cu_{t=0}\right] = \sum_{\theta_{|pg,eg,rg,tg}} \Omega(\theta_{|k,e,r,g}|t,pg,eg,rg,tg,cu_{t=0})E\left(M|\theta\right) \tag{14}$$

Next, moments are weighted with the distribution over pg and $cu_{t=0}$:

$$E\left[M_M|t,eg,rg,tg\right] = \sum_{pg,cu_{t=0}} \lambda\left(pg,eg,rg,cu_{t=0}\right) E\left[M_M|t,eg,rg,tg,pg,cu_{t=0}\right] \tag{15}$$

where $\lambda\left(pg,rg,eg,cu_{t=0}\right)$ is the share of type pg,$cu_{t=0}$ individuals in the specific education/region group. Note that $\lambda\left(pg,eg,rg,cu_{t=0}\right)$ will change with $cu_{t=0}$ as types differ in the speed at which they find employment. $\lambda\left(pg,eg,rg,cu_{t=0}\right)$

[32]The notation $cu_{t=0}$ therefore holds the value of the state variable d at the start of the experiment. The notation $\theta_{|eg}$ refers to the set of state variables excluding the state variable eg. The conditioning on initial unemployment durations is needed for two reasons: 1) to take into account that the distribution across patience types differs across different unemployment durations as more patient types leave unemployment faster, 2) to appropriately adjust for sampling weights such that the model predictions are based on a sample which matches the data on observables (e.g. the share of long-term unemployed). See also Section 5.1 and Section C.2.1.

takes this dynamic selection into account (further details are outlined in Section C.2.1).
In the next step, model predictions are compared to data predictions:

$$\left(E\left[M_D|t,eg,rg,tg\right]-E\left[M_M|t,eg,rg,tg\right]\right)'W\left(E\left[M_D|t,eg,rg,tg\right]-E\left[M_M|t,eg,rg,tg\right]\right) \tag{16}$$

I set the weight matrix (W) to a diagonal matrix with the inverse variance of the data moments in the sample along the diagonal.[33] As a final step I sum over time periods and education, region and treatment status groups and minimize the objective.

To calculate standard errors I create a long vector stacking the vectors of moments from 16 (summed across groups eg, rg, tg) over the different t periods. I then use this long form objective and calculate standard errors for the standard one stage GMM case (see e.g. Cameron and Trivedi (2008)):

$$\text{Var}\left(\Theta\right)=\frac{1}{N}\left(\hat{G}'W\hat{G}\right)^{-1}\hat{G}'W\hat{S}W\hat{G}\left(\hat{G}'W\hat{G}\right)^{-1}$$

where Θ denotes the vector of parameters to be estimated, $\hat{G}$ is the Jacobian matrix and $\hat{S}$ the sample variance co-variance matrix of the long vector of moments.[34]

C.2.1 Dynamic selection

I now explain how to calculate $\lambda\left(pg,eg,rg,cu_{t=0}\right)$, i.e. the share of individuals of type pg who start out the experiment with unemployment duration $cu_{t=0}$. For unemployed $cu_{t=0}=0$ the probability $\lambda\left(1,eg,rg,0\right)$ is equal to $\tau^{rg,eg}_{patient}$, i.e. the estimated share of patient individuals (see Table 21). But for individuals with longer unemployment durations $cu_{t=0}>0$, the distribution over types will have changed as types differ in the speed at which they find employment. $\lambda\left(1,cu_{t=0}=x,eg,rg\right)$ is therefore determined as the relative importance of the patient type in the part of the ergodic distribution with $cu=x$, this expression is then multiplied by $\tau^{rg,eg}_{patient}$. Formally for $x>0$:

[33] In order to avoid excessive weight on the (noisy) moment related to layoffs and employment dynamics, moments #1, #11- #13 in Table 23 receive a lower weight. Further, because the key identifying variation exists in the early stages of the experiment, moments from the early time periods (first 10 periods) receive some extra weight. In practice the importance of this “extra” weighting is not important once the optimization is started from the current optimum. This should mainly be seen as a way to help the optimization process away from local saddle-points during estimation and thus reach the optimum faster.

[34] The dimensions on $\hat{G}$ are thus #timeperiods*moments,#estimated parameters, and for $\hat{S}$ the dimensions are #timeperiods*moments,#timeperiods*moments. N is the number of units in the sample which is 3099.

$$\lambda\left(1, eg, rg, cu_{t=0}=x\right)=\left(\frac{\sum \Omega^{*}\left(\theta \mid pg=1, cu=x\right)}{\sum \Omega^{*}\left(\theta \mid pg=0, cu=x\right)+\sum \Omega^{*}\left(\theta \mid pg=1, cu=x\right)}\right) \cdot \tau_{patient}^{rg,eg}$$

C.2.2 Estimation and optimization

The model solution and estimation is implemented in Ox (`www.doornik.com`). Due to the many steps in model solution and the relatively large computational tasks involved, the model solution is parallelized such that the model and predictions are solved within rg, pg and eg groups. For optimization I use the FiveO optimizer which is a part of the niqlow package for Ox: `http://ferrall.github.io/niqlow/niqlow.ox.html`. The optimum is found by starting out with a series of simplex (NelderMead) searches, and when the optimum is closer I switch to gradient based methods (BFGS). Arriving at model estimates on a 20-core unit takes approximately 3 weeks from initial estimation.

C.3 Estimation details

The different subsections below first present the parameters (and values) which are set prior to estimation. I then present the parameters which are estimated and provide details on the moments which are used in estimation.

C.3.1 Overview state and action space

Table 19 shows the elements of the state space and complements Table 3 in the main text with some additional details about whether the state variable is observed in the data and how it changes over time. Given the different state variables and the grid size for each variable, the potential state space is very large, but it can be heavily reduced by deleting non-reachable and irrelevant combinations of state variables such as unemployment duration dynamics while employed (since $d = 0$ when $e = 1$). [35]

Looking within each education and patience group, there are 834 different relevant states for the control group, 6672 different relevant states for the treatment group in the MR and 18900 different relevant states for individuals in the AR. The state space is larger for the treatment groups due to the inclusion of $\theta_{experiment}$, and it is particularly large for the AR because the TH stage is longer here. In addition there are 2 regions, 3 education groups and 2 patience groups for whom value functions must be solved separately. As the computational tasks are already quite intensive (see Section C.1 below), I can only make limited experimentation with changing the grid size of state variables, however transition

[35]Further, during value function iterations, see section C, the code secures that only relevant future states are visited.

functions and other primitives are generally set up such that they would not change if grid size was increased.

Table 19: Elements of the state space

State variable	Symbol	Grid size	Grid values	Data	Key transition characteristics
Education group	eg	3	$\{0,1,2\}$	Observed	none
Regional group	rg	2	$\{0,1\}$	Observed	none
Treatment group	tg	2	$\{0,1\}$	Observed	none
Time preference group	pg	2	$\{0,1\}$	Unobserved	none
Unemployment duration	d	10	$\{0,\frac{1}{9},...,\frac{9}{9}\}$	Observed	count variable
Job offer	j	6	$\{0,\frac{1}{6},...,\frac{5}{6}\}$	Unobserved	$T_{job}(\alpha,\theta)$, see Equation 4
Meetings status	m	2	$\{0,1\}$	Observed	$\pi_m^{control}$, see Table 20*
Activation status	a	2	$\{0,1\}$	Observed	$\pi_a^{control}$, see Table 20*
Skill level	s	6	$\{0,\frac{1}{5},...,\frac{5}{5}\}$	Unobserved	$\pi_{s,up}$ and $\pi_{s,dw}$
Employment status	e	2	$\{0,1\}$	Observed	$T_{lj}(\alpha,\theta)$, see Equation 5
Treatment stage	ts	3	$\{0,1,2\}$	Observed	count variable (TH, T or PT stages)
Duration in stage	ds	6	$\{0,1,..,5\}$	Observed	count variable**

Note: This table presents the different elements of the state space θ. A time period in the model corresponds to 2 weeks in the data. * The treatment group participate in MEP with certainty in the T-stage of the experiment (see Table 1), in all other stages (and in the control group) transition into future MEP participation is stochastic. ** the duration of a given stage follows the timing of events as in Table 1, i.e. in the MR the TH stage is 1 period, the T stage is 6 periods.

C.3.2 Empirical implementation of the wage function:

The state variable j takes six different values, where $j = 0$ implies that no job offer is currently available. As specified in Table 3 the grid values for j are specified as $\left\{0, \frac{1}{6}, \frac{2}{6}, \frac{3}{6}, \frac{4}{6}, \frac{5}{6}\right\}$. To generate a non-uniform wage distribution, I map these values of j into respective quantiles of the normal cdf Φ to generate a more natural grid on the range of job offers. This also ensures that wage dispersion does not depend on the overall grid size of j as such. To ease interpretation of the parameter estimates across education groups, I additionally add $\sigma^{eg} \cdot |\Phi^{-1}\left(\frac{1}{6}\right)|$ to the wage function (such that the job offer part always affects wages positively). This ensures that a higher σ for a given education group also means that this group has higher average wages.
Formally the wage function for $j > 0$ is therefore determined as:

$$W(\alpha,\theta) = \exp\left(\mu + \sigma^{eg}\tilde{j} + \eta \cdot \mathrm{s} + \sigma^{eg} \cdot |\Phi^{-1}\left(\frac{1}{\#\text{points}(j)+1}\right)|\right)$$

where $\tilde{j} = \Phi^{-1}(j)$.

$\sigma^{eg}j$ represents the search sensitive part of wages, i.e. the part individuals can affect by either accepting a current offer or rejecting it. Note that reservation wages will generally be revised as unemployment duration increases, which is why an analytical expression is not obtainable as in the more standard case, see also Wolpin (1987).

C.3.3 Fixed parameter and values:

I now discuss the parameters in the model which are not estimated, but fixed and set prior to estimation. For an overview of these parameters, see Table 20.

As explained in Section 4 the income of the individual, $Y(\alpha, \theta)$, is determined as the wage $W(\alpha, \theta)$ when employed (presented in equation 3) and UI benefits when unemployed. I set the level of the hourly after-tax UI payment to 66 DKK which corresponds to the hourly maximum UI payment in 2010 after taxes (using the same assumed tax rate as above, see section 2.3). This is also equivalent to the after-tax average hourly wage in 2010 multiplied by the average replacement level in UI around 2010, $192 \cdot (1 - 0.375) \cdot 0.55 = 66$ DKK. See Maibom et al. (2017) for more on UI payments and replacement levels. The UI payment while unemployed is a flat rate, and duration is unlimited.

As explained in Section 4 in the main text, the control group also participates in MEP but of course at a much lower intensity. I set the exogenous probabilities of participating in MEP in absence of the experiment as follows: In absence of the experiment (or in the control group), meetings occur randomly with probability $\pi_m^{control} = 0.15$. Participation in a meeting lasts one period. The probability of participation in an activation program, $\pi_a^{control}$, is 0 during the first 10 weeks of unemployment, hereafter it increases with unemployment duration until an intensity of 0.35. When already in activation, there is a probability of 0.30 that you stay in activation in the next period as well. The parameters are chosen in order to match the meetings and activation intensity in the control group documented in Maibom et al. (2017). The treatment group faces the same participation probabilities as the control group in the TH and PT stages (see Table 1). In the treatment stage they participate in either activation or meetings with probability 1.

I allow for different patience types in the environment. In the implementation $pg = 2$, and the types have a biweekly time preference parameter of $\delta^{impatient} = 0.995$ (the impatient type) and $\delta^{patient} = 0.999$ (the patient type), which correspond to a yearly interest rate of 14% and 3% respectively, see also equation 7. While the time preference parameters are set prior to estimation, the distribution is estimated with parameter $\tau_{patient}^{rg,eg}$. While the discount rate can in principle be estimated exploiting some of the non-stationary features of the environment (see Wolpin (2013)), I treat it as fixed to leverage identification of utility costs of MEP further.

Finally π_{lj}^{MR} is a scale parameter in $T_{lj}(\alpha, \theta)$, see Equation 5 and the discussion there.

Table 20: Other parameters in the model (not estimated)

Symbol	Model	Value (Control group)
$\pi_m^{control}$	Meetings probability*	$\pi_{mp} = 0.15$
$\pi_a^{control}$	Activation probability*	$\pi_a^{control} = \min\{0.1 \cdot d, 0.35\}$
$\delta_{impatient}$	Discount rate, impatient	0.995
$\delta_{patient}$	Discount rate, patient	0.999
UI	UI level	66 DKK
π_{lj}^{MR}	Layoff process	1

Note: This table provides an overview of the parameters which are fixed prior to estimation. * In the treatment stage $(ts = 1)$ $\pi_a^{control}$ and $\pi_m^{control}$ are set to 1 for the treatment group.

C.3.4 Parameters to be estimated:

Tables 21 and 22 provide an overview of the parameters to be estimated. In total I am estimating 43 parameters, and there are 156 model moments (13 moments, 2 regions, 3 education groups and 2 treatment status groups) observed over 35 two-week periods, resulting in 5460 potential predictions, see the discussion in Section 5.2.

Table 21: Estimated parameters: Utility or wages

Symbol*	Model	Note	Dimensions**
γ	Utility	Curvature utility, see equation 2	1
ξ	Utility	Search cost, see equation 1	1
κ^{eg}	Utility	Work cost, see equation 1	dim(eg)
ϕ_m^{eg}	Utility	Meetings cost, see equation 1	dim(eg)
ϕ_a^{eg}	Utility	Activation cost, see equation 1	dim(eg)
$\tau_{patient}^{rg,eg}$	Type	Fraction of patient type	dim(eg·rg)
μ	Wages	Wage constant, see equation 3	1
σ^{eg}	Wages	Return to J, see equation 3	dim(e)
η	Wages	Return to s, see equation 3	1
ρ	Smoothing	Smoothing kernel, see equation 8	1

Note: This table presents the preference and wage parameters which are estimated; see also Section 5.1. Table 20 provides an overview of other model parameters that are not estimated, e.g. the meetings intensity for the treatment and control groups. * The notation κ^{eg} implies that κ is a vector where each element is an education specific entry. **the notation dim(k) implies that the parameter is group-specific and varies with the number of unobserved types (k).

Table 22: Estimated parameters: Transition functions

Symbol	Model	Note	Dimensions*
$\pi^{rg}_{job,d}$**	Job offers	Duration dependence, see equation 4	dim(rg)
π^{eg}_{job}	Job offers	Long-term job offer, see equation 4,***	dim(eg)
$\pi^{eg}_{job,m}$	Job offers	Productive effect (meeting), see equation 4	dim(eg)
$\pi^{eg}_{job,a}$	Job offers	Productive effect (activation), see equation 4	dim(eg)
$\pi_{lj,j}$	Layoff process	Impact of job type, see equation 5,***	1
$\pi^{eg}_{lj,s}$	Layoff process	Impact of skills, see equation 5	dim(eg)
π^{AR}_{lj}	Layoff process	Regional-specific scale effect, see equation 5,***	1
$\pi^{eg}_{up,s}$	Skill level	Appreciation of skills	dim(eg)
$\pi_{dw,s}$	Skill level	Loss of skills***	1

Note: This table presents the estimated parameters which govern the evolution of state variables, see also Section 5.1. *the notation dim(rg) implies that the parameter is group-specific and varies over regions. ** The notation $\pi^{rg}_{job,d}$ implies that $\pi^{rg}_{job,d}$ is a vector where each element is a region specific entry. *** To ensure the existence of an ergodic distribution (see also Section C.1), this parameter must be strictly larger than 0.

C.3.5 Model moments:

Table 23 presents the moments used in estimation. In Section C.2 I explain how to solve for model predictions. The moments are population moments, i.e. #1 gives the share of individuals who lost their jobs transitioning into the current period unconditional on them being employed in the previous period.[36] Note that the time series of moments #1, #5, #8 and #9 are smoothed versions of the data in order to reduce noise due to few observations (the smoother is a span-3 smoother with binomial weights).

The time series used in estimation is 70 weeks or 35 periods in the data and model respectively - see the last column in Table 23 for the exact periods used for each moment. By construction everyone is unemployed in period 1, and therefore employment dynamics are only used from period 2. Moments related to wage/employment dynamics are only used from periods 5-35 to secure an appropriate number of observations in the data. For means and standard deviations on the time series of moments in the data and model respectively, see Tables 7, 8, 10 and 9.

[36]Of course this conditioning is implicit as the model is simultaneously forced to fit the share of individuals in employment.

Table 23: Included time series of moments

#	Data Moment	Model Moment, $M(\alpha, \theta)$, see Table 3	Periods used
#1	Inflow into U	$(1 - wc) \cdot (e)$	5-35
#2	Wages squarred	$(W(\alpha, \theta) \cdot e)^2$	5-35
#3	Wages	$W(\alpha, \theta) \cdot e$	5-35
#4	UE dur squarred	d^2	1-35
#5	E-inflow* UE dur	$wc \cdot (1 - e) \cdot d^2$	1-35
#6	UE stock + inflow	$(1 - e) + (1 - wc) \cdot (e)$	1-35
#7	Employment rate	e	2-35
#8	Inflow into E	$wc \cdot (1 - e)$	1-35
#9	Inflow wages	$wc \cdot (1 - e) \cdot W(\alpha, \theta)$	1-35
#10	Wages conditional on E	#3/#7	5-35
#11	E-Dur	emdur	5-35
#12	Wages * E-dur	$W(\alpha, \theta) \cdot$ #11	5-35
#13	Wages * E-dur squarred	$W(\alpha, \theta) \cdot (\#11)^2$	5-35

Note: This table presents the different moments exploited in estimation. For an introduction of how to construct the final model predictions and $M(\alpha, \theta)$, see Section C.2. For an overview of state variables, see Table 3 and 19. Model and data moments are always calculated based on the whole sample, i.e. not only for individuals in e.g. employment. UE: unemployment; E: employment; dur: accumulated duration in state; emdur: accumulated duration in E. Wages from the data are after imputed taxes and divided by 100. d and *emdur* are capped at 10 and divided by 10 in the data and model. The time series of moments #1, #5, #8 and #9 are smoothed versions of the data in order to reduce noise due to few observations (the smoother is a span-3 smoother with binomial weights). The time series is 35 periods - see the column "periods used" for deviations from this.

C.4 Calculating the CV

The CV is calculated separately for each θ_{init}, the initial state when entering the experiment, defined as states in $\Omega(\theta|t=0)$, with probability mass above 0.01 (see Section 5.1).

$$V\left(\theta_{\text{enviroment}}|\text{tg=treatment}, CV\left(\theta_{\text{init}}\right)\right) = V\left(\theta_{\text{enviroment}}|\text{tg=control}\right) \quad (17)$$

In practice, $CV(\theta_{init})$ is solved as a minimization problem where the objective is the difference in value functions[37] between the treatment and control groups. Subsequently, I calculate the average CV by weighting $CV(\theta_{init})$ with the distribution over states at inflow into the experiment and multiplying by the number of periods with payment, i.e. the accumulated duration of stages TH and T.

Since the utility function is non-linear, solving $CV(\theta_{init})$ for a given θ_{init} implies that the contraction mapping should be resolved for each guess of compensation. Any compensation may change both current and future actions and states. Further, as a part of the individuals in the model are "impatient", I have also tested compensation schemes that only involve payments in the TH or T stage. The difference in the total compensation between these schemes is small and does not affect the results, see Appendix D.5 Table 25. Lastly, the average CV is also affected by education and regional differences in the distribution across states at the start of the experiment. Appendix D.5 Table 25 shows the average CV for a common benchmark distribution and also shows that this does not drive the results reported below.

[37] Note that the choice probability smoothing (or trembling) as in equation 8 does not affect the size of the CV as this smoothing only occurs ex-post and, therefore, does not affect the value function iteration or the value of the different alternatives.

D Model estimates and implications:

In this appendix I provide additional details and results regarding the fit of the model and some counterfactual experiments. This complements the discussion in Section 6. Lastly I also provide additional details and discussions to the results i Section 7 of the paper.

D.1 Supplementary graphs on model fit

Figure 7 focuses on the fit of the model with respect to the employment rate for the control groups. It is therefore a supplement to Figure 2 in the main text.

D.2 Model Estimates and model primitives

In this section I discuss the model's transition functions and other important objects as implied by the estimates in Table 4, such as the probability of getting a job offer, the wage function and the probability of losing a job. Lastly, I present some key moments describing the ergodic distribution of workers underlying the model environment.

Figure 8a shows the return to search as a function of unemployment duration (see equation 4). The model estimates imply strong duration dependence in the return to search – after 20 weeks, the return to search is less than 50% of its initial level. Kroft et al. (2013) report a decline in the average callback rate of around 45% in an eight-month window. My results are thus broadly in line with this, although the decline occurs already within the first 20 weeks in my model.[38]

The duration dependence in the return to search implies that individuals are likely to search more in the initial weeks of unemployment, as illustrated in figure 9a which shows how search decisions differ by unemployment duration. The figure plots the search policy, i.e. the probability distribution over different levels of search activity as determined by the policy function defined in 8, for individuals with 1 and 8 weeks of unemployment. The figure shows that the newly unemployed are more likely to search more intensively (dark colors reflecting higher levels of search) than the longer-term unemployed, all else equal. The level of skills of the unemployed also affects the intensity of search, as illustrated in figure 9b which shows the search policy for individuals with low and high skills. The figure shows that high-skilled workers, all else equal, search at higher levels than low-skilled workers.

[38]Figure 11 Appendix A shows the fit of the model with estimates as in Table 4, but now without duration dependence. This specification is not able to generate the spike initially in outflow rates followed by lower rates in the longer run. Generally different model fits either have too low initial outflow from unemployment, and/or the model tends to overpredict long-term employment levels.

Figure 8b shows the wage function as a function of the job type j. The return to job offers, σ^{eg}, is higher for medium and high educated individuals, which increases the average level and dispersion of wage offers. For low educated workers, the wage function is flat, implying that there is little incentive for low educated workers to reject job offers for better offers in the future on this margin.[39]

Figure 10 plots the per-period probability of losing a job as a function of the job type j or the level of skills s. The figure shows that the type of job not only affects the offered wage, but also the expected duration. This implies that there is an additional cost for the unemployed in changing their reservation wages and accepting a lower j. For low educated workers, their level of skills also affects the probability of losing employment as low-skilled individuals face a higher probability. This is not the case for medium and high educated workers as the parameters are quantitatively small and statistically insignificant for these workers. This aligns well with the educational differences in the hazard rate out of employment in the data; see figure 5 in Appendix B.

Finally, Table 24 presents some key moments in the ergodic distribution $\Omega^*(\theta)$, defined in Section 5.1. Overall, the model environment consists of two different types of individuals. An impatient type who prefers lower levels of search leading to longer unemployment durations and lower skills, and a more patient type who, due to lower discounting of the future, values future employment higher and, thus, searches more, see table 20 for the specific parameterization. The more patient type is generally the dominant one, especially in the MR (see the estimates in Table 21) where the impatient type also has a very low employment rate in the ergodic distribution for low and medium educated workers. Note, however, that the employment rate in the ergodic distribution says something about the long term employment rate for this type of workers only. It is thus silent about the immediate impacts of the experiment and the employment history of impatient workers who are enrolled into the experiment, since they are by construction sampled as either coming directly from employment or with unemployment durations as given in the data (see also the discussion in Section C.2 and C.2.1).

D.3 Model fit - in an alternative specification

To illustrate the importance of duration dependence in the return to search, Figure 11 shows the fit of the model with estimates as in Table 4, but now without

[39] There may be limited dispersion in wage offers for low educated workers (once skill/experience effects are accounted for) as the wage setting in Denmark is also partly coordinated at industry/sector level which sets minimum wage levels (wage floors). In some sectors, these minimum levels are binding for low-skilled workers, limiting the role of wage dispersion for job seekers.

Table 24: Key moments describing the ergodic distribution

Region	Meetings					
Educational group	Low		Medium		High	
Preference for leisure group	Impatient	Patient	Impatient	Patient	Impatient	Patient
Employment rate	0.01	0.82	0.01	0.80	0.62	0.88
Unemployment duration*	8.95	0.98	8.96	1.23	3.11	0.65
Average skill level**	0.02	3.59	0.02	3.42	2.61	3.86
Estimated share τ^{MR}	0.176	0.824	0.001	0.999	0.025	0.975
Region	Activation					
Educational group	Low		Medium		High	
Preference for leisure group	Impatient	Patient	Impatient	Patient	Impatient	Patient
Employment rate	0.14	0.91	0.26	0.88	0.90	0.93
Unemployment duration*	7.65	0.40	6.58	0.69	0.66	0.36
Average skill level**	0.63	4.09	1.13	3.93	3.95	4.22
Estimated share τ^{AR}	0.503	0.497	0.327	0.673	0.435	0.565

Note: The table describes the ergodic distribution $\Omega^*(\theta)$ from which the inflow into unemployment is sampled (see Section 5.1). * This statistic reports the average of d in the ergodic distribution. **This statistic reports the average of s in the ergodic distribution.

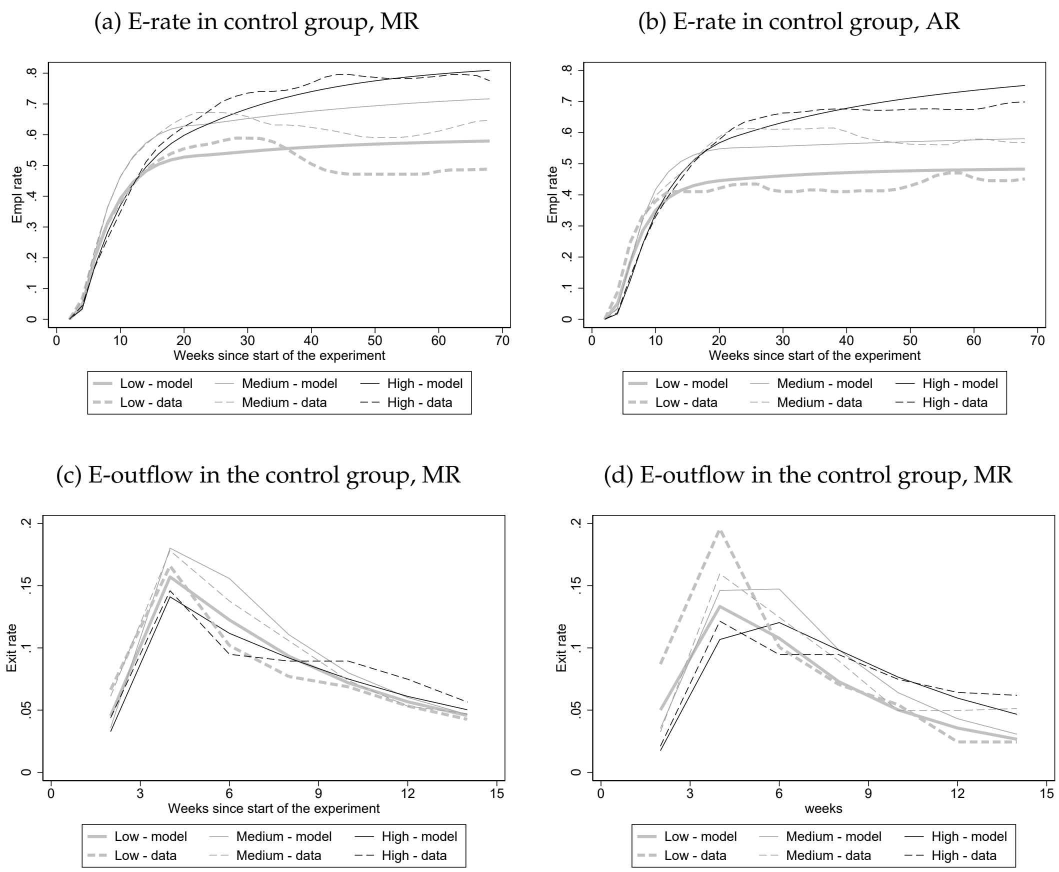
duration dependence. The job offer probability function from equation 4 is now specified as:

$$T(\alpha, \theta) = sc \cdot \left[\pi^{rg}_{job,d} + \pi^{eg}_{job} + \pi_{job,m} \cdot m + \pi_{job,a} \cdot a\right]$$

Figure 11 can be seen as a motivation for why the model in the main text has duration dependence in the return to search, see Section 4. In particular, a "constant return to job search" specification as the one above is not able to generate the spike initially in outflow rates followed by lower rates in the longer run. Either the initial outflow from unemployment is too low (as illustrated in the figure) and/or the model predicts that long-run employment levels will be too high. By including duration dependence in the return to search, individuals "front-load" search, and thereby the model fits outflow rates in both the short and longer run.

Finally, note that the model presented in Section 4 allows a part of the spike in outflow rates to arise due to dynamic selection, where e.g. patient workers search more in the early periods and leave unemployment. The estimates in Table 4 imply that both explanations (dynamic selection and duration dependence) are found to be quantitatively important.

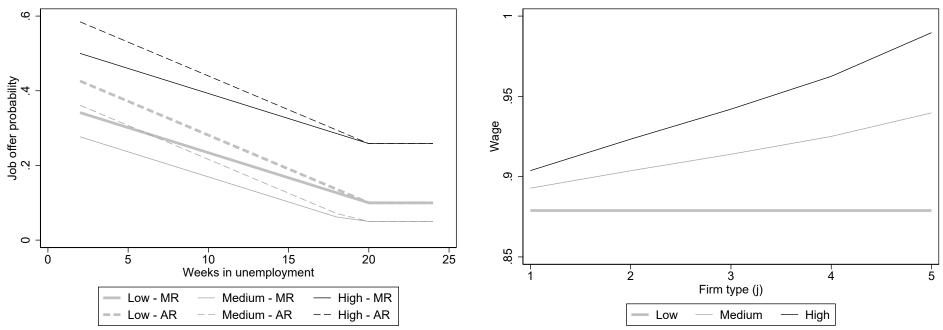
Figure 7: Employment rates in the control groups across time, region and education groups



Note: The top panels (a+b) give the employment rates for individuals in the control group in the model and data (moment #7 in Table 7). The bottom panels (c+d) plot the share of individuals exiting unemployment in a given week (moment #8 in Table 23). MR: Meetings Region, AR: Activation Region

Figure 8: Return to search and wage function

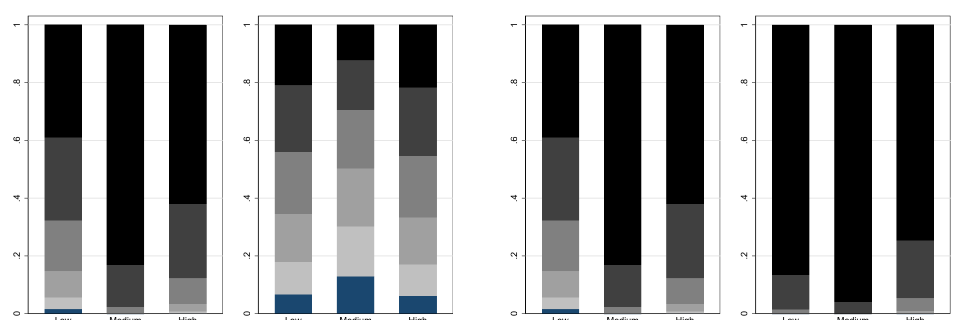
(a) Job offer rates (b) Wages as a function of the job type



Note: Panel (a) plots the probability of receiving a job offer next period (at $sc = 1$) as a function of unemployment duration and for different education levels (low, medium, high) and regions; see also equation 4. Panel (b) plots the wage function as a function of the job type j and for different education levels (low, medium, high), see also equation 3 and Section C.3.2. MR: Meetings Region, AR: Activation Region

Figure 9: Job search policies in different states

(a) Newly (left) vs. longer-term unemployed (b) Lower (left) vs. higher levels of skills

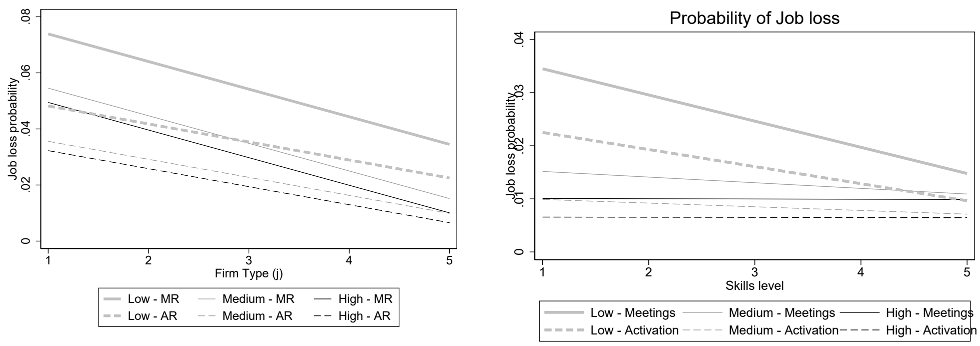


Note: Panel (a) plots the search policy, i.e. the probability distribution (determined by the policy function defined in equation 8) over different levels of search activity for individuals in state θ with 1 and 8 weeks of unemployment ($d = 0$ and $d = 4$). Panel (b) contrasts the search policies for low and high-skilled workers ($s = 0$ and $s = 4$). Both panels plot the policies for patient workers in the Activation Region (AR). Results are reported separately for different education levels (low, medium, high). Dark bar colors reflect higher search intensity, blue color indicates no search ($sc = 0$). The size of a given colored bar reflects the likelihood of this level of search intensity being chosen.

Figure 10: Layoff process

(a) Dependence on job type

(b) Dependence on skill level

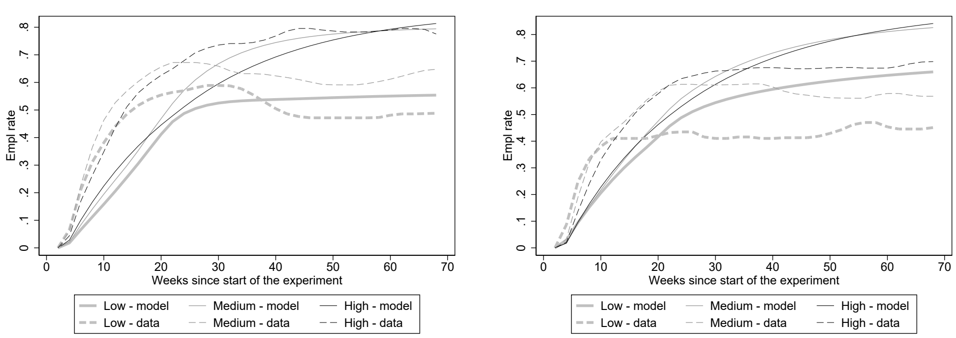


Note: This figure plots the probability of losing employment and becoming unemployed as a function of the job type j or the level of skills s and for different education levels (low, medium, high) and regions, see also equation 5. MR: meetings region, AR: activation region

Figure 11: Eliminating duration dependence

(a) Meetings Region

(b) Activation Region



Note: The figure compares data to model predictions for the control group under the same estimates as in Table 4, but now without duration dependence, see section D.3 .

D.4 Model mechanisms behind the experimental impact

In this section I provide additional illustrations of the behavioral changes underlying the experimental impact as reported in for example Figure 2 in the main text.

Figure 3 and Section 6.2 in the main text argued that individuals in the model primarily respond to a threat of future (costly) MEP participation by increasing their search activity. In Figure 12 I illustrate the quantitative importance of changes in job search more directly by showing how the experimental impacts change, as we replace the policies in the treatment group in states θ with $j = 0$ (where the individual has no job offers) with the choices of the corresponding control group. In this counterfactual, the impacts are generally much smaller than the impacts arising under the benchmark, illustrating that a key driver of the experimental impacts are the changes in job search decisions, and less so changes in decisions about employment entry which are only relevant when $j > 0$, i.e. when there are job offers to choose from.

Overall a decomposition suggests that across region and education groups (with one exception), more than 70 percent of the average experimental impacts during the first 30 weeks arise directly from job search decisions in states where the job seeker does not have any job offers. Note that for low educated workers in the MR, the change in experimental impacts is much smaller compared to the other groups. This is because the treatment group participates in meetings already from week 2 and onward, and they increase the return to search $\pi^{e=1}_{job,mp} = 0.082$ (See Table 4). Closing down this "productive" effect from meetings removes the experimental impact, thus illustrating that the experimental impact for this group is also not driven by changes in employment entry decisions.

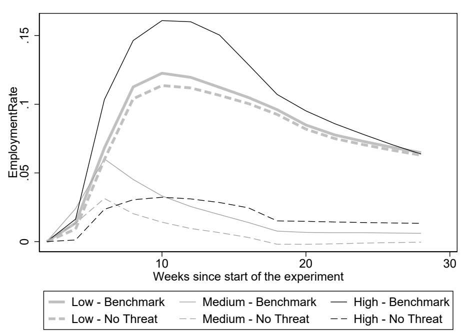
Figure 13 provides additional evidence on the behavioral changes underlying the experimental impact. The figure compares decisions in the control and treatment groups in a particular realization of θ in the MR and AR in the first period of the experiment. The left panel in figure 13 shows the search policy, i.e. the probability distribution over different levels of search activity as determined by the policy function defined in equation 8. Each colored bar represents a choice of a given search intensity, bars are stacked as they by construction sum to one. The right panel illustrates the job policy, i.e. the probability that different job offers are accepted. Each colored bar now represents a different job offer j, and the size of the bar represents the probability that this job offer is accepted.

In figure 14 I show a similar figure for an alternative realization of θ in the MR. Note that the incentive to accept lower job types j is larger in the MR than in the AR as the TH stage is very short. Nevertheless the figures suggest that the primary behavioral change at inflow into the experiment is that individuals search more, and that job decisions generally change little.[40]

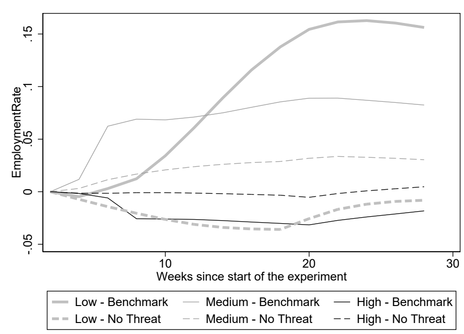
A great advantage of the model is its explicit inclusion of the experiment which implies that we can calculate model predictions over time since start of the experiment. Figure 15 illustrates that the response to the experiment is dynamic. The left panel of figure 15 shows the search policies for a specific $\theta_{enviroment}$ in the TH, T and PT stages. Individuals generally search less in the PT stage compared to the TH stage and often also to the T stage. The reasons for the higher intensity of search in the TH and T stages can differ. In the TH stage, individuals search more to avoid future participation in MEP. In the T stage, individuals may search more to avoid future periods with MEP or because the return to search is higher,[41] or alternatively they search less because the cost of job search is higher due to MEP participation. The right panel in figure 15 shows the search policies for individuals (in a specific $\theta_{environment}$) early in the TH stage $(ts = 0)$ and later in the TH stage, $(ts = 5)$. The figure shows that the intensity of search increases as the threat intensifies, i.e. the closer individuals come to actual participation in MEP.

Figure 12: Decomposing Employment Impacts

(a) E-impact longer run, MR



(b) E-impact longer run, AR



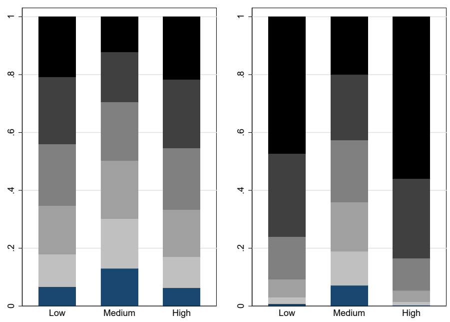
Note: The solid lines in Panels (a) and (b) plot the employment impacts for individuals in the treatment group compared to the control group in the model (similar to figure 2). The dashed lines plot the employment impacts which arise if we replace the policies (search activity) in the treatment group in states θ where $j = 0$ (i.e. where the individual has no job offers) with the corresponding policies of the control group. MR: meetings region. AR: activation region. Results are reported separately for different education levels (low, medium, high).

[40] This, of course, is partly because choices are discrete; with a continuous distribution of job types, small changes would occur. Nevertheless, the main story is the same: the primary channel through which individuals change behavior is that they change how much they search for employment.

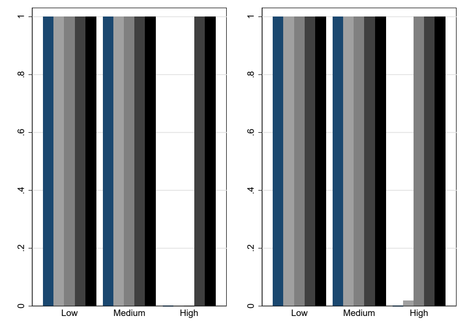
[41] The increase in the return to search caused by MEP is primarily relevant for low educated workers, as other workers have limited benefits from participation in MEP; see Table 4.

Figure 13: Search levels and job decisions

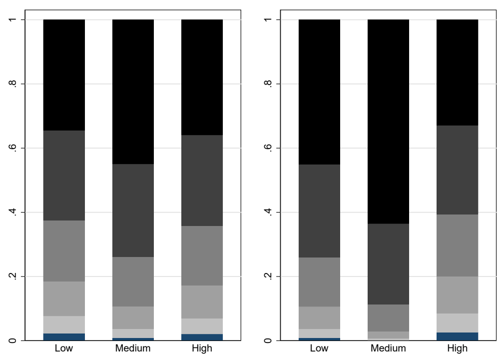
(a) Search - Control (left) vs. Treatment – MR



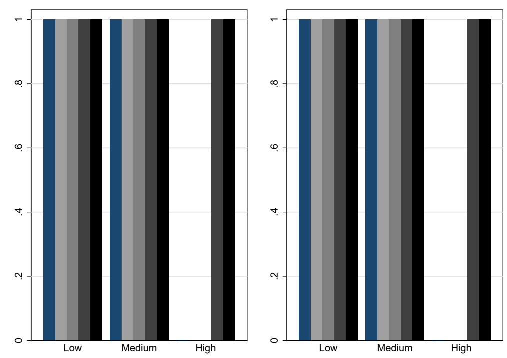
(b) Job offers - Control (left) vs. Treatment – MR



(c) Search - Control (left) vs. Treatment – AR



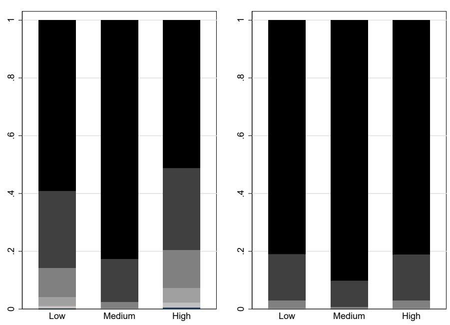
(d) Job offers - Control (left) vs. Treatment - AR



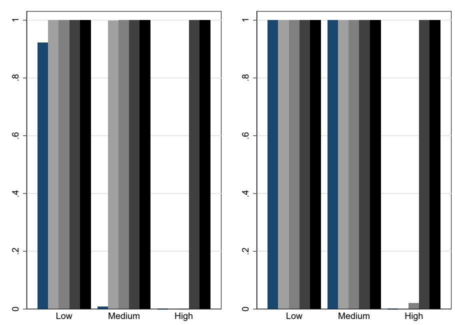
Note: Panels (a+c) plot the search policy, i.e. the probability distribution (determined by the policy function defined in equation 8) over different levels of search activity for patient individuals in the Meetings Region (MR) and Activation Region (AR). Within each panel, the left (right) figure is for control (treatment) individuals in state θ ($d = 3$ and all other state variables set to 0). Dark bar colors reflect higher search intensity, blue color indicates no search ($sc = 0$). The size of a given colored bar reflects the likelihood of this level of search intensity being chosen. Panels (b+d) plot the job policy, i.e. the probability that a job offer j is accepted for the same individuals. Each color represents a different job offer j, the size of the bar reflects the probability that this job offer is accepted. Dark bar colors reflect higher offers. Results are reported separately for different education levels (low, medium, high).

Figure 14: Search levels and job decisions (alternative state) – MR

(a) Search - Control (left) vs. Treatment



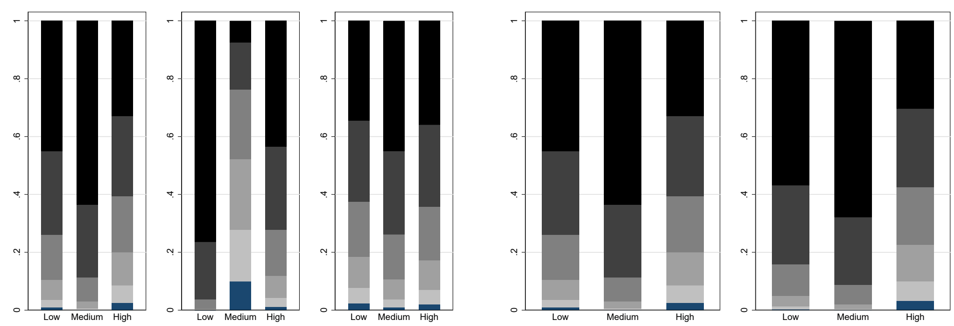
(b) Job offers - Control (left) vs. Treatment



Note: Panel (a) plots the search policy, i.e. the probability distribution (determined by the policy function defined in equation 8) over different levels of search activity for patient individuals in the Activation Region (AR). Within each panel, the left (right) figure is for control (treatment) individuals in state θ (θ has $d = 0$ and all other state variables set to 0). Dark bar colors reflect higher search intensity, blue color indicates no search ($sc = 0$). The size of a given colored bar reflects the likelihood of this level of search intensity being chosen. Panel (b) plots the job policy, i.e. the probability that a job offer j is accepted for the same individuals. Each color represents a different job offer j, the size of the bar reflects the probability that this job offer is accepted. Dark bar colors reflect higher offers. Results are reported separately for different education levels (low, medium, high).

Figure 15: Search decisions in the treatment stages

(a) TH (left), T (middle) and PT stages (b) Early (left) vs. later in the TH stage



Note: The figure plots the search policy, i.e. the probability distribution (determined by the policy function defined in equation 8) over different levels of search activity for patient individuals in state θ in the Activation Region (AR) in the three different treatment stages (panel (a)) or for different durations in the threat stage (panel (b)). Dark bar colors reflect higher search intensity, blue color indicates no search ($sc = 0$). The size of a given colored bar reflects the likelihood of this level of search intensity being chosen. Results reported separately for different education levels (low, medium, high). Keep in mind that high educated workers have no utility costs from participation in activation. TH: threat stage, T: treatment, PT: post treatment

D.5 Compensating variation

In this section I present additional results and robustness checks discussed in the main text in Section 7. All tables report the average total compensation per individual in terms of weeks of UI.

In Table 25 I compare the CV, which is reported in the main text and referred to as CV_Bench in the table, to two alternative compensation schemes CV_1 and CV_2. CV_1 reports the resulting CV when the compensation is paid in the T stage only as opposed to the TH and T stage as in CV_Bench. In CV_2 the compensation scheme is the same as in CV_Bench, but CV(θ_{init}) is weighted with the same benchmark distribution (low educated, meetings region, impatient) for all region, education and patience groups. Overall, Table 25 suggest that the results in the main text are robust to changes in the timing of the compensation, are that they are driven by differences in the distribution of θ_{init} across different groups.

In Table 26 I report the CV and the resulting employment impacts across different counterfactuals where the duration of the TH stage changes. This table illustrates that while a shorter threat stage would likely increase the CV, it actually also increases the impact on job finding, and thereby both benefits and welfare costs vary with the duration of the TH stage.

In table 27 I report the average CV and its (probability weighted) standard deviation, and in Table 28 I show how the CV changes across different states in θ_{init}: These results are discussed in Section 7 and illustrate some key drivers of heterogeneity in the CV.

Comparing low vs. high d states in Table 28 (all else equal) show that the CV is higher for states where the return to search is low since escaping future MEP is more costly from such states. Comparing low and high s levels in Table 28 shows that the CV is higher in states which are already searching intensively in absence of the experiment (i.e. in the control group). Higher skilled (patient) individuals are generally searching intensively for employment in absence of the experiment (as shown in Appendix figure 9b). Due to increasing costs, they thus demand higher compensation than individuals with lower levels of skills and lower levels of search in absence of treatment.

Note that for impatient individuals, the relationship between skills and the CV is actually reversed. These workers discount the future more heavily and are thus searching less intensively for employment in the absence of the experiment. This implies that the cost of responding to the threat of MEP is lower while the gain is still higher for those with higher skills. For this reason, the compensation the high skilled require for additional job search is not as large as that of those lower skilled.

Overall the results reported in Table 28 therefore suggest that the CV is high in two groups of states, The first group consists of states where the return to search (equation (4) and thus employment prospects is low. The second group consists of states where the utility loss of additional job search is high. In contrast, individuals with lower CVs are individuals who, in absence of the threat of MEP, search less intensively for employment, although they would be able to find employment quite quickly. Note that other states with low CVs are states where $j >> 0$, i.e. where individuals already have a decent job offer at the time of the threat. These individuals have readily available alternatives to MEP and therefore require low compensation.

Table 25: Compensating variation per participant under alternative payments

		Meetings Region			Activation Region		
		CV_Bench	CV_1	CV_2	CV_Bench	CV_1	CV_2
Low Educated	Patient	1.34	1.30	1.41	0.80	0.94	0.95
Low Educated	Impatient	4.56	4.43	4.56	6.87	6.55	6.04
Medium Educated	Patient	1.41	1.40	1.51	1.73	1.73	2.21
Medium Educated	Impatient	2.20	2.20	2.18	6.72	6.91	6.19
High Educated	Patient	2.29	2.30	2.35	-0.27	-0.29	-0.32
High Educated	Impatient	3.74	3.68	3.59	-0.31	-0.35	-0.33

Note: This table contrasts the results in Table 5 with results from alternative calculations. The table reports the average total compensation per individual in terms of weeks of UI. CV_1 is the resulting CV when compensation is paid in the T stage only as opposed to the TH and T stage as in CV_Bench. In CV_1, CV(θ_{init}) is weighted with the region, education and patience type specific distribution across states. In CV_2 the compensation scheme is the same as in CV_Bench, but CV(θ_{init}) is weighted with the same benchmark distribution (low educated, meetings region, impatient) for all region, education and patience groups.

Table 26: Compensating variation for different threat stage durations

	Weeks with Threat	Employment Impact	CV
Meetings Region	2	1.96	554 (1.72)
Meetings Region	14	1.73	347 (1.08)
Meetings Region	20	1.73	329 (1.02)
Activation Region	2	2.57	612 (1.90)
Activation Region	14	1.47	494 (1.52)
Activation Region	20	1.03	491 (1.52)

Note: This table shows the effect (resulting CV and employment impact) of different experiments, where only the duration of the threat stage differs. The CV (defined in equation 17) is weighted with the initial distribution across states at inflow into the experiment. The employment impact is the accumulated difference in employment rates during the first year for the treatment and control groups.

Table 27: Compensating variation across regions and workers - with standard deviations

		Meetings Region	Activation Region
Low Educated	Patient	1.34 (0.17)	0.90 (0.24)
Low Educated	Impatient	4.56 (3.37)	6.87 (4.52)
Medium Educated	Patient	1.41 (0.24)	1.73 (1.16)
Medium Educated	Impatient	2.20 (0.20)	6.72 (2.25)
High Educated	Patient	2.29 (0.24)	-0.27 (0.01)
High Educated	Impatient	3.74 (0.35)	-0.31 (0.01)

Note: The table reports the average total compensation per individual in terms of weeks of UI. In parenthesis I report the (probability weighted) standard deviation of $CV\ (\theta_{init})$.

Table 28: Heterogeneity in the Compensating Variation

		Benchmark	Longer UE	Lower skilled
Low Educated	Patient	1.47	1.56	1.23
Low Educated	Impatient	1.43	1.69	5.66
Medium Educated	Patient	1.92	2.23	1.60
Medium Educated	Impatient	1.85	2.18	2.35
High Educated	Patient	2.66	2.85	2.10
High Educated	Impatient	2.39	2.55	3.95

Note: The table reports the CV (defined in equation 17) for 2 different states: newly and longer-term unemployed. Benchmark (Longer UE) is unemployed with 6 weeks (12 weeks) of unemployment ($d = 3$ or $d = 6$). Low-skilled (Benchmark) individuals are individuals "without" skills $s = 0$ ($s = 2$) skill level. All other state variables are 0. Numbers are reported for the meeting region only. The table reports the average total compensation per individual in terms of weeks of UI.

D.6 Details on different components in the welfare assessment:

In Section 7.3 and Table 6 I present and discuss the results from a partial welfare analysis of the randomized experiment studied in this paper. Below I discuss the different elements in this assessment in further detail.

- **Value of increased production** is calculated as the increase in earnings caused by the experiment. The components in this calculation are the difference in weeks of employment within the first year of the experiment (the increase in production) and the payment per week assuming a 37-hour work week and using €23.5 as the average hourly wage. The hourly wage is measured before taxes and comes from Maibom et al. (2017). The final numbers are then weighted with the distribution of education groups within a given region.

- **Operating costs:** The operating costs are from Maibom et al. (2017). The operating costs are simply the difference in the expenditures on all MEP programs within the sample window between treatment and control groups. The low operating costs in the MR are driven by 1) a low cost per meeting and 2) future cost savings from the rapid increase in employment in the treatment group and, thus, less spending on MEP in the future; see Maibom et al. (2017).

- **Costs from increase in production** are calculated as the increase in production multiplied with the weekly costs of production. Weekly costs of production are obtained by multiplying κ^{eg} with a 37-hour work-week.[42] This number is subsequently weighted with the distribution of education groups within a given region.

- **Welfare costs (CV):** The CV (defined in 17) is weighted with the initial distribution of θ_{init}. The numbers are then weighted with the distribution over patience types and education groups within a given region.

- **Welfare costs (CV) for LTU:** The CV (defined in 17) is weighted with the initial distribution of θ_{init} where I only sample states with $d > 6$ into the experiment (and reweigh accordingly).

- **Saved income transfers:** The saved income transfers from the experiment (due to increased job finding) are not included in the welfare assessment. They only represent a redistribution of income, and since I am working under the assumption of 0 marginal costs of providing public funds and do not consider the role of taxes in the model as such, there is no gain to include from a reduction in income transfers (alternatively that amounts to assuming that the saved income transfers are used for alternative government consumption which does not have any benefits). Maibom et al. (2017) include saved income transfers in their assessment of the impact of the experiment on the government budget. See their paper for the exact amount associated with different types of income transfers.

[42]The decision parameters in the model are parameterized to match decision making at the "hourly" level, see section C.3.3.