Assessing Welfare Effects of ALMPs: Combining Structural Models and Experimental Data

Jonas Maibom, Aarhus University

12th April 2015

Job market paper

Very preliminary, please do not quote or circulate

Abstract

In the literature focusing on Unemployment Insurance, Active Labour Programmes (ALMPs) such as meetings at the job centre or workfare (activation) programmes have been presented as a way to control the moral hazard which arise in a market with unemployment insurance. A key prerequisite for this to be the case is that programme participation induces some kind of cost on participants and that participation is compulsory. In this paper we develop and estimate a dynamic discrete choice model of job search in which unemployed individuals participate in active labour market programmes (ALMPs) in order to quantify this cost empirically. The model is estimated using data from a Danish social experiment which provides exogenous variation in the intensity of interactions. The experiment allows us to estimate the individual level costs of these interactions, in particular the cost agents incur when they have to go into either activation or a meeting at the PES. These costs arise because the individual spend a part of their non-market time at the job centre where he has to exert effort and potentially do unpleasant work (and maybe even feel stigmatized). The results suggest that traditional Cost-Benefit calculations (CBA) which do not take the individual loss of non-market time into account overstates the gain from having these programs. The individual level costs are substantial and are important to quantify to assess whether the current mix between ALMPs and UI is optimal.

Introduction:

Across the globe we see labor markets with Unemployment Insurance systems (UI). With such systems follow a concern about adverse selection and moral hazard, and the empirical relevance of such phenomena have now been documented in the literature in several dimensions. Several countries have looked into the design of their UI systems, and some countries have introduced programmes targeting UI recipients such as job search assistance and activation programmes in an effort to re-align incentives and improve the market functioning. Sometimes the term active social insurance is used (e.g. Røed (2008)) to underline that UI is not only a passive transfer of income but instead participation in these programmes serve as a conditionality for receiving benefits.[1] ALMPs with this aim are thus designed to reduce the moral hazard in the labor market by inducing a potential cost on participants. This costs exists because the programmes 'tax' leisure time (remove leisure time) from the unemployed and replace it with for instance time in the job centre where the non-market wage could be high due to uninspiring work (waste of time), unpleasant monitoring of prior job search or stigma.[2] The empirical existence of such costs have been documented in the literature often in the form of threat effects or ex ante effects such as in for instance in Black et. al (2003), Hagglund (2011).

In this paper we will try to quantify this individual level cost by formulating a dynamic discrete choice model and estimate it on data from a Danish social experiment.

As participating in ALMPs is not a choice but (ultimately) a conditionality for receiving UI benefits quantifying the individual level cost is challenging since we have to determine the cost of programme participation indirectly through choices such as intensified search activity or lower reservation wages. In order to determine these effects we need to know what individuals would have done in the absence of "treatment" which is exactly why we estimate the model using data from a social experiment. By modelling both the standard social environment (the environment faced by the control group) and the change in the environment for the treatment group we can identify the costs and gains incurred by the agents as a result of belonging to the treatment group from the difference in behaviour between the treated and the controls. The social experiment is usefull for identification of the model parameters due to two factors, first the experiment provides

[1] On example of this is the Danish labour market model, which is generally referred to as the Flexicurity model and recommended by the EU commission to its member states (European Commission, 2007), here unemployment insurance (UI) is generally very generous (the security component) and the level of employment protection is quite low (flexibility). The sustainability of such a system could be challenged by high structural unemployment rates, e.g. due to low incentives for workers to leave unemployment. Therefore ALMPs are considered a crucial part of the flexicurity model and participation in such programmes is considered both a right and a duty.

[2] These are explanations for while the non-market wage could differ from the market wage and they are essentially explanations for compensating wage differentials (effort in the job centre is unpleasant and thus the "payment" is higher)

exogenous variation in the treatment intensity and secondly the the experiment generates a usefull source of non-stationarity in the data which can further be exploited to learn about both costs and discount rates. From a methodological point of view the model follows in the lines of a novel framework developed in Ferrall (2004). This framework extends the classical work by e.g. Rust (1987) into a setting where we can allow for unobserved non-IID timevarying statevariables, unanticipated (or zero probability) choices and corrections for endogenous sampling (initial conditions). Here we improve on the estimation of the transition probabilities for the unobserved statevariables by relating them indirectly to statevariables (for instance by using moments such as employment duration although this is not a statevariable in the model).

Although ALMPs might be successful in reducing moral hazard in the market by increasing e.g. search activity, the existence of such costs also makes it an open question whether these programmes actually make individuals better off or they would instead prefer lower benefits. The costs implies that some individuals are worse off than before the introduction of ALMPs (and this is in fact why some search more to leave unemployment before being activated) and thus the overall implications for welfare are less clear - a key factor is naturally the size and prevalence of this cost.

How and whether conditionalities such as workfare *can* in fact be welfare improving have been studied quite extensively in the theoretical literature (see next section) which initially focused on the design of anti-poverty programs and how to target transfers to the truly needy (adverse selection or extensive margin). Later work have also looked at moral hazard and how conditionalities might improve welfare (see the next section).

While the theoretical literature have focused on this distinction - and the conditions under which ALMPs can in fact be welfare improving - the empirical literature have focused on a partial evaluating these programmes. In this literature the primary criteria by which we asses the favorability of a particular labor market programme is whether the programme is successful in reducing the duration in unemployment and maybe whether the programme improves the "quality" of future employment. The benefit side of the programmes is thereby determined as the potential gains of increased production (taking account of both ex ante, lock-in and ex post effects) and the saved income transfers whereas the costs are the money spent on caseworkers etc. (appropriately adjusted for MCPF). These effects (the benefits) can then contrasted the costs (administrative and activity costs) of running the programme to determine whether the programme is favourable.

Absent from this calculation is the potential costs internalized by the programme participants due to their participation in a given programme; a part of these costs is the lost non-market time and potential non-pecuniary costs (e.g. stigma or other psychological costs) induced on programme participants. In the words of Heckman, Lalonde & Smith (1999): *"Traditional program evaluations exclude such valuations largely because of the difficulty of imputing the value and quantity of non-market time. By doing this, however, these evaluations value labor supply in the market sector at the market wage, but value labor supply in the non-market sector at a zero wage. By contrast, individuals value labor supply in the non-market sector at their reservation* *wage."*

Ultimately this "assumption" introduces an imbalance between what we as programme evaluators evaluate as "beneficial" and what society (or a social planner) would. Essentially the bias stems from the fact that the unemployed individuals respond to costs which we do not include in our calculations, costs that have been shown to play a non-trivial role in both the theoretical and the empirical literature. The fact that programme evaluations leave out this cost component could imply that we deem programs too favourable - as we would conclude that the programmes which have the largest effects on reducing e.g. unemployment duration are more beneficial regardless of how and what we do with the individuals participating in the programmes. The extent to which this is true, naturally depends on the size of this cost component, and therefore knowledge about the individual costs from participating in ALMPs should be of central interest .

As mentioned above since participation in ALMPs in many settings is not a choice but (ultimately) a conditionality for receiving UI benefits, it implies that we do not see a clear expression of preferences for the programme as such through choices of participants[3] as non-participation also imply a substantial loss in income (e.g. loss of benefits or sanctions) - thus agents hardly never choose not to participate.[4] This leaves us with a fundamental identification problem of this important cost component that ultimately is informative of whether the programme is beneficial. We illustrate this identification problem by estimating the model using only variation in the control group.

In a nutshell the paper will formulate a dynamic discrete choice model of job search and apply it in a Danish labor market setting in an effort to rationalize the variation observed in the experimental data. This exercise allows us to extend the assessments about the cost effectiveness of these programs to include the loss internalized by the unemployed and ultimately we will be able to compare the loss in benefits that the agents would be willing to take to avoid the increased enrolment into ALMPs to the costs and benefits from having the programme. By understanding the mechanisms and the consequences on individual behaviour we can learn about the monetary loss which makes the individual indifferent between going through the treatment and having UI benefits reduced (the compensating variation), furthermore the model will allow us to perform several simulation exercises to explore the effectiveness of ALMPs as the timing of programme participation and the composition of the unemployed changes.

This paper proceeds as follows: in the next section we present related literature, we then present the experiment which we will be using and the data that is available. We proceed showing some key features of the data which our model will aim to replicate. In the next section we present the model and empirical implementation. Finally we present results and conclude.

[3]A literature starting with Moffitt (1983) identifies the stigma/utility cost associated with receiving welfare using exactly individuals on this margin (i.e. comparing take-ups and non-take-ups (extensive margin)). Here we will essentially use variation in the intensive margin (the intensity of the conditionality) and compare the behaviour of individuals in intensive regimes with the similar individuals in less intensive regimes. Variation in the intensive margin is generated by a social experiment and thus exogenous which helps for identification of the utility cost.

[4]For instance in a Danish setting participation in activation programmes is considered a a duty that comes with the right of receiving UI benefits, this implies that non-participation ultimately could imply that the individual loose its UI benefits or at least a part of it for a period of time.

Literature:

Below we present the related literature. The work can be presented among many different dimensions but the idea is to relate the current paper to both theoretical work, methodological work and empirical work.

Theoretical literature:

How and whether conditionalities such as workfare *can* in fact be welfare improving have been studied quite extensively in the literature which initially focused on the design of anti-poverty programs.

The essential problem in this literature was to design systems which are sustainable in a setting where individuals (agents) have more information than the government (principal) which have an objective of for instance securing a minimal level of consumption regardless of working status. Sustainable designs are designs where the benefits are targeted towards individuals who truly needs them. The theoretical literature have shown that conditionalities can improve the targeting efficiency of programmes, but also that there is an important distinction to make between income/benefits and utility gains from workfare policies.

Nichols and Zeckhauser (1982) showed that in order to improve targeting efficiency (in ensuring that only the most "needy" gets UI) transfer programs should restrict the behaviour of recipients. Restrictions could be placed on e.g. income or the allocation of time and could even imply the acceptance on a pure dead-weight costs for instance through completely unproductive tasks which only serve as a way to tax leisure (ordeals). This "screening argument" is stronger if the costs that such ordeals impose vary inversely with the benefits to be received such that costs are lowest for those who really need it, in the example with unemployment this could imply that individuals who can easily get a job have a larger cost of participating in the programmes.

Besley & Coate (1992) show that a government with a redistributive motive can improve the income of the low type (unemployed) by including a workfare requirement (a screening device) as a conditionality and thereby ensuring that high income types do not pretend to be low types (the transfer is incentive compatible). This conditionality is thereby designed to help "align" private and social incentives and it makes the low type individuals better off in terms of income. But the authors also show that this does not imply that agents are better of in terms of utility, in particular the work requirement implies a cost of leisure which is high enough to offset the increase in benefits.

In the papers presented above the main focus is on the the targeting of transfers or the extensive margin (do you claim insurance or not). Andersen & Svarer (2014) perform an analysis focusing of the effects of workfare on the moral hazard (or the intensive margin) in job search in a search and matching model. Their framework is dynamic and their analysis underlines the importance of this as they show that the threat of future participation in workfare increases the search effort of the unemployed before actual participation and lowers his reservation wage. Under a utilitarian criterion the authors show that workfare can in fact improve welfare in their setting.

In conclusion there has been a lot of normative work on whether and under which conditions conditionalities in benefit recipiency can actually be welfare improving. The general conclusion is that workfare can be welfare improving in some settings but it very much depends on the environment. In this paper I try to build on this work and present empirical results.

Experiments and models (methodological):

In recent years much focus in the literature have been on combining economic models with experimental variation. The general idea is that combining strong internal validity with an economic model can be very useful for answering other questions such as knowledge about the mechanisms or counterfactual policies and thus strengthen the usefulness of both approaches. The literature have presented and discussed different ways on how to use experimental variation in the work with structural models. Two different approaches can roughly be characterized on the basis of whether the experimental variation is used as a validation opportunity or as an identification opportunity.

In the former the idea is that we estimate a structural model using the data on the control group, as a validation exercise we now change the programme parameters to incorporate the fundamentals in the environment facing the treatment group and we compare the model predictions to the actual data. Thereby we validate the model we have estimated. In particular Todd & Wolpin (2006) use data from a randomized experiment (PROGRESA) in Mexico to estimate and validate a DCDP model of parental decisions about fertility and child schooling. Their aim is to provide policy advice for what cost effective subsidy schemes look like, thereby the model is used to produce an ex ante evaluation of alternative policies which could reach similar goals as the PROGRESA scheme. The model is estimated on data from the control group and the data from the treatment group is then used in an validation exercise. The idea is that this validation should increase the credibility of the model and thereby also in the various counterfactual experiments that the authors do in order to provide ex ante advice on cost effective policies. what about traditional conditional transfer schemes. Lise et. al. (2006) who focus on the Self-sufficiency Project conducted in Canada.[5] They calibrate a search and matching model using data on the control group and use the data on the treatment group to validate their predictions about the equilibrium effects of the SSP.[6]

Another approach in the literature is to use the experimental variation as an opportunity to learn more about parameters that could not be identified in the absence of this variation. Santiago, Meghir & Attanasio (2012) argue that the effect of a subsidy cannot be evaluated ex ante (thus using variation in the control group) by using variation in child wages and household income

[5] Gautier et. al. (2013) perform a similar exercise using data from an earlier Danish Experiment called "Quickly Back To Work 1"

[6] Other papers are Gautier et.al (2014)

as a surrogate, therefore to fully evaluate the effect of the PROGRESA all variation is needed. Furthermore they argue that the availability of the experiment allow them to estimate the effect of the program on the child wage in treated villages and thereby access the importance of general equilibrium effects from the program. Thus the difference to the papers mentioned above is that the data on the treatment group is used in estimation. [7]

A final key issue in the literature is how the experiment and its potential different phases and sub-treatments are actually incorporated into the model. For instance agents might know that treatment is finitely lived and this might influence their behaviour in settings where the experimental intervention is short.[8] This feature is likely to be particularly important when estimating costs of programme participation in a dynamic setting since the incentives for the treatment group change as they progress through the experiment (every week that come one week closer the expiration of the intensified treatment and thus the future cost associated with programme participation declines). Ferrall (2011) studies the SSP project in Canada and develops a framework taking due account of the non-stationarities implied by the design of the experiment, for instance a waiting period and a qualifying period to qualify for a wage subsidy. Ferrall also shows the importance of these non-stationarities when conducting counterfactual experiments in well defined structural models instead of reduced form frameworks.

In this paper we use the framework developed by Ferrall (2006 & 2011) to deal with the fact that experiment consists of a few relatively short phases (13 weeks) (see model section for more specific details). This allows us to use the non-stationarities implied by the experiment, for instance the waiting period of 13 weeks before an activation wall as information about the model fundamentals. We use the experimental variation for estimation to improve the identification of the model and in particular the utility cost of programme participation. By including the experiment in the model we essentially estimate the model using variation in two different environments (the treated and the controls), and thereby we exploit the exogenous policy variation to learn about the cost that agents internalize when participation is almost obligatory. The only way the model is allowed to change between the two regimes is through the increased treatment regime.

The combination of experimental variation and an economic model is used to improve identification of the costs of programme participation as participation in the programme is random. In a model framework one way to think of it is that the experiment variation allows us to distinguish between for instance i) a large cost of programme participation and a huge costs from increasing the search intensity from ii) a very low cost of programme participation. These two explanations will have very different welfare implications, in i) agents might incur a substantial loss of welfare as they have to participate in "harmful programmes" without us directly observing it in the data, whereas in ii) the agents utility is unchanged. Non-experimental data on individuals participating in ALMPs will not allow us distinguish these explanations without assumptions that allow us to evaluate agents in counterfactual settings, i.e. what they would have done in the absence of treatment. Basically to learn about the cost we would like to compare participants in

[7] Other papers with a similar procedure is Ferrall (2011)

[8] The former also provides an important source of variation which makes the randomized controlled trial literature different from a literature using natural experiments such as policy reforms.

programmes with non-participants at a given point in time and conditional on a limited set of state-variables we would have to assume that these agents are similar except for the programme participation. This is exactly where experimental variation can become very useful as it gives us the opportunity to observe identical agents in different settings and from their differential behaviour, and the imposed structure of the model (how the selection process evolves), analyse the way that the treatment affects individuals. From this we can thereby determine the cost/gains of the treatment which results from an increase in the intensity of ALMPs.

Empirical:

Greenberg & Robins (2007) provide estimates of the value of lost leisure time for participants in the Self-Sufficiency-Project (they determine the gain in consumer surplus instead of the raw gain in income for participants). Using a matching procedure they are able to identify the group of compliers in the experiment (the part of the treatment group which enter employment caused by the subsidy) and for this group they use the earned wage in employment, w^* (including the subsidy) and the same wage without the subsidy, w^n (which the compliers by definition did not accept to work for) as two observations which can be used to bound the individual labor supply curve. Their analysis use the fact that the individual reservation wage for starting to work must be above w^n as the compliers do not work at inflow into the experiment and thus by adding assumptions about the value of w_R and the curvature of the labor supply curve the authors can calculate the part of the gain in income which is offset by increased effort. The framework implicitly assumes that the accepted wages and reservation wages coincide thus a frictional environment is not directly taken into account. The main difference to the current paper is that the Greenberg & Robins (2007) analysis exploit that with a wage subsidy we know the direction and the size of how the value of working changes (assuming away stigma or other non-pecuniary differences between recieving the subsidy or not).

Post-employment outcomes

There is also an empirical literature focusing on the effects of ALMPs on post-unemployment outcomes.

One motivation for this argument is Shimer & Werning (2008) study which shows that changes in reservation wages for workers serve as a sufficient statistic for changes in welfare related to the UI level under a number of different assumptions about the environment (the extension of this work to workfare programmes etc remains to be done). In particular Shimer and Werning show that the more responsive the reservation wage is to changes in UI level the higher the welfare gain. Intuitively the after-tax reservation wage tells us the take-home pay required to make a worker indifferent between working and remaining unemployed. This take home pay transfers directly into consumption and thus it is a valid measure of the workers utility (it is a monotome function of it). And therefore if the reservation does not change at all risk averse workers are not concerned about getting a job but just prefer to stay unemployed and consume UI. This framework we can asses the change in welfare not the absolut size. The absolut size is required when trying to assess optimality of ALMPs as the point about conditionalities is exactly that we make some individuals worse off but society as such better off. Notice that the game here is also about optimality of benefits, but here we treat the level of benefits fixed at a potentially not optimal level and see how workers react. This intuition also suggest why reservation wages might not even be a good proxy as individuals might tradeoff search activity and reservation wages in non-trivial ways.

Lastly for studies on post-employment wages the central identification problem is to solve the selection out of unemployment and thus find suitable individuals for comparison. The model we present below can be seen as one attempt on doing exactly this but here we use an economic model to put structure on, and understand how this process evolves. Here we exploit behaviour in two dimensions to quantify the utility loss from participation in ALMPs namely job search and reservation wages therefore the procedure followed here tries to value the costs of the dimensions where choice/effort is actually exerted to have a measure more closely related to individual level costs. Furthermore the procedure followed here is different from the sufficient statistics approach because we would like to consider not only relative changes but also extrapolate our findings to other design and enviroments. The cost of this is imposing further assumptions.

Data and QBW2:

This section briefly presents the Danish institutional setting, the social experiment and the data we will be using.

Danish institutional setting:

The Danish labour market is characterized as flexible with less employment protection legislation than most continental European countries and much more labour turnover (see e.g. OECD, 2009). It has a tight social security net with near-universal eligibility for income transfers, and is sometimes described as the Flexicurity model (flexibility and security). Active labour market policies are a pivotal element in this model for the labour market, which the EU commission recommends to its member states, referring to Denmark as a model case (European Commission, 2007).

In the 1980s, when unemployment rates were persistently high, the first two features of the Flexicurity model - flexibility in the labour market and the tight social safety net - were already features of the Danish labour market, but active labour market policies were only in their infant stages and not nearly as intensive as they have become today. As the intensity of ALMPs grew structural unemployment fell, and therefore observers have seen intensive active labour market policies as a pivotal component in the Flexicurity model (see e.g.. Andersen & Svarer, 2007) and active labour market policies are among the most intensive in OECD, with around 1.5% of GDP spent per year on active policies.

There are two types of benefits for unemployed workers, UI benefits and social assistance. Approximately 80% of the labour force are members of a UI fund and therefore eligible for UI benefits, while the remaining 20% may receive means tested social assistance. UI benefits are essentially a flat rate. As this paper is only concerned with UI benefit recipients, we shall present the policies that apply to them. The "mutual obligations" principle is a key principle in the current Danish labour market policy. This implies the right of individuals to compensation for the loss of income, but also the obligation to take action to get back into employment. The authorities have an obligation to help the individual improve her situation and has the right to make requirements of the individual concerned.

Under the current rules, an individual who becomes unemployed and is eligible for UI benefits has to register at the local job centre. She then has the obligation to attend a meeting with a caseworker at least every 3rd month. She has the right and obligation to participate in an activation programme after 9 months (6 if below 30 years old) of unemployment and subsequently every 26 weeks. These are the labour market policies that will be faced by individuals in the control groups of the four experiments, who will receive this 'treatment as usual'.

Danish labor market policies have been focused on evidence based policies in recent years and one way to improve on evidence have been through a series of randomized control trials (RCTs). RCTs have established that from the perspective of policy-makers there are potentially quite favourable gains from earlier and intensive active labor market programs (ALMPs) in the form of either meetings or activation programmes compared to the benchmark case where policies are less intense and early. Effects have been found on both job-finding rates but also on subsequent job durations (see e.g.. Maibom, Rosholm & Svarer, 2014). The reported effects can be thought of as one rationale for why the main elements of Danish ALMPs now are contact (through meetings) and activation programmes. But the evaluation says nothing about the effects of these interventions on individual welfare.

Presenting the experiment:

Design

The randomized experiment analysed in this paper are both a part of the QBW2 experiment which essentially consisted of four separate experiments, each with its own treatment and control group. They were conducted in four different regions in Denmark in 2008 in this paper we only use data from two experiments and below we only focus on the key features important for our analysis. The experiment is presented and analysed in Maibom, Rosholm & Svarer (2014) and we refer to their paper for the specific details of the setting and an overall analysis of the experiment and implementation, .

The target population of the experiments are individuals becoming unemployed during weeks 8-29 in 2008 who are eligible for UI benefits. Once an individual registers as unemployed, she is 'randomized' into treatment or control group based on her date of birth. Individuals born on the $16^{th} - 31^{st}$ are assigned to the treatment groups, while those born on the $1^{st} - 15$ are assigned to the control groups. No information was given to the unemployed workers on the selection rule. Hence, while this is technically not random assignment, since it is predetermined by date of birth, we will treat it as such (the analysis in Maibom, Rosholm & Svarer (2014) shows no deviations from random assignment).

The individuals randomized into the treatment groups then receive a letter, during the first week of unemployment, explaining the new treatment to which they will be exposed. This information letter marks the start of the treatment, since the worker may react to the information on the new regime from the day the letter is read. It was not possible to escape treatment by leaving unemployment for a short while and then re-enter later on. In that case, a worker would re-enter the experimental treatment at the stage where she left it. The control group receives 'treatment-as-usual' (defined above).

The treatment group receives the same treatment as the control group plus an extra element, which we now present.

Individuals in the treatment group from the region around Copenhagen had to participate in individual meetings with a caseworker every other week for the first 13 weeks of unemployment, that is, a total of 6-7 meetings during the first 13 weeks of unemployment. Note that, generally, the stated main intention of both group and individual meetings was counselling of the unemployed; no explicit extra monitoring was required to take place by the public authorities, but naturally this says nothing about the perception of the meetings from the point of view of the unemployed.

Individuals in the treatment group from the region around Aarhus would be required to participate in an activation programme for at least 25 hours per week from week 14 in unemployment until week 26. This experiment - the activation wall - was designed specifically to investigate the presence of ex ante effects due to the knowledge of having to participate in an activation program, as well as ex post effects of actually having participated.[9]

Data:

The data are extracted from administrative registers merged by the National Labour Market Authority into an event history data set, which records and governs the payments of public income transfers, records participation in ALMPs, and has information on periods of employment. The administrative data are used for determining eligibility for UI benefit receipt and for determining whether the job-centres meet their requirements in terms of meetings and activation intensities. The information is therefore considered highly reliable. The event history data set includes detailed weekly information on: labour market status and history (employment, unemployment, in education, on leave, etc.). Labour market status is calculated based on information from the register on payments of public income transfers and the data will also tell us whether individuals are employed or not using information from the E-income register, containing information from employers about their employed workers. The event history data set is subsequently merged with two other datasets BFL and IDA to obtain information about monthly wages, hours and education levels.

Implementation:

The analysis in Maibom, Rosholm & Svarer (2014) documents that to a large extend the treat-

[9] Note that in order to test specifically for the ex ante effect in an experimental setting, there should have been no actual treatment taking place from week 13 onwards. For our analysis the assumptions implied by the model allows us to test for the existence of such effects

ment protocol is implemented although there is also imperfect compliance with the treatment protocol in the sense that the the meetings and activation intensity is not as high as intended (70% versus 100 % by design). While there are many reasons why this could happen we will ignore this feature in the model below as agents might react solely to the threat and thus we assume that non-participation in treatment in a given week is truly exogenous an unexpected.

Findings:

The findings from the two interventions we study here is that meetings lead to a 10% increase in the employment rate within first 2 years and that the activation wall produce results of similar size. The effects are long lasting and after 5 years there is still a statistically significant difference in the accumulated time spent in employment between the control and treatment group. Subgroup analysis show that it especially younger workers who respond to the activation wall. Estimates from a duration model suggests both the presence of effects ex ante and subsequent employment duration effects. There are also interesting gender differences where females generally respond faster than males. For more details see Maibom, Rosholm & Svarer (2014).

Description:

The data is divided into sub-samples depending on the educational level of the individual and the age. There are 3 educational levels: low (individuals with only primary education), medium (individuals with vocational education), high (individuals with further education) and 2 age groups (young and old).

The sample size within subgroups is reported in Table 1 below.
[10]

Table 1: Observations

Groups	1	2	3	4	5	6
Control group	115	207	395	308	326	155
Treatment (Meetings)	65	111	151	181	59	61
Treatment (Activation)	53	62	248	128	222	103

Data and model

This section gives a short description of some key features in the data which serve as motivation for how the model is specified.

[10] This obviously rest on an assumption of comparable labour markets between the different regions in Maibom, Rosholm & Svarer (2015) this assumption is analysed

Figure 1.left below show the evolution in the employment rates from inflow into the experiment and onwards. The figure shows a rapidly increasing employment rates within the first 20 weeks (10 2-week bins). After the first 20 weeks the employment level stabilizes. The figure show differences in the inflow into employment initially where it is clear that individuals in the middle education group find jobs faster than both the low and high education groups. But in after 20 weeks there is a clear educational ordering in the employment level. The employment rate is around 70% for individuals with high education and it slowly increases whereas the employment level is around 55% for individuals in the middle group. On the contrary the employment rate for individuals with a low level of education the employment rate is around 40 % and pretty stable from week 20 and onwards.

The model which will be presented below will offer different explanations for decreasing outflow rates and differences across education levels, these are duration dependence in job offer probabilities, differences in wage offers and differences in preferences (both in terms of observables and unobservables).

Figure 1: Employment and outflow rates in the control group

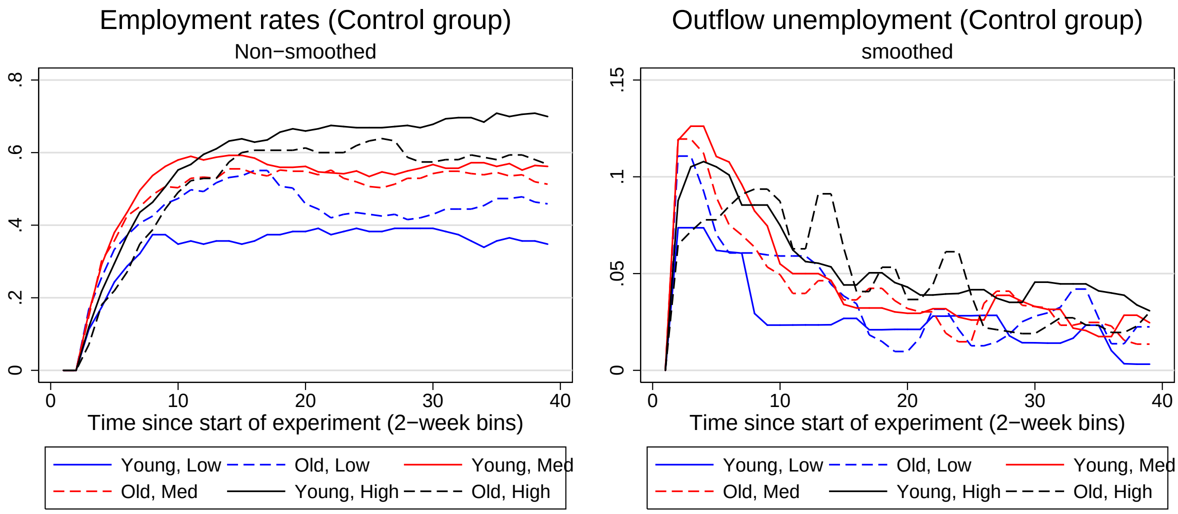


Figure 2 shows the evolution in wages for employed workers since experiment start and Table 2 reports some details for the distribution of after tax wages.[11]

The figure shows that wages increase with employment duration. Both the level and the growth rate of wages differs by education. At the same there is considerable variation within educational groups. Differences in wages and wage patterns will be important for how individuals value employment, therefore the model will allow for all these features through a search sensitive component of wages (different wage offers) and stochastic human capital accumulation while employed. The human capital level will be unobserved to the econometrician.

[11] After tax wages are calculated assuming a tax rate of 37.5 % which was the average tax rate for an unemployed worker in 2008 (see Maibom, Rosholm and Svarer (2015))

Figure 2: Wage-profiles in the control group

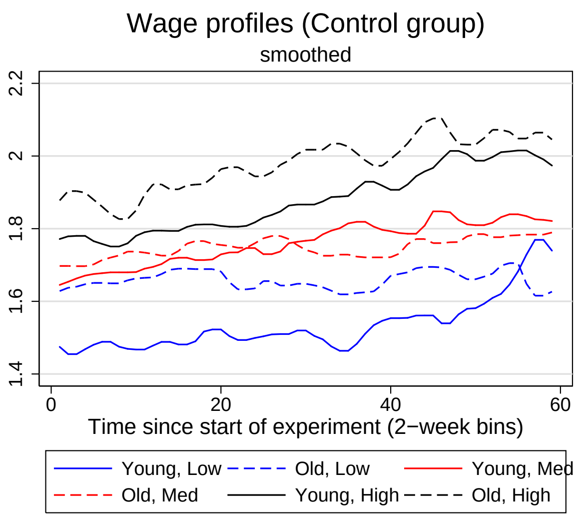


Table 2: Distribution of after-tax wages

	Mean	Std. dev.	P5	P25	P50	P75	P95
Wage	102	21.1	68.10	87.02	100.52	116.17	139.74

Description of the model:

The model is based on the framework developed in Ferrall (2011, 2006). Here this framework is adapted such that it describes the social enviroment faced by unemployed individuals in the Danish labor market. The model is a sequential random search model and is cast as a discrete choice dynamic program where the choice set consists of a discrete choice of search activity and if a job offer arrives whether to accept it or not. The social enviroment is stationary and ergodic. It is characterized by job offer rates, wages, duration dependence in unemployment, stochastic human capital accumulation in employment and depriciation at inflow into unemployment. Employed individuals face an exogneous probability of a layoff. The transitions probabilities depend on characteristics of the agents in ways that will be specified below. Importantly the enviroment is characterized by unemployment insurance and ALMPs which consists of two main elements namely contact and activation.

To learn about the effects from ALMPs, and to have usefull variation which help identifying the individual level costs of programme participation, a non-stationary and finitiely lived experiment is introduced into this enviroment (see more below). Adding the experiment to the model implies that we have a framework which allows us to distinguish between different effects during the unemployment spell related to the existence of ALMPs and at the same time take into account that the experiment QBW2 is known by the agents to be a finite lived intervention in this setting.

Timing:

The enviroment outside the experiment is set to be stationary and agents are infinitely lived. Essentially these assumptions allows us to track out an underlying steady state distribution of workers from the snapshot data of a selected population that we have available (namely the inflow into unemployment at a given point in time). Ferrall (2004) shows the conditions required for existence of an ergodic distribution. When these are fullfilled the assumptions allows us to correct for the endogeneous sampling over the statespace (correcting for initial conditions) although we have timevarying non-IID unobserved statevariables (see more below).

DMP problem:

The model of job search is a dynamic discrete choice model. This implies that when choosing levels of job search or whether to accept a job offer or not, agents are aware of the effects of their current actions on future returns as well as the role of uncertainties. While agents are assumed to be unaware of what their future realizations of for instance job offers are, they are assumed to have perfect knowledge with regard to the probability distribution from which these future shocks will be drawn. This implies, taht when looking for a job offer the agent will have to weight the present costs associated with searching for work against the possible gains in future remuneration if you are able to secure a higher job offer (Lippmann and McCall, 1976, McCall, 1970???). Similarly agens are aware that while not working in this period they do not gain any experience, and thus decrease their future emloyment prospects.

Let choices be contained in α and let θ contain the value of the state (notation is similar to Ferrall (2011)). The value of a given (α, θ) combination at a given point in time can then be expressed as the following Bellman equation as the sum of the current reward (utility from current choices) and a future reward which is then also a function of the current choices and position in the statespace:

$$\begin{aligned} \forall \alpha \in A(\theta), \quad v(\alpha, \theta) &= U(\alpha, \theta) + \delta E\left[V(\theta')\right] \\ &= U(\alpha, \theta) + \delta \sum_{\theta'} P\left\{\theta' | \theta, \alpha\right\} V(\theta') \end{aligned}$$

At each point in time the agent solves his decision problem choosing the actions that gives him the highest value and therefore the value function can be determined as:

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

Notice that given a position θ the choice of an agent is deterministic. This also implies that if we observe two agents with the same θ doing different things our model is basically rejected. In the litterature this has been handled in two ways. Rust (XXX) adds a continuous unobserved statevariable to the utility function in the model referred to as a tasteshifter. Since this variable is unobserved the reason two "identical" agents is now prescribed to different values for the tasteshifter. Rust () shows that when this tasteshifter follows the extreme value distribution we can analyutically solve for an expression of the choice probabilities and by modifying the contraction mapping slightly (it now becomes a log sum instead of the sum above) we can calculate the choice probabilities of the model. The main argument for adding the tasteshifter is thus to smooth choice probabilities. Here we instead follow a procedure introduced by Eckstein & Wolpin, 1999. In order to break the "curse of zero probability events" we smooth choice probabilities *ex post* instead of using *ex ante* tasteshifters in the utility function. We smooth choice probabilities using a logistic kernel ($\rho > 0$):

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

The smoothing is very similar to taste shifters, if two choices have very similar valuefunctions choice probabilities will be close to each other, choices which implies values "a lot" below the optimal one will imply that $\tilde{v}(\alpha, \theta)$ is low and therefore choice probabilities will be low. The higher rho the less smoothing. The smoothing formulation can also be seen as arising from a particular type of error structure in the behavioral model (ie that additive taste shifters follow a particular distribution) ie there is an underlying additive shock which can rationalize the ex post smoothing. While the expression above looks almost identical to the one in Rust (1994) there is one fundamental difference. Here we smooth ex post while the standard Rust model adds a tasteshifter to the model which implies that agents take the existence of shocks to utility into account when they solve for optimal values. By smoothing ex post we introduce a wedge between the decision rule agents *anticipate* they will follow and what happens in reality (sometimes this is reffered to as allowing for zero probility or unanticipated events). Ultimately the difference is that the contraction mapping in Rust (1994) is slightly modified according to the equations above (his expected value function becomes a logsum).

Choices:

While unemployed agents have two choices (collected in the vectorα). These choices are choices of the level of search **a**ctivity $\left(a \in \left\{0, \frac{1}{3}, \frac{2}{3}, 1\right\}\right)$ and a choice of whether to accept a given job offer (**m**arket status) ($m \in \{0, 1\}$). These two choices capture the central channels through which individuals can affect their own labor market status and thus where ALMPs can affect individual behaviour towards obtaining employment. Individuals can for instance increase their search effort to leave unemployment as programme participation is percieved as unpleasant or that they increase or decrease reservation wages. For search activity we allow for choices on both the extensive margin (to actively search or not) and the intensive margin to allow for responses in both dimensions during the unemployment spell. For instance this allows for a discouragement effect as unemployment progress or alternatively an intensification of search activity when the risk of participation in ALMPs increases. In the model we describe search intensity with 4 different levels (search **a**ctivity $a \in \left[0, \frac{1}{3}, \frac{2}{3}, 1\right]$).

The model is solely a model for the choice of the extensive margin for employment. The intensive margin is assumed fixed and constant across jobs. To model the intensive margin of employment other characteristics of the employment situation would be neccessary, for instance detailed data on working hours, other benefits and tax schemes. Further notice that the labor supply decision is conditional on having recieved a job offer (there is a search friction), and further I do not allow for on the job search (Job to job transitions and subsequent changes in wages will be attributed to accumulation of human capital in the model). Lastly it is assumed that the agent has no influence on whether he is separated from his current job (the analysis in Maibom, Rosholm & Svarer, 2014 found effects on employment duration which is captured through growth in human capital).

Since there is no job-to-job transitions or endogenous job separations from employment in the model, the choice problem basically pauses while the agent goes through a spell of employment and is the resumed when falling back into unemployment. While there could be important effects through both channels the data will not allow us to determine the reason for job separations and furthermore the potentials for increasing the value of employment through job-to-job transitions is captured through stochastic human capital accumulation in the model. The idea of the model is now very similar to Gilleskie (XXXX), ie we only solve the optimization problem for the agents when they are unemployed. We still need to track the agents in their jobs also because it is random when they are hirred and we need to follow the evolution of statevariables.

Statespace:

The state space summarize all relevant information in the enviroment that influence decision makers in making his decisions (wages, employment status, wage process). The *current* position in the statespace is collected in state vector θ and is known by the agent when making choices. The statespace consists of a time-invariant part and a time-varying (determininstic and stochastic) part. The time-invariant part divide agents into different demographic groups and types, and this part of the state space is by construction unaffected by the choices agent make within the enviroment.

The time-varying part of the statespace evolves partly stocastically and therefore the agent does not know the future position of the statespace θ' but will form expectations. Lastly to incorporate the experiment into this framework the statespace is extended with statevariables ensuring that treated agents progress through different phases of treatment.

Below we will briefly present the different state variables (for a more details see the overview towards the end of this section).

Time invariant states

Demographic groups (**d**) are distinguished by the education level of the agent (low, medium or high skilled) and by the age at inflow into the experiment (young or old workers). Demographic group status is observed by the econometrician. The enviroment is also composed on an unknown (finite) number types (unobserved types (**k**)). The distribution of types is allowed to differ across demographic groups as in Ferrall (1997). The type status is unobserved to the econometrician.

Time-varying states:

The time-varying statevariables are a collection of variables describing the (i) unemployment situation and the (ii) employment situation. In the former we have variables for the unemployment duration in current spell (**cu**), search sensitive earnings offer (**o**), meetings or activation participation status (**mp**/**ap**), loss of job entering this time period (**l**).

For the employment situation we have variables such as the skill level based on past experience (**ce**), employment status (**e**).

Unemployment duration keeps track of how long the agent have been unemployed in the current spell (since last job loss), this in turn affects the probability that job offers arrive (see more below). Wage offers represents the search sensitive component of wages which is mapped into an actual wage offer through a wagefunction. When employed the skill level of the agent evolves stochastically and this also affects his wage. The meeting (activation) indicator indicate whether agents currently participate in one of the programmes.

Experiment statespace:

As the experiment QBW2 represents a finitely-lived intervention in this otherwise stationary enviroment the experiment is included into the model by extending the statespace with two statevariables which serve as "accounting variables". This allows decisions of agents to differ with where in the experiment they are. These variables are: treatment phase (**f**), counting variables for # periods in current phase (**c**). Together these variables allow agents to experience for instance 6 periods of increased meetings intensity or to go through a "waiting" phase knowing that in 6 periods they will be enrolled into an early activation scheme. The extent to which the choices of agents differ with the values of these variables informs us about the costs (and benefits) of programme participation.

Primitives:

Utility:

The static version of the problem can generally be thought of in the context of a generalized Roy Model. The utility from being in a given state/choice combination is determined by the income recieved subtracted any costs incurred (pecuniary and non-pecuniary). Importantly the agent recieve disutility from exerting effort either through search activity ($a \neq 0$) or from working ($m = 1$). There is also a cost related to the participation in an ALMP, this cost depends on the type of programme that individuals participate in (ie. either a meeting or activation), this is due to the fact that these programmes are very different in content, duration and scope and therefore costs might be very different.

The immediate payoff from a given (α, θ) combination is described as:

$U(\alpha, \theta) = Income(\alpha, \theta) - Cost(\alpha, \theta)$

$Income(\alpha, \theta) = \mathcal{B}(\mathrm{m} > 0) \cdot W(\alpha, \theta) + \mathcal{B}(\mathrm{m} = 0) \cdot UI(\alpha, \theta)$

$Cost(\alpha, \theta) = W_{max}\left(\bar{\theta}\right) \cdot (\xi a + \kappa_0 m + \phi_{ap} \cdot ap + \phi_{mp} \cdot mp)$

$UI(\alpha, \theta) = \gamma W_{UI}(\alpha, \theta)$

where ϕ_i measures costs (both pecuniary and non-pecuniary) from participating in a programme in income equivalents. ξ determines the cost of search, here we assume that this cost is linearly increasing in the intensity. Costs are expressed as a fraction on maximum wages (in the optimization process we therefore restrict $\xi, \kappa_0, \phi_{ap}, \phi_{mp}$ to lie on the unit interval) which is a function of $\bar{\theta} = \theta_{ce=CE,sc=SC}$ where the search sensitive component and the level og human capital is evaluated at the highest possible value. See more about wages below. This implies that costs are not uniform but vary with demographic group and type.

This specification can be thought of as an opportunity costs such that the cost of effort also depends on how this effort is valued in the market, a high wage earner thus have a larger opportunity cost of effort as his time in general is more valuable. The representation is thus chosen to value individuals income and costs at similar metric, it would be inconsistent to allow income to vary with types but costs not to.

Note that the utility function is linear in the parameters which implies that agents are risk neutral as in the standard search model. This also implies that there is no immediate argument for insurance in this model and thus this model will not be able to answer questions about optimality of UI. Sometimes the insurance problem is divided into steps such that the individual is maximizing income and subsequently smoothing income over time ie there is an underlying model of optimal savings and assets allocation problems (this requires the existence of capital markets).

Active labor market programs:

In this model ALMPs enter in two ways:

(i) through a loss in utility (fixing the incentive problem) and (ii) through a potential increase in the probability of a job offer in the period after programme participation (qualification problem).

(ii) is included to allow the programme to also have some productive effects while (i) would imply that the interactions between the PES and the unemployed is viewed as unpleasant from the point of wiev of the unemployed. There are different ways in which (i) could be the rationalized.

Broadly speaking we can represent the individual level costs as the sum of several components.

$cost(intensity) = monitoringeffect(effort) + psychological(stigma) + timeuse(lostleisure)$

These are all potential explanations for why an agent might dislike an increase in contact with the job center.

Firstly contact implies that the agent needs to exert effort (and losses leisure) for instance participation in either program requires travel time to the job center and participation in the programme. Furthermore it is not clear how the agent values his time spent at the job center ("non-market" wage). For instance the presence of a stigma effect from partipating in the programme or just a compensating wage differentials story could be used as an explantion for why agent might value time they don't have to spent at the job center higher than time they don't have to work. The presense of for instance a stigma component would imply that programme participants valuate their time spent in ALMPs at very different rates than normal search actvitiy or loss of leisure. The existence of stigma associated with public transfers was introduced in Moffitt (1983) in an effort to explain why take up to welfare programmes where limited in spite of substantial potential income gains. Arguably in an almost universal UI system the stigma component associated with actual takeup is probably limited and at the same time the replacement level is higher, but meetings at the job center or participation in "useless" activation programmes could still generate substantial disutility.

Secondly contact with the PES can be percieved by the unemployed as an increase in the degree of monitoring of his search activity this implies that the risk of getting caught increases for individuals searching insufficiently. The later effect primarily applies to individuals who do not search sufficiently and thus this would be a subset in the pool of unemployed. There is a litterature on monitoring effects of UI (started with beckers paper on crime) but there has been no attempt to distinguish the non-market wage effect from the monitoring effect (generally the papers assume that the interaction with the job center is so little that it is neglible). In principle the experimental setup should allow us to distinguish between the two explanations if we assume that the monitoring risk is constant throughout the treatment period whereas the non-market wage effect declines because the number of meetings left declines as the experiment progresses.

The above suggests that we can rationalize e.g. increased search effort through a number of different mechanisms. Given the data at hand we focus on the sum of these components here. Researcher would be greatly interested in the decomposition but for evaluation of the specific programme the sum is sufficint and a decomposition would rely heavily on how we specify the model (essentially it would be identified from functional forms and the assumptions made about timing and how agents are affected).

(i) and (ii) provide different explantions for why interactions with the PES can increase the job finding rate for unemployed individuals. The two explanations can be distinguished by looking at the timeprofile of individual behaviour. For instance an increase in the inflow to employment in the weeks prior to programme participation or within the first weeks is informative of the size of the utility cost component (in the litterature this is known as the threat effect), whereas outflow rates after programme participation informs us about the qualification effect. Again contrasting these rates with the control group where programme participation is smaller allows us to separate the effects from duration dependence. Notice that if ALMPs rely increase the job offer probability then we would expect a reverse threat effect for individuals who unexpectedly experience an increase in the intensity of interactions (a socalled attraction effect). The empirical litterature suggests effects in the opposite direction suggesting that the disutility of ALMPs is one important channel.

Wages:

The wage function is modelled as follows:

$W(\alpha,\theta) = \mathcal{B}(\text{fp} > 0) \cdot \exp\left(\tau\Phi^{-1}(\text{fp}) + \left(\eta_0^{educ}\right) \cdot \text{ex} + \eta_2 \cdot \text{age\_gr} + \chi_{Type}^{educ,age}\right)$

$W_{max}(\alpha,\theta) = \exp\left(\tau\Phi^{-1}(\text{fp}_{max}) + \left(\eta_0^{educ}\right) \cdot \text{ex}_{max} + \eta_2 \cdot \text{age\_gr} + \chi_{Type}^{educ,age}\right)$

The functional form implies that we get the well known mincer equation in log wages.

The parameter τ measures the importance of fp which represents the frictional (search sensitive) component of the wage (a draw of firm productivity). It implies that similar individuals can be paid differently simply due to the frictions in the markets which implies that wageoffers arrive randomly. The presense of a search sensitive component in wages creates an optimal stopping problem in the sense that agents form a reservation wage which for offers above the reservation wage agents accept the job offer, for offers below agents reject the offer and keep searching. In a stationary setting the reservation wage can be expressed analytically (see eg. Wolpin (XXXX)), in this setting this is harder as for instance the presense of the experiment makes the setting inherently non-stationary, also the reservation wage will be revised during the unemployment period as unemployment duration increases.

η_2 allows for differences in the intercept of wages between young and old workers andη_0 is a vector of education specific returns to experience/human capital which is unobserved by the econometrician. While an agent is employed he stochastically accumulates human capital (for instance by learning by doing) and thus his wage increases. The existence of stochastic (unobserved) human capital allows the value of employment to be different between two from the point of wiev identical individuals in ways which are allowed to correlate and change over time. In the the estimation the education specific returns and the evolution of human capital is identified as we match on moments of employment duration and wages.

When unemployed the agents recieve unemployment insruance:

$W_{UI}(\alpha,\theta) = UI$

Unemployment insurance is determined as a fixed amount of money assuming that all individuals qualify for the maximum amount of benefits. Lentz (XXXX) estimates that around 90% of the unemployed workers in XXXX qualify for this amount of money and therefore this justifies the assumption. Furthermore we are not modelling eligibility here as the unemployed targeted are newly unemployed (with deviations as documented above) and since the elibibility of UI was 4 years in this period.

Jobs:

Jobs are generated when an unemployed recieves a job offer which he accepts. Jobs end with probability $\pi_{lj} = \pi^{educ} \cdot \left(1 - \frac{ce}{CE+1}\right)$ where CE denotes the highest possible level of human capital agents can obtain. The specification thus implies that job separation probabilities decline linearly in how "productive" workers are. This generates duration dependence in employment as workers who have been employed for longer periods are also more likely to have accumulated more human capital and thus less likely to exit to employment. Essentially this specification would allow a finitely lived intervention such as intensified contact with the PES to generate employment duration effects if unemployed individuals leave unemployment earlier and we evaluate the experiment with incomplete spells.

Joboffers:

Job offers arrive with probability π_w. At inflow into unemployment the agent have no job offers (sc = 0). The probability that a job offer arrives in the next period is determined as a function of search activity and unemployment duration. We follow the specification in Wolpin (1987) for the functional form of duraiton dependence.

$\pi_w = \mathrm{a}\cdot\Phi\left(\pi_{w1} + \left[\pi_{w_2}^{age} + \pi_{w3}^{educ}\right]\cdot \mathrm{cu}\right)$

This formulation assumes that agents need to be actively searching in order to recieve job offers, furthermore the probability of recieving an offer can be decomposed into a duration dependent term and a constant term. The later term gives the probability of a long term unemployed recieving a job offer. [12]

If employers use duration in unemployment as a screening device (such as what has been suggested in the litterature, see e.g. Fabian Lange (XXX) and bezil (1995)) we expect π_{w2}, π_{w3} to be negative. At the same time we allow for the "spurious" negative duration dependence in the form of dynamic selection as we have both unobservedable types and differences in the stock of human capital across agents. Furthermore we expect π_{w2}^{old} to be negative to match empirical facts such as that unemployment duration is increasing in age (see e.g. XXXX). In our model we allow for one alternative explanation for this namely that there skills are obsolete and thus when they separate from employment they "loose" their skills with probability π (see below).

Human capital:

The process for human capital evolves as follows a jump process. While employed the stock of human capital appriciates stochastically by one unit every period with probability π_{app}. When an employed agent is separated from his job he looses his skills with probability $\pi_{picedep}$. This is meant to capture that the skills he has accquired through his employment histroy so far have become obsolate and thus his expected wage will be lower in the future (as he will basically have to start from scratch for instance in a new sector).

Solution of the model:

Given the framework outlined above the solution of the model follows in the following steps (for more details see the appendix):

i) Solve for $V(\theta)$ using the contraction mapping properties

Ferrall (2004) gives the conditions under which $\Gamma(\theta)$ is a contraction mapping.

ii) Calculate the policy function, $P(\alpha|\theta)$ as given in (XX)

With the policy function we know how agents choose for each position in the statespace. If all states where observable we could estimate the transition parameter in the transition matrix

[12] note that from the assumptions of the model π_w cannot be 0 for high unemployment durations, as then the enviroment is not ergodic

$P(\theta'|\alpha,\theta)$. However as states (and some actions) are unobserved *and* change in non-IID ways we need to track the evolution in the statespace over time from an initial distribution (which will be defined below). Therefore we solve for how the distribution changes over time integrating out choices by using the structure that is created by the model.

iii) Solve for the state-to-state transition matrix:

$P_s(\theta'|\theta) = \sum_{\alpha} P(\alpha|\theta) P(\theta'|\alpha,\theta)$

The state-to-state transition function allows us to track the evolution of the statespace from some t to some t+k explointing that the model is markovian (thus iterating on a markov chain). Thus given an initial distribution over states we can solve for the distribution of states at a given point in time and by defining som measurements (defined below) we can relate the model to data. Since some statevariables is unobserved we do not have an initial distribution over states. Instead we again use the structure of the model and the enviroment, here the existence of an ergodic distribution over states (thus the steady state distribution over workers and types which exists). Ferrall (2004) provides the assumptions needed for an ergodic distribution to exist.

iv) Solve for the ergodic distribution for which it holds that the distribution at time t is identical to the distribution at time t+1:

$P_{-\infty}(\theta) = \sum_{\theta'} P(\theta'|\theta) P_{-\infty}(\theta)$

The ergodic distribution gives us the distibution of individuals in the economy at a given point in time. From this we can then determine the inflow into unemployment and thus start the markov chain. The existence of the distribution also imply that we can correct for initial conditions and endogenous sampling. For instance as documented in the data section above a part of the sampled population in the experiment consists of individuals which have been unemployed for some time. These individuals comprise a negatively selected subgroup of the group of individuals becomming unempoyed in earlier periods. The model will have to take this process of dynamic selection into account in order not to inaccurately mix selection bias with the actual structural parameters.

v) Apply sample selection rules to the the ergodic distribution

This final step creates a sample that matches the data on observable terms (e.g. unemployment duration) but also takes account of the dynamic selection on unobservables since inflow into unemployment. Using the state to state transition function and the corrected initial distribution over observable and unobservable states we can now solve for the distribution over states for each timeperiod since t=0.

These 5 steps now enables us to relate the predictions of the model to the actual data and thus learn about the structural parameters. In the next section we explain how.

Estimation and Identification:

The model is estimated using the method of moments.[13] The moments chosen to match on will be presented below and reflect changes in states that affect conditional choice probabilites and also choices generated by the model. Theese moments are then compared to the equivalents in the data, a metric is formed and the distance between the predictions by the model under a certain set of parameters and the data is minimized by changing the model parameters.

To relate the model to the moments calculated from the data we proceed in 3 steps.

i) Define a measurement $Y(\alpha, \theta)$

This could be for instance the employment status at a given point in the state space.

ii) Calculate the expected measured result

$E(Y|\theta) = \sum_{\alpha} P(\alpha|\theta) Y(\alpha, \theta)$

The expected measured result gives us the expected value of the measurement conditional on a position in the statespace. Using the initial distribution over states and the markovian structure of the problem we can now determine how the expected measured result evolves over time and weight measurements a given positions in the statespace with the corresponding distribution over states. This gives us a timeseries of moments. The moments are thus determined conditional on time and the timeinvariant states: unobserved type and demographic group. Subsequently we then weight moments with the distribution over unobserved types.

$$E[Y_M|d,t,g] = \sum_k \lambda(k,g,e,d) \sum_{a \in A(\theta)} P\{\alpha|\theta\} Y(\alpha,\theta)$$

Using the data similar moments conditional on time, demographic group and treatment status can be obtained and thereby matched to model predicitions. This will form a metric that expresses how similar model predictions are to data predictions overall. The metric is:

$$(E[Y_D|d,t,g] - E[Y_M|d,t,g])' W^{-1} (E[Y_D|d,t,g] - E[Y_M|d,t,g])$$

Where the weight matrix is chosen to be the variance of the moments in the sample. The method of moments now proceeds by minimizing the objective presented above.

The estimation thus proceeds as a nested fixed point algorith similar to the one in Rust (XXX). The model can now be solved for a given set of parameters, the objective can be evaluated and parameters can be updated and the procedure reiterates.

Moments:

[13] Note that these are not simulated moments but expected values calculated by exploiting the structure the model impose. A recent paper by Heckman XXX (IER, XXXX) documents that the siulation error that exists in models exploınting simulated moments can affect the estimates in non-trivial ways.

The model is estimated using moments capturing employment dynamics and wage dynamics.
Employment dynamics:

- fraction who lost a job
- unemployment duration squared
- duration of current employment spell
- stock and inflow into unemployment
- inflow into employment
- product of inflow into employment and unemployment duration

Wages

- stock of accepted wages, wages squared
- accepted wages and inflow wages
- inflow wages

Identification:
Identification of the model concerns whether the model parameters can be recovered *given* the data available. Here the parameters of the model are identified by restrictions (generated by the model) on how the moments can vary across treatment groups, over time, within and across demographic groups. The model includes three forms of "exclussion restritions" (independent variation affecting only one part of the model e.g. the preferences) under the assumption that the model is a good description of reality. In particular we have "exclussion restrictions" in job offer rates (unemployment duration), wages (human capital) and preferences (ALMP participation).

Firstly we are trying to learn about preferences and the wage distribution from accepted wage offers only. Essentially we are trying to separate preferences from wage function, and the problem is that there are two explanations for why the e.g. young individuals generally do not work to the same extent as older individuals: either he just dislikes work or alternatively his wageoffers are lower than other groups of workers. To separate the two explanations we need some variable that always affects wage offers without also changing the preferences (an exclussion restriction). The existence of such a variable implies that we can make a within group comparison (i.e. compare young workers for different values of this variable) and thereby we that they get higher wageoffers this then informs of about the cutoff point, ie where wages become so high that employment is chosen. In the model the process of human capital serves as such a variable.

Secondly the existence of a search friction emplies that unemployed are unemployed **either** because she rejected a job offer or because she did not recieve one. Again since we do not have any information on whether the unemployed recieved a job offer or not, we want to distinguish between the two using accepted wages only. To separate these two explanations we need another exclussion restriction. This time a variable that only affects job offer probability as then we can determine whether individuals with high offer probabilities go into employment to a higher extent, if not it must be a preference argument. Ie we get to fix the type of the individual and then within this type we have a group of individuals who gets more job offers than the others, thereby we learn something about the preferences of this type of individuals.

Finally note that the treatment variation generates another form of exclussion restristions as here we essentially exogenously vary the cost of being in unemployment. Notice also that the non-stationarity of the experiment thereby also generates exogenous variation in the value of future which allows us to estimate the demographic specific discount rates. The variation exploited for instance differences in when different demographic groups start to respond to events in a near (or far) future. Rust showed that the discount rate was non-parametrically non-identified in a stationary (infinite horizon) model, but later papers have exploited non-stationarities for instance due to time limited UI benefits to estimate the discount rates (see eg. XXXX,XXXX).

To assess whether the imposed structure and the selected moments where sufficient to recover the structural parameters a "baby-version" of the model with the main central mechanisms have been simulated and subsequently the generated data where used in estimation to check whether the chosen parameter values could be recovered. Although this is by no means a formal proof of identificaiton nor an actual monte carlo exercise it still provides a good indication of whether the model is identified.

Results:

In this section we present the results from the estimation. Showing some key parameters and implications of the estimated model and then we proceed by giving some evidence of the fit of the model.

We then test the predictive quality of the model and finally we discuss the implications of the estimates and in particular we assess the importance of the individual level costs of participating in ALMPs.

Predictions of the model:

The figure below shows a number of central predictions from the model. Figure 3 shows the evolution in job offer rates with the duration in unemployment. The figure shows clear duration dependence which is decreasing in the level of education but still substantial for high educated individuals who after 10 periods (2.5 months) face a job offer rate which is around 15 % of the job offer rate they had at inflow.

Figure 4 shows the evolution in wage offers as a function of the level of human capital. Again the difference across education levels is substantial and it is growing in the level of human capital due to education specific returns which are increasing in the education level.

Figure 3: Job offer rates

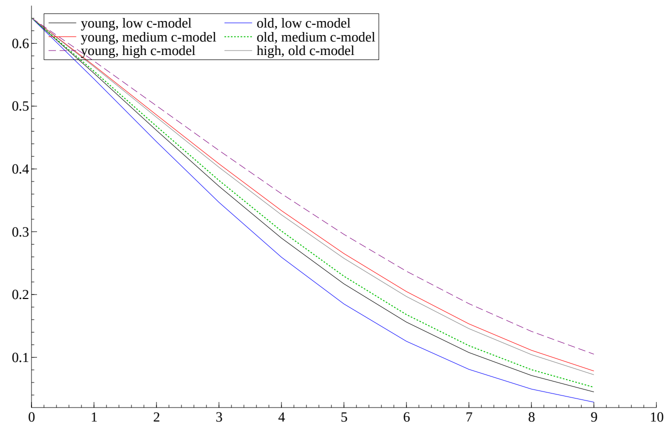
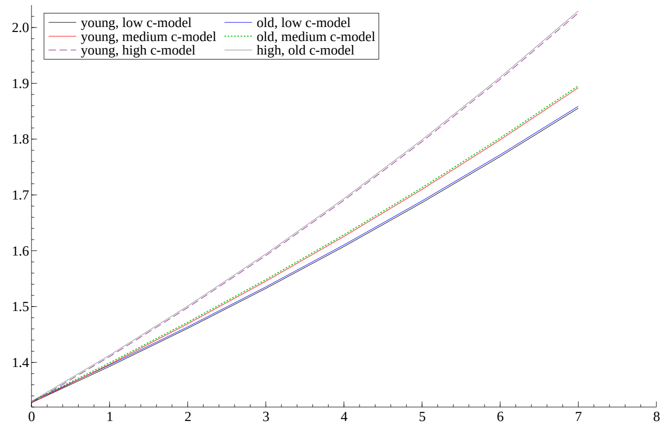


Figure 4: Wage offer function



Fit of the model:

The figure below compares the model moments with the data for a number of moments.

Figure 5 shows that the model is able to generate both high initial outflow and subsequently decreasing inflow rates. Duration dependence is the main explanation for this decrease.

Figure 6 shows that the model is not able to match the distribution of accepted wages at the current stage for individuals with low education. For higher levels of education the fit looks more reasonable although there is still room for improvement.

Implications of the fit:

Table 3 reports the estimates of ϕ_{ap}, ϕ_{mp}. These are the per period costs which the experiment has implies for individuals in the treatment group in the Table these are converted into hourly wages.

Figure 5: Inflow rates (data vs model)

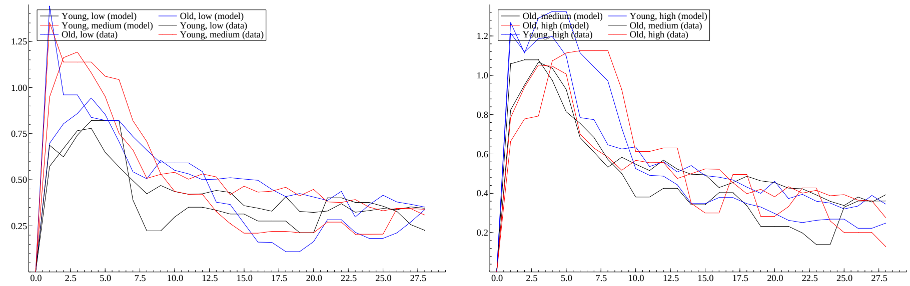
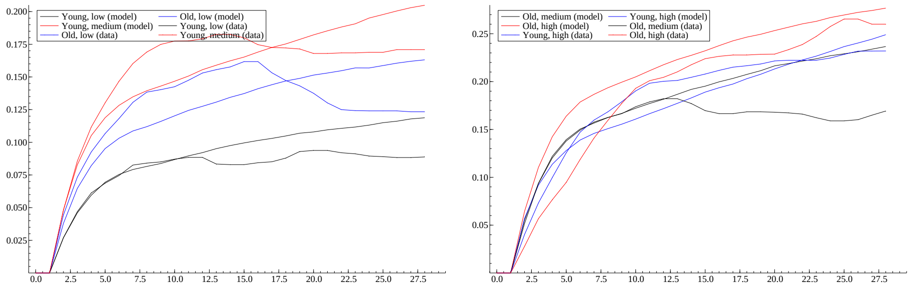


Figure 6: Accepted wages (data vs model)



The cost of partipating in activation is much higher that the corresponding one for meetings but when we take into account that meetings is a much shorter intervention the hourly non-market wage from participating is actually higher for meetings. Thus unemployed would prefer an hour in activation compared to an hour in meetings. Both costs are substantial.

Table 3: Estimates of the cost of ALMP participation (hourly wage in ALMPs)

Estimates		*in Euros*					
Group		Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Two week wages		*1200*	*1360*	*1480*	*1200*	*1360*	*1480*
Hourly wage ϕ_{mp}	0.02	48	54.4	60	48	54.4	60
Hourly wage ϕ_{ap}	0.10	12	13.6	14.8	12	13.6	14.8

Finally we redo the CBA presented in Maibom, Rosholm & Svarer (2015) to take into account the value of lost nonmarket time which the intensified ALMP schedule implied. The calculations are reported in Table 4. We also adjust the value of increased production by subtracting the loss of leisure for individuals who obtain work. This way we bring the CBA closer towards actually reflecting the effects on welfare from the experiments. The table shows that the traditional cost benefit analysis substantially overestimates the value of social programmes by assuming that the value of lost leisure is 0. This is particulary true in cases where the programme requires some effort from the individual which he regards as unpleasant as in such cases the non-market wage can be substantially different from the wage in the market sector. In the case of meetings the gain of the programme falls by 40% and in the case of activation the gain dissapears.

Table 4: Cost Benefit Analysis (meetings)

After 52 weeks (males, experiment B):	Costs	Corrected MCPF
Individual Meetings		
Saved income transfers	722	144
Saved programme costs	-233	-268
Saved total costs		-124
Acc. gain in employment (weeks)		1.93
Value of increased production		1405
Net result of CBA (in €)		**1256**
Loss in individual non-market time		-207
Net result		**1074**
Loss in leisure from increased production	0.11*1480*1.93	-314
New net result		**760**

Table 5: Cost Benefit Analysis (meetings)

After 52 weeks (males, experiment C):	Costs	Corrected MCPF
Activation:		
Saved income transfers	847	169
Saved programme costs	-390	-468
Saved total costs		-299
Acc. gain in employment (weeks)		2.04
Value of increased production		1489
Net result of CBA (in €)		**1190**
Loss in individual non-market time		-888
Net result		**302**
Loss in leisure from increased production	0.11*1480*2.04	-332
New net result		**-30**

Conclusion:

In the literature focusing on Unemployment Insurance, Active Labour Programmes (ALMPs) such as meetings at the job centre or workfare (activation) programmes have been presented as a way to control the moral hazard which arise in a market with unemployment insurance. A key prerequiste for this to be the case is that programme participation induces some kind of cost on participants. The theoretical literature have focused on whether these programmes are indeed optimal since the existence of such costs makes participants in the programmes worse of. Whether this is optimal crucially depends on how unemployed value these programmes but since these programmes serve as conditionalities for the recipiency of UI the individual valuation is not directly observable.

In order to quantify this valuation this paper developed a dynamic model with discrete choices capturing key behavioural channels which can be affected through interactions between unemployed and public authorities (the PES). The model was estimated using data from a Danish social experiment which provides exogenous variation in the intensity of interactions. This allowed us to estimate the individual level costs of these interactions, in particular the cost agents incur when they have to go into either activation or a meeting at the PES. These costs arise because the individual spend a part of their non-market time at the job centre where he has to exert effort and potentially do unpleasant work (and maybe even feel stigmatized).

The results suggest that traditional CBA calculations which do not take the individual loss of non-market time into account overstates the gain from having these programs. The individual level costs are substantial and are important to quantify to assess whether the current mix between ALMPs and UI is optimal.

References:

Andersen, T. M. & Svarer, M. (2014): The Role of Workfare in Striking a Balance between Incentives and Insurance in the Labour Market, Economica, Vol. 81, No. 321, pp. 86–116

Besley, T. & Coate, S. (1992): Workfare versus Welfare Incentive Arguments for Work Requirements in Poverty-Alleviation Programs, American Economic Review, Vol. 82, No. 1, pp. 249-261

Black, D. A., Smith, J. A., Berger, M. C. & 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, Vol. 93, No. 4, pp. 1313-1327

Ferrall, C. (2012): Explaining and Forecasting Results of the Self-Sufficiency Project, The Review of Economic Studies, Vol. 79, No. 4, pp. 1495-1526

Graversen, B. K. & Van Ours, J. (2008): How to Help Unemployed Find Jobs Quickly: Experimental Evidence from a Mandatory Activation Program, Journal of Public Economics, Volume 92, pp. 2020-2035.

Heckman, J. (2010): "Building Bridges between Structural and Program Evaluation Approaches to Evaluating Policy." Journal of Economic Literature, 48(2): 356-98.

Heckman, J. J., Lalonde, R. J. & Smith, J. A. (1999): The Economics and Econometrics of Active Labor Market Programs, Handbook of Labor Economics, Elsevier, edition 1, volume 3, number 3

Kreiner, C. & Tranæs, T. (2005): Optimal Unemployment Insurance with Voluntary and Involuntary Unemployment, The Scandinavian Journal of Economics, Vol. 107, No. 3, pp. 459–474

Maibom, J,, M. Rosholm and M. Svarer (2015), "Experimental Evidence on the Effects of Early Metetings and Activation", Unpublished Manuscript (Revise-Resubmit Scandinavian Journal of Economics)

Rosholm, M. & Svarer, M. (2008), The Threat Effect of Active Labour Market Programmes, The Scandinavian Journal of Economics, Vol. 110, No. 2, pp. 385–401

Santiago, A., Attanasio, O. & Meghir, C. (2012): Education Choices in Mexico: Using a Structural Model and a Randomized Experiment to Evaluate Progresa, The Review of Economic Studies, Vol. 79, No 1, pp. 37-66.

Todd, P., Wolpin, K. (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, Vol. 96, No. 5, pp. 1384-1417.

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

Appendix

Statespace:

- *notation: EX0 refers to name in statespace.ox (T1 is column 1 in Theta matrix)*

- an argument for not making grids too high is the limited sample size!!! we will only have limited observations in certain states.... on the other hand the grid should be wide enough for the model to fit!

-

-

Exogenous statevariables:

- *ie does the transition depends on the point of the statespace you are currrently in?*

EX0 (T1):

EX2 (T3): meeting status (mp), $mp \in \{0,1\}$

- at any point in while in unemployment you participate in a meeting with probability π_{mp}

Endogenous statevariables:

- *here the transition depends on the current position in the statespace*

EX1 (T2): Lost job entering the period (l), $l \in \{0,1\}$

- includes endogenous and exogeneous job loss. Jobs end with probability π_l

- data/ identifying moment: the outflow from employment, as all exits are exogenous job losses,

TH0 (T4): current earnings offer / search component (**sc**), $o \in \{0, 1, ..., \text{WR}\}$

- represents the search-sensitive component of wages (allows else identical workers to be paid differently).. through the wage function the offer maps into a wageoffer

- *transition:* a jump process where the probability of a jump (π_e) from current state depends on search effort..

$\pi_e = \mathcal{B}(m=0, e=0) \cdot [\pi_{w1} + \pi_{w2}\mathcal{B}(a=1)]$

$\Pr(e'|\alpha,\theta) = \pi_e \cdot \frac{\mathcal{B}(e' \in E_j)}{|E_j|} + (1-\pi_e) \cdot \mathcal{B}(e'=e)$

- Data: only accepted wages are observed. Observed wages follows: $\Pr(\text{observed wage}) = \Pr(\text{acceptance}|\text{wageoffer}) \cdot \Pr(\text{wageoffer}|\text{search status}) \cdot \Pr(\text{search status})$, therefore clearly endogenous

Identifying moments: accepted wages in the data should tell us something about the wagestructure of the data, and through an exclussion restriction we learn aboth the offer equation

TH1 (T5): employment status (**e**),

- needed to track past choices (accepting employment or not is stochastic, so we need to save the decision to determine current position in statespace)

- *transition:* lagged choice variable (m)

TH2 (T6): accumulated unemployment ($au = \{0, 1, .., 5\}$)

- to allow for the fact that the probability of activation is increasing in UE duration and later on duration dependence.

- Transition: if unemployed grows with 1, capped at 12; $cu' = \mathcal{B}\,(p = 0) + cu$

- considerations: maybe less relevant in HIG2 context but can later on be used to measure effect of duration dependence on offer arrival rates, also should the number reset when finding employment or is it accumulated through all states? initially we reset the number

TH3 (T7): level of humancapital(**ce**)

-

TH4 (S8): Enrolled into Activation programme (**ap**)

transition: probability of activation (π_{ap}) increases linearly in unemployment duration, you cannot participate in activation within the first month of unemployment

– transition: enrolement happens with prob π_{ap}, conditional on unemployment and $cu > 2$

- considerations: not equally likely.. maybe allow for activation to affect experience (ie ce))

- Data: observed

–> problem with transition function if we do not allow meetings and activation to happen at the same time... to do this we should specify a stateblock I guess!

TH5 (S9): UI category (**ui**)

- needed to relate UI benefits to the level of wages that individual was paid before inflow into current unemployment spell

- I will never be able to separate HC component from search sensitive component in wages in the data; but policy makers do not do this either..

Statevariables related to experimental groups

- statevariables which tracks the change in the enviroment faced by the treatment group when they are enrolled into the experiment which represents a finitely lived intervention in the otherwise stationary enviroment

RC (S10): clock for current phase (**c**)

- count the number of weeks spent in unemployment in the current phase

transition:

PH (S11): Treatment phases (**f**), $f \in \{0, 1, 2\}$

- 0 = waiting phase in region 2 (treatment phase in region 4)

- 1 = treatment phase 2 in region 2

transition:

Solution of the model:

This part of the appendix explains how the model is solved.

The solution of the model follows in the following steps:

i) Solve for $V(\theta)$ using the contraction mapping properties

We use the method of successive approximations (the process can be speeded up using the error bounds suggested by McQuad, Porteus (see Rust (XXXX))).

The method basically iterates on the Bellman equation from an initial guess $V_0(\theta)$ untill $|V_n(\theta) - V_{n-1}(\theta)| < \epsilon$.

ii) Calculate the policy function, $P(\alpha|\theta)$

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

iii) Solve for the state-to-state transition matrix

where $\dim(P(\theta'|\alpha,\theta)) =$#states*#states, $\dim(P(\alpha|\theta)) =$#actions*#states

$P_s(\theta'|\theta) = \sum_\alpha P(\alpha|\theta) P(\theta'|\alpha,\theta)$

iv) Ferrall (2004) proofs the existence of an ergodic distribution, we can solve for it using methods presented in Judd (another contraction mapping):

- $P_{-\infty}(\theta') = \sum_{\theta'} P(\theta'|\theta) P_{-\infty}(\theta)$

v) Apply sample selection rules from the ergodic distribution such that you end up with a sample that matches the data on observable terms (e.g. unemployment duration) but also takes account of the dynamic selection on unobservables since inflow into unemployment.

Using the state to state transition function and the corrected initial distribution over observable and unobservable states we can now solve for the distribution over states for each timeperiod since t=0.