Home Sweet Home? Job Search with Commuting and Unemployment Insurance

Elisa Guglielminetti, Rafael Lalive, Philippe Ruh, Etienne Wasmer

Home Sweet Home? Job Search with Commuting and Unemployment Insurance*

Elisa Guglielminetti†, Rafael Lalive‡, Philippe Ruh§ and Etienne Wasmer¶

Abstract

Unemployed workers seek jobs that are ideally both well paid and not too far from their homes. But are they willing to compromise on wages and commuting distances as their unemployment spells increase? After a few months of unemployment, we find that job seekers do indeed accept significantly lower paying jobs and also accept jobs that are located further away from their homes. However, based on quasi-experimental variations in the duration of unemployment benefits, we find that the loss of benefits does not explain why the long-term unemployed are willing to commute further from home. In particular, for workers who previously held jobs in the same municipality where they lived (whom we term *local workers*), unemployment benefits instead *raise* the commuting distance for the jobs they accepted. We estimate a job search model where job seekers target search in space that has higher costs for searching more remotely. The model predicts that search costs for jobs located both in the home municipality and at a distance from home increase over time, but do so relatively more for jobs located in the home municipality. This suggests progressive exhaustion of the pool of good offers close to home. A set of counterfactual policy exercises show that the exhaustion of unemployment insurance benefits reduces the chances to get jobs at a greater distance because the loss of benefits increases the implicit cost of searching further from home.

*We would like to thank the editor and four anonymous referees for their comments on a previous version of this paper. We also thank seminar participants at the LIEPP internal workshop, the LSE economic geography seminar, the Regional and Urban Economics seminar at PSE and in particular our discussant François Fontaine, the HEC-Lausanne/LIEPP joint meeting in Lausanne, MIT seminar, Berkeley lunchtime seminar, the IAB Nuremberg conference, the UCL Workshop on Labor Mobility, the Housing Market and Labor Market Outcomes, the European Economic Association meeting in Toulouse, the joint Econ-IHS Vienna and in particular Josef Zweimuller, Joan Monras, Chris Pissarides, Jordi Gali, Jean-Marc Robin, Antonella Trigari and Philip Kircher, Gerard van den Berg. Philippe Ruh acknowledges funding from the Austrian National Science Research Network "Labor and Welfare State" of the Austrian FWF. Etienne Wasmer acknowledges support from ANR-11-LABX-0091 (LIEPP) and ANR-11-IDEX-0005-02.

†Bank of Italy

‡Université de Lausanne

§University of Zurich

¶NYUAD

1 Introduction

Job loss and the resulting loss of income are associated with large declines in welfare. In the absence of perfect self-insurance, many countries have unemployment insurance (UI) programs, which provide income support by replacing lost wages. The event of losing a job triggers search for a new one, which may have different attributes. While wages are of course important, commuting distance is another job attribute, which is also under the control of job seekers.[1] If the new job is further away, this poses higher disutility costs for individuals and households. It is therefore important to consider commuting distance when studying job search, especially given that, unlike wages, commuting distance is hard to insure directly. Unemployment insurance can not provide time transfer, and no private insurance would take on the commuting risk because search activity can not be observed.

In this paper, we ask to what extent job seekers are willing to accept jobs with lower pay, longer commutes, or both, as their unemployment spell increases. Job seekers may indeed become less selective as they approach the end of unemployment benefit coverage and shift from a generous unemployment insurance regime to a less generous unemployment assistance program. Losing unemployment benefits may then force job seekers to make concessions both in terms of wages and commuting distances. Therefore, as their unemployment continues, job seekers should be ready to accept lower paying jobs as well as jobs that are located further away from home. Whether and how job seekers change their search strategies over time is important. Those job seekers who can trade off between wages and commutes will be able to locate new jobs faster, which then leads to better functioning labor markets. But which job seekers trade off wages and commutes over the course of their spell, by how much and why this happens, has rarely been documented so far.[2] Since spatial job search strategies may respond to policy and in particular to unemployment insurance, more research is needed to understand them.

We focus on the role of unemployment insurance (UI) because UI is the key policy instrument to tackle unemployment. Since UI provides benefits to job seekers for a specified duration, job seekers make adjustments to their job search strategies when the benefits end. UI may either help or hinder regional labor market adjustment. While unemployment insurance can act as a subsidy for searching further away from home, and allow people to take more risks, it can also increase the value of remaining unemployed, which could lead to job seekers refusing job offers futher from home and hence, limiting their geographic mobility (Moretti, 2013).[3]

[1] Heterogeneity in non-wage attributes has even been found to be slightly larger than that of wage attributes e.g. Hall and Mueller (2018). Many job seekers report that a primary reason for rejecting a job offer is for too high distance (Rupert and Wasmer, 2012a). Workers who commute longer are less satisfied with their life, consistent with high commuting costs (Frey and Stutzer, 2002).

[2] Several studies however document the tradeoff between wages and commutes for workers. Notably, van den Berg and Gorter (1997) estimated the determinants of the willingess to commute for Dutch job seekers, focusing on the tradeoff at a specific point in the spell of these workers.

[3] Job seekers may find a new job and move to a municipality that is close to that new job. This behavior is rare in the context we analyse and we implicitly assume that job seekers do not have this option. Commuters travel about 70 minutes to and from work in the US, and about 60 minutes in Germany, the UK, and France (OECD, 2010).

Textbook models of job search incorporate unemployment benefits but not commuting distances, while in reality, the decision to accept a job will depend on both wages and commuting costs. An extended job search theory emphasizes a reservation strategy that includes both a reservation wage and a reservation commuting distance, which are tightly linked. In this extended theory, job seekers trade off between higher wages and shorter commuting distances, which is represented by an upward sloping reservation frontier. Unemployment insurance raises the reservation wage, thereby lifting the reservation frontier. Job seekers covered by unemployment insurance will be more selective and reject job offers paying lower wages or jobs that are located too far from home. If job seekers search for jobs irrespective of location, accepted wages will be higher and commuting distance will be shorter for job seekers with unemployment insurance as compared to those without.

With this framework in mind, we analyze changes in wages and commuting distances between two consecutive jobs, using unique administrative data from Austria, covering the years 1990 to 2004. The data cover almost 300,000 male job seekers, aged between 20 and 54 years, who were laid off. The changes in Austria's rules regarding the duration of UI benefits provide a useful source of quasi-experimental variation in the value of unemployment benefits. We indeed observe a fairly high dispersion in the wages and commuting distances between two consecutive jobs. This suggests that both margins are relevant for unemployed individuals.

A first exploration of the data leads to the following empirical findings. We first provide a direct estimate of the reservation wage and how it varies with commuting distance using an original approach, based on a simple premise: laid off workers would accept the job they lost, so their reservation wage is below their previous wage, holding distance constant. Given this, we infer the reservation wage from job seekers who accept a wage that pays less than their previous wage. The reservation wage is the lowest wage job seekers accept, so movements in low wage acceptance can be traced to the reservation wage. Job seekers who accept a job that pays more than their previous wage identify the wage offer distribution, and the arrival rate of job offers. We estimate this relation using maximum likelihood, allowing for observed and unobserved heterogeneity.

Reservation wages increase significantly with distance. The cost of one hour of commuting (both ways), i.e. the increase in the reservation wage induced by commuting, is between 9% and 15% of the daily wage, or about an hourly wage for a full-time worker. Job seekers who lose unemployment benefits have about 5% lower reservation wages. Job seekers trade off wages and commuting time, and the exhaustion of unemployment benefits reduce the reservation wage, which is consistent with a simple job search framework that integrates commuting time.

We then study accepted wages and commutes over the course of the unemployment spell. We find that newly unemployed workers are more likely to accept high wage jobs than low wage jobs, but as the unemployment spell increases, job seekers are more willing to accept lower wages. As regards to commuting, there is a source of heterogeneity concerning the location of the job previously held. Workers who worked in their home municipality prior to getting laid off (whom we term *local* workers) increasingly accept jobs located outside their home municipalities as their unemployment spells lengthen. The average length of their commutes (including those keeping a job in the home municipality) also moderately increases. However, the length of their commute conditional on working in another city is not affected. Instead, those previously working outside the home municipality (whom we term *non-local* workers) accept longer commutes outside their home municipality. Despite this, the share finding a new job in the home municipality increases somewhat in time, so overall, the unconditional commute distance is constant. Finally, both local and non-local workers accept lower wages as their spells increase. These patterns appear overall to be consistent with unemployment benefit exhaustion. Job seekers who run out of unemployment benefits look for jobs more widely, both in terms of wages and commuting distance.

We therefore analyze the effects of unemployment insurance coverage using quasi-experimental changes in the potential benefit duration (PBD). We find that job seekers who are still covered by unemployment insurance earn 2.2% higher wages as compared to job seekers who just lost coverage, suggesting that loss of benefit coverage reduces the reservation wage. In contrast, UI coverage does not reduce the length of commutes. Commuting distance is even longer among covered job seekers and the proportion accepting a job outside their home municipalities is higher among covered job seekers as compared to those who lost coverage. The effects of UI coverage, however, differ again between local and non-local workers. *Non-local* workers still covered by unemployment insurance accept higher wages but not shorter commuting times, compared to job seekers who have lost coverage. Among *local* workers, UI coverage has the opposite effect: coverage increases commutes, mainly through fewer job seekers getting jobs in the home municipality, and coverage has no effect on wages. These results are surprising since job seekers should want to benefit both from higher wages and shorter commutes when they are still covered and the results suggest that unemployment insurance does not explain why job seekers widen their search as their spells get longer.

We next assess the adequacy of standard search theory with these empirical facts. In standard search theory, whereby we mean non-targeted search, agents trade-off the benefit and costs of accepting an offer endowed with a wage and a distance. By non-targeting, we mean that offers are randomly and passively drawn from a joint distribution: in particular, workers do not control the distribution of distances. The costs of rejecting offers is the combination of time discounting and risking the loss of unemployment benefit coverage. As time passes, workers are therefore ready to accept "packages" of wages and distance that have lower utility over time, hence lower wages and higher commute distances. We find that the empirical evidence on duration dependence is indeed broadly consistent with non-targeted search theory.

However, the quasi-experimental evidence points to the need of introducing more spatial ingredients into theory. We thus propose a parsimonious model consistent with all evidence, including the quasi-experimental one. We extend the standard partial equilibrium search model *à la* McCall (1970) by allowing for targeted search in space which evolves over the course of the unemployment spell. In our model workers react to financial incentives (benefit coverage), as in the standard theory, but further control the area of search and the effort in different locations. We introduce targeted search in a parsimonious way, which is inspired by the data and is sufficient to replicate most of the empirical findings: we distinguish between home city and other locations to account for the peculiar role of the city of residence and explain the different behaviors of local and non-local workers.

In our model job seekers look for jobs at home or elsewhere, and within a certain distance that they choose: searching for a job entails a cost, and this cost differs by whether job seekers look for jobs in their home city, or elsewhere. Job seekers also choose the reservation wage for a given commute distance. Newly unemployed workers are covered by unemployment insurance, but they can subsequently lose it for a reduced level of benefits, entering in the unemployment assistance regime. Search costs at a distance may change with time in unemployment due to many reasons (lack of self-confidence, loss of motivation on the side of the job seeker, or simply statistical discrimination on the side of the employer (Kroft *et al.*, 2013), or when job seekers lose benefit coverage. We assume that both occur simultaneously and thus cannot distinguish one mechanism from the other, but this may deserve further investigations in the future. By introducing targeted search, we capture that job seekers may have better access to job information at home because of informal networks or spatial proximity. Finally, the pool of local offers in the home municipality may exhaust faster than the pool of jobs offered at a higher distance. Hence, job search costs may vary in space, in time and across workers' type: we see them as a proxy of several underlying mechanisms described above which we are not able to separately identify.

We estimate the model using information on the rate at which job seekers leave unemployment to jobs located at home, and elsewhere. These so-called sub-hazard rates are driven by search at home, or search elsewhere, and inform on the extent to which job seekers face search costs; we purge heterogeneity from hazard rates adopting a non-parametric approach. Accepted wages and commutes provide information on the distributions of wage and distance offers, while the cost of commuting is calibrated by using our novel estimates. Inspired by empirical findings, we provide separate estimates for local and non-local workers.

We find that job seekers face search costs ranging from 6.5 to 14% of their wage rate, not far from the roughly 5-10% time job seekers spend searching every day. For local workers searching at home is about three times less costly than searching elsewhere: this difference in search cost is sizable. Searching at home is five times more costly for non-local workers, who instead have a comparative advantage in searching for a job in a broader geographical area. Search costs are low in the first month of the unemployment spell but threefold for job seekers still unemployed 14 months from entering unemployment, when they are no longer eligible for unemployment benefits. Unemployment benefits generate a dis-incentive effect by raising the value of unemployment, but this effect is attenuated by the low costs of searching in the initial phases of the spell.

Based on these estimates, we simulate behavior of job seekers to understand better how UI coverage and search costs affect accepted wages and commuting times over the spell. The unemployed reduce their reservation wage as they lose benefit eligibility. At the same time, they also reduce their search radius as they approach benefit exhaustion, and this, because of two conflicting reasons. Job seekers would enlarge their radius of search once they lose benefits because the value of remaining unemployed one more period is reduced, but they also face higher search costs from searching far away from home, which lead them to reduce their search area. The net effect, is, in our setting, negative. Counterfactual simulations show that search radius would, indeed, increase if search costs did not increase after benefits run out. The restriction of the search area would imply a decrease in accepted commuting times over the spell; however, search effort also decreases over time as more and more job seekers face the high search costs. Search effort decreases by more in the city of residence: local workers in particular lose their comparative advantage in looking for local jobs and start searching more broadly. Hence, the share of of local job seekers finding a job in their home city slightly declines over time, thus explaining the moderate increase in unconditional commuting times observed in the data. These behaviors translate into lower accepted wages, and somewhat longer accepted commutes as spells lengthen, a pattern we see clearly in the empirical evidence on duration dependence.

We further perform counterfactual simulations to read the quasi-experimental evidence on the effects of UI coverage through the lens of the model. Recall that UI coverage had no effect on commuting times of non-local workers. This finding is fully consistent with our model once we allow benefits to change over time but keep search costs constant: in this case commuting times are flat. On the contrary, the empirical estimates showed that UI coverage allows local workers to broaden their range of search: these behavior is consistent with a simulation in which the cost of looking for a job in one's home city remains constant over the spell but the cost of looking for a job elsewhere increases at benefit exhaustion. This result suggests that unemployment insurance has an additional role beyond the traditional one: by offering employment services and providing information of job openings, it can broaden geographic search, especially for workers with local prior jobs.

Relation to the literature Our findings tie into several literatures. First, several classical theory papers have introduced commute distance.[4] Racial differences have been analysed through the lens of distance and access to jobs in the spatial mismatch literature following Kain (1968).[5] The articulation

[4]Crampton (1999) has a discussion of the optimal location of vacancies and their number, illustrated by the classical papers by Seater (1979), Chirinko (1982) and more recently van Ommeren *et al.* (1997).

[5]Papers include Holzer (1986; 1987; 1988), Ihlanfeldt (1997), Zax and Kain (1996), Brueckner and Zenou (2003) and Coulson *et al.* (2001) and are summarized in Gobillon *et al.* (2007) and Zenou (2009); see also van Vuuren (mimeo) and Nenov (2015).

between commuting decisions and mobility decisions has also been analyzed recently.[6]

Second, the role of local labor markets has been investigated in important papers by Cheshire (1979), Rogerson (1982) and more recently Manning and Petrongolo (2017b), Gobillon *et al.* (2011) and Marinescu and Rathelot (2018a). The latter find in particular that job seekers applications from a particular website, CarreerBuilder.com, decrease by 35% every 10 miles of distance between the applicant's address and the vacancy, and that workers are generally located close enough to the vacancies. Manning and Petrongolo (2017b) using local vacancy data and job flows in the UK, show convincingly that local labor markets overlap, an intuition we develop in our model where workers search both at home and at a distance, with a cost of prospecting further away that is convex and even discontinuous between the home city and elsewhere. They also find a decay of job applications with distance: as they report, *"Our estimates imply that the probability that a random job 5 km distant is preferred to a local random job is only 19%."*, which is both large and small: it is large in the sense that local jobs are almost 3 times more likely to be preferred to jobs distant by 30km, and small in the sense that a local area where individuals search is within a circle of several kilometers. Our theory is in line with these observations and with both Manning and Petrongolo (2017b) and Marinescu and Rathelot (2018a): in equilibrium, workers and job cluster, but the cost of prospecting away from residence can be important and workers' strategy in space is to apply in an area of endogenous size, and not only in the immediate neighborhood. Finally our work is connected to the large literature measuring the value of time across different transportation modes.[7] Recent papers, using experimental setups, have investigated the role of information on search strategies, including the broadness of search.[8] The literature on directed search, both in the labor and in the housing market is related[9], since targeting is the first dimension of directed search, although we keep the analysis in partial equilibrium and without considering strategic interactions between job seekers.

Third, our paper also ties to a literature on the role of unemployment insurance for job finding and job quality. Ehrenberg and Oaxaca (1976) were the first to look at the effect of unemployment insurance on post-unemployment outcomes and find positive effects of unemployment benefits on post unemployment wages for different age groups and gender.[10] Several recent studies, based on regression discontinuity designs, find little or no effects of Potential Benefit Duration (PBD), mostly looking at

[6]See Rupert and Wasmer (2012b) and applied to ethnic unemployment gaps in Gobillon *et al.* (2014) for commuting vs mobility decisions.

[7]With an interesting distinction between short and longer distances (see Brownstone and Small (2005) for road use and Hammadou and Jayet (2003) for longer transportation times, as well as a discussion of commmuting modes in the underlying theory in Manning and Petrongolo (2017b)).

[8]See notably Altmann *et al.* (2015) and Belot *et al.* (2015).

[9]See Faberman and Menzio (2017), Menzio and Moen (2010), Gautier *et al.* (2016) and Moen and Rosén (2011).

[10]Addison and Blackburn (2000) and Centeno and Novo (2006) show a an effect of unemployment benefits on post unemployment wages.

wage or job stability.[11]

This paper complements existing literature, providing a novel approach to studying the costs of commuting based on the reservation wage inferred from data that is readily available. We document that commuting is different from wages, and highlight one explanation for this, costs of search and how it changes in space, with unemployment insurance, and across workers. We document that this is important for changes to unemployment insurance.

Organization The paper is organized as follows. Section **2** provides background information and information on the data and presents evidence on job search and the spatial dispersion of commuting distances, based on our rich data set of unemployment spells in Austria. Section **3** investigates and then estimates commute costs. Section **4** studies the evolution of accepted wages and distances over time and the impact of UI on these dimensions, using a quasi-experimental setting. Section **5** presents a model with targeted search and time varying benefits. It then estimates the model and highlight how targeted search affects job search decisions. Section **6** concludes.

2 Background

2.1 Institutions and Setting

Austria is a relatively small country yet with potentially large commute distances due to the presence of the Alps and the particular longitudinal shape: the maximum distance from west to east is around 700 kilometers. Cutting through Münich in Germany, the distance between the northwestern city of Bregenz to Wien (Vienna) is 618 kilometers and six hours drive.

According to the 2001 census, 92% of the total workforce commuted and 86% of the total workforce commuted daily. In terms of commuting modes, 67% of the daily commuters cover the major commuting distance by car, 20% commute by public transport and 13% either walk or commute by bicycle. 68% of the daily commuting individuals work in a different municipality than they live in. Some job seekers re-locate rather than commute to their new place of work but, compared to the US, residential mobility in Austria is low. For Austria, less than 6% change the residential municipality and less than 1.6% cross the county border annually. For the US, Fischer (2002) shows that between 10-15% change residence every year, and more than 5% leave the county of residence. Also, fewer than 5% of all job seekers in Austria change the residence over the turn of unemployment.[12]

[11] Card *et al.* (2007), Lalive (2007), van Ours and Vodopivec (2008), Le Barbanchon (2012) find little evidence on wages. Centeno and Novo (2009) detect a positive impact on the match quality for individuals at the bottom of the wage distribution. Caliendo *et al.* (2013) find that the unemployed who obtain a new job close to benefit exhaustion are more likely to leave subsequent employment and receive lower wages than than their counterparts with extended benefit duration. Schmieder *et al.* (2013) study the effects of PBD changes on re-employment wages in Germany finding sharp negative effects of PBD extensions for older workers, and both Degen (2014) and Nekoei and Weber (2014) find positive effects of PBD on wages.

[12] Sources: CPS 2001 Statistik Austria, own calculations from tax records.

The institutional setting also allows to study commuting patterns in relation to the value of unemployment. Job seekers may have access to unemployment benefits (UB). The level of unemployment insurance (UI) is calculated relative to base earnings, and all job seekers who worked for at least one year out of the previous two years are eligible for it.[13] Base earnings are multiplied by the replacement rate to calculate unemployment benefits. Benefits are capped from below and above, the cap being adjusted annually for inflation. The potential duration of unemployment benefits (PBD) is a function of past work experience and age. For instance, job seekers who have been working for a at least 6 out of the previous 10 years, and are 40 years or older when registering for unemployment benefits receive 39 weeks of unemployment benefits compared to 30 weeks if they are less than 40 years old. A similar discontinuity exists at age 50, where PBD increases from 39 to 52 weeks, for job seekers who worked 9 out of the previous 15 years. Job seekers are expected to search actively for a new job, and accept any job offer in an area of two hours commuting, one way.

Once unemployment benefits are exhausted, individuals are eligible for means tested Unemployment Assistance (UA) benefits. The means test includes in particular family income and wealth which makes it unlikely for many individuals to actually be eligible for UA benefits. Conditional on getting UA benefits they can be fairly high, as much as 92% of UB. Job seekers on UA need to re-apply for UA once every 26 weeks, and can do so indefinitely.

2.2 Data and Sample

We combine data from different sources in our analysis. First, the Austrian Social Security Database (ASSD) contains detailed information on the work history for all private sector workers from 1972 to present (Zweimüller *et al.*, 2009). ASSD contains both a unique plant and person identifier. Second, the unemployment register contains detailed information on both UI and UA benefits for the years 1988 to 2007. Third, we use data from a road trip planning firm to measure travel time between any two municipalities.[14]

From ASSD, we obtain all unemployment spells that last at least for 7 days. ASSD provides unemployment spell duration in days, and non-employment duration, the number of days between the new and the previous job. Non-employment duration is our key measure of elapsed spell duration since it is not mechanically affected by longer potential benefit duration. We then add information about the previous and next employment spell to each unemployment spell. For the relevant employer-employee

[13] Base earnings refer to average earnings in the base period, the previous calendar year for job seekers who start a spell in July and December of the year before the previous one for job seekers who enter unemployment in January to June.

[14] Our data set only contains individuals who live and work in Austria. Hence we do miss commuters across national borders. Official statistics suggest that we do not miss out many cases. From the census 2001, there are 3.6 millions individuals listed as employed of which 57,730 (1.59%) said they live in Austria but work abroad, mostly in Germany. We know the precise number of Austrian cross border workers only for Switzerland. Namely in 2013Q3 there were 8,119 Austrians who crossed the border at least once a week to work in Switzerland. Back in 2002Q3 the figure was 6,985. Conversely, the tax data authority indicates that of those who have to pay taxes in Austria, 5.8% live abroad and this latter number also includes individuals temporarily living abroad.

relation before and after unemployment, we obtain the following variables: exact date of termination and start of the relation, average daily wage (yearly contribution to the social security system divided by the number of working days), municipality of employer, industry affiliation of the employer. For the individual we know the month of birth and gender and we can calculate tenure on either job, experience, sickness, occupation (blue/white collar).

From the unemployment register, we obtain the municipality of residence, the UI and UA benefit level, education and information on the family situation. We use ASSD to add information on benefits. The two variables age and experience allow us to calculate the potential benefit duration for UI benefits. The ASSD data allow us to determine the basis on which benefit are calculated, which is typically different from the previous wage. We can identify the unemployment spells from the ASSD data in the unemployment register.

The third data set contains travel time by car and road distance in kilometers between any pair of municipalities in the year 2000. Distance is measured between the centroids of the municipalities, while for Vienna we identify the 23 districts and treat each of them as separate municipalities. Hence, for each unemployed individual we calculate commuting distance as the average travel time by car from the municipality of residence to the municipality of the employer, both before and after the unemployment spell. Travel time by car probably captures opportunity costs of travel better than road distance. Commuting time is between municipality centroids, rather than door-to-door, so actual commuting time is different from commuting time measured in our sample. For instance, workers who live and work in the same city may have commutes of between 0 to 5 to 10 minutes while in our data these commutes all show up as commutes of zero minutes. We correct for measurement error in commuting times for workers who live and work at the same location in our analysis of the costs of commuting.[15]

Our analysis is based on the following sample. First, we focus on unemployment spells starting between January 1990 and December 2004, a period during which the age dependent rules for potential benefits were in place. Second, we include individuals aged 20 to 54 at the start of unemployment. We do not want to include older individuals to avoid interactions between unemployment and early retirement, which is strong in Austria as assessed in Inderbitzin *et al.* (2013). Third, we exclude individuals with a commute of more than two hours (either before or after losing their job), because these individuals are less likely to be commuting every day. Fourth, we exclude job seekers who quit voluntarily and those who return to the same employer. We also exclude women, because our measure for wage, the average daily wage, confounds hours and the wage rate; we rather focus on men because virtually all of them work full time.

[15]Commuting times for job seekers who work in the home city are censored from the left, i.e. while their actual commuting times my be between 0 and 5 to 10 minutes, their stated commuting time is zero. We address this issue in a Tobit type fashion. Job seekers who work outside the home city contribute to the likelihood through their density. Job seekers who work in the home city contribute to the likelihood with the probability that a commute lasts less than 6 minutes rather than through their density (which is unknown; the shortest non-zero commute in the data is 6 minutes).

Table 1: Summary Statistics

	Mean	Std. Dev.
A. Outcomes		
Non-employment Duration (Weeks)	25.18	39.99
Daily Wage, After (EUR)	56.08	21.05
Daily Wage, Before (EUR)	57.44	21.51
Commute, After (Hrs)	.439	.409
Commute, Before (Hrs)	.413	.394
B. Unemployment Insurance		
UI Replacement Rate	.407	.172
UI Benefit Duration	31.67	6.40
UA Replacement Rate, Exhausters	.113	.185
C. Characteristics		
Age 30-39 Yrs	.309	
Age 40-39 Yrs	.235	
Age 50-56 Yrs	.048	
Compulsory Education or Less	.42	
Upper Secondary or Tertiary Education	.58	
Married or Cohabiting	.43	
Immigrant	.207	
Tenure > 3 yrs	.255	
Worked in City	.39	
Lived in City	.373	
Manufacturing	.412	
Services	.546	
Observations	283,776	

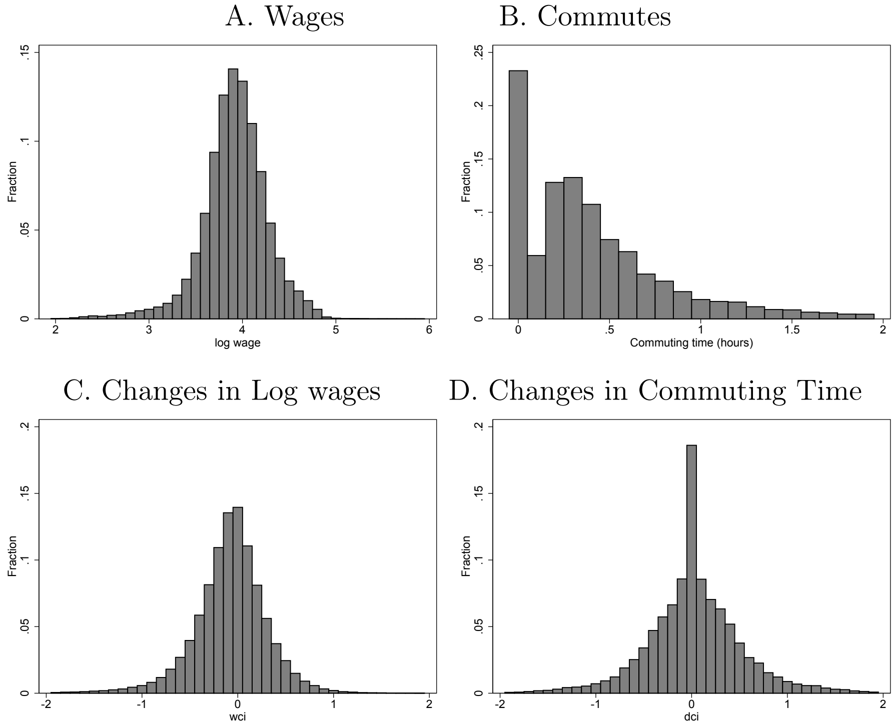
Notes: Table provides descriptives on non-employment duration, wages, and commuting time, both before and after an unemployment spell. The unemployment insurance (UI) benefit duration informs on the number of benefit weeks available to the individual, and the UI benefit replacement rate gives the proportion of the wage prior to unemployment that is replaced by UI for those job seekers who leave unemployment before exhausting benefit weeks. Job seekers who exhaust benefits, exhausters, may be eligible for unemployment assistance (UA). The UA replacement rate for exhausters informs on how much of the pre-unemployment wage UA replaces for all who leave unemployment after UI benefits have ended. The UA replacement rate for the eligible conditions on UA benefit eligibility. Panel C gives information on characteristics of job seekers.

2.3 Descriptive Statistics

Table 1 shows summary statistics on key variables in our dataset. Panel A provides information on spell duration, wages, and commuting distance, both before and after unemployment. Job seekers look for a job for about 25 weeks on average, but the standard deviation of non-employment is large and indicates that some job seekers look for a job substantially less, and some do so for substantially more than 25 weeks. Job seekers earn 57 Euros before entering unemployment, and 56 Euros when leaving unemployment, so daily wages do not change much on average. Job seekers commuted for about 25 minutes, or 0.41 of an hour, before losing their job, and for about 26 minutes after leaving unemployment. Neither wages nor commuting times change much between unemployment spells.

Panel B provides information on unemployment insurance. Job seekers have access to unemploy-

Figure 1: Distribution of Wages, Commutes, the Tradeoff and their Variations



Notes: This figure provides a histogram of the logarithm of the accepted daily wage offered by a new job (top left panel A), a histogram of the level of accepted distances (one-way, measured in hours) offered by a new job (top right panel B). The bottom panels (C and D) show how accepted wages and average commuting distance vary with respect to the previous job.

ment benefits for 32 weeks, and unemployment insurance replaces about 41% of the wage earned prior to entering unemployment to covered job seekers. Exhausters receive about 11% of daily wages prior to unemployment.[16] Job seekers lose three quarters of their earnings upon benefit exhaustion on average, but those who receive assistance see little decline in their earnings.

Panel C provides information on education and other characteristics. Most job seekers are young, between 20 and 29 years, or 30 to 39 years. About 24% of all job seekers are 40-49, and only 5% of all job seekers are 50-57 years old. About 42% of all job seekers have compulsory education or less, 54% completed apprenticeship training, and the remaining 4% have acquired upper secondary or tertiary education. 43% of all job seekers are married, or cohabiting with a partner. 21% of all job seekers are immigrants. About 26% of job seekers worked more than three years with their previous employer, and are thus eligible for severance pay. About 39% of all job seekers worked in a city prior to job loss, where a city is a municipality with more than 100,000 inhabitants in 2000, and 37% of all job seekers live in a city. Most job seekers either worked in manufacturing, 41%, or services, 55%, with the remaining job seekers working in agriculture, prior to job loss.

Figure 1 shows a histogram of accepted log of daily wage (A), and a histogram of accepted one-way

[16] Eligible unemployment assistance recipients, 30% of all job seekers who exhaust benefits, receive 38% of pre-unemployment earnings in unemployment assistance benefits.

commutes in hours (B). Note the spike in bin 0, reflecting the large number of workers living in the same city as their job. Panel C shows wage changes between two consecutive jobs. They are fairly symmetric around their mean of about 4 log points, while accepted commuting times are concentrated at the home location. Mean accepted wages are about 3.92 at or close to home, and increase rapidly to a level of slightly above 4 as commutes get longer. Panel D shows the large dispersion in commute changes, with many changes above +30 minutes or below minus 30 minutes, reflecting an active degree of search in various places away from the previous workplace city.

3 Commuting Costs

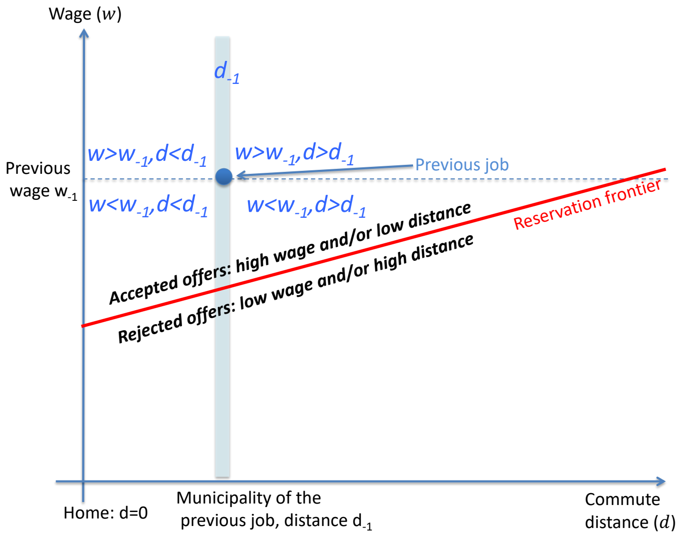
In this Section, we discuss whether job seekers care about commuting time. Commuting needs to be important in order to affect search strategies of job seekers. An large number of papers show that commuting matters for workers, but much less so for job seekers.

Suppose job seekers decide about which jobs to accept or reject based on whether the value of the job exceeds the value of remaining unemployed for one more period. The value of a job, $W(w, d)$, increases with the wage rate w, and decreases with commuting time d. The value of remaining unemployed one more period is $U(\mathcal{B})$ where $\mathcal{B}$ are unemployment benefits. Job seekers will accept all job offers that are at least as good as remaining unemployed one more period, i.e. those with $W(w, d) \geq U(\mathcal{B})$. The job offer whose value is the same as the value of remaining one more period in unemployment is $W(R(d), d) = U$, where $R(d)$ is the lowest wage that makes a job seeker indifferent between working a job at distance d, or remaining unemployed, or reservation wage. Figure 2 shows the reservation wage, which makes a job seeker indifferent between accepting or rejecting a job offer with characteristics (w, d). Figure 2 also shows the previous job, represented by the particular point (previous wage denoted by w_{-1}, previous commute distance denoted by d_{-1}), located above the reservation frontier because job seekers are laid off from the previous job and would accept the same job again.

The level of the reservation wage at home, the intercept of the reservation frontier, depends on the generosity of unemployment insurance, the level and the duration of benefits. When benefits are exhausted, job seekers enter a period when unemployment benefits cease to be paid, decreasing the reservation wage at home. Job seekers who exhaust benefits accept jobs that pay less, or are located farther from home, compared to the situation before losing benefits. Because workers need to be compensated for commutes, unemployment insurance encourages job seekers to reject job offers, especially those located far from home. Unemployment insurance decreases geographic mobility and the capacity of labor markets to absorb regional shocks (Moretti, 2013). This representation is flexible and does not rely on any particular theory determining the value of unemployment and of employment, it is however sufficient at this stage to investigate the data and derive key predictions on each of the mechanisms.

We first look into whether there really is a trade-off between wages and commuting times in the data. Measuring reservation wages is challenging. Many workers accept jobs that pay less than their stated reservation wage, or reject jobs that pay substantially more than their reservation wage (van den Berg and Gorter, 1997; Hall and Mueller, 2018). We develop a novel approach to infer the reservation

Figure 2: Reservation Frontier and Acceptance-Rejection Areas



wage directly from data on accepted wages and spell durations.[17] This approach can be implemented for job seekers who have been laid off from their previous job. In a stationary environment, layoffs would accept an offer to return to their pre-unemployment job, i.e. the reservation wage is below the pre-unemployment wage. Every period, job seekers receive job offers at a rate that depends on their search intensity and market tightness, and accept or reject them based on whether the wage offered is greater than the reservation wage for the required commute.

In this setting, job seekers who accept a high wage, one that pays more than the previous job, provide information on the wage offer distribution, censored from below at the previous wage. We estimate both the mean and standard deviation of the distribution of offered wages, assumed to be log normal, from wages that pay more than the previous wage, accounting for censoring at the previous wage. Job seekers who accept a high wage also provide information on the arrival rate of job offers, both at home and everywhere else. Job seekers who accept a bad job, one which pays less than the previous wage, provide information on the reservation wage. Jobs that pay less than the previous wage lie between the reservation wage and the previous wage. Movements in the transition rate from

[17]This Section summarizes our more detailed developments in Appendix A.1. This approach of learning about reservation wages is not affected by sample selection, that occurs because job seekers are looking for a job that is better than the reservation job. Our approach only relies on data on accepted wages. Others have worked directly with data on reservation wages and maximum commuting times van den Berg and Gorter (1997, e.g.), Krueger and Mueller (2016). Observing reservation strategies directly is very interesting and informative but surveys on this topic are often prone to measurement errors and challenging to interpret.

unemployment to bad jobs therefore inform on movements in the reservation wage.[18]

We address observed heterogeneity by including information on the previous job, and age, and in an otherwise homogeneous subsample. We address unobserved heterogeneity as recently suggested by Bonhomme *et al.* (2017a), in two steps. In the first step, we use *kmeans* clustering to allocate job seekers to two groups that differ in terms of their distributions of spell durations, accepted wages, and distances. We rely on all available data for any job seeker, because identification of unobserved heterogeneity greatly improves with repeated observations on individuals.[19] In the second step, we estimate our model and allow differences in the levels of the reservation wage, the arrival rate, and the mean of wage offers between the groups that we identify in the first step.[20]

In Austria, the potential benefit duration (PBD) depends on age for workers with long work experience. Since August 1989, the potential duration of benefits is 30 weeks for job seekers who are less than 40 years old. Job seekers who are 40 years or older are eligible for 39 weeks of unemployment benefits, and workers who are 50 years or older are eligible for 52 weeks, or one full year, of unemployment benefits. This design allows comparing a treated group, who is older than the threshold age and has long PBD, to a control group, who is younger than the threshold age and has short PBD.

We use this approach to infer reservation wages in a sample of workers that are 39-40, or 49-50 years old. Job seekers who are older than the age thresholds, at 40 years or 50 years, are covered by UI longer than workers who are younger the age thresholds. This allows us to isolate the effects of UI coverage. We adopt a narrow age bandwidth to ensure that differences in age between treated and control groups are not confounding results. We have run models separately for each age group, but present joint estimates to summarize our findings. We allow for heterogeneity in age by modeling an age effect in the arrival rate, the wage offers, and the reservation wage. We estimate parameters using maximum likelihood. The model fits well the distributions of spell durations (see Figure A.2 in Appendix A.1).

Table 2 shows estimation results for married Austrian job seekers with high education (apprentice

[18]Our approach is built on several key assumptions. First, we assume that all job seekers would accept the job they held prior to unemployment. This condition is likely satisfied in our sample of job seekers who were laid off from the previous job, i.e. the value of their previous job is higher than the value of unemployment. Results are robust to reservation wages which are up to 10% higher than the previous wage. Second, we estimate our model assuming that offered wages have a log normal distribution and this knowledge is essential in recovering reservation wages. Assumptions on the shape of the wage offer distribution can probably be relaxed, as long as the distribution belongs to a parametric family. Third, we assume that job search is undirected with respect to wages. During the period of our study, the late 1980s until the early 2000s, job advertisements did not mention wages so job seekers did not have the information needed to direct their search. Only recently job advertisements start mentioning a wage.

[19]Appendix A.2 provides background on our approach. Panel data on spells are challenging because the likelihood of observing a new observations of one individual depend on the realization of survival time in the previous spell. We have very long panel data where this problem should be, to some extent at least, mitigated.

[20]We explored more flexible specifications with differences in the standard deviation of wage offers as well. Results are robust. The standard approach to deal with unobserved heterogeneity is the one developed by Heckman and Singer (1984), who suggest to integrate out unobserved heterogeneity. This method is difficult to implement, especially in single spell data. Bonhomme *et al.* (2017a)'s approach to deal with unobserved heterogeneity works better than a fixed effects approach since the first stage clustering step removes the need to estimate a fixed effect for every job seeker. We also address measurement error in distance that occurs when job seekers work in the same municipality that they live in by modeling the spatial distribution of job offers.

or more) and less than three years of tenure.[21] Estimates allow for two groups that differ along unobserved dimensions, the baseline group, and the second group. The difference between the second and the baseline group is captured by the variable *uohet*. The baseline job seekers have offers arriving at rate 0.10 ($= e^{-2.266}$) per week during the first 15 weeks of unemployment, and similar for job seekers in the second group (estimates in the λ panel).Previous wage and commuting distance are standardized to have mean zero and standard deviation one. Arrival rates increase strongly for those with a high previous wage (by 52 percent for a one std. dev. increase in wage ($= \left(e^{.419} - 1\right) * 100$), and decrease strongly for those who commuted far (by 22 percent for a one std. dev. increase in distance ($= \left(e^{.254} - 1\right) * 100$) . Job seekers in the age 50 threshold have 20% lower job offer arrival rates than job seekers around the age 40 threshold. Compared to weeks 0 to 14, the job offer arrival rate in weeks 15 to 34 is significantly higher, and somewhat, but not statistically significantly, lower in weeks 35 to 60. Benefit exhaustion increases the job offer arrival rate, but not significantly so.

Job seekers draw wage offers from a log normal distribution with baseline mean 3.92 (50.4 Euros per day) in weeks 0 to 14 of the spell, and standard deviation of wage offers is .32 (parameters in the μ panel; log standard deviation of -1.14). Wage offers drawn by job seekers in the second group have the same mean as wages drawn by the baseline group. Job seekers who had a high wage prior to unemployment receive higher offers: a one standard deviation increase in the previous wage increases the mean wage offer by 10 percent ($= e^{.105} * 100$) . Wage offers do not depend on the commute distance of the previous job. Wage offers are, on average, identical for job seekers at the age 50 threshold and for job seekers at the age 40 threshold. Wage offers decrease somewhat in weeks 15-24, by about 7%; they further decline by about 5% in weeks 25-34 but there is no further negative duration dependence pattern thereafter. Offered commutes follow an exponential distribution, with log hazard parameter 0.278 for the baseline group, and 0.503 for the second group (parameters in the g panel). These parameters imply that the baseline group faces a distribution of job offers with mean commute of 45 minutes (=1/exp(.278)*60 minutes), and the second group faces average commutes of 36 minutes.

The baseline reservation wage is 3.80 in weeks 0 to 14 (44.7 Euros per day), about .11 log points lower than the mean wage offer distribution. The second group has a 8% higher reservation wage compared to the baseline group. Both the previous wage and the previous distance play a role, the previous wage increasing the reservation wage, and the previous distance decreases it. Unlike the job offer arrival rate, the reservation wage does not differ between job seekers around 50 years of age, and job seekers around 40 years of age. Older workers experience longer spell durations because of low offer rates, not high reservation wages. Job seekers who exhaust their benefits have 5% lower reservation wages compared to job seekers who have not lost their benefits yet. Job seekers accept on average

[21] We have estimated separate models for both age thresholds but find estimates to be qualitatively similar. We have estimated this model also for 4 additional groups, and find broadly similar estimates across these groups. Table A.1 in Appendix A.1 shows the full reservation frontier estimates for three groups of Austrian job seekers with less than three years of tenure.

Table 2: Reservation Frontier Estimates

λ	const	-2.266	(0.114)
	uohet	-0.052	(0.079)
	prev wage	0.419	(0.054)
	prev dist	-0.254	(0.075)
	age $>$ 45	-0.249	(0.069)
	weeks 15 to 24	0.454	(0.070)
	weeks 25 to 34	0.334	(0.093)
	weeks 35 to 44	-0.076	(0.115)
	weeks 45 to 60	-0.102	(0.129)
	exhaust	0.114	(0.098)
R	const	3.797	(0.023)
	uohet	0.078	(0.016)
	prev wage	0.299	(0.006)
	prev dist	-0.094	(0.021)
	age $>$ 45	-0.005	(0.013)
	2τ	0.088	(0.009)
	exhaust	-0.050	(0.021)
μ	const	3.924	(0.034)
	uohet	0.031	(0.019)
	prev wage	0.105	(0.010)
	prev dist	0.055	(0.020)
	age $>$ 45	-0.005	(0.018)
	weeks 15 to 24	-0.068	(0.021)
	weeks 25 to 34	-0.055	(0.026)
	weeks 35 to 44	-0.004	(0.034)
	weeks 45 to 60	-0.063	(0.035)
$ln\sigma$	const	-1.138	(0.035)
g	const	0.278	(0.026)
	uohet	0.225	(0.045)
$Pr(w > R)$		0.562	
lnL		-16393.9	
N		3662	

Note: Distance is the one way commuting distance in hours, uohet is a dummy that identifies the second unobserved heterogeneity group (Appendix A.2), exhaust = 1 after benefit exhaustion. The set of dd parameters capture spell duration dependence, where the reference are workers in unemployment for 14 weeks or less. μ is the mean of the wage offer distribution, with (log) std. deviation given by $ln\sigma$. g refers to the parameters of the log hazard of the exponential distance distribution.

56% of the job offers they receive, and reject the rest because the wage offer does not compensate for commuting time enough.

Preliminary analyses suggest that commuting costs are concave in commuting time. We adopt a parsimonious concave parametrization of commuting costs $c(\rho) = \frac{2\tau\sqrt{\rho}}{0.5}$. The reservation wage increases with the square root of commuting time ρ, and 2τ is the marginal commuting cost for a commute of one hour (one way, or two hours both ways). We find that commuting costs increase with distance. Job seekers who have to commute for more than one hour (both ways), ask for an additional compensation of around 9% of the reservation wage, or about 7% of the average daily wage. The cost of a half hour commute (both ways one hour) is also sizable, adding up to 12% of the reservation wage, or about 9% of the daily wage. Considering that the hourly wage is about 12.5% of a daily wage, the cost of commuting amounts to 73% of the hourly wage.

We have estimated the same model for four additional subgroups, with similar, or slightly higher costs of commuting (Table A.1 in Appendix A.1). The average commuting costs across the sub-samples is between 9% and 15% of the daily wage, or about one hourly wage rate for workers with 8 hour work days. Ordinary least squares (OLS) estimates, not reported but available on request, indicate that the cost of commuting one hour, both ways, is about 1% of average daily wage, or 8% of the daily wage rate. This estimate is much lower than the 14% of the daily wage, or about one hourly wage rate, based on the inferred reservation wage. Learning about the cost of commuting from average accepted wages is challenging, because movements in the average wage do accurately reflect movements in the reservation wage. In our context, this leads to severely under-estimating the costs of commuting. With few exceptions, the literature has focused on commuting costs of workers. Van Ommeren *et al.* (2000) infer the costs of commuting from the tradeoff between wages and commutes of employed workers, and find a cost of commuting of 50% of the average hourly wage rate, which is more in line with our approach but nonetheless somewhat lower. Van Ommeren and Fosgerau (2009) finds commuting costs that are larger than the average hourly wage rate. Commuting costs are large and we now turn to analyzing how this affects job search over the unemployment spell.

4 Accepted Wages and Commutes

This Section shows how accepted wages and commutes change over the course of the unemployment spell. The Section then provides evidence on how unemployment benefit coverage affects accepted wages and commutes.

4.1 Spell Duration

We now investigate the pattern of job search over time. As spells lengthen, more and more job seekers exhaust unemployment benefits. In line with the evidence in the previous Section, job seekers should accept lower wages and farther commutes as the spell lengthens. Figure 3 analyses in greater details this pattern by time spent in unemployment, and Table A.2 presents estimates that control for heterogeneity.[22] Job seekers commute about 27 minutes to their new job during the initial parts of their spell. On average, commuting time is slightly lower, 25 minutes, for job seekers leaving unemployment after 9 to 10 months of unemployment. This mild commuting times decrease with time in unemployment does not seem consistent with the intuition from job search. However, two other facts seem to go in a different direction. First, the fraction of workers getting a job in the city of residence declines over time, hence more people search away from home (left middle panel). Second, commute changes increase over time (right bottom panel) suggesting that unobserved heterogeneity is important: both facts must be integrated in a richer search model with spatial targeting.

Table 3 complements the analysis of Figure 3 and reports duration dependence in accepted wages and distances adopting an empirical strategy that controls for characteristics, and year effects, and absorbs fixed effects across 181 cells of job seekers who are identical with respect to characteristics and unobserved heterogeneity.[23] Results for all job seekers, Panel A of Table 3, show that wages decrease initially very strongly over the course of the unemployment spell, and the decrease becomes less strong as the spell gets longer. Duration dependence is substantial, job seekers who leave unemployment after 6 to 11 months lose 9 percentage points on the pre-unemployment wage. There is another, but less sizable, decline in wages for long-term job seekers, losing around 10 percentage points on the pre-unemployment wage. Commutes do not change much between months 6 to 11, but increase, significantly, by 0.017 hours, or about 1 minute. Commutes can lengthen if more job seekers accept a job outside their home municipality, or if commutes get longer outside home. Overall, job seekers commute farther because they accept longer commutes outside their municipality while the proportion working in the home municipality remaining unchanged.

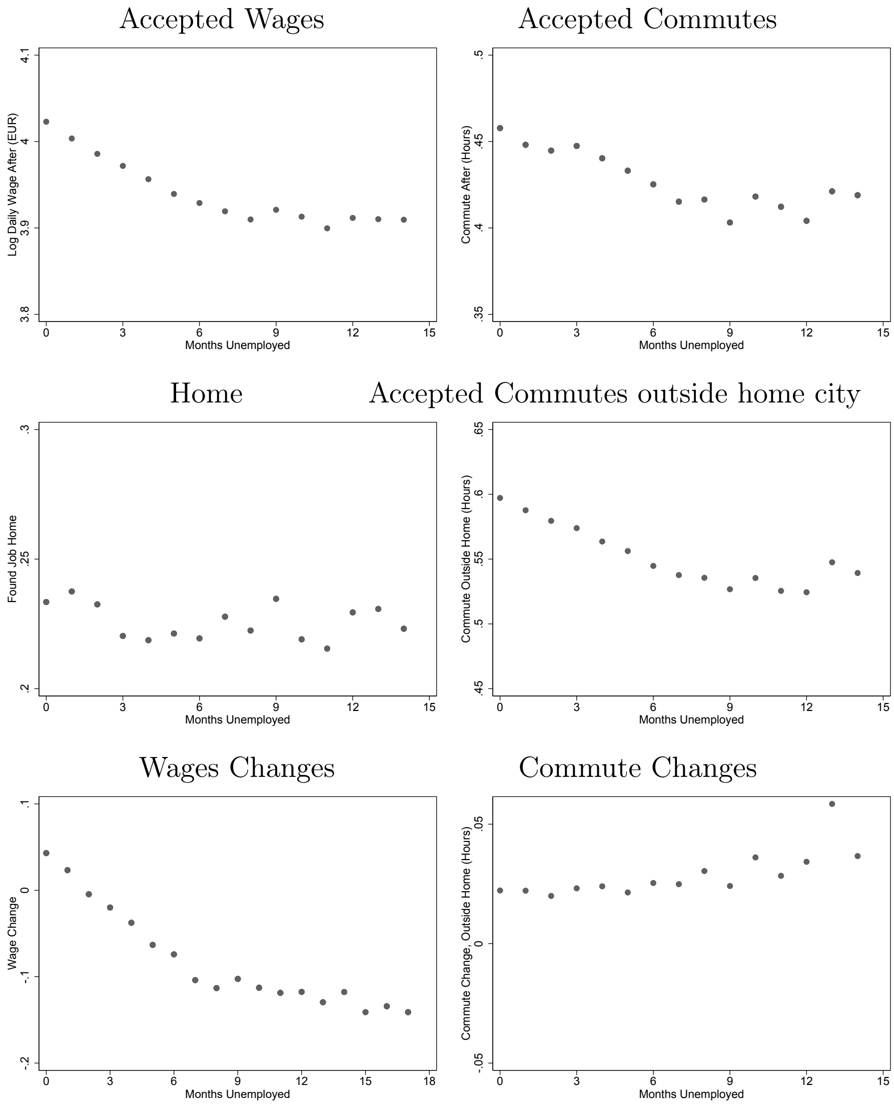
Job seekers might broaden search activity in ways that depend on their previous job. We probe heterogeneity of search responses by whether a job seeker previously worked at the home municipality, a local worker, or outside the home municipality, a non-local worker. Local workers have less schooling, are more likely to be immigrants, and their home municipality is smaller compared to non-local workers, but age is balanced (Table A.3). Local workers commute much less before the unemployment spell, and also considerably less after leaving unemployment compared to non-local workers. These patterns suggest that local and non-local workers might adapt their search strategy differently, especially concerning commuting distance.

Panels B and C of Table 3 show results for local and non-local workers. The duration dependence

[22] Job seekers in our sample have different benefit exhaustion dates, but all of them approach benefit exhaustion as the spells lengthen. We have also conducted analyses using time to benefit exhaustion rather than elapsed unemployment duration. Much of the response occurs before exhaustion because job seekers anticipate the end of benefits. The pattern of results is identical, a strong response of wages and a small response of commuting distance.

[23] We have compared the robustness of our empirical strategy with respect to a simple regression of the pre-to-post unemployment change in wage or commute, and with respect to a panel identification strategy that compares the same job seeker over time. Table A.2, in the appendix, shows the results.The absorbing strategy delivers results that are comparable to both, the simpler change strategy, and the equally involved panel strategy.

Figure 3: Accepted Wages and Commutes and Spell Duration



Notes: The figure shows for all workers, by elapsed unemployment duration, expressed in months, the evolution of mean accepted wages and distances (row 1). Row 2 shows fraction working in the home municipality and average commutes of those who find a job outside the home municipality. Row 3 shows pre-to-post unemployment changes in accepted wages and commutes. All evidence is based on raw data.

Table 3: Duration Dependence in Accepted Wages and Commutes

	Wage	Commute	Home	Commute (Outside Home)
A. All				
	wc	dc	home	dc
months6to11	-0.0881***	0.0031	-0.0017	0.0053**
	(0.0021)	(0.0023)	(0.0022)	(0.0025)
months12to15	-0.1045***	0.0174***	0.0052	0.0261***
	(0.0051)	(0.0049)	(0.0046)	(0.0053)
R2	0.041	0.013	0.028	0.028
N	262145	267263	267263	206218
B. Local				
	wc	dc	home	dc
months6to11	-0.0873***	0.0106**	-0.0249***	-0.0064
	(0.0045)	(0.0043)	(0.0054)	(0.0051)
months12to15	-0.0966***	0.0278***	-0.0298***	0.0164
	(0.0102)	(0.0093)	(0.0112)	(0.0112)
R2	0.040	0.021	0.017	0.053
N	62873	64045	64045	36362
C. Non-local				
	wc	dc	home	dc
months6to11	-0.0880***	0.0029	0.0073***	0.0051**
	(0.0024)	(0.0026)	(0.0022)	(0.0025)
months12to15	-0.1069***	0.0103*	0.0146***	0.0170***
	(0.0059)	(0.0053)	(0.0047)	(0.0051)
R2	0.043	0.011	0.031	0.017
N	199272	203218	203218	169856

Notes: Table regressions of pre-to-post unemployment changes (wc, dc) vary with spell duration. Months6to11 is a dummy that takes the value 1 for spells ending after 6 to 12 months, months12to15 is a dummy for spells ending after 12 to 15 months, which is the maximum duration in the estimation sample. All results absorb unobserved and observed heterogeneity across 181 cells, and control for demographics and year effects.

in wages is very similar for both types of job seekers, losing about 9-10 percentage points on the pre-unemployment wage as soon as unemployment duration exceeds 6 months. In contrast, local and non-local workers differ in terms of how they broaden search in space. Long-term unemployment lengthens local workers' commutes by up to .03 hours, or 1.8 minutes, by lowering the share of local workers who return to work at home (Table 3B). Long-term unemployment has an ambiguous effect on commuting of non-local workers, raising the proportion working at home, while also lengthening commutes outside the home municipality (Table 3C). The net result is no strong effect of job search duration on the length of commutes.

Results in Table 3 appear consistent with benefit exhaustion playing a major role in broadening job search. Loss of unemployment insurance coverage, which happens after 12 months at the latest, should make job seekers more willing to accept low wages, or lengthy commutes, or both. We now turn to assessing whether unemployment benefit coverage is indeed the most important force that affects how broadly job seekers are looking for jobs.

4.2 Unemployment Benefits Coverage and Accepted Jobs

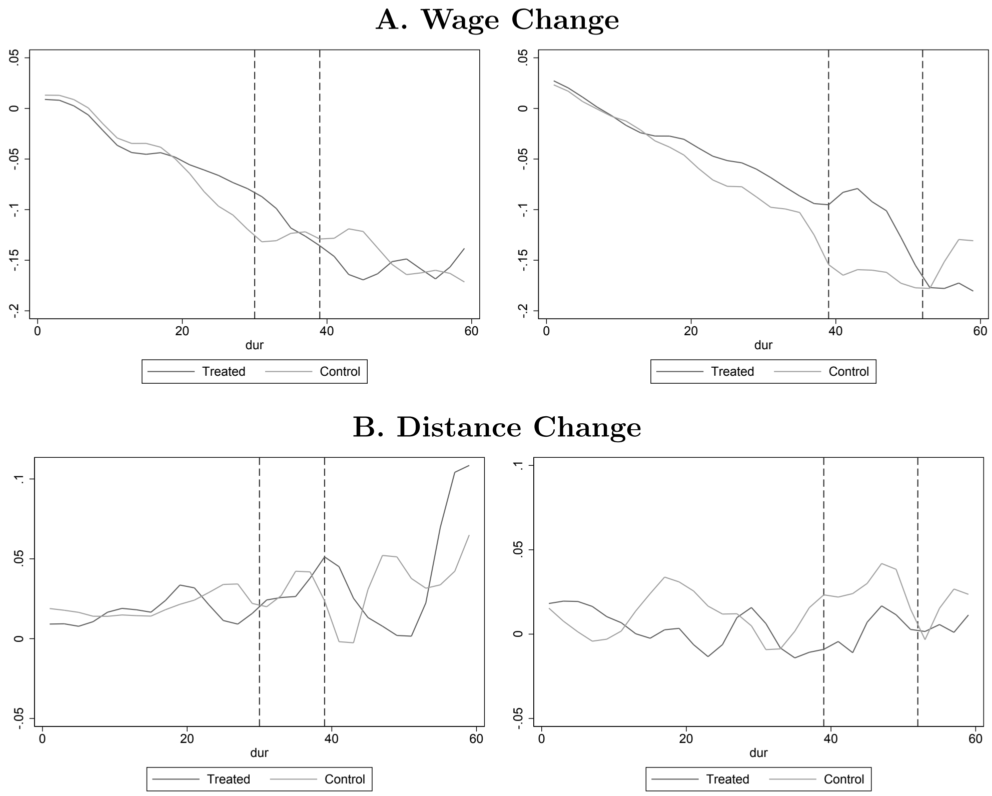
This Section discusses how unemployment benefit coverage affects job seekers in a quasi-experimental setting, robust to unobserved heterogeneity. Our empirical design is the same as in Section 3. In Austria, the potential benefit duration (PBD) depends on age for workers with long work experience. Since August 1989, the potential duration of benefits is 30 weeks for job seekers who are less than 40 years old. Job seekers who are 40 years or older are eligible for 39 weeks of unemployment benefits, and workers who are 50 years or older are eligible for 52 weeks, or one full year, of unemployment benefits. This design allows comparing a treated group, who is older than the threshold age and has long PBD, to a control group, who is younger than the threshold age and has short PBD.

Figure 4A reports accepted wages for the 30 to 39 week extension (left) and for the 39 to 52 week extension (right).[24] Vertical dashed lines indicate the period when the treated group, with long potential benefit duration, is still covered by UI, while the control group has already lost benefit coverage. Job seekers in either group accept similar wages up until about five to ten weeks before the control group will exhaust benefits, when control job seekers accepted wages start to decline rapidly. Treated job seekers continue to leave unemployment with fairly high wages until approaching benefit exhaustion. After benefit exhaustion accepted wages are very noisy, due to the small samples, but treated and control group job seekers accept similar wages again. Figure 4B reports accepted distances for the 30 to 39 week extension (left) and for the 39 to 52 week extension (right). Accepted distances are similar for both treated and control job seekers in the 30 to 39 week extension, with strong fluctuations towards the end of the spell. In the 39 to 52 week extension, treated job seekers accept shorter distances throughout the spell until their benefits lapse. Unlike for wages, there is no clear pattern across the two benefit extension experiments for distance. Raw data suggests that UI coverage raise accepted wages, but has no systematic effect on accepted commutes.

We adopt a regression discontinuity design (RDD) to assess the effects of the value of unemployment on job search decisions. The RDD contrasts a control group, job seekers aged just below the age threshold, to a treated group, job seekers who are at or just older than the threshold. We estimate an RDD specification (1) that captures the effects of UI coverage. Δ_i indicates that the job seeker is older than the age threshold for extended benefits, Dur_i is an indicator for spells that end in a period when job seekers in the treated group still feel covered, while job seekers in the control group lose or will soon loose coverage. Specifically, the during indicator, Dur_i, switches to one in the period five weeks before the control group looses benefits and stays one until five weeks before the treated group

[24]Our analysis is very much inspired by Caliendo *et al.* (2013) and Schmieder *et al.* (2016) who study wages of job seekers before and after benefit exhaustion, but not commuting times.

Figure 4: Accepted Wages and Distances, Before and After Benefit Exhaustion



Notes: Figure shows pre-to-post unemployment changes in accepted wages and distances for treated and control job seekers. Left column shows job seekers at age threshold 40, where control job seekers are eligible for 30 weeks of benefits (dashed line), and treated job seekers are eligible for 39 weeks of benefits (dashed line). The right column shows the corresponding analysis at the 50 year age threshold, where control job seekers are covered for 39 weeks, while treated job seekers are covered for 52 weeks. Job seekers are within two years of the age threshold.

loses benefits. The shift by five weeks is meant to capture that accepted wages already diverge before benefit exhaustion (Figure 4A), presumably because job seekers start looking for jobs in anticipation of losing coverage (Marinescu and Skandalis, 2018). Aft_i is a dummy that takes the value one for spells that end after the during period. A_i is normalized age, age minus threshold age, and X_i is a vector of the control variables we discussed in Table 1. We provide results based on the following specification

$$y_i = \alpha + \beta\Delta_i + \gamma\Delta_i \times Dur_i + \delta\Delta_i \times Aft_i + \gamma_1 Dur_i + \delta_1 Aft_i + +f(A_i, \Delta_i) + X_i'\eta + \epsilon_i \qquad (1)$$

The parameter β, an unknown function $f(A_i, \Delta_i)$, and $X_i'\eta$ and are standard elements of an RDD specification.[25] The parameter γ captures the effects of UI coverage, comparing treated job seekers who are still covered by UI to control job seekers who have already lost UI coverage. The parameter δ captures whether behavior converges in the treated and control group once both groups of job seekers have lost benefit coverage, a placebo estimate. We estimate the treatment effects adopting a linear normalized age specification and an ad hoc bandwidth of 5 years. All estimates control for previous commute and wage, demographics, and previous job information along with year dummies.

A central assumption of the RDD is that the assignment variable can not be manipulated and we find no kink in the density of job seekers entering unemployment (Figure A.4 in the Appendix.) Even if the RDD is valid for the overall sample, it may not be valid for job seekers leaving unemployment in the during phase. We assess this concern by comparing the characteristics of job seekers on either side of the threshold (Table A.6). Many characteristics are balanced, but immigrants and job seekers with long tenure are significantly over-represented, and job seekers with long-tenure are under-represented in the period when UI coverage differs. We have reproduced the findings in Table 4 in a sample that excludes immigrants and job seekers with long tenure. Table A.7, in the Appendix, reproduces those results and finds the same qualitative patterns as in our main table. Our results are not driven by imbalance in terms of observed characteristics.

Table 4 shows the effects of UI coverage on job acceptance decisions. Panel A, column lnw shows results for accepted wages. Job seekers who are eligible for extended unemployment benefits accept the same wages as job seekers without extended benefits when both groups are still covered by benefits (coefficient above), or when both groups lost coverage (coefficient aboveXafter). However, job seekers with extended benefits receive 2.2% higher wages in the period when they are still covered while the control group has run out of benefits (coefficient aboveXduring). Job seekers with extended coverage commute as much as job seekers without extended coverage, regardless of UI coverage (column dist). Job seekers with extended coverage are less likely to find a job at home when still covered (column home) which is interesting because a simple view that job seekers trade off wages and commuting distance would have more job seekers finding a job at home. Column distPos shows effects of coverage

[25] Results are not sensitive to the presence of control variables X_i.

on commuting positive distances, the intensive margin of commuting, but there is no result for the whole sample. The final column, *Jvalue*, reports effects on the change in the log flow value of jobs, wage substracting the costs of commuting.[26] Unemployment insurance coverage raises the value of new jobs by 1.8%.

Panels B and C explore whether UI coverage effects for local workers differ from effects for non-local workers. UI coverage does not increase wages for local workers, but leads to an increase in commuting distance of around 4 minutes (=.062*60). Commutes increase because 7.9 percentage points more local workers accept jobs located outside the home municipality when still covered by UI, which is a sizeable fraction of the 43% local workers returning to a job in the home municipality. Unemployment insurance does not affect the flow value of new jobs accepted by local workers. UI coverage raises re-employment wages of non-local workers, Table 4C, but has no effects on average accepted commutes. UI coverage reduces the loss in the flow value of the new job, compared to the old job, because of its positive effects on wages. Unemployment insurance is very valuable for non-local workers, raising the flow value of new jobs by 2.7%.

Job seekers with more than three years of tenure are eligible for severance pay (Card *et al.*, 2007). We further explore the role of potential liquidity constraints, in Appendix Table A.5, and find that UI coverage raises wages and lengthens commutes for workers with less than three years of tenure, who are not eligible for severance pay, and therefore more likely to be liquidity constrained. UI coverage does not affect job quality for workers with more than three years of tenure, who are less likely to be liquidity constrained.

Loss of unemployment insurance coverage can explain why job seekers become broader in terms of accepted wages. In contrast, unemployment insurance broadens search among local workers, by encouraging them to accept jobs located outside the home municipality. Non-local workers also accept jobs located somewhat further away from their home, conditional on working outside the home municipality. Loss of unemployment benefits does not rationalize why job seekers search more broadly as their unemployment spells lengthen. We now explore a framework where access to job information, or search costs, change over the course of their unemployment spell.

5 Targeted Search: Model and Estimates

This Section develops a model to account for the facts reported in previous part, estimate it and run counterfactual experiments. It introduces targeted search into an otherwise standard (without spatial targeting) model of job search with time-delimited unemployment insurance. It estimates this augmented model by implementing a minimum distance criterion, where the distance is measured as the sum of squared percentage deviations of each target from its empirical counterpart, and illustrate

[26] $Jvalue$ is calculated using the log wage (lnw) and the commuting distance (d) in the new job, or $Jvalue = lnw - c(d)d$ where $c(d)$ is the commuting cost function from Section 2.

Table 4: Effects of Benefit Coverage on Accepted Wages and Distances

Panel A. All job seekers					
	lnw	dist	home	distPos	Jvalue
above	0.001	-0.000	-0.001	-0.001	0.001
	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)
aboveXduring	0.022***	0.012	-0.018**	0.006	0.018**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
aboveXafter	-0.000	-0.002	0.003	-0.001	0.000
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
R2	0.207	0.145	0.056	0.169	0.191
N	89909	89909	89909	68848	89909
Panel B. Local workers					
	lnw	dist	home	distPos	Jvalue
above	-0.004	-0.006	0.005	-0.004	-0.003
	(0.009)	(0.011)	(0.014)	(0.014)	(0.009)
aboveXduring	0.005	0.060***	-0.077***	0.031	-0.010
	(0.016)	(0.018)	(0.023)	(0.022)	(0.016)
aboveXafter	-0.008	-0.009	-0.003	-0.018	-0.006
	(0.012)	(0.013)	(0.017)	(0.016)	(0.013)
R2	0.176	0.023	0.014	0.063	0.164
N	21441	21441	21441	11874	21441
Panel C. Non-Local workers					
	lnw	dist	home	distPos	Jvalue
above	0.003	0.001	-0.003	0.000	0.002
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
aboveXduring	0.027***	-0.002	-0.000	-0.003	0.027***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
aboveXafter	0.001	0.001	0.009	0.006	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R2	0.214	0.152	0.038	0.232	0.201
N	68468	68468	68468	56974	68468

Notes: Table shows the effect of prolonged potential benefit duration (PBD) on accepted wages and distances. Panel A reports combined RDD estimates for an extension of benefits from 30 to 39 weeks, for job seekers who cross the 40 year threshold, and an extension of PBD from 39 to 52 weeks, at age 50 years (Table A.4 shows separate estimates). The table provides RDD estimates for the accepted log wage, lnw, accepted distance, dist, whether the new job is in the home municipality or not, home, positive accepted distance, and change in the flow value of a job, i.e. wage change - commuting cost, according to estimates in Table 2. During is the period when treated job seekers are still covered by unemployment while the control group anticipates losing benefits, i.e. weeks 25 to 35 for job seekers losing benefits at 30 or 39 weeks, and weeks 35 to 47 for job seekers losing benefits after 39 or 52 weeks. After is the period after the during period. Above identifies job seekers who are eligible for prolonged PBD when the difference in remaining benefits are 20%. AboveXduring provides estimates of how being eligible for benefits affects accepted wages and distances. AboveXafter provides a specification test. All estimates include control variables for education, marital status, immigrant status, and whether job seekers had more than three years of tenure or not. The sample comprises job seekers less than five years away from the age threshold, and includes linear trends in age around the age threshold.

what ingredients are needed to best fit the data. It finally provides counterfactual simulations on the role of unemployment insurance for targeted job search.[27]

5.1 Reservation strategies and the trade-off between distance and wages

Space is assumed to be bi-dimensional and jobs are spread in space. In the landscape, there are some particular points, such as home city, and other particular cities, such as cities where friends and relatives live, and cities where workers previously worked. Home is a particularly important point in space as it defines commute distance. Individuals are assumed to be immobile and therefore do not move, so that the main decision is to accept or reject the job offer.[28]

Time is continuous. Agents discount the future at rate r when employed. Their present discounted value (PDV) of utility is denoted, when employed, by $W(w, \rho)$ where w is the wage and ρ is an index of distance; when losing one's job, the unemployed have a PDV denoted by U_c where the subscript c stands for covered unemployed workers (they receive unemployment insurance $\mathcal{B}_c$). If uncovered, the PDV of unemployment would similarly be denoted by U_u; we assume $\mathcal{B}_u < \mathcal{B}_c$. To simplify, we assume that all employed workers are eligible to unemployment insurance upon losing one's job, while the transition from eligibility to non-eligibility follows a Poisson process of rate α, and once non-eligible, job seekers remain non-eligible. Hence, the potential benefit duration PBD defined in the empirical Sections is on average $1/\alpha$. At this stage, we make no further assumption, but we will extend the model for estimation in letting the transition to uncovered be associated with other changes in parameters, such as different search cost at a higher distance (due varying self-confidence for remote search). We will make no assumption here on the relative changes, just let it vary and be estimated to fit specific moments.

The utility of the employed combines income and disutility of commute time, at this stage in an unspecified way: $u^w = u(w, \rho)$ increasing with labor income (w) and decreasing in commute time at a distance ρ. Denote by s the job separation rate and $F(w, \rho)$ the distribution of job offers. One has the following recursive Bellman equation as:

$$rW(w, \rho) = u^w + s\left[U_c^* - W(w, \rho)\right] \tag{2}$$

where U_c^* is the optimal PDV of unemployment given the search strategies described later on. One defines a reservation frontier for covered and uncovered workers ($j = c, u$) in (w, ρ) as the set of wages $R_j(\rho)$ such that $W(R_j(\rho), \rho) = U_j^*$ and it is immediate that the reservation wage $R_j(\rho)$, $j = c, u$ is

[27] See Appendix B for model developments and additional results.

[28] This assumption simplifies greatly the analysis and is not too counterfactual since the mobility rate in Austria is rather low (less than 6%). See van den Berg and Gorter (2012) for a generalization of earlier works (van den Berg and Gorter (1997), Van Ommeren *et al.* (2000)) with the possibility of moving instead of waiting for a better job offer at a smaller commute distance.

implicitly defined by the equality:

$$u(R_c(\rho), \rho) = r_e U_c^* \tag{3}$$

$$u(R_u(\rho), \rho) = r_e U_u^* - s\left[U_c^* - U_u^*\right] \tag{4}$$

for the covered workers and uncovered workers respectively. It follows that the two reservation curves for covered and uncovered workers are a simple translation of each other, with a gap that is monotonically increasing in $U_c^* - U_u^*$. These two equations rationalize the setup expressed in Figure 2. The reservation commute distance for a given wage, denoted by ϱ is the reciprocal of the wage, $\varrho_j(w) = R_j^{-1}(w)$ for $j = c, u$.

A shift of the reservation value U_c^* is obtained from many factors; any policy change in unemployment insurance or a more difficult access to credit may vary U_c^* for a given generic search strategy denoted by Σ (effort, targeting, range of search, detailed below). Since Σ is endogenous, the policy change affects U_c^* both directly and through a change in Σ. The envelope argument applies: for instance, a change in $\mathcal{B}_c$ by $d\mathcal{B}$ leads to a change in U_c^* by

$$\frac{dU_c^*}{d\mathcal{B}} = \frac{\partial U_c}{\partial \mathcal{B}} + \frac{\partial U_c^*}{\partial \Sigma}\frac{\partial \Sigma}{\partial \mathcal{B}}$$

but the second term at the optimum effort is zero. Then, a positive shift in U_c^* moves the reservation wage curve $R_c(\rho)$ upwards: it increases the reservation wage for a given commute distance. A positive shift in U_c^* moves the reservation distance curve $\varrho_c(w)$ downwards: it reduces the acceptable distance for a given wage. Further, any shift in U_c^* affects the expected wage and the expected commute distance in opposite directions. One can also characterize the slope of the reservation wage, which is:

$$\frac{dR_c}{d\rho} = \frac{-u'_\rho}{u'_w} \geq 0$$

It varies potentially with the distance, as the marginal rate of substitution may not be constant with distance. To fix ideas, we assume that utility is linearly separable in income and commute cost, as this is enough to replicate the facts from the empirical Sections. By defining $v(w)$ and $c(\rho)$ as the utility from income and the cost of commute distance, respectively, we can write:

$$u(w, \rho) = v(w) - c(\rho), \tag{5}$$

with $v' > 0$; $v'' \leq 0$ and $c'(\rho)>0$. Therefore, equation (3) leads to

$$v(R_c(\rho)) = c(\rho) + rU_c^*$$

It is easy to show that, under linear utility for income $v"(w) = 0$, a sufficient condition for concavity of the reservation wage function is a concave commute cost function. With concave utility of income, concavity of the commute cost function is no longer sufficient and the curvature must be more important to obtain a concave reservation wage function in distance.[29] In the literature cited in introduction, the distinction between short and long commute distances may suggest that the convexity is not uniform, and workers may actually enjoy a short commute, especially if the commute can be used to other activities (such as without exhaustiveness grocery shopping, sport/leisure or picking up kids). Longer commute in a regional train or bus may also lead to work or enjoy leisure (the WIFI connected google buses were reported to be an example of intense Netflix watching). Eventually, the cost of commute must become convex, with fatigue and the increased probability of disruption, lack of connectivity and traffic congestion. In what follows, we will report the counterpart of the empirical investigation of commute cost with a log wage function being concave in the commute distance: in the range of commute distances, a first order approximation will lead to the wage being a concave function of distance, but out of the range, for longer distances, the first order approximation is no longer valid and the cost expressed in terms of the wage would become convex in distance.

5.1.1 Spatially targeted job search and duration dependence

Our framework follows recent literature that shows job seekers target search around their homes, with a cost. In particular, both Marinescu and Rathelot (2018b) and Manning and Petrongolo (2017a) find a decay in search strategies with distance, but also an overlap of search strategies. To be consistent with these findings, we allow for targeted job search in two ways.

The first one, at the most basic level, entails defining a broad area of search around home. For instance, individuals may decide to only look for jobs in a range of 40 minutes of commute around home, because searching for jobs further away from home is costly. Within that area, they may search more or less intensively at effort λ. With formal notations, individuals may restrict their search to all locations such that $\rho < D$, where D is the endogenous length of the radius of search. Within that radius, they may or may not accept an offer even inside the radius if the wage is insufficient. Similarly, an offer that would have reached them outside the radius may have led to job acceptance if the wage was large enough: however searching in larger areas is more costly due to transportation cost and limited earnings of some unemployed workers. Hence, we see D as the outcome of a trade-off between higher search costs and higher range of acceptable offers.

Second, we allow job seekers to target job search effort to their home municipality. This assumption is motivated by the empirical evidence that shows that a mass of job seekers find a job in their home town even if they used to work in a different location (Figure 3). We therefore define the specific search effort at home as λ^H. There are reasons for targeting the home town, e.g. lower commuting costs and family ties; the on-spot flow of information may also positively affect job search success. But whether job seekers target search to home or elsewhere is an outcome of their optimization process.

[29] See Appendix B.1.

In our model, searching at home differs in terms of the costs incurred by the job seeker, not in terms of the efficiency of looking for jobs. This modeling choice does not preclude that search efficiency might differ across locations. A realistic view is perhaps that both, search costs and efficiency will differ by location in the real world. Job seekers may have lower cost and better return to looking for a job at home. We have opted for a modeling route that allocates all differences to a search cost channel, but may, perhaps, interpret results through both the costs and efficiency lens.

These simple extensions of the partial equilibrium job search model will capture most of the empirical insights. So, the search strategy is a 3-dimensional vector: $\Sigma = (D_j, \lambda_j, \lambda_j^H)$ with cost of each of the dimension denoted by $C_j(D_j, \lambda_j, \lambda_j^H)$. Recall that the level of benefits is generically denoted by $\mathcal{B}_j,\ j = c, u$ for covered and uncovered job seekers, with $\mathcal{B}_u < \mathcal{B}_c$. The flow utility of the unemployed is denoted by:

$$u(\mathcal{B}_j, D_j) = v(\mathcal{B}_j) - C_j(D_j, \lambda_j, \lambda_j^H), \quad j = c, u$$

where effort depends on the eligibility to unemployment insurance or assistance. All decision variables are indexed by $j = c, u$ for covered and uncovered workers, as well as parameters of the model (in particular search costs). In what follows, we assume that discount factors are constant over time, and that any change in household liquidity will arise from an observationally equivalent parameter, the structure of search costs, as that structure and discount rates cannot be separately identified.

$$rU_c^* = \underset{D_c,\lambda_c,\lambda_c^H}{\text{Max}} \quad r_c U_c = v(\mathcal{B}_c) - C_c(D_c, \lambda_c, \lambda_c^H) + 2\pi\lambda_c \int_{w,\rho<D_c} Max[W(w,\rho) - U_c; 0]dF(w,\rho) + \alpha(U_u^* - U_c)$$
$$+\lambda_c^H \int_w Max[W(w,0) - U_c; 0]dF(w,0) \tag{6}$$

$$rU_u^* = \underset{D_u,\lambda_u,\lambda_u^H}{\text{Max}} \quad r_u U_u = v(\mathcal{B}_u) - C_u(D_u, \lambda_u, \lambda_u^H) + 2\pi\lambda_u \int_{w,\rho<D_u} Max[W(w,\rho) - U_u; 0]dF(w,\rho)$$
$$+\lambda_u^H \int_w Max[W(w,0) - U_u; 0]dF(w,0) \tag{7}$$

Note also that for covered workers and workers getting a job offer, an increase in the level of assistance $\mathcal{B}_u$ has an entitlement effect, that it raises the value of W through the future possibility of collecting benefits, without affecting the current value of unemployment U_c^*. One thus expects that covered workers accept more easily a job offer when $\mathcal{B}_u$ increases; the same effect is true for an increase in $\mathcal{B}_c$ but this is more than compensated by the increase in current U_c^* so that the overall effect is to decrease job acceptance. The first order conditions on optimal search strategies are reported in Appendix B.2 and will be used in the estimation of the model discussed below.

5.2 Estimating a model of Targeted Search

With this framework in mind, we now want to better understand to what extent targeted search affects the duration dependence and UI coverage patterns we documented in Section 4. The primary purpose of our estimates is to produce simulations of job seekers' strategies along with accepted wages and distances; in our model these outcomes evolve over the spell because covered and uncovered workers enjoy higher or lower benefits and potentially face different search costs. Calibrating some parameters based on descriptive statistics, in particular average replacement rates of UI and assistance, we estimate the model to fit the distributions of accepted wages and commutes, and infer search costs from exits to jobs at home and elsewhere. The estimated pattern of search costs will thus capture the dynamics of exit rates to different locations which is left unexplained by the exhaustion of UI coverage. The set of moments we use is deliberately kept small so we can assess the fit of our estimates in terms of many dimensions that were not used in estimation.

Several parameters, listed below, are calibrated and are common to all workers, based on descriptive statistics and the estimate of the reservation frontier (Sections 2.3 and 3; see Table 5). We calibrate the annual interest rate to 5%; the unemployment insurance (UI) benefits $\mathcal{B}_c$ and the unemployment assistance (UA) benefits $\mathcal{B}_u$ are 40% and 11% of the average accepted wage, consistently with Table 1. The Poisson transition rate from the covered to the uncovered state, α, is equal to 0.125 per month to obtain a Potential Benefit Duration (PBD) of 32 weeks. The monthly transition rate from employment to unemployment, or separation rate, is set to 1%, so that the yearly separation rate is between 12 and 13%.

For the commuting cost we use a functional form close to the empirical estimates of the reservation wage (see Section 3), $c(\rho) = \frac{2\tau}{0.5}\sqrt{\rho}$, where the cost is multiplied by two to take into account round trip commuting. We set the cost of commuting $2\tau/rU_c$ equal to 0.12, the weighted average of the empirical estimates across the five largest sub-groups in our sample (see Table A.1 in Appendix A.1).[30]

We adopt an iso-elastic and additively separable specification for the flow of utility of income: $v(\omega) = \frac{\omega^{1\text{-}\sigma}}{1-\sigma}$ for $\omega = w, \mathcal{B}_c, \mathcal{B}_u$ and the utility flow net of cost of search is assumed to be:

$$u_j^u(\mathcal{B}_j, D_j) = \frac{\mathcal{B}_j^{1\text{-}\sigma}}{1-\sigma} - \left[D_j^\eta + c_j^{\lambda^H}(\lambda^H)^\eta + c_j^\lambda(\lambda)^\eta\right] \tag{8}$$

where $c_j^{\lambda^H}$ and c_j^λ are scale parameters of the iso-elastic cost function. We fix the elasticity η to be equal to 1.5 and as a robustness check we let it vary between 1.2 and 2.5. As for the discount factors, risk-aversion may vary with the employment status or the eligibility to benefits, but this is subsumed by

[30] The empirical estimates of the reservation wage are based on the following specification: $\ln(R) = C + \frac{\hat{2\tau}}{0.5}\sqrt{\rho} +$ *covariates*, with $\hat{2\tau} = 0.12$ on average over the five sub-groups. In the model we instead specify the reservation wage in levels: $R_c = rU_c + \frac{2\tau}{0.5}\sqrt{\rho}$. By taking logs we obtain: $\ln(R_c) = \ln\left(rU_c + \frac{2\tau}{0.5}\sqrt{\rho}\right) = \ln\left(1 + \frac{2\tau}{0.5}\sqrt{\rho}/(rU_c)\right) + \ln rU_c$, which can be approximated as $\ln(R_c) \simeq \ln rU_c + \frac{2\tau}{0.5}\sqrt{\rho}/rU_c$, that is exactly as in the empirical part. Then, the coefficient which multiplies the square root of distance is $\frac{2\tau}{0.5}/rU_c$ from which we derive the equality with the empirical estimate: $2\tau/rU_c = 2\hat{\tau} = 0.12$.

Table 5: Job search model: parameter determination

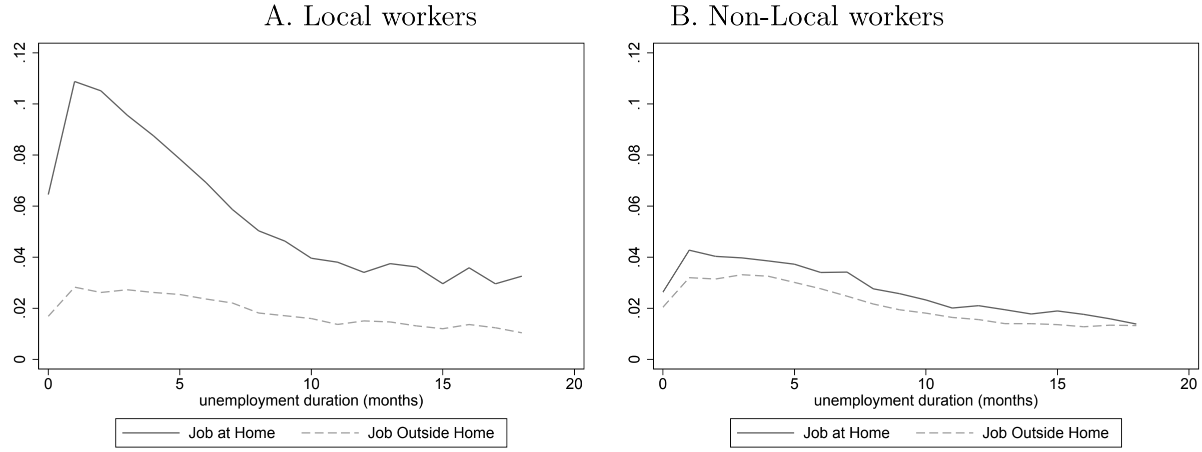
Fixed parameters		
r	Discount rate	0.0042
s	Separation rate	0.01
η	Elasticity of the search cost	1.5
σ	Relative risk aversion	0
$w^{\max}$	Maximum daily wage	150
Calibrated parameters		
$\mathcal{B}_c/\mathbb{E}(w)$	Replacement rate UI	0.4
$\mathcal{B}_u/\mathbb{E}(w)$	Replacement rate UA	0.11
$1/\alpha$	Potential Benefit Duration	32 weeks
2τ	Cost of commuting	0.12

variations in search costs structure over time and in space, as a proxy for these underlying mechanisms. Hence, we keep the simplest specification here, and assume that workers are risk neutral (σ =0).

We provide separate estimates and simulations for local workers, those who worked in their home city, and non-local workers, who worked outside their home municipality. Local workers differ from non-local workers (Table A.3) and their duration dependence and UI coverage patterns differ in terms of commuting distance (Tables 3 and 4). The distinction between local and non-local workers removes an important, but not exclusive, source of heterogeneity. Hence, to get the targets for the estimation procedure, we further purge the data from *ex ante* individual observed heterogeneity. Specifically, we form cells of job seekers with respect to observed characteristics, e.g. education, age, previous industry, citizenship, and marital status. We address unobserved heterogeneity adopting the Bonhomme *et al.* (2017b)'s approach, like in the previous Section (see section A.2 for details).

We estimate the mean and standard deviation of the distribution of offered wages and distances assuming a bivariate independent lognormal distribution. The parameters of the distribution of job offers are estimated in order to match the empirical first and second moments of wages and distances accepted by job seekers who exit unemployment when they are still covered by UI (after 1 month in unemployment) and find a job outside their home town (which is instead modeled as a mass point). To estimate the search costs (c_c^{λ}, c_u^{λ}, $c_c^{\lambda^H}$, $c_u^{\lambda^H}$) we use sub-hazard rates, that is the rates at which unemployed workers exit their status for a given outcome. To obtain the corresponding targets in the data we remove unobserved heterogeneity in a two step approach. We first estimate hazards within each cell, we then aggregate the group specific hazards using the size of each cell at the beginning of the unemployment spell. This non-parametric two step approach does not rely on a proportionality

Figure 5: Transitions to High Wage Jobs



Notes: This figure provides sub-hazard rates to jobs in the municipality where job seekers live (home city), or elsewhere (outside home city). The transition rate to jobs elsewhere is divided by 2π to adjust for the difference in geographic area. Local workers are those who had a job at the home municipality prior to entering unemployment, non-locals worked elsewhere. Local workers have a comparative advantage in finding jobs at home, compared to non-local workers.

assumption and deals with heterogeneity in a flexible way (see section A.2).[31] Indeed, we find that duration dependence of the unemployment exit hazard reduces through our procedure, indicating that we have dealt with an important confound for our estimates.

More formally, the hazard rate for a group of worker $j = c, u$ (in the data respectively at 1 and 14 months of unemployment) defined as the exit rate of job seekers from the unemployment pool, is:

$$haz_j = 2\pi\lambda \left[\int_0^{D_j} \int_{R_j(\rho)}^{w^{\max}} dF(w)dG(\rho) \right] + \lambda^H \left[\int_{R_j(0)} dF(w) \right]$$

The hazard rate depends on the wage and distance distributions as well as on the reservation strategy (reservation wage and search radius) and effort. Since we are interested in estimating the parameters of the search costs of effort (c_j^λ and $c_j^{\lambda^H}$) we isolate their effects by looking at sub-hazard rates. For instance, the $sub - haz(d > 0)$ is the exit rate of job seekers still unemployed at time t, and leaving for a job that is more distant with respect to the home city ($d > 0$); $sub - haz(d = 0)$ measures who finds a in the city of residence, instead. These are defined in Appendix B.3 (equations 19 and 20).

The empirical sub-hazard rates used as targets are plotted in Figure 5. We can notice several interesting patterns. First, all transition rates spike after one month and decline afterwards: after 14 months in unemployment the probability of finding a job is reduced by 70%. Second, in each sub-sample the transition rate to jobs located in the worker's home city is substantially higher than the exit rate to more distant jobs. Third, local job-seekers find a job faster than non-local ones, with almost double transition rates in their city of residence .

[31] An alternative would be to fit a mixed proportional hazard model (MPH). Alvarez *et al.* (2016) reject the MPH model in the Austrian context.

We recover search effort λ_j and λ_j^H from the sub-hazard rates using the first order conditions for optimal search (14-15), and back out the marginal costs of search. Our estimates match both exit rates at the beginning of the unemployment spell and after 14 months, in order to take into account the strategies of both covered and uncovered job seekers. Appendix B.5 provides a more detailed description of the estimation procedure and checks the identification strategy over simulated data. To summarize, for each sub-sample we have 8 targets (the first and the second moments of accepted wages and distances and four transition rates) for 8 parameters (four moments of offered wages and distances and four search costs): they are summarized in Appendix Table B.1.

5.3 Results

In this Section we show how the estimated model of targeted job search fits the data on different dimensions beyond the ones used as targets; we will also show that the search costs play a crucial role in explaining the observed dynamics. Table 6 reports the main outcomes of the model, distinguishing between those having an empirical counterpart (observed outcomes) and the underlying unobserved search strategies (unobserved outcomes). The model fit measures the average mismatch between the simulated moments and the corresponding empirical ones. The model fits relatively well also the moments not directly targeted in estimation procedure, both measured in relative terms (covered relative to uncovered workers) and in levels; the average loss in levels is 11.7% for local workers and 3% for the others. This measure is based on the share of workers finding a job in their city of residence and on average accepted wages and distances (including also those workers who find a job in their home town).[32]

More than 40% of local workers find a local job and this share declines very little over the unemployment spell; the model slightly underestimates this percentage but nicely matches the difference with non-local workers: only 17% of them find a job in their home town and this does not depend on the length of the spell. Average daily wages accepted by covered workers are between 57 and 59 Euros and decline by about 5 Euros after 14 months in unemployment. The model fits well not only the levels (which was expected given that one of the target of the estimation procedure was average wages accepted by covered workers conditional on finding a job outside the municipality of residence), but also the dynamic, which was not targeted. Also, average commuting time considering all job seekers is about 19 minutes (0.32 hours) for covered local workers and 29 minutes (0.48 hours) for non locals: this barely changes over the spell, with uncovered local workers commuting almost 2 minutes more and non-locals 1 minute less. The model predicts a slightly higher increase in commutes for local workers over the spell and almost flat commuting time for non-locals.

[32] The overall accepted wage is a weighted average of the mean wage earned in the home city and the average wage accepted for a job located elsewhere; the weights are the transitions rates to jobs in the home town and elsewhere, respectively. The same applies to average accepted commuting time.

Table 6: Main endogenous variables of the model

	Local workers				Non-Local workers			
	Data		Model		Data		Model	
	1m	14m	1m	14m	1m	14m	1m	14m
Observed outcomes								
Average wage (euros per day)[a]	57.3	52.5	55.2	50.9	58.8	53.8	57.8	53.1
Average commuting time (hours)	0.32	0.35	0.35	0.40	0.48	0.46	0.48	0.49
Average wage (euros per day)$\|$ $d > 0$	57.3	52.5	57.3	52.3	58.8	53.8	58.8	53.9
Average commuting time (hours)$\|$ $d > 0$	0.57	0.59	0.57	0.57	0.58	0.56	0.58	0.58
Share finding a job at home	44.0	41.0	37.0	30.5	16.6	17.0	17.2	15.9
Hazard rate	0.29	0.12	0.29	0.12	0.24	0.11	0.24	0.11
$sub - haz(w > w_{-1})$	0.144	0.049	0.109	0.032	0.116	0.037	0.091	0.030
$sub - haz(w < w_{-1})$	0.105	0.058	0.177	0.087	0.095	0.055	0.154	0.082
$sub - haz(d > d_{-1})$	0.178	0.082	0.178	0.082	0.096	0.043	0.088	0.041
$sub - haz(d < d_{-1})$	0.000	0.000	0.000	0.000	0.127	0.043	0.157	0.070
$sub - haz(d = 0)$	0.109	0.036	0.109	0.036	0.043	0.018	0.043	0.018
Not observed outcomes								
Reservation wage at average distance[b]	NA	NA	45.1	39.2	NA	NA	45.9	40.1
Search radius	NA	NA	2.16	1.92	NA	NA	2.27	2.00
Weekly job offer arrival rate outside home city	NA	NA	0.135	0.042	NA	NA	0.160	0.053
Weekly job offer arrival rate in home city	NA	NA	0.049	0.012	NA	NA	0.021	0.007
Acceptance rate	NA	NA	0.336	0.522	NA	NA	0.320	0.471
Total search costs relative to average wage	NA	NA	0.141	0.068	NA	NA	0.128	0.065
Model fit on targeted moments[c]			0.0000				0.0000	
Model fit on relative non-targeted moments[d]			0.0689				0.0540	
Model fit on non-targeted moments (levels)[e]			0.1175				0.0304	

Notes: Local workers used to work in their home town before unemployment ($d_{-1} = 0$); non-local workers worked in a different city ($d_{-1} > 0$).

[a] Average accepted wages and commute times refer to all job seekers, including those who find a job in their home town.

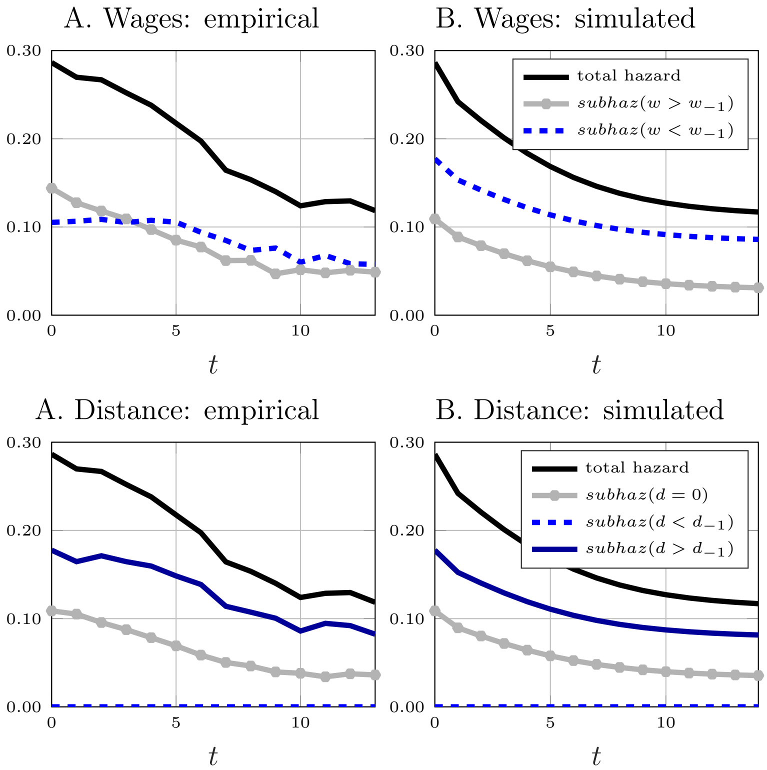
[b] NA stands for "not available" in the data.

[c] The model fit is the sum of absolute percentage deviations of the simulated targeted moments from the empirical ones divided by the number of targets. It thus includes the sub-hazard rates $sub-haz(d > 0)$ and $sub-haz(d = 0)$ both after 1 and 14 months in unemployment; it further includes covered workers' average accepted wage and distance conditional on finding a job outside the home city.

[d] This statistics is computed on the ratio between moments related to workers exiting unemployment after 1 and 14 months. It consists of the sum of absolute deviations of ratios calculated on simulated moments from the ones calculated on the data divided by the number of targets. The moments included are the share of job seekers finding a job in their home city, and average accepted wage and distance of all job seekers.

[e] The model fit is the sum of absolute percentage deviations of the simulated non-targeted moments from the empirical ones divided by the number of targets. It includes all moments used in the statistics d) both after 1 and 14 months in unemployment.

Figure 6: Empirical and simulated hazard rates: local workers

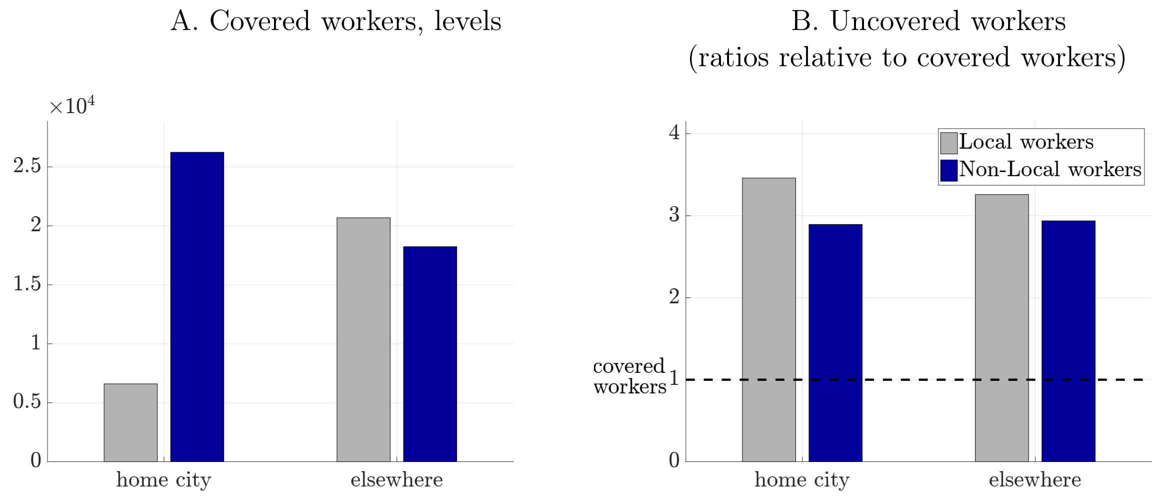


Notes: This figure reports the empirical (left) and simulated (right) hazard rates for local workers. Exit hazards are split by wage (better vs. worse) in the top row, and by distance (home vs. elsewhere) in the bottom row. Empirical exit rates are corrected for heterogeneity (see section A.2).

We can further assess the fit of the model on the transition rates to either better or worse paid jobs and to jobs located in the home city or elsewhere. Figure 6 reports the simulated hazard rates and compare them with the empirical estimates for local workers (after removing observed and unobserved heterogeneity; Figure B.8 shows results for non-local workers). Estimates replicate the decrease in the absolute hazard and in the sub-hazard rates, with magnitudes comparable to the empirical ones for commuting distance. The simulated exit rates to better paid jobs are of similar magnitude of the empirical ones while the simulated transition rate to worse paid jobs are larger than those observed in the data. Overall, the fit is satisfactory, especially if one remembers that none of the exit rates related to wages were directly targeted in the estimation.

Figure 7 represents the estimated search costs per efficiency unit of search (i.e. divided by the corresponding exit rates) of covered workers (panel A) and of uncovered job seekers relative to the others (panel B). It shows, first, that for local workers who are covered, the cost of search in the city of residence is lower than the cost of effort elsewhere. For non-local workers, the opposite is true. Second, for covered local workers the search cost in their home city is estimated to be approximately a fifth of the one faced by the non-local workers. Third, the costs faced by uncovered workers are approximately

Figure 7: Estimated search costs per efficient unit of search



Notes: Local workers are those who used to work in their home town before unemployment ($d_{-1} = 0$); non-local refers to job seekers who worked in a different city ($d_{-1} > 0$). In panel A search costs are divided by the corresponding hazard rates to make them comparable.

three times those faced by the newly unemployed; in other words, covered workers are relatively more efficient in searching for a job. Several mechanisms can lead to deteriorating search outcomes. Kroft *et al.* (2013) show, in an audit study, that job seekers who have been unemployed for a while have worse chances to obtain a job interview, which documents that employers are less willing to hire long-term unemployed. Job seekers may also face higher search costs because of discouragement. This explains why the transition rates decline over the unemployment spell, and more so those to better paid jobs. This may also arise from a general phenomenon of job offers exhaustion, or from credit constraints affecting the utility value of search costs, featured by the scale parameter of search cost functions. In addition, if search costs increase by a factor 2 to 3 upon loss of unemployment eligibility, this increases faster for local workers in the home city, hence suggesting that local job exhaustion threatens more the local workers who have a higher relative cost efficiency at home.

Furthermore, we find that the total cost of search lies between 6.5 and 14% of the average accepted wage, depending on the sub-sample and the worker status; this is somewhat higher than the time spent by unemployed people in employment related activities, which is on average 5% of the time spent by employed in their main job, according to European Time Use Survey conducted in 2000.[33] Job seekers who used to work in their home town are encouraged to provide more effort because of relatively higher efficiency, thus pushing up overall search costs; moreover, in both sub-samples uncovered workers reduce effort due to the high costs they face.

The estimated distributions of offered wages and distances outside the municipality of residence are represented in Appendix Figure B.1. Table B.1 shows that the mean of wage offers implied by

[33] Austria did not participate in the survey; here we report average values among the participating countries.

model estimates is between 42 and 43 Euros per day, with a standard deviation of 13 Euros: since this distribution is common to all job seekers, this value is lower than the baseline mean of 50.4 Euros found in the empirical estimates for job seekers exiting unemployment within 14 weeks (see Table 2). The average offered commuting time is around 40 minutes (66% of an hour), very close to the empirical estimate (mean commute between 36 and 45 minutes): accepted commutes outside the municipality of residence are much less affected than wages by the duration of the unemployment spell, thus bringing closer model and empirical estimates for such distribution.[34]

We now want to better understand how search costs affect wages and commuting times of job seekers and their evolution over the unemployment spell. Note that in our setting duration dependence is caused by job seekers switching from the covered to the non-covered state, calibrated to the average potential benefit duration (Table 5). Duration dependence thus arises because of three factors: i) changes in unemployment benefits (from UI to the assistance regime); ii) time-varying costs in looking for a job in one's home city; iii) time-varying costs in looking for a job outside one's home city. In the following analysis we perform counterfactual simulations which allow to disentangle the three channels and show their contribution to the impact of duration dependence and UI coverage as found in the data (Tables 3 and 4).

Figure 8 shows average commuting time for local workers (Figure B.9 provides the same information for non-local workers). The black solid line is based on our estimates and suggests that commuting time increases moderately over the course of the unemployment spell, quite in line with the empirical evidence. Figure 9 also shows the maximum search radius which is, initially, wide: job seekers would be willing to commute for almost 2.2 hours, and it decreases over time to around 2 hours. This behavior stems from two counteracting effects. On the one side, benefit exhaustion pushes job seekers to widen the range of search, as described by the simulation that fixes the search costs parameters of the uncovered workers (c_u^{λ} and $c_u^{\lambda_H}$) to the corresponding values for the covered workers (c_c^{λ} and $c_c^{\lambda_H}$, respectively; blue dashed line). On the other side, the increase in the cost of looking for a job far away from the city of residence discourages broader search: this is evident in the simulation with constant benefits and time-varying search costs (grey squares). In our simulation the second effect prevails, and the area of search restricts over the spell. Despite this tightening of the search radius, job seekers do not accept jobs located closer to home as their spells lengthen: the fraction accepting a job in the home municipalityslightly decreases over time, thus determining an increase in unconditional accepted commuting times. This effect is entirely explained by the time-varying structure of search costs: as time goes, local workers are more exposed to local jobs exhaustion and need to search more broadly.

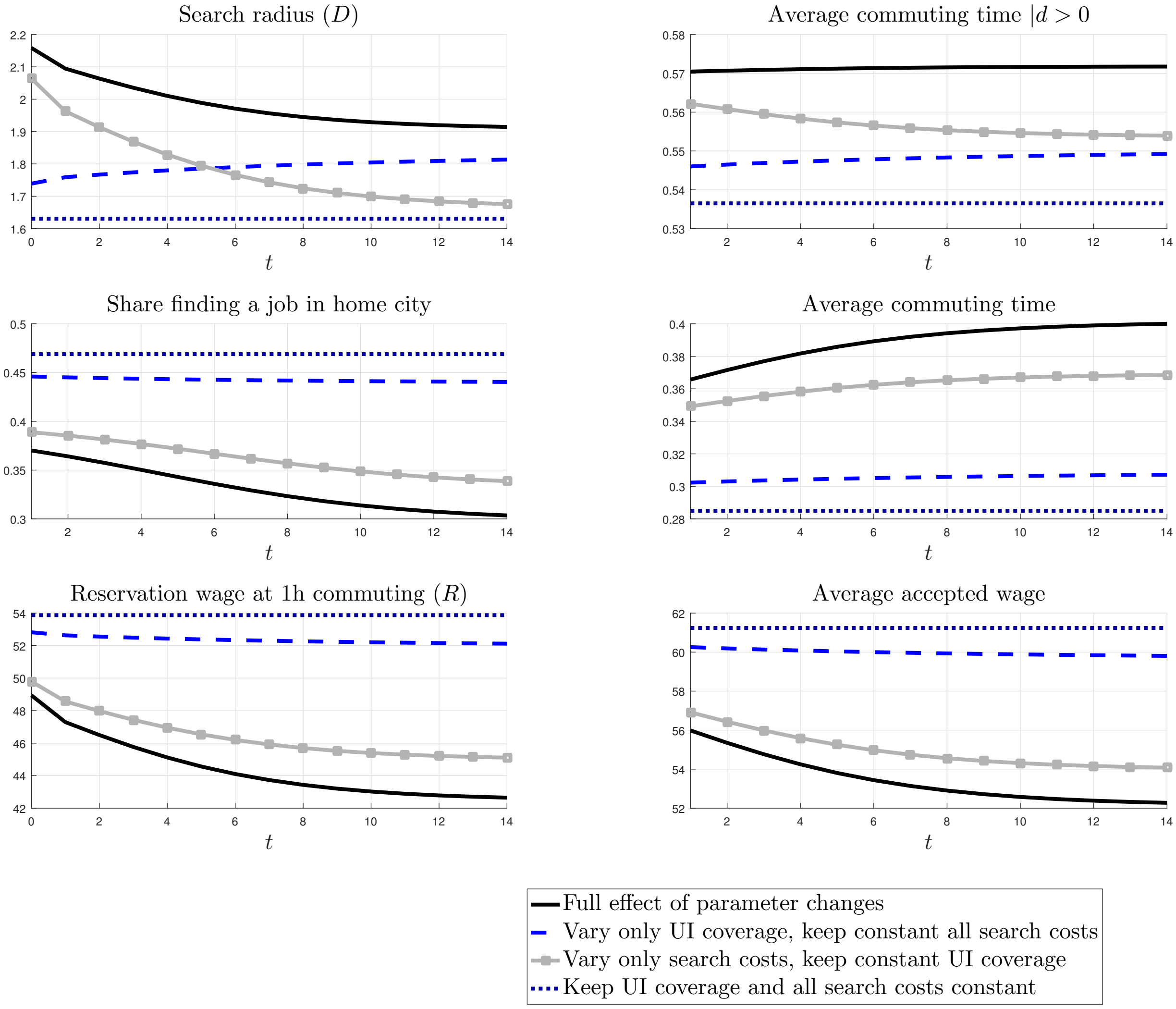
[34]Estimates of the unobserved search strategies in the model are similar to those in section 3. the results of the empirical approach. The reservation wage at mean accepted distance is estimated to be around 45 Euros per day in the early stage of the spell, in both approaches. In the model of this section, the weekly job offer arrival rate, once considering both search in the home city and elsewhere, is close to 10%, as in the empirical estimates of Section 3. The acceptance rate in this section is somewhat lower, between 32 and 33% for covered job seekers, a result related to the wage distribution being shifted towards lower values compared to the one estimated in Section 3.

Figure 8 also provides simulations of the reservation wage and average accepted wage. The baseline simulation, solid dark line, shows that job seekers ask for at least 49 Euros per day on a job that entails to commute for one hour one-way. As job seekers lose unemployment insurance coverage, the reservation wage decreases to somewhat more than 42 Euros. Accepted wages for all jobs are about 57 Euros per day and decrease to just below 54 Euros after 14 months. The factual simulations replicate well the time profile of accepted wages (Figure 3 and Table 3). The counterfactual simulation that keep search costs constant over the unemployment spell raises the reservation wage to more than 52 Euros per day, and the reservation wage no longer declines much over the course of the unemployment spell (blue dashes); the level and the dynamic of the reservation wage is mainly explained by the costs of looking for jobs, which affect the value of remaining unemployed for one more period (grey squares). The pattern of accepted wages follows very much the pattern of reservation wages.

To summarize, the baseline simulation broadly replicates the duration dependence in accepted wages and commuting times (Figure 3 and Table 3), with a key role of time-varying incentives of looking for jobs in space, here captured by search costs.Figure 9 also provides additional simulations which allow search costs to vary differently over the spell depending on the location. The grey squared line reports a simulation where search at home remains cheap, while the costs of searching outside home increase when benefits are exhausted. In this case, job seekers adopt a search radius that narrows over time, as in the baseline simulation, and accepted commutes decrease substantially over the course of their unemployment spell. Uncovered job seekers, who face high costs of looking for a job outside home, engage in very much search at home, and the proportion working at home increases from about 50% in the initial phase of the spell to 80% after 14 months. The dark blue dotted line shows a counterfactual scenario where job seekers who lose unemployment coverage face the same cost increase for search at home as in the baseline, but constant costs of looking for a job outside their home city. Job seekers who face this search cost structure adopt a search radius that increases over time, and accept longer commutes than in any of the other scenarios, mainly because they are less likely to find a job located in their municipality of residence.

The counterfactual simulations represented in Figure 9 can rationalize the pattern of unemployment insurance coverage effects. Consider the simulation that keep the search costs at home low, but increase the search costs outside home when job seekers exhaust benefits (grey squares). In this setting, job seekers increasingly accept jobs at home, as they lose access to job information elsewhere. Unemployment insurance coverage can broaden geographic search, decreasing the share of job seekers that find a job at home, a pattern we found for local workers (Table 4). While counterfactual, we believe that this setting could be realistic. Search costs outside home are arguably directly affected by whether a job seeker is eligible for benefits or not. The public employment service provides access to information on job openings, and caseworkers counsel job seekers on how to apply for jobs. The support in job search related activities can be even more important for local workers, who were not

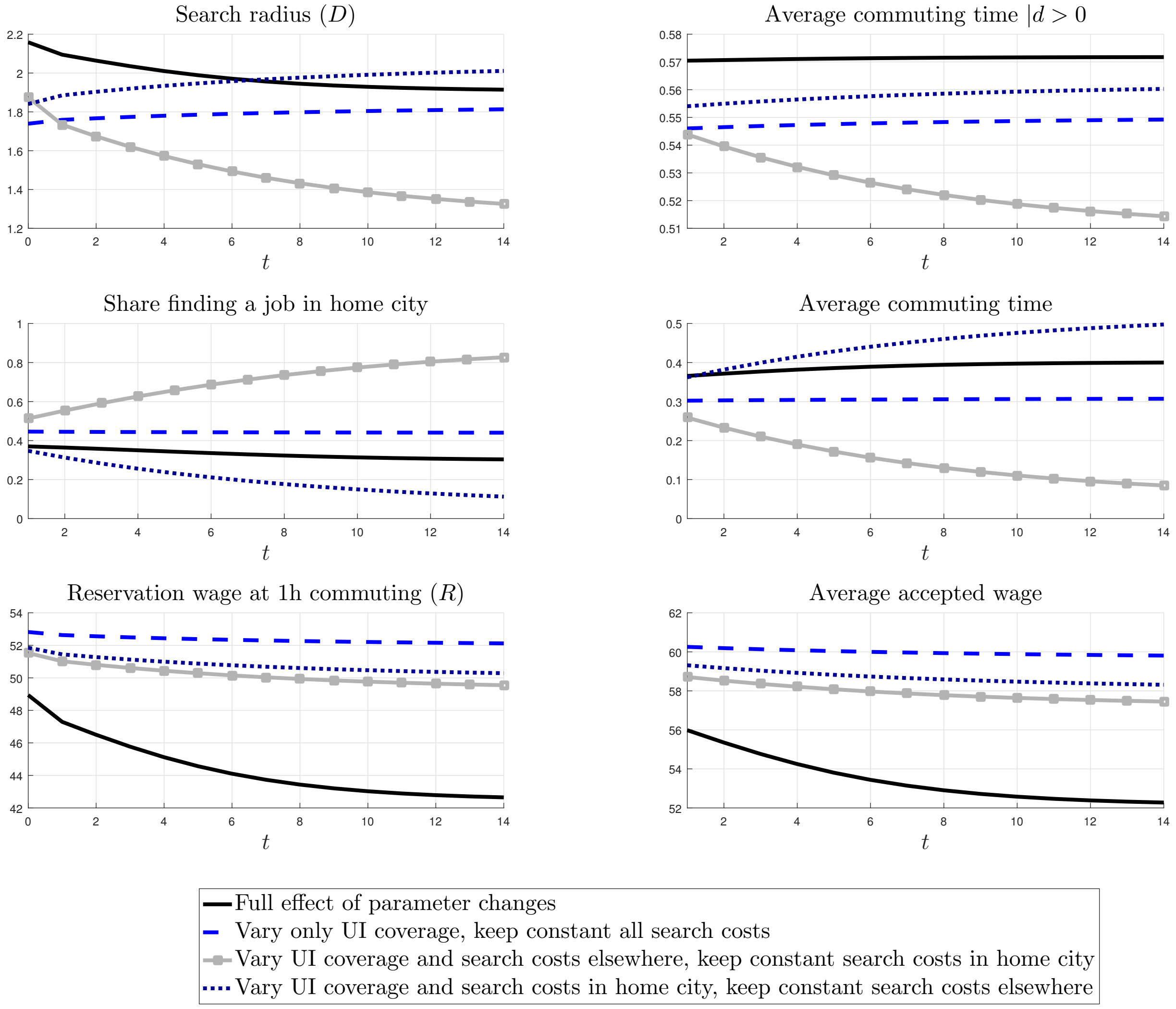
Figure 8: Counterfactual scenarii for local workers: effects over time



Notes: This Figure shows simulations of the average accepted commuting time and three key elements, the search radius, average commuting time outside home, the proportion of job seekers finding a job in the home municipality. The figure also shows average accepted wages, and reservation wages, all by spell duration, in months. The figure presents four scenarii (i) both coverage and search costs change at benefit exhaustion (solid line), (ii) coverage changes at benefit exhaustion, but search costs do not (dashed line), (iii) search costs change at benefit exhaustion but coverage does not (dotted line), and (iv) neither coverage nor search costs change at benefit exhaustion.

exposed to labor markets other than the very local one. This may explain the asymmetric effects of UI on local and non-local workers (Table 4). Search costs at home might be less sensitive to unemployment benefit coverage, to the extent that information on job openings circulates in social networks.

Figure 9: Counterfactual scenarii for local workers: effects over time



Notes: This Figure shows simulations of the average accepted commuting time and three key elements, the search radius, average commuting time outside home, the proportion of job seekers finding a job in the home municipality. The figure also shows average accepted wages, and reservation wages, all by spell duration, in months. The figure presents four scenarii (i) both coverage and search costs change at benefit exhaustion (solid line), (ii) coverage changes at benefit exhaustion, but search costs do not (dashed line), (iii) coverage and search costs outside home change at benefit exhaustion but search costs at home do not (dotted line), and (iv) coverage and search costs at home change at benefit exhaustion but search outside home do not.

6 Conclusions

Job seekers look for jobs that pay well and are located close to home. Commuting time is a relevant dimension of workers choices, perhaps the only job attribute over which they have a control, and commuting distances involve large disutility costs that are hard to insure. How much job seekers are willing to compromise on high wages and short commutes, and how does this compromise varies as their spells lengthen, is the key question we asked here.

We found that job seekers indeed accept lower paid jobs over time, and jobs located further away from home. Unemployment insurance and its loss over time is the main potential rationalization of this pattern: when benefits run out after some time, this forces job seekers to accept worse jobs.

However, quasi-experimental estimates of the effects of unemployment insurance show that coverage increases wages, but coverage does not shorten commutes. Higher unemployment insurance fosters wider geographic search among job seekers who worked in their home municipality. Unemployment insurance coverage empirically implies that wages decrease as spells lengthen, but suggests that commutes would even decrease when job seekers exhaust benefits.

These findings can be rationalized by a theory of job search targeted in space. We estimate a simple framework where job seekers control their effort to get jobs in the home municipality and elsewhere. The costs of searching differ between home, and elsewhere, and varies over time. Results show that for local workers looking for jobs at home is less costly than looking for jobs elsewhere, while the opposite is true for non local ones. Moreover, the costs of searching more than triple as job seekers exhaust benefits and enter long-term unemployment.

This framework can replicate the patterns in our data well, better than a framework that assumes that search costs are constant. The increase in search costs as job seekers exhaust benefits reduce accepted wages, and lengthen accepted commutes, compared to a world where search costs remain as low as in the initial phases of the unemployment spell. Job seekers accept much longer commutes when search costs outside the home municipality remain low even after unemployment benefits lapse. Search costs are a key determinant of accepted wages and commutes.

Our findings suggest that unemployment insurance is not an impediment to greater flexibility in regional labor markets. Search costs decrease the geographic flexibility of labor markets, especially in cases where search outside the home municipality becomes more costly. Labor market policy could address the increase in search costs by providing job seekers access to job information regardless of their eligibility for unemployment benefits. Measures to improve search effectiveness could also increase the geographic flexibility of the labor market.

The policy implications of extending unemployment insurance coverage depend on the interpretation of the change in search costs following the loss of coverage. The variation in search costs upon eligibility loss varies across location of search. This may proxy different forces. One such are behavorial factors: time spent unemployed makes people less forward looking and less confident in their ability to get job offers far away, as if they were scared by being far from home. Another one is time variation in the marginal utility of monetary search costs, proxying liquidity constraints or time-varying risk aversion. Overall, this suggests that unemployment insurance has both the conventional impact on accepted wages (it raises them) but also improves welfare through non-monetary channels: it allows workers with low propensity to search away from their (sweet) home, to expand their range of search.

A Empirical Appendix

A.1 Estimating the reservation frontier

We develop a novel approach to infer the reservation wage directly from data on accepted wages and spell durations. This approach can be implemented for job seekers who have been laid off from their previous job. In a stationary environment, layoffs would accept an offer to return to their pre-unemployment job, i.e. the reservation wage is below the pre-unemployment wage. Every period, job seekers receive job offers at a rate that depends on their search intensity and market tightness, and accept or reject them based on whether the wage offered is greater than the reservation wage for the required commute.

In this setting, job seekers who accept a high wage, one that pays more than the previous job, provide information on the wage offer distribution, censored from below at the previous wage. We estimate both the mean and standard deviation of the distribution of offered wages, assumed to be log normal, from wages that pay more than the previous wage, accounting for censoring at the previous wage. Job seekers who accept a high wage also provide information on the arrival rate of job offers, both at home and everywhere else. Job seekers who accept a bad job, one which pays less than the previous wage, provide information on the reservation wage. Jobs that pay less than the previous wage lie between the reservation wage and the previous wage. Movements in the transition rate from unemployment to bad jobs therefore inform on movements in the reservation wage.

Conceptually, this approach works by artificially censoring wages at the previous wage, a known censoring point, instead of at the reservation wage, which is not known. Artificial censoring helps us get estimates of the parameters of the wage distribution even without knowing reservation wages. We then use this information, along with information on the shape of the distribution, to back out the reservation wage of job seekers who accept a low paid job. A central requirement for our approach to work is that information from the upper tail of the wage distribution can be used to lower tail of the wage offer distribution.

Empirical patterns in the data that illustrate identification of the parameters of the model. Figure A.1A shows the distribution of accepted wages, censored at the mean previous wage[35]. Below the censoring point, the vertical dashed line, we have no data so the density of the uncensored wages is missing. To recover the parameters of the uncensored distribution, we estimate a standard tobit type model that corrects for censoring and recover the mean and the standard deviation of the underlying uncensored distribution, and standardize accepted wages. The unadjusted density, black dots, of accepted standardized wages is always above the dashed standard normal. We then adjust the density, multiplying it with the probability that wages are uncensored, to recover the density of uncensored

[35]In our empirical setting, the censoring point is individual specific as all job seekers have a different previous wage. We simplified illustration of identification but our empirical procedure accounts for the full heterogeneity of censoring points.

wages. The adjusted density, grey diamonds, coincides with the standard normals. This is how we recover the wage distribution from wages that are higher than the previous wage.

The transition rate from unemployment to regular jobs contains information on search activity and the reservation wage (Figure A.1B). Transitions to jobs occur when a job offer arrives, at a rate we call λ, and job seekers accept that job offer because it pays more than the reservation wage, $\lambda Pr(w > R)$ where R is the reservation wage. Figure A.1B shows the transition rate to jobs for two groups of job seekers. The control job seekers, who are eligible for 39 weeks (or 9 months) of benefits, and 48-49 years old, and the treated job seekers,who receive benefits for one year, and are 50-51 years old[36]. Transitions to jobs are initially low, peak at around 3 months, and decrease again after that. Job seekers in the control group have a higher exit rate from unemployment than job seekers in the treated group, especially in month 9, the month of benefit exhaustion. From 10 months onward, both groups of job seekers find jobs at a similar rate. Changes in the exit rate could be due to job offer arrival, which depends on search effort, or movements in the reservation wage.

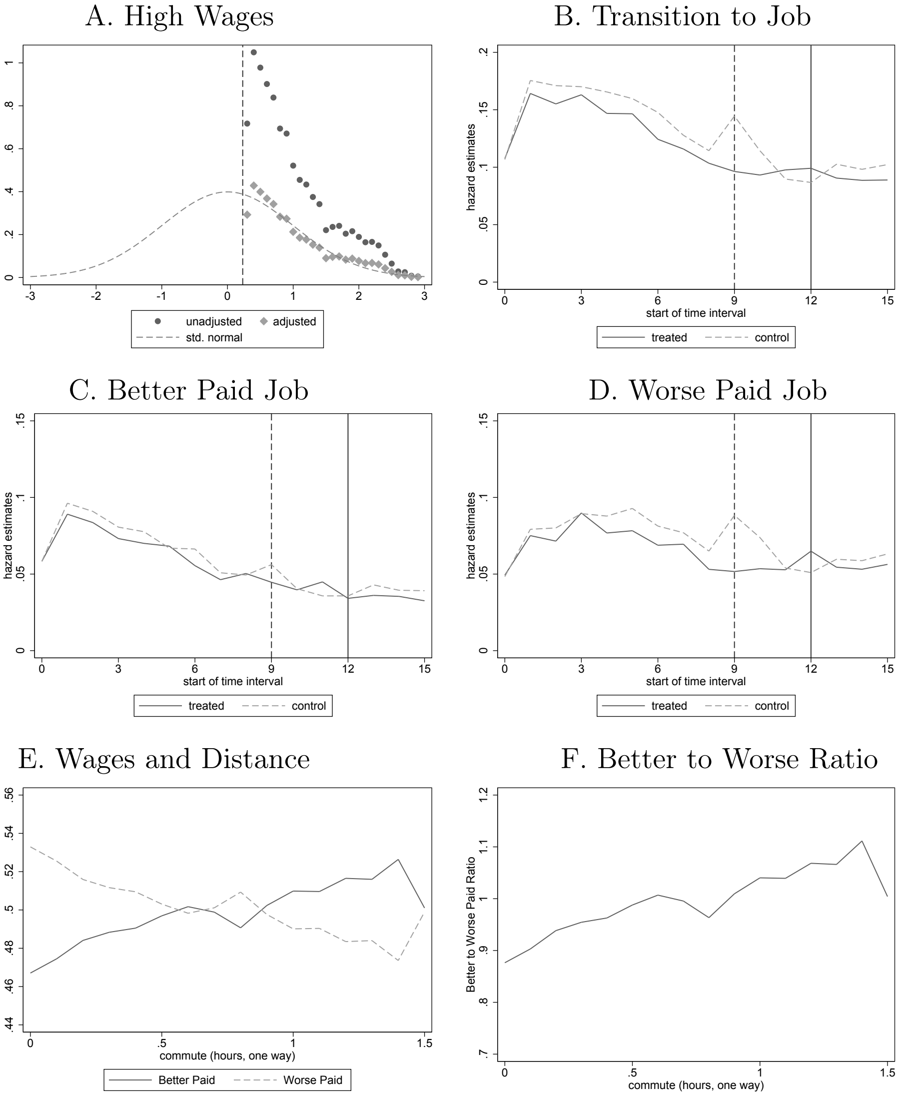
Transitions to better paid, or worse paid, jobs provide separate information on arrival rate effects and effects due to movements in the reservation wage. Figure A.1C and Figure A.1D show transitions to better, and worse, paid jobs, to learn more about changes in search activity, and changes in the reservation wage. Transitions to jobs that pay better than the previous job (Figure A.1C) reveal information on job offer arrival which depends on search activity and the probability that the job offer pays more than the previous wage, i.e. $\lambda Pr(w > w_{-1})$ where $Pr(w > w_{-1})$ is the probability that a wage is better than the previous one. We know this high paid probability, so the remaining movements in the transition rate to better paid jobs are due to search. Figure A.1C suggests that the control group leaves unemployment somewhat faster, especially in the period before benefits end for the control group, and both groups have similar exit rates to high wages onwards. Search activity does not appear to be much affected by exhaustion of unemployment benefits.

Transitions to worse paid jobs provide information on search intensity and the reservation wage (Figure A.1C, i.e. $\lambda Pr(w_{-1} > w > R)$. If job seekers did not adjust the reservation wage, the transition patterns for control and treated job seekers would be identical for worse paid jobs and better paid jobs. Instead, we find that the transition rate to worse paid jobs becomes substantially higher for control job seekers during and after benefits exhaust for control job seekers, and before benefits exhaust for treated job seekers. This pattern suggests that the reservation wage decreases sizeably when job seekers exhaust unemployment benefits.

Panels E of Figure A.1 shows the proportion of bad and good jobs accepted by job seekers conditional on the commuting distance from home (Panel F shows the ratio of bad to good jobs accepted). When commuting distance is low more job seekers leave unemployment with a wage that is lower than

[36]The patterns are similar for job seekers aged 38-41 years who are eligible for 30 weeks, or 39 weeks of benefits, respectively. These analyses are available upon request.

Figure A.1: Transitions to Jobs and Accepted Wages



Notes: This figure provides the descriptive evidence that identifies wage offers, search activity, and the reservation wage in a context of benefit extension. Panel A shows the density of wages, censored at the mean of the pre-unemployment wage (dashed line), both unadjusted and adjusted for censoring by multiplying the unadjusted density with the probability of being in the sample. High wages provide information on the shape of the distribution of wage offers. Panel B shows the transition rate from unemployment to jobs, i.e. of jobs offered to job seekers and accepted by those. Panel C provides transitions to job that pay more than the pre-unemployment job, informing on search intensity. Panel D shows the transitions from unemployment to jobs that pay less than the previous job (Worse), informing on search activity and the reservation wage. Panel E shows how the proportion of job seekers accepting a better paid job, and the proportion of job seekers accepting a worse paid job, vary with one-way commuting distance to the new job. Panel F shows the ratio between better to worse paid jobs accepted as commuting distance increases. This ratio increases because, as job seekers move away from home, their reservation wage increases, so they accept less low paid jobs. Job seekers are within two years of the age 50 threshold who have 39 weeks of benefits (Control, below 50), or 52 weeks of benefits (Treated, 50 or older). Vertical line indicate benefit exhaustion, dashed for Control and solid for Treated job seekers.

they earned before entering unemployment. But as commuting distance increases, job seekers accept fewer worse paid jobs. Job seekers who accept longer commutes are less likely to do so for less pay than before they entered unemployment.

We now discuss construction of the likelihood function. Job seekers are eligible for unemployment benefits for P time periods. We assume wage offers follow a log normal distribution so $w \sim N(\mu(t), \sigma)$ whose mean, μ, may depend on unemployment duration, t, to capture that firms may observe unemployment and condition on it when they offer wages. The main parameters of the model also depend on heterogeneity, both observed and unobserved, which is implicit here but will be made explicit below when we discuss parametrization. The reservation wage $R(P-t, \rho)$ is a function that depends on remaining benefits, $P-t$, because, as job seekers near benefit exhaustion, their value of unemployment, which determines the reservation wage, decreases. The reservation wage also depends on commuting distance if job seekers take into account that they will have to commute to a new job that is not located at home. Job seekers receive job offers at rate $\lambda(P-t, t)$, which depends on remaining benefits because the value of searching hard may be affected, and elapsed duration of unemployment, t, since search costs may increase as spells lengthen.

We now construct the likelihood contribution of job seeker i who leaves unemployment for a job that pays wage w_i at commuting distance ρ_i after t_i periods of unemployment. Let $R(P_i - t_i, \rho_i) \equiv R_i$, and $\mu(t_i) \equiv \mu_i$, and $\lambda(P_i - t_i, x_i) \equiv \lambda_i$. Job seekers who accept a high wage in a place located no farther than their previous job draw that wage from a distribution of wages that is censored from below at the previous wage w_{-1}. These job seekers contribute to the likelihood $f(w_i|w_i > w_{-1,i}) = \phi(\tilde{w}_i)/[(1-\Phi(\tilde{w}_{-1,i}))\sigma]$ where $\tilde{w}_i \equiv (w_i - \mu_i)/\sigma$ is the standardized wage which follows the standard normal distribution $\tilde{w}_i \sim N(0,1)$ with density $\phi()$, and cumulative $\Phi()$. Job seekers who accept a high wage in a place located farther away from home than their previous job are censored from below either by their previous wage, or, in less than one% of all cases, by their reservation wage if they accept a job that is located farther away from home than the previous job. Job seekers who accept a high wage provide information on $f(w_i|w_i > max(w_{-1,i}, R_i)) = \phi(\tilde{w}_i)/[(1-\Phi(max(\tilde{w}_{-1,i}, \tilde{R}_i)))\sigma]$. Job seekers who accept a high wage identify the parameters of the wage offer distribution, μ_i and σ.

Job seekers who accept high paid jobs also identify the wage offer arrival rate λ_i. To see this, consider their transition rate from unemployment to a high paid job. Job seekers receive this job offer at rate λ_i and accept it with probability $Pr(w_i > w_{-1,i})$, so the transition rate from unemployment to regular job is $\lambda_i[1-\Phi(\tilde{w}_{-1,i})]$. From the accepted wages, we can infer $\tilde{w}_{-1,i}$ so $1-\Phi(\tilde{w}_{-1,i})$ is known. The transition rate from unemployment to a high paid job is also known, so λ_i is identified.

Job seekers who accept a low wage identify the reservation wage. The transition rate from unemployment to a low paid job is $\lambda_i Pr(w_{-1,i} > w_i > R_i) = \lambda_i[\Phi(\tilde{w}_{-1,i}) - \Phi(\tilde{R}_i)]$, i.e. the chance of receiving a job offer multiplied with the probability that the job seeker accepts a wage that pays more than the reservation wage but less than the previous wage. The probability that job offers lie below the previous wage, $\Phi(\tilde{w}_{-1,i})$, is known. The reservation wage, which is not known, can be backed out from observed transition rates of job seekers who accept low paid jobs.

We identify the distribution of distance offers from job seekers similar to the distribution of wage offers adopting an exponential commuting distance specification. Let $exp(g_i)$ be the hazard of the distribution of commutes, so $S_G(\rho) = exp(-exp(g_i)\rho)$ is the survival function of commutes, i.e. the proportion of offered commutes that are longer than ρ. Job seekers who accept a job at their home city, whose actual commutes are left censored in our data, contribute to the likelihood through the probability that their commutes are shorter than 6 minutes, or 0.1 hours, the shortest cross municipality commute in the data, or $F_G(0.1) = 1 - exp(-exp(g_i)0.1)$. Job seekers who commute no farther than their previous job contribute the density of offered commutes $g(\rho_i) = exp(g_i)exp(-exp(g_i)\rho_i)$. Job seekers who commute farther than the previous job contribute to the likelihood through the probability of accepting a job that is farther than the previous one but less than two hours away from home, which is the maximum commuting distance we observe in the data, e.g. $exp(-exp(g_i)\rho_{-1,i}) - exp(-exp(g_i)2)$ where $\rho_{-1,i,}$ is commuting distance before the unemployment spell.

Job seekers who remain unemployed for t_i periods also provide information. We know that each period z, before t_i, job seeker received a job offer at rate $\lambda_i(z)$, but we do not know where the job was located. We cannot reconstruct the exact probability that the job seeker rejects this job offer, but we can reconstruct the expected rejection probability. This probability is $E_G[Pr(w < R(P-z,\rho))]$ where $G()$ is the distribution of job offers. Job seekers stay unemployed if they do not receive a job offer, with probability $1-\lambda_i(z)$, or if they receive a job offer but decline it, with probability $\lambda_i E_G[Pr(w < R(P-z,\rho))]$. A job seeker remains unemployed until t_i, the period of exit or right censoring, with probability $S(t_i) = \Pi_{z=0}^{z=t_i}[(1-\lambda_i(z)) + \lambda_i(z)E_G[Pr(w < R(P-z,\rho))] = \Pi_{z=0}^{z=t_i}[1-\lambda_i(z)E_G[Pr(w > R(P-z,\rho))]$, or $S(t_i) = exp(-\int_0^{t_i}\lambda_i(z)E_G[\Phi(\tilde{R}(P-z,\rho))]dz)$ in continuous time.

The probability of remaining unemployed for t_i periods depends on an expectation over the distribution of job offers in space. We estimate this expectation adopting simulated maximum likelihood. We specify a grid with a total of $J = 9$ points equally spaced between .1 to . 9, and solve for commuting time at each grid point, and obtain all the interior deciles of the commuting distance distribution. We then calculate the rejection probability at each commuting time decile. The expected probability of rejecting a wage offer after z periods of unemployment is

$$\hat{E}_G[Pr(w > R(P-z,\rho,x)] = \sum_{j=1}^{J}(1-\Phi(\tilde{R}(P_i - z_i, x_i, \rho_j)))/J \qquad (9)$$

This estimate becomes increasingly accurate as sample size increases, as long as the number of grid points increases with sample size. Changing the grid to have more points does not appreciably affect our estimates.

Let $u_i = 1$ if a job seeker finds a job within the observation window, and $u_i = 0$ if a spell is right censored. Let $h_i = 1$ if a job seeker accepts a wage that is larger than the previous wage, so $h_i = I(w_i > w_{-1,i})$. Let $f_i = 1$ if a job seeker commutes longer, so $f_i = I(\rho_i > \rho_{-1,i})$, and $hs_i = 1$ if a job seeker works in the home municipalits, or $hs_i = I(\rho_i = 0)$. The contributions to the log likelihood are as follows

$$lnL_i = lnS(t_i) + u_i[\quad ln\lambda_i(t_i) + h_i lnf(w_i) + (1-h_i)lnPr(w_0 > w_i > R_i)$$

$$+hs_i F_G(0.1) + f_i(S(\rho_{-1,i}) - S_G(2)) + (1 - f_i - hs_i)g(\rho_i)] \tag{10}$$

Our approach allows for both observed heterogeneity, including information on the previous job, and age, and in an otherwise homogeneous subsample. We address unobserved heterogeneity as recently suggested by Bonhomme *et al.* (2017b), in two steps. In the first step, we use kmeans clustering to allocate job seekers to groups that differ in terms of their distributions of spell durations, accepted wages, and distances. We rely on all available data for a job seeker, because identification of unobserved heterogeneity is greatly improved with repeated observation on individuals.[37] In the second step, we estimate our model and allow differences in the levels of the reservation wage, the arrival rate, and the mean of wage offers wage offers between the groups that we identify in the first step (see the following Section for more information).[38]

We now discuss how we parameterize the wage offer distribution, arrival rate, and reservation wage. The vector x_i contains an intercept, and information on whether a job seeker is in the baseline, or the second, unobserved heterogeneity group. along with the pre-unemployment wage (standardized to have mean zero and std. dev. 1) and distance (in hours), and whether a job seeker is in the threshold group age 50, compared to the threshold group age 40. A second vector, dd_i, contains dummies for duration dependence in five intervals, weeks 0 to 14 (the reference), weeks 15 to 24, weeks 25 to 34, weeks 35 to 44, and weeks 45 to 60. We artificially right censor spells that last longer than 60 weeks because these spells do not provide information on the behavior around benefit exhaustion. We have chosen duration dependence so that it does not coincide with the benefit exhaustion at 30 weeks, 39 weeks, and 52 weeks. Our parametrization of the mean of the wage offer distribution is as follows

[37] Panel data on spells are challenging because the likelihood of observing a new observations of one individual depend on the realisation of survival time in the previous spell. We have very long panel data where this problem should be, to some extent at least, mitigated.

[38] We explored more flexible specifications with differences in the standard deviation of wage offers as well. Results are robust. The standard approach to deal with unobserved heterogeneity is the Heckman and Singer (1984) approach who suggest to integrate out unobserved heterogeneity. This approach is difficult to implement, especially in single spell data. Bonhomme *et al.* (2017b)'s approach to dealing with unobserved heterogeneity works better than a fixed effects approach since the first stage clustering step removes the need to estimate a fixed effect for every job seeker. We also address measurement error in distance that occurs when job seekers work in the same municipality that they live in by modeling the spatial distribution of job offers.

$$
\begin{aligned}
\mu(t_i, x_i) &= \mu_x' x_i + \mu_d' dd_i \\
\sigma &= exp(\alpha)
\end{aligned}
$$

where μ_x is a vector of parameters that reflect the effects of heterogeneity, and μ_d is a vector that captures how time in unemployment affects wage offers.

In addition to heterogeneity and duration dependence, the job offer arrival rate may be affected by changes in search intensity triggered by benefit exhaustion. We have explored various ways to capture the effects of benefit exhaustion. The simplest specification allows the job offer arrival rate to shift in the periods when job seekers just below the age thresholds, at 40 and 50 years, lose benefits while job seekers who are just above the benefit threshold still are eligible. Specifically, let $e_i^l = 1$ for job seekers aged 39 years old and find a job aftr they exhausted benefits but before the older job seekers will, in weeks 30 to 39. Also, $e_i^l = 1$ for the job seekers who are 49 years old and find a job during weeks 39 to 51, and e_i is zero for everyone else. Our arrival rate of job offers specification is

$$\lambda(P_i - t_i, t_i, x_i) = \lambda_x' x_i + \lambda_d' dd_i + \lambda_e e_i^l \tag{11}$$

where λ_x is a vector of parameters that reflect the effects of heterogeneity, and λ_d is a vector that captures how time in unemployment affects wage offers, and λ_d is a scalar that measures the effect of benefit exhaustion on the arrival rate of job offers.

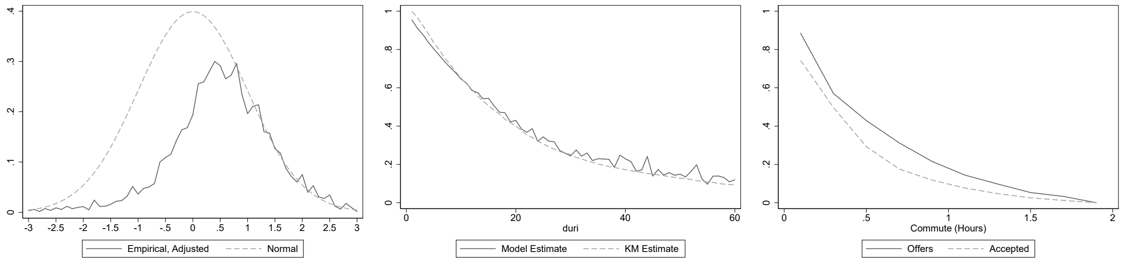
We parametrize the reservation wage to reflect changes due to benefit exhaustion and heterogeneity, but we do not allow for genuine duration dependence. Theory states that the job offer arrival rate is an element of the reservation wage, and allowing for duration dependence in the arrival rate but not the reservation wage appears contradictory. But note that the effects of the arrival rate on the reservation wage are ambiguous. Movements in the wage offer distribution might also introduce duration dependence in the reservation wage, but we have found duration dependence in the wage offers to be small. We capture benefit exhaustion in the reservation wage also through the shift in the reservation wage that occurs when benefits are exhausted. We see movements in the reservation wage already close before benefits end, and our simple benefit exhaustion specification captures those fairly well. Without duration dependence, we can capture benefit exhaustion through $e_i^r = 1$ if $P_i - t_i < 0$, and $e_i^r = 0$ otherwise. We adopt the following parametrization of the reservation wage

$$R(P_i - t_i, x_i) = \gamma_x' x_i + \gamma_e e_i^r \tag{12}$$

Let c_i be a vector that contains one intercept, and a dummy for each unobserved heterogeneity group. We then parametrize the (log) hazard of the distance distribution as follows

Figure A.2: Assessing Fit: Wages and Durations

A. Wages B. Unemployment C. Commutes



Notes: This figure shows the distribution of accepted wages (A), corrected for censoring, along with the standard normal benchmark. Graph B shows the empirical Kaplan-Meier estimate of the proportion of job seekers still unemployed between 0 and 6 weeks, and the survivor function implied by the model. C shows the distribution of commute offers and the distribution of accepted commutes as a function of commuting distance.

$$g(x_i) = \gamma_g' c_i \tag{13}$$

Table A.1 provides parameter estimates for the five largest sub-groups in our sample. The table header highlights the characteristics of job seekers in each sample. Results suggest that the slope of the reservation frontier, the parameter 2τ varies somewhat across demographic subsamples. The effects of benefit exhaustion on the reservation wages is also negative and significant in all sub-samples except job seekers with low tenure and high education who are not married. The effects of benefits on exits varies more strongly with demographics. Point estimates are positive but not significantly different from zero for three groups, negative and not significant for one group, and positive and significantly different from zero for immigrants.

Figure A.2 shows the model fit with respect to the distribution of accepted wages, commutes, and survival in unemployment. Figure A.2A shows the density of accepted standardized wages, corrected for the probability wages are censored from below by the reservation wage. Specifically, we estimate the density of standardized wages using a standard rectancle kernel density estimator, producing an estimate of $\hat{f}(\tilde{w}|\tilde{w} > \tilde{R})$ where $\tilde{w} = (w - \mu)/\sigma$ is the standardized wage and $\tilde{R} = (R - \mu)/\sigma$ is the standardized reservation wage. Without censoring, this density should coincide with the standard normal. We multiply the density of accepted wages by the probability that wages are censored, i.e. $\hat{f}(\tilde{w}|\tilde{w} > \tilde{R}) * Pr(\tilde{w} > \tilde{R}) = \hat{f}(\tilde{w})$. Adjusting the censored density for censoring fully recovers the underlying density of wages which have not been affected by censoring. Figure A.2A shows that the adjusted density of wages coincides with the standard normal for wages from 0.6 upwards, which is about at, or above, the previous wage. Below the previous wage, more and more mass is missing, because job seekers are rejecting those offers as being too low, below their reservation wage.

Figure A.2B compares the proportion of job seekers still unemployed as a function of time spent unemployed according to our model (solid line), to the Kaplan-Meier estimate of the same proportion that uses just raw data. The Kaplan-Meier estimate is somewhat higher in the intial weeks of the spell,

Table A.1: Reservation Frontier Estimates: Full Parameter Estimates

Samples	Austrian	Yes		Yes		Yes		Yes		No	
	Married	Yes		Yes		No		Both		Both	
	Education	High		No		High		High		Both	
	Tenure	Low		Low		Low		High		Low	
λ	const	-2.266	(0.114)	-2.837	(0.081)	-2.781	(0.116)	-2.076	(0.226)	-2.185	(0.128)
	uohet	-0.052	(0.079)	-0.144	(0.061)	0.588	(0.180)	0.006	(0.153)	-0.168	(0.080)
	prev wage	0.419	(0.054)	0.096	(0.033)	0.249	(0.058)	0.387	(0.073)	0.407	(0.054)
	prev dist	-0.254	(0.075)	-0.170	(0.073)	-0.178	(0.085)	-0.470	(0.121)	-0.351	(0.086)
	age $>$ 45	-0.249	(0.069)	-0.144	(0.055)	-0.079	(0.092)	-0.182	(0.110)	-0.345	(0.075)
	dd2	0.454	(0.070)	0.433	(0.058)	0.447	(0.073)	0.632	(0.134)	0.629	(0.075)
	dd3	0.334	(0.093)	0.300	(0.082)	0.411	(0.115)	0.205	(0.149)	0.705	(0.105)
	dd4	-0.076	(0.115)	-0.024	(0.105)	0.107	(0.145)	0.227	(0.164)	0.174	(0.130)
	dd5	-0.102	(0.129)	-0.295	(0.113)	-0.099	(0.180)	-0.272	(0.182)	0.024	(0.160)
	exhaust	0.114	(0.098)	-0.082	(0.123)	0.099	(0.135)	0.129	(0.108)	0.239	(0.093)
R	const	3.797	(0.023)	3.527	(0.074)	3.583	(0.051)	3.892	(0.026)	3.606	(0.020)
	uohet	0.078	(0.016)	0.144	(0.052)	0.282	(0.037)	0.075	(0.018)	0.030	(0.011)
	prev wage	0.299	(0.006)	0.231	(0.017)	0.276	(0.012)	0.284	(0.007)	0.224	(0.005)
	prev dist	-0.094	(0.021)	-0.346	(0.088)	-0.191	(0.041)	-0.126	(0.026)	-0.089	(0.019)
	age $>$ 45	-0.005	(0.013)	0.025	(0.040)	0.050	(0.024)	0.000	(0.013)	0.004	(0.011)
	2τ	0.088	(0.009)	0.114	(0.019)	0.151	(0.021)	0.104	(0.010)	0.126	(0.009)
	exhaust	-0.050	(0.021)	-0.081	(0.067)	0.018	(0.035)	-0.074	(0.022)	-0.042	(0.018)
μ	const	3.924	(0.034)	3.927	(0.023)	3.918	(0.036)	3.842	(0.066)	3.687	(0.040)
	uohet	0.031	(0.019)	0.049	(0.017)	0.063	(0.046)	0.001	(0.032)	0.051	(0.021)
	prev wage	0.105	(0.010)	0.114	(0.008)	0.128	(0.011)	0.124	(0.012)	0.054	(0.010)
	prev dist	0.055	(0.020)	0.084	(0.020)	0.099	(0.024)	0.108	(0.029)	0.141	(0.023)
	age $>$ 45	-0.005	(0.018)	0.006	(0.016)	-0.048	(0.025)	0.006	(0.026)	0.005	(0.020)
	dd2	-0.068	(0.021)	-0.082	(0.019)	-0.054	(0.025)	-0.123	(0.032)	-0.068	(0.023)
	dd3	-0.055	(0.026)	-0.060	(0.025)	-0.104	(0.034)	-0.063	(0.038)	-0.110	(0.029)
	dd4	-0.004	(0.034)	-0.085	(0.034)	-0.066	(0.045)	-0.056	(0.042)	-0.044	(0.038)
	dd5	-0.063	(0.035)	-0.089	(0.036)	-0.136	(0.051)	-0.047	(0.046)	-0.114	(0.043)
$ln\sigma$	const	-1.138	(0.035)	-1.283	(0.029)	-1.165	(0.041)	-1.078	(0.054)	-1.092	(0.037)
g	const	0.278	(0.026)	0.374	(0.032)	0.321	(0.031)	0.397	(0.032)	0.368	(0.030)
	uohet	0.225	(0.045)	0.217	(0.058)	0.068	(0.129)	-0.058	(0.063)	0.309	(0.053)
$Pr(w > R)$		0.562		0.896		0.703		0.385		0.508	
lnL		-16393.9		-11403.7		-9266.5		-12390.1		-15459.0	
N		3662		2370		2097		2660		3,295	

Note: Table shows parameter estimates for the reservation frontier estimates. Arrival rate of job offers, reservation wage, wage and distance offer distributions are jointly estimated. Married is married or cohabiting, high education is apprenticeship or higher, low tenure is less than three years of tenure with the previous employer. Distance is the one way commuting distance in hours, uohet is the difference in reservation wage intercepts, exhaust $= 1$ after benefit exhaustion, and home is the difference in the logs of the arrival rate of offers at home and elsewhere. The set of dd parameters capture spell duration dependence, where dd2 $= 1$ in weeks 15 to 24, dd3 $= 1$ in weeks 25 to 34, dd4 $= 1$ in weeks 35 to 44, and dd5 $= 1$ from weeks 45 to 60. Spells artificially right censored at 60 weeks.

the both estimates are fairly similar, until about week 25. Thereafter, the Kaplan Meier estimate is somehwat higher, perhaps 1-2 percentage points, than the model estimate.

Figure A.2C compares the survival functions of the observed distribution of commutes with the estimated distribution of offered commutes. The distributions of commutes are identical at zero and 2 hours, by construction. Job seekers accept commutes of between 0 and 0.5 hours more likely than those that are longer than 0.5 hours, one way. The shape of the accepted distribution and the offered distribution are very similar suggesting that our simple, exponential, specification of accepted commutes captures the salient features of the accepted commutes. The density of accepted jobs is below the density of job offers because job seekers reject job offers that are below their reservation wage.

A.2 Addressing Heterogeneity

We address heterogeneity using data from two sources. We use information on background variables age, education, marital status, immigrant status, municipality of residence, and industry to form cells in the data of people who are identical with respect to observed heterogeneity. We then adopt the Bonhomme *et al.* (2017b) approach to identify unobserved heterogeneity. Specifically, we use the kmeans cluster algorithm to find two groups of job seekers who form homogeneous clusters in terms of three outcomes (long-term unemployment, accepted commute, and wage), 20 exit destinations[39] and the background variables. Kmeans identifies two groups, allocating 83% to one group, and 17% to the second group.

We then create cells of job seekers who are identical in terms of observed and unobserved characteristics. Specifically, we use binary indicators on being older than 45 years, having tertiary education, being married or cohabiting, being an immigrant, whether the municipality of residence is a city, and two industry indicators together with the binary indicator that identifies the unobserved heterogeneity cell of each job seeker, a set of eight binary indicators, to form a total of 181 unique cells. Job seekers within these cells are identical in terms of observed and unobserved heterogeneity.

We correct unemployment exit hazards for unobserved heterogeneity as follows. Exit hazards suffer from excess negative duration dependence bias induced by unobserved heterogeneity. Essentially, at the beginning of a spell, both job seekers with good and bad exit prospects are in the sample. As the spell lengthens, the job seekers with good exit prospects disappear from the sample, and those with bad job prospects remain. As a result, the unemployment exit hazard approaches that of the job seekers with bad exit prospects.

A common approach to dealing with unobserved heterogeneity bias consists in modeling the exit process as a mixed proportional hazard model. However, structural hazards need not be proportional,

[39] These destinations are based on indicators regarding the wage change (wMinus means more than 4 percent increase, wZero means no more than 4 percent change, wMinus means wage decreases by at least 4 percent), or commute change (dPlus means strictly longer commute, dZero means exactly same commute, dMinus means strictly shorter commute, or Home means new job is located in home municipality). Our analysis is based on these exit indicators, both on their own, or in pairs these e.g. wPlusdPlus means higher wage and longer commute, etc.

so we correct for unobserved heterogeneity in a way that does not force us to assume proportional hazards. We calculate a non-parametric exit hazard for each group of job seekers that are identical with respect to observed and unobserved heterogeneity. We use the Stata ltable command, using the by() option to identify the cells in the data. We obtain estimates of up to 181 exit rates and these are not affected by unobserved heterogeneity bias since job seekers are (next to) identical within each cell. We then form an average exit hazard for the full population as the weighted average of the group specific hazards, where the weights reflect the size of each group at the start of the unemployment spell.

This two step approach addresses unobserved heterogeneity. Figure A.3 displays the raw hazards (dashed lines), and the heterogeneity corrected hazards (solid lines), for both local workers and non-local workers (we perform the heterogeneity correction of hazards separately for the two types of workers). Raw hazards are similar to corrected hazards in the initial phases of the spell, but raw hazards decline faster than heterogeneity corrected ones. The ratio of the raw exit hazard to the heterogeneity corrected hazard, in the bottom of Figure A.3, is flat and close to one initially, but declines gradually and then faster as the spell lengthens. Raw hazards have (too) strong negative duration dependence, suggesting that heterogeneity bias is quantitatively important. Our estimates in section 5, fit hazards that are corrected for unobserved heterogeneity, thereby addressing an important concern in the literature. Our model in section 5 fits unemployment exit hazards, by destination.

Our estimates of the duration dependence in accepted wages and commutes relies on the availability of the wage and commute prior to unemployment. The wage earned prior to entering unemployment captures unobserved aspects of the job seeker, and so does the pre-unemployment commute. Table A.2 reports several estimates of the duration dependence in accepted wages and commutes which are based on pre-to-post unemployment changes in wages and commutes. These estimates are robust to flexibly controlling for observed and unobserved characteristics, or panel identification. Table A.2 shows that duration dependence in accepted wages and commutes differs strongly when wages and commutes are measured in levels (column 1), or pre-to-post unemployment changes (column 2). Duration dependence remains similar in regressions that analyse changes (column 2), regressions that absorb cells (column 3), or regressions that exploit variation across unemployment spells for job seekers (column 4). This pattern suggests that an empirical strategy that builds on changes and absorbs cells addresses concerns with unobserved heterogeneity.

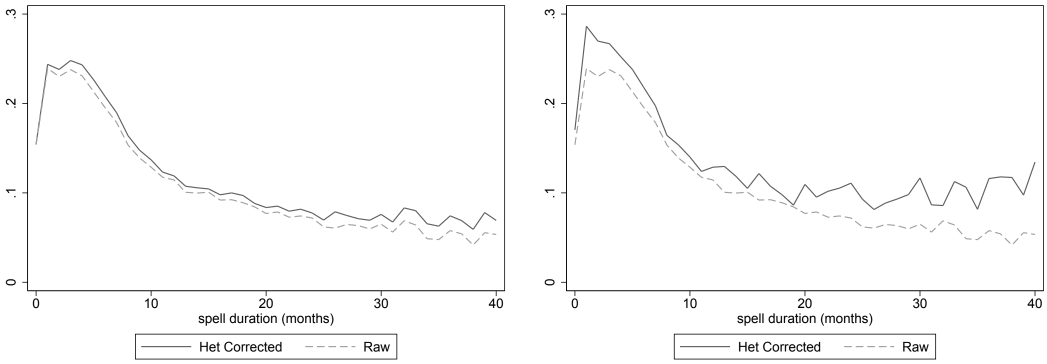
A.3 Supplemetary Evidence

Table A.3 provides descriptive statistics on non-local workers, local workers, the difference in means, and the p-Value for a test of same means. The test of similar means rejects for most characteristics, thus, statistically, non-local workers and local workers are not the same. Indeed, local workers are much more likely to live and have previously worked outside cities, they are more likely to work in manufacturing

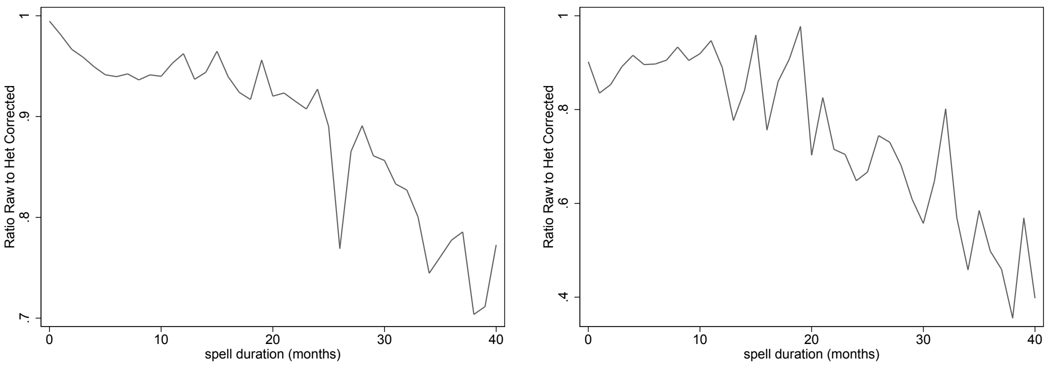
Figure A.3: Duration Dependence in Raw and Heterogeneity Corrected Hazards

Non-Local Workers — Local Workers

A. Hazards



B. Hazard Ratio



Notes: The top figure shows the raw unemployment exit hazard (dashed) and the average unemployment exit hazard (solid), corrected for heterogeneity across 181 cells of individuals. The bottom figure shows the ratio of the raw hazard to the heterogeneity corrected hazard. Values below 1 indicate that the raw hazard falls more with unemployment than the heterogeneity corrected hazard.

Table A.2: Duration Dependence in Accepted Wages and Commutes

	Level	Change	Absorb	Panel
A. Wage				
	lnw	wc	wc	wc
months6to11	-0.0765***	-0.0902***	-0.0881***	-0.0748***
	(0.0020)	(0.0021)	(0.0021)	(0.0041)
months12to15	-0.0941***	-0.1080***	-0.1045***	-0.0997***
	(0.0045)	(0.0051)	(0.0051)	(0.0100)
R2	0.063	0.027	0.041	0.031
N	267254	262145	262145	262145
B. Distance				
	dist	dc	dc	dc
months6to11	-0.0138***	0.0040*	0.0031	0.0149***
	(0.0021)	(0.0023)	(0.0023)	(0.0048)
months12to15	-0.0158***	0.0184***	0.0174***	0.0303***
	(0.0043)	(0.0049)	(0.0049)	(0.0110)
R2	0.037	0.010	0.013	0.008
N	267263	267263	267263	267263

Notes: Table regressions of accepted wages and distances (lnw, dist), or pre-to-post unemployment changes (wc, dc) vary with spell duration $monthsNonemp$. Column Level explains wage and commuting time in (log)levels; column Change explains the change in wage and commuting time, and column Absorb controls for unobserved and observed heterogeneity across 181 cells. Column Panel identifies effects for the same individuals across unemployment spells. All estimates control for demographic controls and year effects.

Table A.3: Summary Statistics

	Non-Local (NL)	Local (L)	Difference L-NL	p-Value
A. Outcomes				
Non-employment Duration (Weeks)	25.228	25.041	-.187	.294
Daily Wage, After (EUR)	56.643	54.299	-2.344	0
Daily Wage, Before (EUR)	58.192	55.065	-3.127	0
Commute, After (Hrs)	.474	.326	-.148	0
Commute, Before (Hrs)	.543	0	-.543	0
B. Unemployment Insurance				
UI Replacement Rate	.404	.417	.013	0
UI Benefit Duration	31.689	31.612	-.077	.007
UA Replacement Rate, Exhausters	.114	.109	-.005	.005
C. Characteristics				
Age 30-39 Yrs	.311	.303	-.008	0
Age 40-39 Yrs	.234	.238	.004	.032
Age 50-56 Yrs	.048	.048	0	1
Compulsory Education or Less	.414	.439	.025	0
Upper Secondary or Tertiary Education	.586	.561	-.025	0
Married or Cohabiting	.433	.419	-.014	0
Immigrant	.2	.227	.027	0
Tenure > 3 yrs	.235	.318	.083	0
Worked in City	.423	.286	-.137	0
Lived in City	.401	.286	-.115	0
Manufacturing	.404	.436	.032	0
Services	.557	.514	-.043	0
Observations	215,776	68,000		

Notes: Table provides descriptives on local workers, those who worked in the municipality they live, and non-local workers, those who worked outside their home municipality. The table shows information on non-employment duration, wages, and commuting time, both before and after an unemployment spell. The unemployment insurance (UI) benefit duration informs on the number of benefit weeks available to the individual, and the UI benefit replacement rate gives the proportion of the wage prior to unemployment that is replaced by UI for those job seekers who leave unemployment before exhausting benefit weeks. Job seekers who exhaust benefits, exhausters, may be eligible for unemployment assistance (UA). The UA replacement rate for exhausters informs on how much of the pre-unemployment wage UA replaces for all who leave unemployment after UI benefits have ended. The UA replacement rate for the eligible conditions on UA benefit eligibility. Panel C gives information on education and other characteristics.

and are more likely to have worked for at least three years (long tenure). Other elements, e.g. age, education, and marital status do not differ much between local and non-local workers. Non-employment duration is relatively similar, but local workers earn lower wages, both before and after unemployment, and have shorter commutes after leaving unemployment. The commute before unemployment is much longer for non-local workers, but this is by construction.

A.4 Supplementary Results for PBD Extension

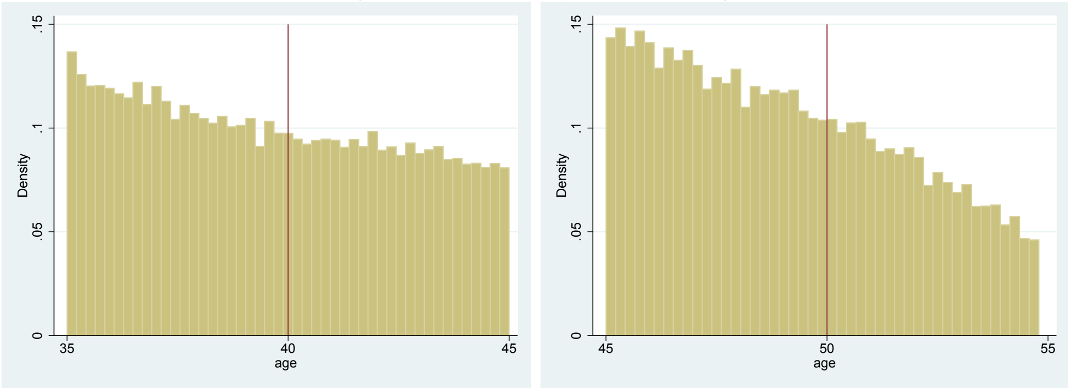
Table A.4 shows effects of extended benefits by age threshold. Panel A shows results at the 40 year threshold, panel B shows results at the 50 year threshold. Main results, in Table 4 combine results on both thresholds.

Table A.4: UI coverage effects for age thresholds

	lnw	dist	home	distPos	Jvalue
Panel A. Extension from 30 to 39 weeks, at age 40					
	lnw	dist	home	distPos	Jvalue
above	-0.005	-0.001	-0.004	-0.002	-0.006
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
aboveXduring	0.023**	0.021**	-0.024**	0.011	0.017*
	(0.009)	(0.010)	(0.011)	(0.011)	(0.009)
aboveXafter	-0.000	-0.002	-0.002	-0.005	0.000
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
R2	0.195	0.141	0.053	0.163	0.179
N	56295	56295	56295	43372	56295
Panel B. Extension from 39 to 52 weeks, at age 50					
	lnw	dist	home	distPos	Jvalue
above	0.011	0.000	0.002	-0.000	0.010
	(0.007)	(0.009)	(0.010)	(0.009)	(0.007)
aboveXduring	0.024*	-0.008	-0.001	-0.005	0.026*
	(0.014)	(0.014)	(0.016)	(0.015)	(0.014)
aboveXafter	-0.004	-0.002	0.017	0.009	-0.003
	(0.011)	(0.010)	(0.012)	(0.011)	(0.011)
R2	0.227	0.151	0.061	0.180	0.214
N	33614	33614	33614	25476	33614

Notes: Table shows the effect of prolonged potential benefit duration (PBD) on accepted jobs in the period when treated job seekers are still covered by unemployment while the control group anticipates losing benefits. Table A shows an extension of benefits from 30 to 39 weeks, for job seekers who cross the 40 year threshold, and Table B shows an extension of PBD from 39 to 52 weeks, at age 50 years. The table provides RDD estimates for the pre-to-post unemployment change in log wages (wc), the pre-to-post unemployment change in commuting time (dc), and dJvalue is the pre- to post-unemployment change in the flow value of a job, i.e. wc - 0.12*2*dc, where 0.12 is the cost of one hour of commuting, and dc is the one-way commuting time. Diff is the relative difference in remaining unemployment benefits between job seekers with long PBD and job seekers with short PBD, subtracting 0.2. Above identifies job seekers who are eligible for prolonged PBD when the difference in remaining benefits are 20%. AboveXdiff provides estimates of how the treatment effect varies with the relative difference in remaining benefits. All estimates include control variables for education, marital status, immigrant status, and tenure (in years). The sample comprises job seekers less than five years away from the age threshold, and includes linear trends in age around the age threshold.

Figure A.4: Density Tests of Age



Notes: Figure shows the density of age for the sample with benefit extension at age 40 on the left, and with benefit extension at age 50, on the right. Vertical line indicates benefit extension age. The test proposed by McCrary (2008) does not reject the null hypothesis that there is no manipulation of age at entry into unemployment because the density at the threshold is what one would expect from behavior far from the threshold.

Job seekers may be constrained to search everywhere in space due to liquidity constraints. Table A.5 discusses the role of liquidity constraints. Job seekers who worked for three years or longer for the same employer are entitled to a severance package of two months of pay Card *et al.* (2007). The top panel (A) provides results for job seekers with three years of tenure or more (Eligible for Severance Pay). These job seekers should not be liquidity constrained since they received a sizeable amount of cash on hand at the beginning of the unemployment spell. Job seekers with severance pay earn substantially higher wages, an increase of 0.241. Interestingly, job seekers with more remaining benefits also improve somewhat in terms of reduced commuting time, but not significantly so. The flow value of jobs increases by 0.259. The bottom panel (B, Not Eligible for Severance Pay) provides results for job seekers with less than three years of tenure, who may be liquidity constrained or not. Results are very much in line with baseline estimates. Wages increase by 0.124, about one half of the response of wages of job seekers with severance pay. This stronger wage response is mainly due to better insurance of high paid jobs. Commuting times are not insured by the presence of benefits, and the flow value of unemployment increases 0.131 which is equal to the wage response. These sub-sample results suggests that liquidity could contribute somewhat to explaining why commuting times are much less responsive to changes in the value of unemployment.

B Theory Appendix

We first explain the problem for the individual worker and derive an optimal search strategy. Later on we add duration dependence as stochastic changes of some parameters, such as search cost functions.

B.1 Properties of the reservation wage curve

In the setup of Section 5, the slope of the reservation frontier is given by:

Table A.5: Extending PBD: by cash on hand

A. Eligible for Severance Pay

	lnw	dist	home	distPos	Jvalue
above	0.001	0.009	0.008	0.018*	0.000
	(0.008)	(0.009)	(0.011)	(0.010)	(0.008)
aboveXduring	0.013	-0.006	-0.016	-0.013	0.013
	(0.013)	(0.014)	(0.016)	(0.015)	(0.013)
aboveXafter	0.005	-0.007	-0.006	-0.012	0.005
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
R2	0.191	0.121	0.056	0.140	0.176
N	29206	29206	29206	21892	29206

B. Not Eligible for Severance Pay

	lnw	dist	home	distPos	Jvalue
above	0.001	-0.005	-0.004	-0.009	0.001
	(0.005)	(0.007)	(0.007)	(0.007)	(0.006)
aboveXduring	0.027***	0.022**	-0.020*	0.014	0.022**
	(0.009)	(0.010)	(0.011)	(0.011)	(0.009)
aboveXafter	-0.003	0.002	0.005	0.004	-0.003
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
R2	0.216	0.154	0.056	0.181	0.200
N	60703	60703	60703	46956	60703

Notes: Table shows the effect of prolonged potential benefit duration (PBD) on accepted jobs in the period when treated job seekers are still covered by unemployment while the control group anticipates losing benefits, separated by a proxy for liquidity constraints, and by whether job seekers worked in their home municipality, or not. The tables shows combined estimates, based on two experiments, an extension of benefits from 30 to 39 weeks, for job seekers who cross the 40 year threshold, and an extension of PBD from 39 to 52 weeks, at age 50 years, for both sub-groups. The table provides RDD estimates for the pre-to-post unemployment change in log wages (wc), jobs that pay worse than the pre-unemployment job (wMinusSharp), the pre-to-post unemployment change in commuting time (dc), and the proportion of job seekers commuting to the same previous workplace (dZero). Diff is the relative difference in remaining unemployment benefits between job seekers with long PBD and job seekers with short PBD, subtracting 0.2. Above identifies job seekers who are eligible for prolonged PBD when the difference in remaining benefits are 20%. AboveXdiff provides estimates of how the treatment effect varies with the relative difference in remaining benefits. All estimates include control variables for education, marital status, immigrant status, and tenure (in years). The sample comprises job seekers less than five years away from the age threshold, and includes linear trends in age around the age threshold.

Table A.6: Balancing Tests

	highEduc	marrCohab	immigrant	tenHi	largeWP	largeRP	ild2	ild3
above	0.009	-0.009	-0.013**	0.007	0.001	0.004	0.002	-0.004
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
aboveXduring	-0.007	-0.007	0.021**	-0.030***	-0.000	0.006	0.002	0.000
	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
aboveXafter	0.008	0.012	0.027***	-0.001	0.005	-0.001	0.009	-0.010
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
R2	0.045	0.024	0.025	0.060	0.020	0.028	0.030	0.025
N	89909	89909	89909	89909	89909	89909	89909	89909

Table tests balance of control variables across treated, with extended benefits, and control job seekers in the periods before benefits run out (above) seekers are covered by UI and control job seekers are note (aboveXduring), and after benefits have run out (aboveXafter). Estimates include a linea fication in age minus threshold age, and a dummy that separates the 40 year threshold from the 50 year threshold. highEduc is apprenticeship or hi hab is married or cohabiting, tenHi refers to job seekers with more than three years of tenure, largeWP refers to job seekers who have worked in a ci e than 100,000 inhabitants, and largeRP refers to job seekers who live in a city, ild refers to the production sector, and ild3 refers to the services sec

Table A.7: Effects of Benefit Coverage on Accepted Wages and Distances (Sensitivity Analysis)

Panel A. All job seekers					
	lnw	dist	home	distPos	Jvalue
above	-0.001	-0.009	-0.006	-0.016**	0.000
	(0.006)	(0.008)	(0.008)	(0.008)	(0.006)
aboveXduring	0.030***	0.023*	-0.014	0.018	0.026**
	(0.011)	(0.012)	(0.013)	(0.012)	(0.011)
aboveXafter	-0.001	0.004	0.008	0.009	-0.000
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
R2	0.218	0.150	0.056	0.171	0.205
N	46272	46272	46272	36178	46272
Panel B. Local workers					
	lnw	dist	home	distPos	Jvalue
above	-0.026*	-0.030*	0.021	-0.029	-0.020
	(0.014)	(0.017)	(0.022)	(0.021)	(0.014)
aboveXduring	0.014	0.053*	-0.085**	0.002	-0.001
	(0.026)	(0.029)	(0.036)	(0.034)	(0.026)
aboveXafter	0.001	-0.005	-0.004	-0.016	0.001
	(0.021)	(0.022)	(0.027)	(0.028)	(0.021)
R2	0.184	0.022	0.016	0.062	0.171
N	9379	9379	9379	5201	9379
Panel C. Non-Local workers					
	lnw	dist	home	distPos	Jvalue
above	0.006	-0.004	-0.013	-0.013	0.005
	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)
aboveXduring	0.034***	0.015	0.000	0.015	0.032***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
aboveXafter	-0.001	0.007	0.015	0.016	-0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
R2	0.224	0.155	0.038	0.228	0.215
N	36893	36893	36893	30977	36893

Notes: Table shows the effect of prolonged potential benefit duration (PBD) on accepted wages and distances for Austrian job seekers with short tenure (immigrants and job seekers with long tenure are not balanced over the course of the unemployment spell). Panel A reports combined RDD estimates for an extension of benefits from 30 to 39 weeks, for job seekers who cross the 40 year threshold, and an extension of PBD from 39 to 52 weeks, at age 50 years (Table A.4 shows separate estimates). The table provides RDD estimates for the accepted log wage, lnw, accepted distance, dist, whether the new job is in the home municipality or not, home, positive accepted distance, and change in the flow value of a job, i.e. wage change - commuting cost, according to estimates in Table 2. During is the period when treated job seekers are still covered by unemployment while the control group anticipates losing benefits, i.e. weeks 25 to 35 for job seekers losing benefits at 30 or 39 weeks, and weeks 35 to 47 for job seekers losing benefits after 39 or 52 weeks. After is the period after the during period. Above identifies job seekers who are eligible for prolonged PBD when the difference in remaining benefits are 20%. AboveXduring provides estimates of how being eligible for benefits affects accepted wages and distances. AboveXafter provides a specification test. All estimates include control variables for education, marital status, immigrant status, and whether job seekers had more than three years of tenure or not. The sample comprises job seekers less than five years away from the age threshold, and includes linear trends in age around the age threshold.

$$\frac{dR_c}{d\rho} = \frac{c'_\rho(\rho)}{v'_w(R_c(\rho))} > 0$$

and the second derivative is:

$$\frac{d^2R_c}{d\rho^2} = \frac{c"_\rho}{v'_w} - \frac{c'_\rho v"_w}{(v'_w)^2}\frac{dR_c}{d\rho} = \frac{c"_\rho}{v'_w} - \left(\frac{c'_\rho}{v'_w}\right)\frac{v"_w}{v'_w} \gtrless 0$$

When $v'' = 0$, we have that

$$\frac{d^2R_c}{d\rho^2} = \frac{c"_\rho}{v'_w} \gtrless 0$$

depends only on the curvature of the commuting cost function.

B.2 First order conditions on search strategies

Simple expressions for the first order conditions on the optimal search radius D and the optimal search intensities λ and λ^H are obtained, by equalizing the marginal costs to the marginal benefits:

$$C'_\lambda(\lambda^*, D^*) = \frac{2\pi}{r+s}\int_0^D \left[w^{\max} - R(\rho) - \bar{F}(w^{\max}) + \bar{F}(R(\rho))\right] dG(\rho) \tag{14}$$

$$C'_{\lambda^H}(D^*, \overrightarrow{\lambda}^*) = \int_{R(0)} S(w,0)dF(w) \tag{15}$$

$$C'_D(\lambda^*, D^*) = \frac{2\pi\lambda^*}{r+s}\left[w^{\max} - R(D^*) - \bar{F}(w^{\max}) + \bar{F}(R(D^*))\right] g(D^*) \tag{16}$$

The main comparative statics with respect to $\mathcal{B}_j$ $j = c, u$ and for r are easy. A higher value of $\mathcal{B}_j$ raises the reservation wage and reduces the hazard rate, while an increase in the discount rate r makes the job seekers less choosy but also less prone to exert effort, so that the impact on the hazard rate is ambiguous.

B.3 Hazard and sub-hazard rates with respect to the previous job

The analysis that follows takes into account undirected search around home as well as the directed search towards only one focal point, the city of residence. The unemployment exit hazard is shaped by search intensity, search radius, and reservation wage as follows:

$$haz_j = 2\pi\lambda_j\left[\int_0^{D_j}\int_{R_j(\rho)}^{w^{\max}} dF(w)dG(\rho)\right] + \lambda_j^H\left[\int_{R(0)} dF(w)\right]$$

for $j = c, u$.

The unemployment exit hazard depends on search intensity λ_j, search radius D_j, and on the reservation wage $R_j(\rho)$. Job seekers who search hard, or have a large search radius, or have a low reservation wage, will leave unemployment for a regular job faster. The unemployment exit hazard contains information on all three endogenous variables.

We decompose the total exit hazard into sub-hazard rates that reflect the quality of jobs the unemployed might find: paying better or worse, or being farther or closer to home than the previous job, like in a competing-risks framework.

Under the assumption that determinants of job search have not varied since the previous episode of unemployment, the search radius includes the previous distance, and the reservation wage is below the wage earned in the previous job: job seekers would accept the previous job if offered again to them. The sub-hazard rates are then easy to write as:

$$sub - haz_j(w > w_{-1}) = 2\pi\lambda_j \int_0^{D_j} \int_{w_{-1}}^{w^{\max}} dF(w)dG(\rho) + \lambda_j^H \left[\int_{w_{-1}}^{w^{\max}} dF(w)\right] \tag{17}$$

$$sub - haz_j(w < w_{-1}) = 2\pi\lambda_j \int_0^{D_j} \int_{R_j(\rho)}^{w_{-1}} dF(w)dG(\rho) + \lambda_j^H \left[\int_{R_j(0)}^{w_{-1}} dF(w)\right] \tag{18}$$

$$sub - haz_j(d > 0) = 2\pi\lambda_j \int_0^{D} \int_{R_j(\rho)}^{w^{\max}} dF(w)dG(\rho) \tag{19}$$

$$sub - haz_j(d = 0) = \lambda_j^H \left[\int_{R_j(0)}^{w^{\max}} dF(w)\right] \tag{20}$$

B.4 Dynamics of the pool of covered and uncovered job seekers

Let us denote by $N_c(t)$ and $N_u(t)$ the number of covered and uncovered unemployed workers at time t for a given cohort entering unemployment at time $t = 0$. We have, for all $t > 0$:

$$dN_c/dt = -(haz_c + \alpha)N_c$$

$$dN_u/dt = -haz_u N_u + \alpha N_c$$

These first order partial differential equations are easy to solve. In particular, we have that:

$$N_c(t) = N_c(0)e^{-(haz_c+\alpha)t} \tag{21}$$

$$N_u(t) = N_u(0)e^{-haz_u.t} + \frac{\alpha e^{-haz_u.t}}{haz_c + \alpha - haz_u} N_c(0) \left(1 - e^{-(haz_c+\alpha-haz_u)t}\right) \tag{22}$$

where both lines are obtained in fixing the integration constant to get the initial value at time $t = 0$ (entrance into the unemployment spell). Further, if all new entrants are covered, we have that $N_u(0) = 0$. The two equations (21) and (22) determine the fractions of each of the two groups, that is, the covered and uncovered job seekers in the population of applicants.

B.5 Model estimation

As explained in Section 5.2, we first set the parameters for which we have some information; then we jointly estimate the parameters of the job offers distributions and the search costs by minimizing a minimum distance criterion.

Formally, let θ be a p-vector of structural parameters to be estimated which affects the model outcomes $y(\theta)$. We can then define a set of $q \geq p$ of moments in the data (m_{data}) and in the model ($m_{model}(\theta)$). Then, the objective is to solve:

$$\min_{\theta} \psi(\theta)'\psi(\theta)$$

where $\psi(\theta) = (m_{model}(\theta) - m_{data})/m_{data}$, that is the relative distance between the moments calculated on simulated data and the empirical ones: this relative measure allows us to jointly consider moments with different orders of magnitude.

In our application we need to estimate 8 parameters: the mean and the standard deviation of wage and distance offers and four search costs related to different worker's status (covered or uncovered) and search location (home city or elsewhere). We rely on exact identification ($q = p = 8$): each of the 8 selected moments provides information on a given parameter.

The job offers distributions ($F(w)$ and $G(\rho)$) are unobserved in the data but can be inferred by accepted wages and distances. In the specific case of independent distributions, the expected accepted wage is equal to:

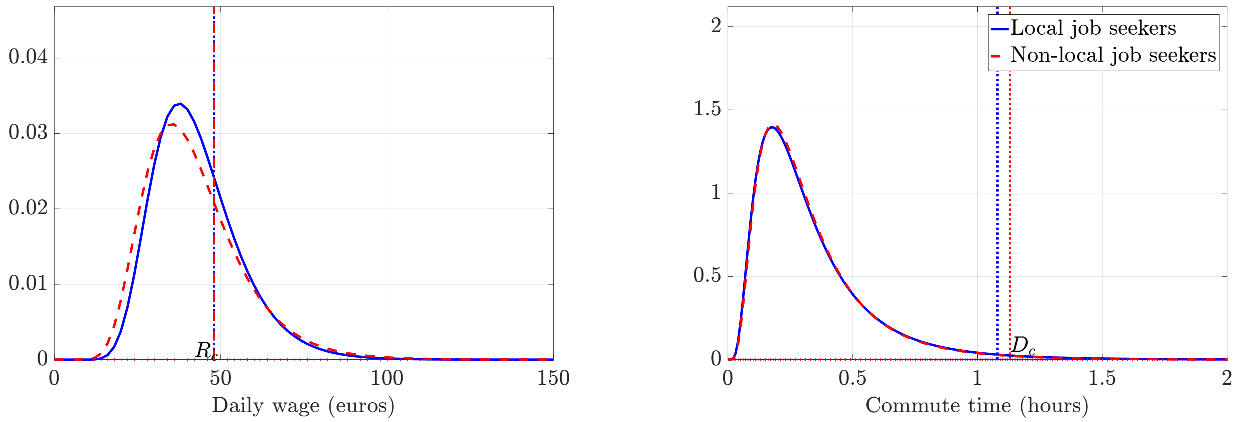
$$\mathbb{E}\left(w_j\right) = \frac{\int_0^{D_j} \int_{R_j(\rho)}^{w^{\max}} w dF(w) dG(\rho)}{\int_0^{D_j} \int_{R_j(\rho)}^{w^{\max}} dF(w) dG(\rho)}$$

where $j = c, u$ and the distributions are not indexed because we assume to be the same for covered and uncovered workers. In the same vein we can compute the expected accepted commute distance:

$$\mathbb{E}\left(\rho_j\right) = \frac{\int_{R_j(0)}^{w^{\max}} \int_0^{\rho^{\max}(w)} \rho dG(\rho) dF(w)}{\int_{R_j(0)}^{w^{\max}} \int_0^{\varrho_j(w)} dG(\rho) dF(w))}$$

where $\rho^{\max}(w) = \min\left(\rho_j(w),\ D_j\right)$, i.e. the smallest between the reservation distance for a given wage ($\rho_j(w)$) and the search radius. Since the reservation wage and the reservation distance are both outcomes of the model we can easily compute model-consistent accepted wages and distances for given $F(w)$ and $G(\rho)$. We thus estimate the parameters of the job offers distributions by matching the mean and the standard deviation of wages and commute times accepted by workers finding a job outside their home city after one month in unemployment, who correspond to covered job seekers in our setup;

Figure B.1: Job offers distributions
A. Wages B. Commutes



the estimated distributions are represented in Figure B.1.[40]

Search costs of effort are obtained by matching the exit rates to one's home city or elsewhere . We target these moments at different times, i.e. after the 1st and the 14th months in unemployment. In the model, for a given set of parameters the dynamics are driven by the relative share of workers belonging to the covered or uncovered state, respectively. Then, we compare the dynamics of the endogenous outcomes of the model obtained by the time-varying composition of the unemployment pool with the empirical moments calculated on our Austrian data. Hence, in each period the targeted sub-hazard rate is a weighted average of the sub-hazard rate of covered and uncovered workers, where the weights are represented by the share of workers in these two states. As time goes, the share of uncovered workers increases, thus leading the dynamic of the targeted moment.

B.5.1 Evaluating the identification strategy

To check the soundness of our identification strategy we estimate the model on simulated data and verify that the parameter estimates converge to the true values: results are reported in Figure B.2 and and B.3, where the black dashed lines represent the true parameter values and colored solid lines the estimated values over the steps of the algorithm for different initial values. Figure B.5.1 plots the evolution of the loss function as the model fit improves over the estimation procedure; the loss function includes the percentage deviations of the simulated sub-hazard rates and accepted wages and commute distances from the targeted moments..

The estimation procedure well identifies the moments of the distributions and the search costs: only c_u^λ, which captures the cost faced by uncovered workers in looking for a job outside their city of

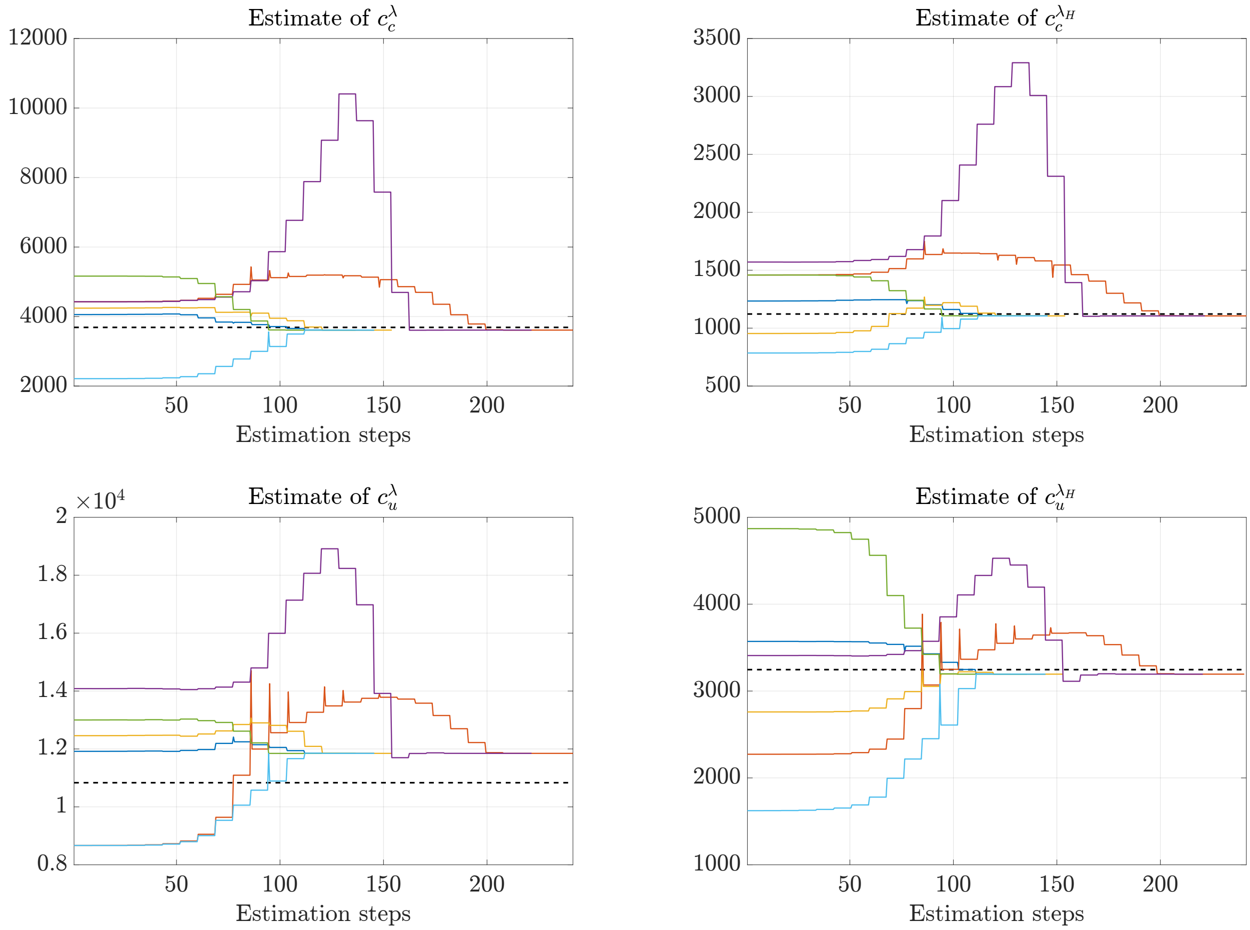
[40]Our setup is further complicated by the mass point of job offers in the municipality of residence. In the estimation approach we avoid this concern by using only moments regarding job seekers who find a job outside their home city.

Table B.1: Targets and estimated parameters

Targets		**Estimated parameters**	
		Local workers	
Average wage (euros per day) $\|d > 0$[a]	57.3	Average offered wage $\|d > 0$	42.9
Average commuting time (hours) $\|d > 0$[a]	0.57	Average offered commuting time $\|d > 0$	0.67
Std. dev. wage (euros per day) $\|d > 0$[a]	17.7	St. dev. offered wage $\|d > 0$	13.1
Std. dev. commuting time (hours) $\|d > 0$[a]	0.37	St. dev offered commuting time $\|d > 0$	0.49
$sub - haz(d > 0)$, after 1m	0.178	Cost of search outside home city, covered workers (c_c^λ)	3674.6
$sub - haz(d > 0)$, after 14m	0.082	Cost of search outside home city, uncovered workers (c_u^λ)	11973.1
$sub - haz(d = 0)$, after 1m	0.109	Cost of search in home city, covered workers ($c_c^{\lambda^H}$)	718.3
$sub - haz(d = 0)$, after 14m	0.036	Cost of search in home city, uncovered workers ($c_u^{\lambda^H}$)	2484.8
		Non-Local workers	
Average wage (euros per day) $\|d > 0$	58.8	Average offered wage $\|d > 0$	42.0
Average commuting time (hours) $\|d > 0$	0.58	Average offered commuting time $\|d > 0$	0.66
Std. dev. wage (euros per day) $\|d > 0$	20.6	St. dev. offered wage $\|d > 0$	14.8
Std. dev. commuting time (hours) $\|d > 0$	0.37	St. dev offered commuting time $\|d > 0$	0.47
$sub - haz(d > 0)$, after 1m	0.202	Cost of search outside home city, covered workers (c_c^λ)	3688.0
$sub - haz(d > 0)$, after 14m	0.094	Cost of search outside home city, uncovered workers (c_u^λ)	10834.1
$sub - haz(d = 0)$, after 1m	0.043	Cost of search in home city, covered workers ($c_c^{\lambda^H}$)	1121.8
$sub - haz(d = 0)$, after 14m	0.018	Cost of search in home city, uncovered workers ($c_u^{\lambda^H}$)	3246.3

Notes: Local workers are those who used to work in their home town before unemployment ($d_{-1} = 0$); non-local refers to job seekers who worked in a different city ($d_{-1} > 0$).
[a]The targeted mean and standard deviation of accepted wages and commute times only regard job seekers who find a job outside their city of residence while they are still covered by UI (i.e. after 1 month in unemployment).

Figure B.2: Parameter estimates on simulated data



residence, is slightly overestimated.

Figure B.3: Estimates of the moments of the job offers distributions on simulated data

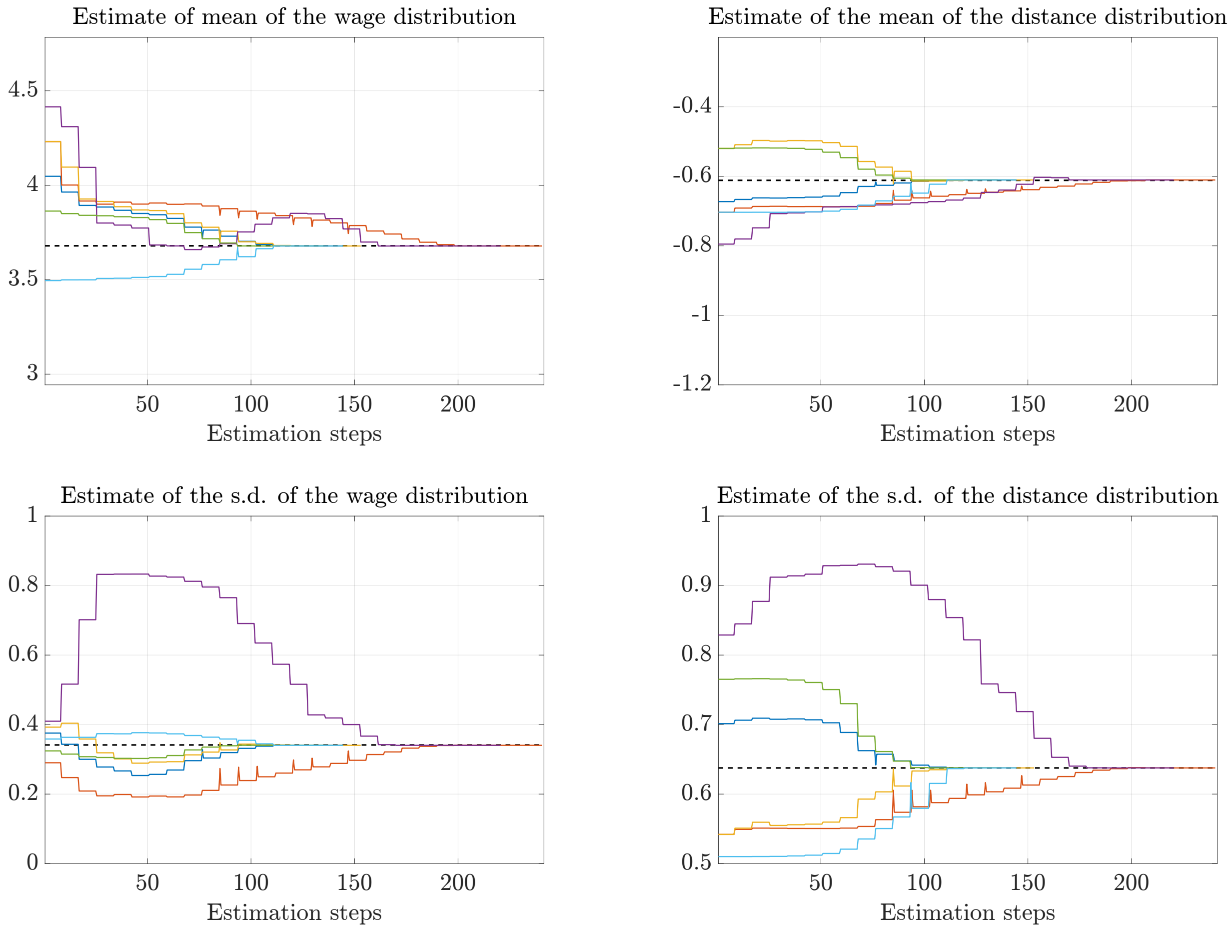


Figure B.4: Estimation on simulated data: loss function

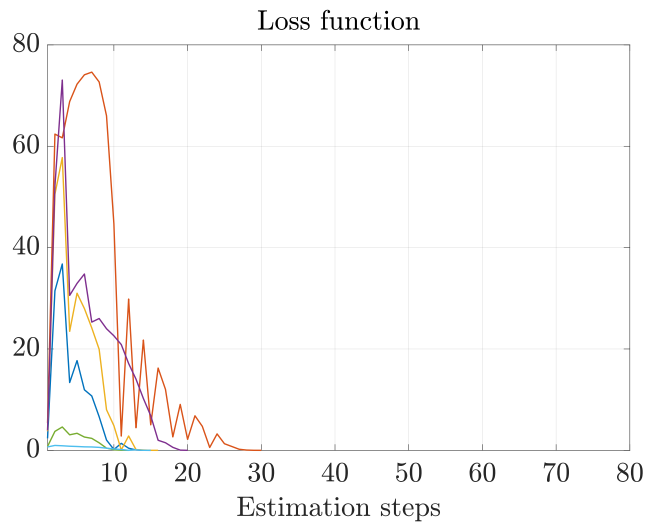
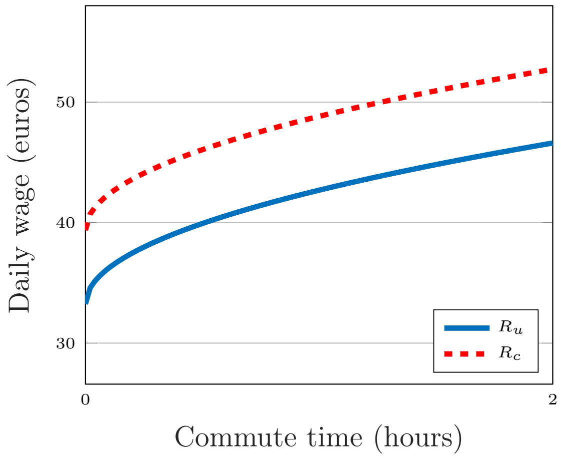


Figure B.5: Simulated reservation frontiers: reservation wage as a function of the commute distance

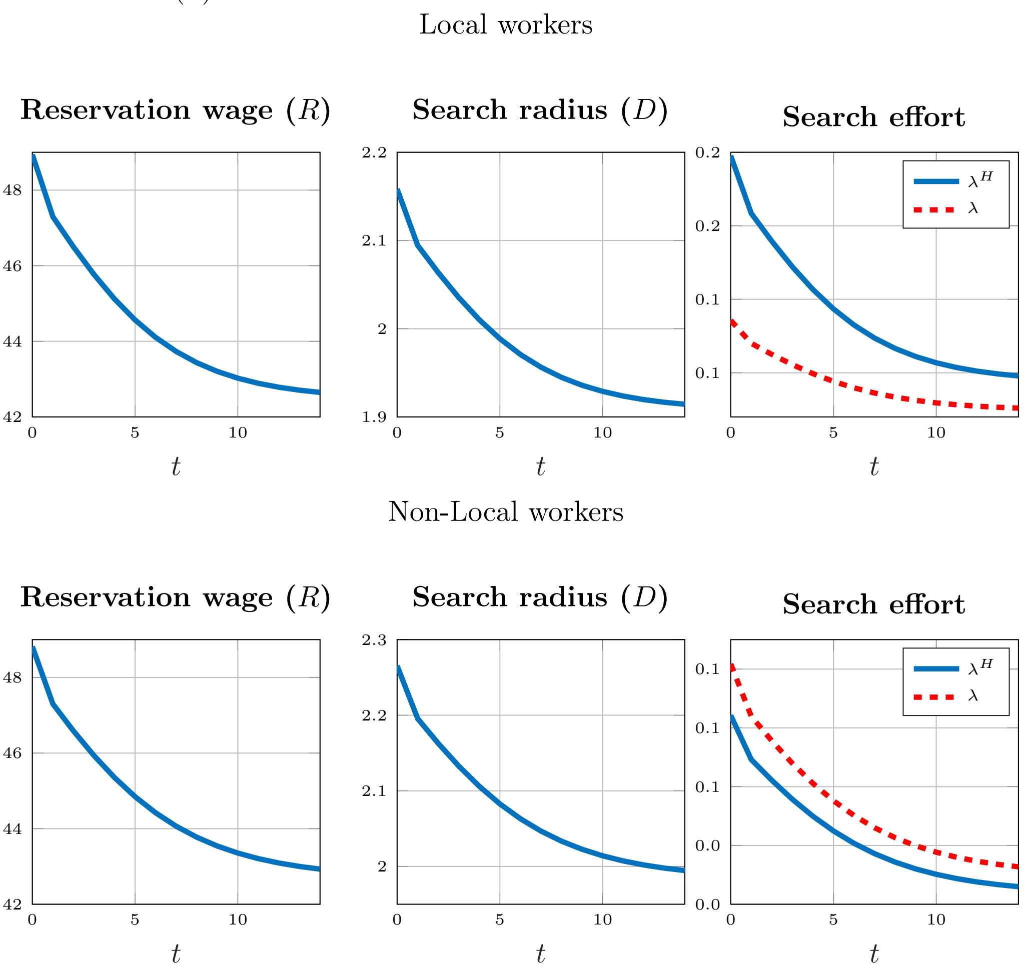


Note: Solid line: uncovered unemployed workers; dashed line: covered unemployed workers .

B.6 Supplementary Results

The simulated reservation frontier, the counterpart of the theoretical Figure 2, is represented in Figure B.5: since we assume a concave commuting cost in line with the empirical evidence, the reservation frontier is also concave. Figure B.6 plots the evolution of the search strategies over the unemployment spell: as time goes, job seekers are more willing to accept wage cuts compensated by lower distances. Because uncovered workers face higher search costs, they reduce the prospecting area as well as effort. Figure B.7 represent the dynamics of accepted wages and commutes: wages decline in both sub-samples while commutes are broadly stable, with different tendencies for local and non-local workers which are in line with the data. Figure B.8 further represents the comparison between empirical and simulated sub-hazard rates for non local workers. Finally, Figures B.9 and B.10 show the counterfactual simulations for non local workers.

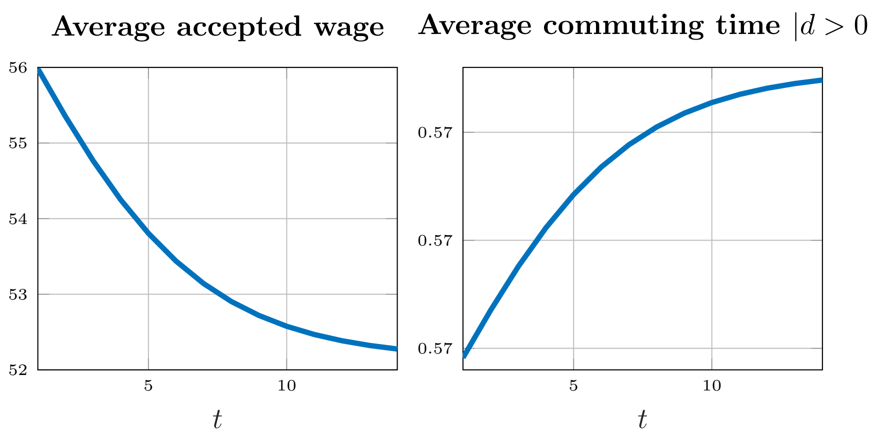
Figure B.6: Search strategies. Reservation wage, search radius and intensity of effort in the same city (λ^H) and in other cities (λ).



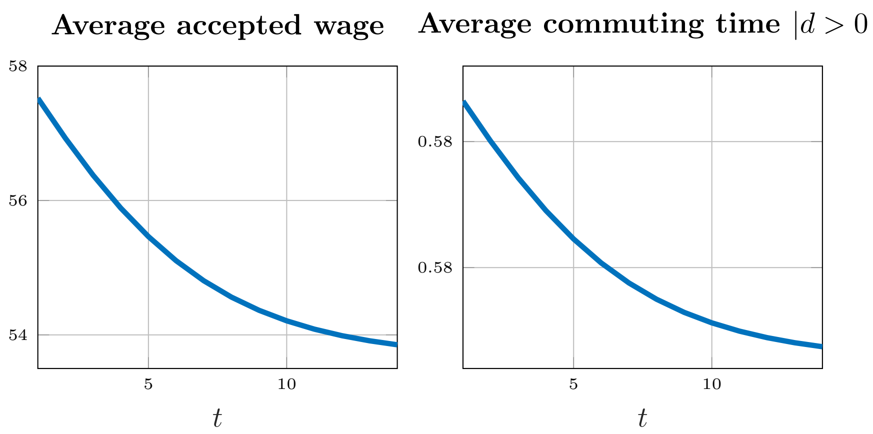
Note: Local workers used to work in their home town before unemployment ($d_{-1} = 0$); non-local workers worked in a different city ($d_{-1} > 0$).

Figure B.7: Average accepted wage and commuting time over the unemployment spell

Local workers



Non-Local workers



Note: Local workers used to work in their home town before unemployment ($d_{-1} = 0$); non-local workers worked in a different city ($d_{-1} > 0$).

Figure B.8: Empirical and simulated hazard rates: non-local workers

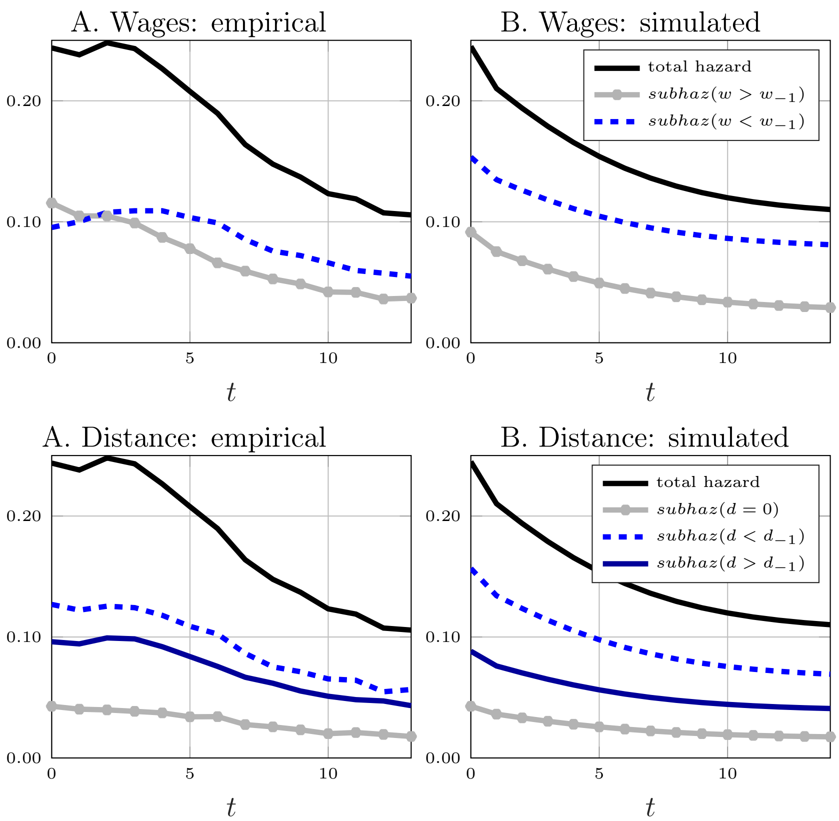
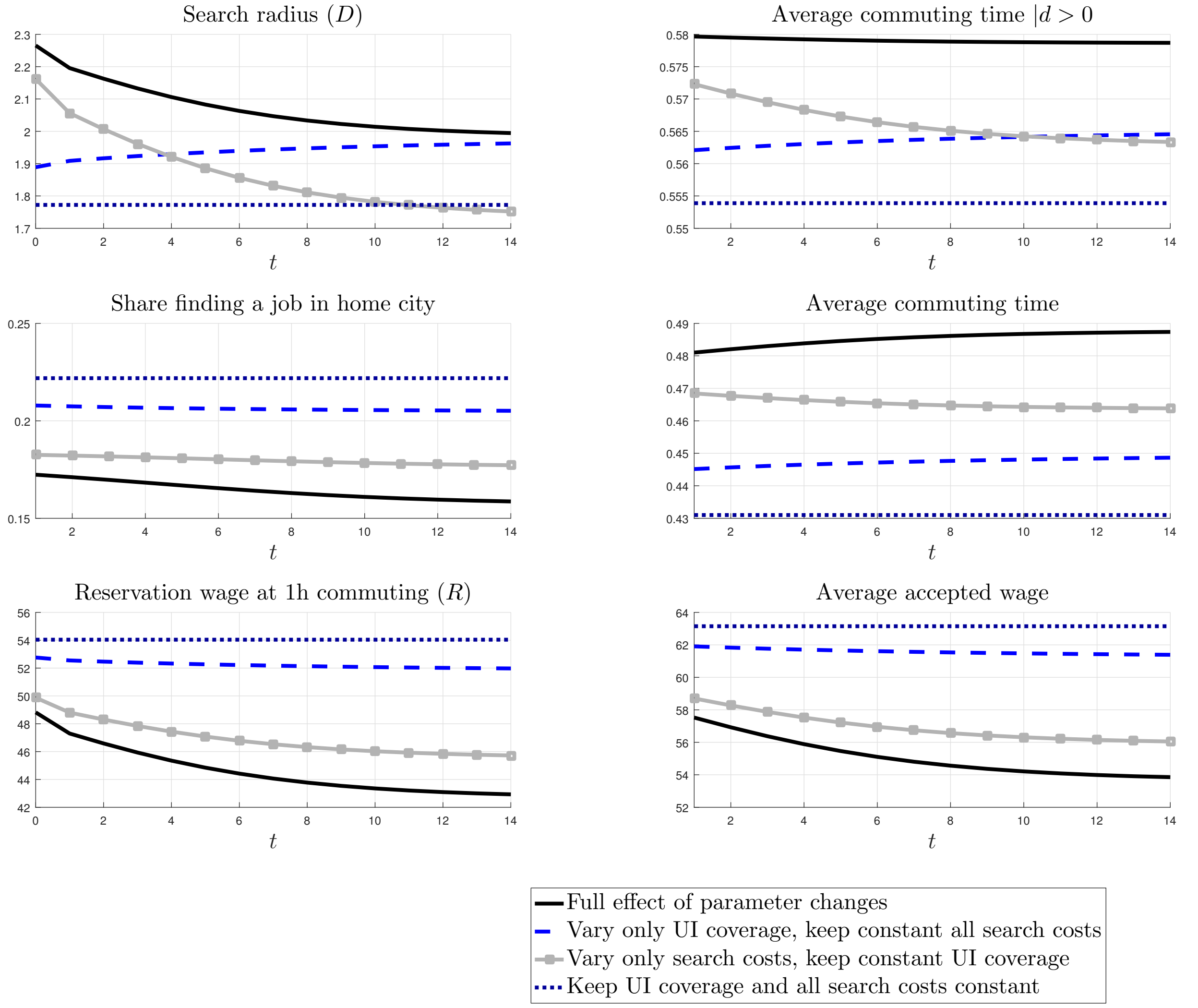
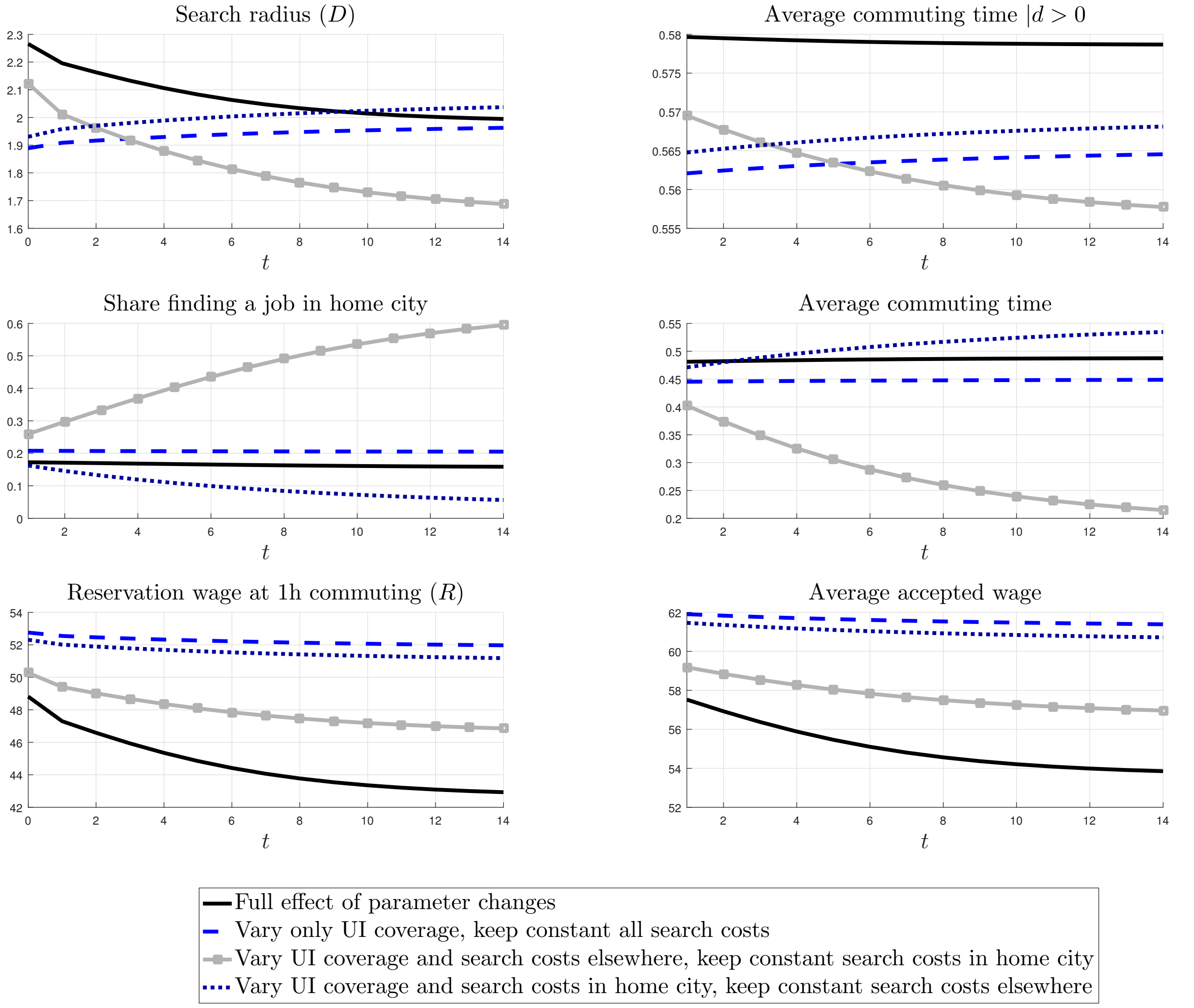


Figure B.9: Counterfactual scenarii for non-local workers: effects over time



Notes: the black solid line is the full effect of time-varying UI coverage and search costs according to model estimates.

Figure B.10: Counterfactual scenarii for non-local workers: effects over time



Notes: the black solid line is the full effect of time-varying UI coverage and search costs according to model estimates.

References

Addison, J. T. and Blackburn, M. L. (2000). The Effects of Unemployment Insurance on Postunemployment Earnings. *Labour Economics*, **7**(1), 21–53.

Altmann, S., Falk, A., Jager, S., and Zimmermann, F. (2015). Learning about Job Search: A Field Experiment with Job Seekers in Germany. Discussion Paper 10621, CEPR.

Alvarez, F. E., BoroviÄkovÃ¡, K., and Shimer, R. (2016). Decomposing Duration Dependence in a Stopping Time Model. Working Paper 22188, National Bureau of Economic Research.

Belot, M., Kircher, P., and Muller, P. (2015). Does Searching Broader Improve Job Prospects? A Field Experiment. Meeting Papers 530, Society for Economic Dynamics.

Bonhomme, S., Lamadon, T., and Manresa, E. (2017a). Discretizing unobserved heterogeneity. Technical report, IFS Working Papers.

Bonhomme, S., Lamadon, T., and Manresa, E. (2017b). Discretizing Unobserved Heterogeneity. Technical report, University of Chicago.

Brownstone, D. and Small, K. A. (2005). Valuing Time and Reliability: Assessing the Evidence from Road Pricing Demonstrations. *Transportation Research Part A: Policy and Practice*, **39**(4), 279–293.

Brueckner, J. K. and Zenou, Y. (2003). Space and Unemployment: The Labor-Market Effects of Spatial Mismatch. *Journal of Labor Economics*, **21**(1), 242–262.

Caliendo, M., Tatsiramos, K., and Uhlendorff, A. (2013). Benefit Duration, Unemployment Duration and Job Match Quality: A Regression-Discontinuity Approach. *Journal of Applied Econometrics*, **28**(4), 604–627.

Card, D., Chetty, R., and Weber, A. (2007). Cash-on-hand and Competing Models of Iintertemporal Behavior: New Evidence from the Labor Market. *The Quarterly Journal of Economics*, **122**(4), 1511–1560.

Centeno, M. and Novo, A. (2006). The impact of unemployment insurance on the job match quality: A quantile regression approach. *Empirical Economics*, **31**(4), 905–919.

Centeno, M. and Novo, A. (2009). Reemployment Wages and UI Liquidity Effect: a Regression Discontinuity Approach. *Portuguese Economic Journal*, **8**(1), 45–52.

Cheshire, P. C. (1979). Inner Areas as Spatial Labour Markets: a Critique of the Inner Area Studies. *Urban Studies*, **16**(1), 29–43.

Chirinko, R. S. (1982). An Empirical Investigation of the Returns to Job Search. *The American Economic Review*, **72**(3), pp. 498–501.

Coulson, E. N., Derek, L., and Ping, W. (2001). Spatial Mismatch in Search Equilibrium. *Journal of Labor Economics*, **19**(4), 949–972.

Crampton, G. (1999). *Urban Labour Markets*, volume 3, chapter 39, pages 1499–1557. Amsterdam: Elsevier Science B.V.

Degen, K. (2014). Winning versus Losing: How Important are Reservation Wages for Nonemployment Duration? working paper, University of Lausanne.

Ehrenberg, R. G. and Oaxaca, R. L. (1976). Unemployment Insurance, Duration of Unemployment, and Subsequent Wage Gain. *American Economic Review*, **66**(5), 754–66.

Faberman, J. and Menzio, G. (2017). Evidence on the relationship between recruiting and the starting wage.

Fischer, C. S. (2002). Ever-More Rooted Americans. *City I& Community*, **1**(2), 177–198.

Frey, B. S. and Stutzer, A. (2002). What can economists learn from happiness research? *Journal of Economic literature*, **40**(2), 402–435.

Gautier, P., Albrecht, J., and Vroman, S. (2016). Worker replacement. *Review of Economic Dynamics*, **19**(218?231).

Gobillon, L., Selod, H., and Zenou, Y. (2007). The Mechanisms of Spatial Mismatch. *Urban Studies*, **44**(12), 2401–2427.

Gobillon, L., Magnac, T., and Selod, H. (2011). The Effect of Location on Finding a Job in the Paris Region. *Journal of Applied Econometrics*, **26**(7), pp. 1079–1112.

Gobillon, L., Rupert, P., and Wasmer, E. (2014). Ethnic Unemployment Rates and Frictional Markets. *Journal of Urban Economics*, **79**(0), 108 – 120. Spatial Dimensions of Labor Markets.

Hall, R. E. and Mueller, A. I. (2018). Wage Dispersion and Search Behavior: The Importance of Nonwage Job Values. *Journal of Political Economy*, **126**(4), 000–000.

Hammadou, H. and Jayet, H. (2003). La Valeur du Temps pour les Déplacements à Longue Distance: une Évaluation sur les Données Françaises. **42**.

Heckman, J. and Singer, B. (1984). A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica*, **52**(2), 271–320.

Holzer, H. J. (1986). Reservation Wages and Their Labor Market Effects for Black and White Male Youth. *The Journal of Human Resources*, **21**(2), pp. 157–177.

Holzer, H. J. (1987). Informal Job Search and Black Youth Unemployment. *The American Economic Review*, **77**(3), pp. 446–452.

Holzer, H. J. (1988). Search Method Use by Unemployed Youth. *Journal of Labor Economics*, **6**(1), pp. 1–20.

Ihlanfeldt, K. R. (1997). Information on the Spatial Distribution of Job Opportunities within Metropolitan Areas. *Journal of Urban Economics*, **41**(2), 218 – 242.

Inderbitzin, L., Staubli, S., and Zweimüller, J. (2013). Extended Unemployment Benefits and Early Retirement: Program Complementarity and Program Substitution. (7330).

Kain, J. F. (1968). Housing Segregation, Negro Employment, and Metropolitan Decentralization. *The Quarterly Journal of Economics*, **82**(2), pp. 175–197.

Kroft, K., Lange, F., and Notowidigo, M. (2013). Duration dependence and labor market conditions: Evidence from a field experiment. *The Quarterly Journal of Economics*, **128(3)**, 1123–1167.

Krueger, A. B. and Mueller, A. I. (2016). A contribution to the empirics of reservation wages. *American Economic Journal: Economic Policy*, **8**(1), 142–79.

Lalive, R. (2007). Unemployment Benefits, Unemployment Duration, and Post-Unemployment Jobs: A Regression Discontinuity Approach. *American Economic Review*, **97**(2), 108–112.

Le Barbanchon, T. (2012). The Effect of Potential Unemployment Benefits Duration on Unemployment Exits to Work and on Job Quality. *Crest working paper 2012-21*, **CREST Centre de Recherche en Economie et Statistique**.

Manning, A. and Petrongolo, B. (2017a). How Local are Labor Markets? Evidence form a Spatial Job Search Model. *American Economic Review*, **107**.

Manning, A. and Petrongolo, B. (2017b). How local are labor markets? Evidence from a spatial job search model. *American Economic Review*, **107**(10), 2877–2907.

Marinescu, I. and Rathelot, R. (2018a). Mismatch unemployment and the geography of job search. *American Economic Journal: Macroeconomics*, **10**(3), 42–70.

Marinescu, I. and Rathelot, R. (2018b). Mismatch Unemployment and the Geography of Job Search. *American Economic Journal: Macroeconomics*, **10**.

Marinescu, I. and Skandalis, D. (2018). Direct Evidence on the Impact of Unemployment Insurance Duration on Job Search. Working paper, CREST.

McCall, J. J. (1970). Economics of information and job search. *Quarterly Journal of Economics*, **84 (1)**, 113–126.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, **142**(2), 698–714.

Menzio, G. and Moen, E. R. (2010). Worker replacement. *Journal of Monetary Economics*, **57(6)**(623-636).

Moen, E. R. and Rosén, Å. (2011). Incentives in competitive search equilibrium. *The Review of Economic Studies*, **4**(6), 733–761.

Moretti, E. (2013). Unemployment Benefits Should Encourage Geographic Mobility.

Nekoei, A. and Weber, A. (2014). Does Extending Unemployment Benefits Improve Job Quality? NRN working papers 2014-04, The Austrian Center for Labor Economics and the Analysis of the Welfare State, Johannes Kepler University Linz, Austria.

Nenov, P. T. (2015). Regional Reallocation and Housing Markets in a Model of Frictional Migration.

OECD (2010). *Family Database, LMF2.6*.

Rogerson, P. (1982). Spatial Models of Job Search. *Geographical Analysis*, **14**(3), 217–228.

Rupert, P. and Wasmer, E. (2012a). Housing and the labor market: Time to move and aggregate unemployment. *Journal of Monetary Economics*, **59**(1), 24–36.

Rupert, P. and Wasmer, E. (2012b). Housing and the Labor Market: Time to Move and Aggregate Unemployment. *Journal of Monetary Economics*, **59**(1), 24 – 36. Carnegie-NYU-Rochester Conference Series on Public Policy at New York University on April 15-16, 2011.

Schmieder, J. F., von Wachter, T., and Bender, S. (2013). The Causal Effect of Unemployment Duration on Wages: Evidence from Unemployment Insurance Extensions. NBER Working Papers 19772, National Bureau of Economic Research, Inc.

Schmieder, J. F., von Wachter, T., and Bender, S. (2016). The Effect of Unemployment Benefits and Nonemployment Durations on Wages. *American Economic Review*, **106**(3), 739–777.

Seater, J. J. (1979). Job Search and Vacancy Contacts. *The American Economic Review*, **69**(3), pp. 411–419.

van den Berg, G. and Gorter, C. (1997). Job Search and Commuting Time. *Journal of Business and Economic Statistics*, **15**(2), 269–81.

van den Berg, G. J. and Gorter, C. (2012). Job Search and Commuting Time ? August 10, 2012. Technical report, Working Papers.

Van Ommeren, J. and Fosgerau, M. (2009). Workers' marginal costs of commuting. *Journal of Urban Economics*, **65**(1), 38 – 47.

van Ommeren, J., Rietveld, P., and Nijkamp, P. (1997). Commuting: In Search of Jobs and Residences. *Journal of Urban Economics*, **42**(3), 402 – 421.

Van Ommeren, J., Van Den Berg, G. J., and Gorter, C. (2000). Estimating the Marginal Willingness to Pay for Commuting. *Journal of Regional Science*, **40**(3), 541–563.

van Ours, J. C. and Vodopivec, M. (2008). Does Reducing Unemployment Insurance Generosity Reduce Job Match Quality? *Journal of Public Economics*, **92**(3-4), 684–695.

van Vuuren, A. (mimeo). On-the-job Search and City Structure. Technical report, VU University Amsterdam and Tinbergen Institute.

Zax, J. S. and Kain, J. F. (1996). Moving to the Suburbs: Do Relocating Companies Leave Their Black Employees behind? *Journal of Labor Economics*, **14**(3), pp. 472–504.

Zenou, Y. (2009). *Urban labor economics*. Cambridge University Press.

Zweimüller, J., Winter-Ebmer, R., Lalive, R., Kuhn, A., Wuellrich, J.-P., Ruf, O., and Büchi, S. (2009). Austrian Social Security Database. *IEW - Working Paper Series No. 410*.