Institut für Höhere Studien
Institute for Advanced Studies
Vienna

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MSc Economics

Nonemployment and occupational mobility: Life-cycle evidence from the National Longitudinal Survey of Youth

A Master's Thesis submitted for the degree of
"Master of Science"

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Vienna, June 8, 2016

MSc Economics

Affidavit

I, Andreea Rotărescu

hereby declare

that I am the sole author of the present Master's Thesis,

Nonemployment and occupational mobility:
Life-cycle evidence from the National Longitudinal Survey of Youth

29 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and that I have not prior to this date submitted this Master's Thesis as an examination paper in any form in Austria or abroad.

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Abstract

This thesis uses lifelong labor market histories from the 1979 National Longitudinal Survey of Youth to study how occupational mobility relates to the duration of nonemployment (or jobless) spells. An empirical model which takes into account the duration of all spells experienced by an individual is estimated using Bayesian methods. The main finding is that the timing of the decision to change occupations matters when it comes to jobless spells duration. Those spells which immediately precede an occupation change take longer to exit from. On the other hand, spells beginning after one's first occupation change have shorter durations. Posterior predictive checks reveal that the model underestimates the dispersion of nonemployment duration which is observed in the data.

1 Introduction

It has long been documented that there is a negative correlation between unemployment duration and job finding rates.[1] Furthermore, the incidence of long unemployment spells appears to rise during recessions. For illustration, Figure 1 shows the evolution of the share of long-term unemployed, which has clearly increased during the past two recessions. This well known empirical regularity (Hornstein 2012) has spurred a substantial amount of research about why this is the case.

There are two main factors which are believed to play a role in the fall of the job finding rate with unemployment duration. The first one is often labeled as "true duration dependence" and implies that individuals who have been unemployed for a long time have a harder time finding a job because of the length of the current spell they are experiencing. The other factor is individual heterogeneity, which presumes that people differ in their ability to secure employment and that prolonged unemployment duration arises from an increase in the share of individuals with low job finding rates among those unemployed.

A related question addresses the roles of entry into and exit from unemployment in the cyclical fluctuation of the unemployment rate. The variation attributable to the entry rate emphasizes the importance of heterogeneity and composition effects: during recessions, disproportionately many persons with inherently low job finding rates become unemployed, leading to a higher incidence of long-term unemployment. As for the contribution of the exit rate, it opens up the possibility for true duration dependence to play an important role.[2]

One step towards a more nuanced analysis of the above questions is to identify potential sources for individual heterogeneity and study to what extent they contribute to explaining the distribution of unemployment duration. A natural candidate is the working experience – be it within an industry, an occupation, or a firm – that an individual possesses when searching for a job. Ljungqvist and Sargent (1998) were among the first to consider the link between the skills gained while employed and the unemployment rate. Unemployment spells in this context are seen as a depreciation of the human capital accumulated in the past.

This thesis contributes to the literature on human capital and unemployment by studying the connection between the timing of occupational decisions and the

[1] See Clark and Summers (1979) for early evidence on this phenomenon from the US, and Elsby et al. (2013) for a more recent account of unemployment dynamics in OECD countries.

[2] In a slight abuse of terminology, I use the phrases "job finding probability" and "exit rate from unemployment" interchangeably, abstracting from transitions between unemployment and being out of the labor force.

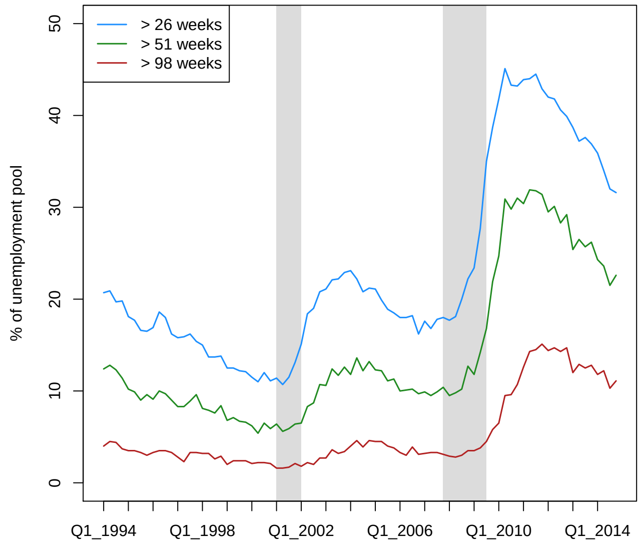


Figure 1: Share of long-term unemployed

Notes: Shaded areas represent NBER recessions. Estimates of people unemployed for longer than 26 weeks are seasonally adjusted. Estimates of people unemployed for longer than 51 weeks or longer than 98 weeks are not seasonally adjusted. Source: US Bureau of Labor Statistics.

duration of the employment gaps experienced by individuals over their entire career. The main research interest is to determine how changing occupations can affect the labor market outcomes of an individual. The long-term perspective is made possible by the 1979 National Longitudinal Survey of Youth (NLSY79). The survey follows the lives of a representative sample of Americans born between 1957 and 1964, and documents their weekly labor force history for the entire period for which they are in the sample. This allows me to reconstruct the sequence of all employment gaps of an individual and link their duration to the occupations held before and after these gaps. The empirical approach is to fit a statistical model where the duration of each jobless spell is exponentially distributed with a rate depending on individual, as well as spell-specific characteristics.

The thesis is structured as follows: section 2 reviews the related literature, section 3 describes the dataset, while section 4 presents descriptive statistics on the variables of interest. In section 5 I describe the empirical model and report the results; section 6 checks the quality of the fit by comparing several observed quantities, some of which are not explicitly targeted by the model, to their estimated counterparts. Finally, section 7 concludes.

2 Related literature

This thesis relies on two pillars of existing literature. The first one is concerned with explaining unemployment volatility and the distribution of unemployment duration, whereas the second one centers around the effects of human capital on labor market outcomes. This section summarizes the contributions which were most important in shaping the analysis in this thesis.

2.1 Unemployment volatility and duration distribution

In an early paper, Clark and Summers (1979) document that unemployment is highly concentrated among those with long unemployment spells. By analyzing the composition of the unemployment pool, the authors find that a relatively small fraction of the unemployed exit unemployment within a short period of time. Their findings challenge the view that most people experience frequent and shortly lived periods of unemployment. Although the authors did not focus on the cyclical fluctuations in unemployment, they recognize that explaining long-term unemployment requires taking these fluctuations into account. It is this strand of the literature that I turn to next.

In an important contribution, Shimer (2012) develops an accounting framework for measuring the probability of entry into and exit from unemployment. He uses aggregate data on the unemployment rate to conclude that the variation in the exit rate from unemployment accounts for about three quarters of the fluctuation in unemployment, whereas the entry rate is responsible for only one quarter. This finding is in opposition to an earlier strand of literature arguing that the variation in unemployment is primarily driven by the cyclical variation of inflows into unemployment (Darby et al. 1986). The conclusion in Shimer was reached by using data on short-term unemployment, and is based on the assumption that all workers are *ex ante* identical. When relaxing this homogeneity assumption, individual characteristics such as the reason for being unemployed and demographic variables (age, gender, race, marital status, education, geographic region) are found to be immaterial in lowering job finding probabilities during recessions.

Hornstein (2012) shows that the distribution of unemployment duration implied by Shimer's homogeneous agent model, which only uses data on total and short-term unemployment, underestimates the actual amount of medium (5-26 weeks) and long (more than 26 weeks) unemployment spells. Therefore, he extends Shimer's approach by incorporating worker heterogeneity and time-varying exit and entry rates from unemployment. This new accounting scheme distinguishes between two types of workers, one with a low and the other with a high job finding probability, labeled as short-term and long-term unemployed respectively. This aspect of the model introduces unobserved heterogeneity in the unemployment pool. The accounting scheme also allows for the short-term unemployed to become of the long-term unemployed type during an unemployment period, thus making true duration dependence possible.

Similar to the conclusion in Shimer (2012), Hornstein (2012) finds that exit rates from unemployment are the main source of variation in the unemployment rate. However, Hornstein also finds that the effect of true duration dependence is negligible and that the volatility of long-term unemployment accounts for most of the observed unemployment rate volatility. The latter finding stresses the importance of *ex ante* worker heterogeneity, which differs from the conclusion reached by Shimer. In other words, the long-term unemployed have a hard time finding a job because they had lower job finding rates before becoming unemployed and not because their chances of finding a job deteriorated while being unemployed.

Hornstein (2012) also finds that, during recessions, the job finding probability of the long-term unemployed decreases relatively more than that of the short-term unemployed. The author develops a matching model where the long-term unemployed have lower job finding probabilities because they produce less productive matches upon employment. The intuition behind the model is that the relatively stronger decrease in the exit rates of the long-term unemployed increases their fraction among the unemployed. If these individuals are less likely to be in a productive match with an employer, then during recessions the expected productivity of a match decreases, discouraging employers to post vacancies. This mechanism is able to generate significant unemployment volatility.

The papers mentioned so far rely on cross-tabulations and variance decomposition based on data from the Current Population Survey (CPS), which does not follow individuals over long periods of time.[3] Morchio (2015) departs from both practices by using data from the NLSY79 to document a series of stylized facts about lifetime unemployment and constructs a model of directed search which is consistent with these facts. By looking at life-long weekly work histories, Morchio finds that two thirds of the amount of unemployment observed in individuals between 35 and 50 years of age can be attributed to 10% of the sample, which supports the view that there is heterogeneity in job finding rates across individuals. Next, the author shows that unemployment is persistent over the life-cycle, meaning that those who are in the top decile of the unemployment distribution

[3] The CPS design is such that a person is in the sample for four months, out for eight, and back in for another four months. There are ways of matching individuals across months, but these procedures are error prone, meaning that the CPS is not an ideal source for long-term studies.

when young (20-30 years old) are likely to be in the same decile during prime age (35-50 years old), even after controlling for other observable characteristics. The final finding is that those at the top of the prime-age unemployment distribution start their careers having similar job finding rates as the rest of the sample, but the gap between them increases with age, to the disadvantage of the former. At the same time, the job separation rate of those most unemployed lies consistently and significantly above the separation rate of the rest of the sample.

Taken together, the findings above motivate Morchio (2015) to incorporate heterogeneity, information frictions, and employer learning in his model. Workers can be of either high or low type and the type is initially unknown by workers and potential employers alike. The type of the workers becomes gradually known from their labor market histories as workers draw from a type-specific match quality distribution upon employment. This logic is reminiscent of the matching mechanism developed by Hornstein (2012), where low job finding probabilities are a sign of poor match quality.

The stylized facts in Morchio (2015) show that youth unemployment is a strong predictor of the amount of unemployment one will experience later in life. However, there are other possible determinants of life-time unemployment. A sizable body of literature deals with the role played by human capital decisions in one's labor market outcomes. While Morchio does condition his measure of prime-age unemployment on occupation and concludes that its importance is dwarfed by labor market history, the human capital literature provides ample evidence in support of its relevance. I now turn to a brief survey of this research.

2.2 Human capital and labor market outcomes

Human capital can be broadly categorized by how it was accumulated into firm-specific, industry-specific, and occupation-specific human capital. In a seminal paper, Jacobson et al. (1993) stress the firm specificity of human capital by analyzing administrative data from Pennsylvania. Their main finding is that high-tenure displaced workers suffer earnings losses of 25% as late as five years after their displacement. This finding is robust across different industries and labor market conditions.

The opposite conclusion is found by Neal (1995) who uses data from the Displaced Workers Surveys to document that wage returns to industry tenure are significant and likely outweigh firm-specific factors. The evidence brought by Neal is that among displaced workers, those who switch industries exhibit greater losses than those who find a job in their predisplacement industry. Also, the negative correlation between wage losses and predisplacement work experience is weaker for those who stay in the same industry.

Parent (2000) reaches similar conclusions as Neal (1995) using two different datasets: the NLSY79 and the Panel Study of Income Dynamics (PSID). Parent asks whether the positive wage returns to tenure with the current employer persist once total industry tenure is accounted for, and finds that this is not the case. To obtain these results, the author regresses hourly wages on employer tenure, industry tenure, total work experience, and an indicator for whether employer tenure is less than one year. Also included in the regression are three fixed effect components meant to account for unobserved individual heterogeneity, for the quality of the employer-worker match, and for the quality of the employer-industry match. To deal with the endogeneity arising from the likely correlation between the unobserved individual effect and the match quality components with the tenure variables, Parent instruments for the tenure variables using an approach proposed by Altonji and Shakotko (1987). This method has been widely used in the subsequent literature dealing with the wage returns to human capital.

In a recent influential paper, Kambourov and Manovskii (2009) refine the method described above by additionally controlling for occupations in a similar way as is done for industries. The authors motivate this extension by arguing that industries employ a variety of different skills and industry affiliation is therefore an inappropriate measure of human capital. Their empirical results show that the firm- and industry specificity of human capital lose their significance once occupations are accounted for. This could mean that the importance of industry tenure observed in previous research was primarily driven by occupation-specific experience, with which it is highly correlated. These findings sparked a renewed interest in the role of occupations in shaping labor market outcomes.[4]

Sullivan (2010) extends the approach of Kambourov and Manovskii (2009) by running the wage regressions separately for all one-digit occupations. The author argues that imposing the same return to human capital for all occupations is a strong assumption, since different occupations require skills which are variably difficult to acquire. His results support this claim by showing that the relative importance of industry- and occupation-specific tenure varies by occupation. For instance, craft workers benefit most from occupation experience, whereas managers draw most returns from industry experience. Professional occupations, on the other hand, exhibit high returns to both industry and occupation tenure. Nevertheless, the average returns to five years of occupational tenure are substantial and range between 15-25%.

All the papers mentioned so far are primarily interested in measuring the

[4]For an early treatment of occupations as determinants of earnings, see Shaw (1984, 1987).

wage returns to different types of work experience. Considerably less research is devoted to gauging the long-term effect of skill accumulation on other important labor market outcomes, such as unemployment duration and job finding rates. One step in this direction was made by Wiczer (2015) who develops a directed search model where agents vary by their occupation, and different occupations react differently to business cycle shocks. Some occupations are more seriously affected than others and individuals are "attached" to their occupation, meaning that they look for jobs in the same occupation in order not to lose the human capital they accumulated on the job. Those individuals who search for jobs in occupations harshly affected by negative productivity shocks face relatively longer unemployment periods, thereby generating the thick upper tails of the duration distribution observed in the data. The model, however, completely abstracts from true duration dependence and only studies composition effects.

Another attempt at characterizing the upper tails of the unemployment duration distribution was made by Schmillen and Möller (2012), only this time using a purely empirical approach. They use administrative data from Germany spanning 25 years to measure the effects of early occupational decisions on the amount of lifetime unemployment experienced by individuals. They find that lifetime unemployment is highly concentrated, with 5% of the sample accounting for half of the observed amount of unemployment. Motivated by this finding, the authors employ quantile regressions for the 75th up to the 95th percentiles of lifetime unemployment.

The main contribution of Schmillen and Möller (2012) is to develop a measure of the *ex post* advantageousness of one's first occupation at age 25, which serves as the main explanatory variable. This measure is based on the employment growth and employment fluctuation of a given occupation over the sample period. The results show that choosing an occupation with a low employment growth rate or a high standard deviation of the fluctuation component significantly increases lifetime unemployment. As a robustness check, the authors run the regressions on the subsample of those who switched occupations at least once during their careers. It turns out that a disadvantageous first occupation still significantly increases lifetime unemployment, suggesting that a poor occupational choice when young has long-lasting effects on the time spent unemployed. Furthermore, changing occupations will not offset this effect.

This discussion raises the question of how occupational decisions relate to one's employment prospects and unemployment duration. In this thesis, I build on the findings of Schmillen and Möller (2012) and refine their analysis by considering *all* jobless spells ever encountered by an individual along with the occupational choices surrounding every spell.

3 Data

The NLSY79 is an ongoing panel data set which documents the lives of a representative sample of Americans who were between ages 14 and 22 at the time of their first interview in 1979. The survey contains information on a variety of life aspects, with particular emphasis on labor market behavior, educational achievements, and family life. Interviews were held annually from 1979 to 1994 and biennially ever since; the last available survey round took place in 2012. The unique feature of this survey, which makes it particularly well-suited for the topic of this thesis, is the fact that at each interview respondents are asked to give a detailed account of their employment history since their last interview. This allows for the creation of weekly records documenting the complete labor market history of the respondents up to their most recent interview date.

The analysis is restricted to the men between 18 and 55 years of age from the nationally representative sample of the survey.[5] Those who report serving in the military, working as farmers, or being self-employed are excluded. Similar restrictions are imposed in the related literature, as for example in Parent (2000) and Kambourov and Manovskii (2009). I also exclude those who were employed for less than 40% of their careers, as well as those exhibiting employment gaps longer than four years, in order to avoid the issues of weak labor market attachment and discouragement. Furthermore, only those individuals are kept, whose labor market careers span five years or longer and do not contain any period of more than 52 consecutive weeks which are unaccounted for.[6] These restrictions insure a complete account of reasonably long labor market histories. Table 1 shows how many cases were dropped after sequentially applying the above described sample restrictions.

3.1 Nonemployment spells

The main object of the analysis are nonemployment (or jobless) spells, defined as periods when the person is either unemployed or out of the labor force (OLF), which immediately succeed and are succeeded by periods of employment. The

[5]The NLSY79 initially included a supplemental sample of people serving in the military and a supplemental sample of Hispanic, black, and economically disadvantaged nonblack/non-Hispanic respondents.

[6]I use the term "career" to denote the period starting when the person turned 18 and ending when the person leaves the sample.

Table 1: Sample restrictions

Reason	Persons dropped	% of total sample
In supplemental sample	6575	51.83
Female	3108	24.50
Spent >1 year in the military	281	2.22
Career spans <5 years	61	0.48
Spent <40% of career employed	145	1.14
Worked >3 years as farmer	87	0.69
Was self-employed for >3 years	420	3.31
Had >52 consecutive weeks unaccounted for	101	0.80
Had at least one spell >4 years	60	0.47

Source: Own calculations using the NLSY79

Table 2: Number of nonemployment spells

Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
1	4	6	7	9	45

Source: Own calculations using the NLSY79

reason why this definition does not distinguish between the states of being unemployed and OLF is that whenever a respondent reports a mixed employment gap consisting of each of these states, only the fraction of the time spent in either state is retrievable from the data, whereas the exact timing of each state is not.[7] Table 2 summarizes the distribution of the number of spells in the sample.

Although primarily an artifact of the data coding procedure, the joint treatment of the unemployed and OLF statuses is not a cause of great concern, for the following reasons. First, for individuals to be considered unemployed, they must be available for work and must have actively searched for a job within the past four weeks. This definition is likely to capture only those individuals who search with an intensity above a certain level and to rule out those who are still willing to take up a job but whose search intensity does not qualify them as unemployed (Kudlyak and Lange 2014).[8] Furthermore, considering only employment gaps entirely classified as unemployment would significantly underestimate the amount of time spent between jobs and would likely bias the analysis. One disadvantage of pooling the unemployed and OLF statuses is that this definition will occasionally capture, for instance, those still in school or those disabled. This shortcoming is addressed by controlling for young age, when some persons might still be enrolled in school, and by excluding those with long spells (see sample

[7]The reported number of weeks spent unemployed during a gap is arbitrarily assigned to the middle portion of the gap and the remaining weeks are given the OLF code.

[8]For a theoretical treatment of how simply waiting for a job may be a productive activity in finding a job, see Hall (1983).

restrictions above).

Since the primary focus lies on occupational choices surrounding nonemployment periods, the spell sample is restricted to include only cases with valid occupation observations both before and after the spell. After these refinements, the final sample consists of 1745 persons observed over a median period of 1677 weeks and having a total of 12,312 nonemployment spells.

3.2 Occupations

Occupations need to be encoded using the same classification system, in order to make them comparable throughout the years and to avoid spurious changes. The raw occupation data is coded using the 1970 and the 2000 US Census classification systems. A comprehensive crosswalk transforming these classifications into a set of 386 occupation categories is provided by Meyer and Osborne (2005). I chose to use a slightly modified version thereof which is documented in Dorn (2009) and consists of 330 different occupation codes. The advantage of the latter crosswalk is that it defines somewhat broader categories which contain codes from all the original Census classifications, making it possible to track every group of occupations over the years. To make the division by occupational categories tractable, I use an aggregation scheme provided by Autor and Dorn (2013) which summarizes the 330 codes into six categories: (1) managerial and professional specialty occupations; (2) clerical and retail sales occupations; (3) low-skill service occupations; (4) precision production, craft, and repair occupations; (5) machine operators, assemblers, and inspectors; (6) transportation, construction, mechanics, mining, and farming occupations.

Using the above categories, all employers reported by respondents to the survey are assigned an occupation. Sometimes, several occupations are recorded for the same employer, in which case I select the most frequently mentioned occupation to characterize the job.[9] This approach is often used in the related literature, which treats within-firm occupation (industry) changes as coding errors and only considers occupation (industry) changes to be genuine if they are accompanied by an employer switch (see for example Neal 1999). The NLSY79 user guide warns about the presence of occupational and industry miscoding, especially before 1994, when coders did not have access to previously reported occupations.[10] This lends support to the approach which only considers simultaneous occupation

[9] In the NLSY79, a job is equivalent to an employer, hence the two terms will be used interchangeably throughout the thesis.

[10] Starting in 1994, the interviews became computer-assisted and were loaded with the previously reported occupation, about which the respondent was asked whether it was still accurate.

and employer changes.

This approach is not uncontested. Kambourov and Manovskii (2009) use the availability of retrospectively coded occupation and industry variables from the PSID, which are more reliable than the raw codes, to compare different ways of identifying true occupation switches. They document that, for the PSID, conditioning an occupation switch on an employer switch identifies roughly half of the true switches and only about two thirds of these switches are genuine. In a recent paper using the NLSY79, Sullivan (2010) documents that less than a fifth of employment spells with a single firm involve an occupational switch. Given this relatively low incidence, I chose to neglect these switches and opted for the method assigning to each employer the most frequently reported occupation.

4 Descriptive evidence

From the way I defined occupations and jobless spells, there are three possible outcomes following a spell.[11] The first one occurs when the individual returns to the same employer as the one before the spell; the second outcome is when one changes occupations and works for a different employer; the third outcome is when the individual takes up the same occupation as the one before the spell, but switches to a different employer.

Table 3 shows how many spells end in each of the three outcomes by several spell-specific characteristics of the individuals experiencing them. Also shown is the mean duration of the spells originating from individuals in the corresponding categories. Table 3 shows that the fraction of those who return to their previous employer is increasing in age, whereas the fraction of those switching their occupation decreases with age. This shows that older individuals are less frequently observed to change any aspect of their employment relationship. This general trend is visible even after disaggregating age groups into finer bins, as Figure 2 shows. Interestingly, the middle-aged group between 36-45 years old exhibits markedly longer spells when compared to both their younger and their older counterparts. Regarding the geographic region, it is noteworthy that those who start their spell in the southern region of the US spend on average two more weeks without a job.

Turning now to education, it is interesting to see that the most educated group is least likely to return to the same employer and also least likely to change their occupation. One interpretation could be that those who invested most in their skills by acquiring specialized education are not as prepared to waste

[11] Unless otherwise specified, "spell" used on its own refers to a jobless spell.

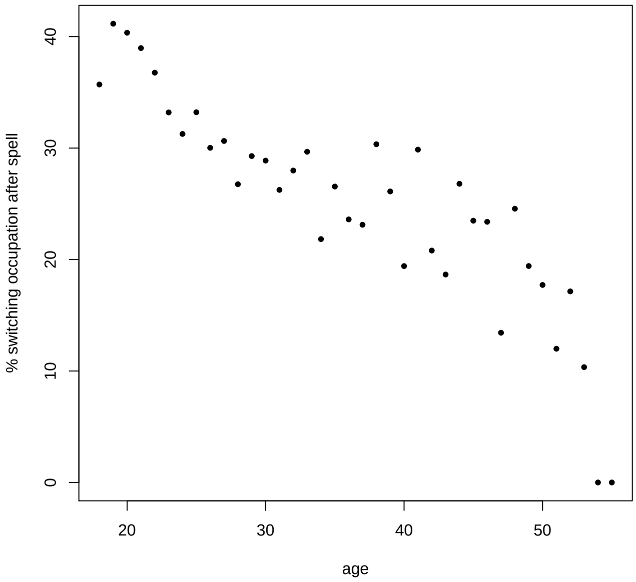
Table 3: Switching behavior and mean duration by individual characteristics at spell onset

At spell onset:	% being recalled	% switching occupations	% switching firm only	Duration (weeks)
Age				
18-25 years	38.30	37.01	24.68	16.87
26-35 years	40.16	28.15	31.69	15.99
36-45 years	41.40	24.21	34.39	20.68
46-55 years	55.04	18.10	26.86	16.18
Region				
Northeast	40.42	30.64	28.95	16.14
Northcentral	45.93	31.88	22.19	16.75
South	35.96	32.13	31.91	18.48
West	36.21	32.83	30.97	16.33
Education				
$\leq$ 12 years	42.62	31.17	26.21	17.09
13-15 years	38.36	36.32	25.33	17.95
$\geq$ 16 years	31.04	26.32	42.65	15.08
Marital status				
Never married	37.09	36.67	26.24	18.29
Married, spouse present	47.24	22.70	30.06	14.38
Other	37.64	30.70	31.66	17.67
Occupation				
Managers/ professionals	36.38	23.67	39.95	16.22
Clerical/ retail sales	30.45	48.39	21.16	18.44
Low-skill services	33.42	42.26	24.32	19.71
Production/ craft	45.26	47.20	7.54	14.20
Machine operators	49.21	36.09	14.70	15.73
Transport/ construction/ mining/ farm	44.46	24.11	31.44	16.64
Recession				
No	39.76	31.47	28.76	16.49
Yes	41.65	33.61	24.74	19.38

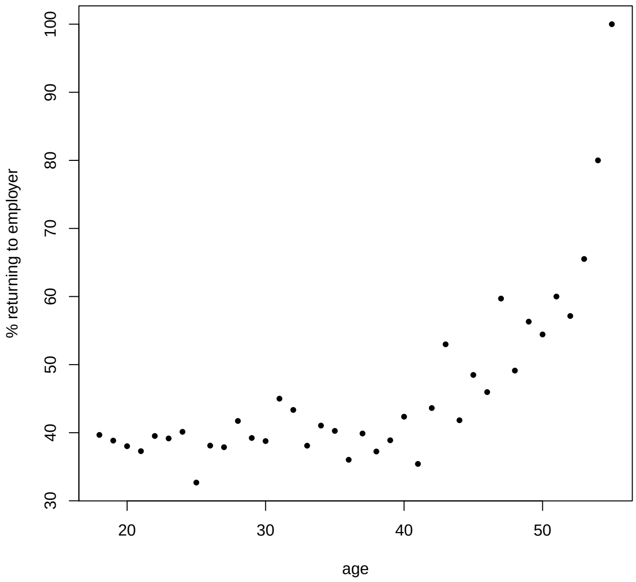
Source: Own calculations using the NLSY79

their accumulated human capital by switching occupations. The most frequent outcome in this group is to remain in the same occupation and change only one's employer. It is also this highly educated group which experiences the shortest average spell duration. Marital status also reveals interesting patterns. Married persons are most likely to return the previous employer in the wake of a jobless spell. One possible explanation could be that searching for a new employer as well as learning a new occupation are time-consuming and risky processes, which one might try to avoid in the presence of family obligations and responsibilities.

When looking at the most recent occupation held by those who enter a jobless spell, a striking feature is that those in precision production occupations are by far the least likely group to switch only their employer but remain in the same occupation. One potential explanation could be that the skills required for such



(a) % switching occupation after spell by age



(b) % returning to previous employer after spell by age

Figure 2: Switching behavior by age

Table 4: Number of occupation switches and jobless spells, and percent of career spent jobless by individual characteristics

	# switches to new occ.	# all occ. switches	# jobless spells	% career jobless
Race				
Hispanic	2.16	5.03	6.94	11.14
Black	2.22	5.45	6.91	12.62
White	2.05	4.62	7.08	9.05
Highest degree				
No high school	2.13	5.74	10.03	13.01
High school	2.09	4.72	6.87	8.22
Some college	2.34	5.30	7.01	9.68
Bachelor's degree	2.16	4.75	6.61	8.85
Master's degree or higher	1.75	3.52	7.45	11.03
First occupation				
Managers/ professionals	1.96	4.94	5.70	8.38
Clerical/ retail sales	2.11	4.54	6.25	9.11
Low-skill services	2.37	5.50	7.43	10.76
Production/ craft	2.60	5.56	8.06	9.24
Machine operators	2.31	4.78	8.11	10.27
Transport/ construction/ mining/ farm	2.26	5.28	7.60	9.67

Source: Own calculations using the NLSY79

a job are highly firm-specific and hardly transferable across firms in the same line of business. Interestingly, precision workers are also the ones with the smallest average duration, meaning that on average it takes them least to overcome a job loss. As would be expected, spells starting in a recession take on average three more weeks to recover from.[12]

Table 4 categorizes several summary measures of a worker's entire career by some key individual characteristics. The first column represents the average number of times when an individual has switched to a completely new occupation, i.e. to an occupation which he has never held before. It can be seen that irrespective of the category in which they lie, individuals opt for a new occupation approximately twice during their careers. A similar picture emerges from the second column, which represents the average number of times a person has changed occupations, irrespective of whether he is new to the target occupation or not. It appears that all groups switch back and forth between occupations approximately five times during their career.

When it comes to the total number of jobless spells, education appears to be important. Those who have not completed high school find themselves more

[12]A spell is considered to start in a recession if the month of its onset falls between the peak and the trough of an NBER business cycle. For a table of NBER business cycles reference dates, see `http://www.nber.org/cycles.html` (last accessed on May 28, 2016).

frequently without a job than those who have at least a high school degree. Concerning the fraction of one's career spent jobless, several aspects are worth noting. Recall that persons are observed for about 30 years, so even small percentage point differences are relevant. Race and ethnic background appears to play an important role, with white persons spending the smallest fraction of their careers without a job. High school dropouts experience the highest relative amount of lifetime nonemployment when compared to other education groups. Note that the elevated value for those with at least a Master's degree likely represents an artifact of the way jobless spells were defined: being enrolled in school is coded as being out of the labor force which in turn is considered as nonemployment. Finally, classifying people according to their first occupation shows that those who start their careers in low-skill service occupations and in machine operating occupations face the longest lifetime period of joblessness.

5 An empirical model of nonemployment spell duration

The model I estimate takes advantage of the full amount of detail present in the data by taking into account the duration of all nonemployment spells a person experiences. Schmillen and Möller (2012) add up the duration of distinct spells to create the total amount of unemployment of an individual, which serves as their dependent variable. Such an approach discards information on the timing and the number of spells. It is conceivable that individuals who experience many short spells are different from those with few long spells. Also, the within-individual variation in spell duration is not negligible: in my sample, the median of the within-individual standard deviation of spell duration lies at 14 weeks, meaning that duration varies substantially even when holding the individual fixed. By using all duration observations available in my sample, I hope to overcome the loss of information associated with aggregating the spells of an individual.

The model equations are shown below. The key ingredients of the model consist of an individual fixed effect denoted by $\log(\lambda_i)$, time-invariant regressors included in Z_i, and spell-specific regressors included in X_{ji}, where i denotes the individual and j denotes the spell. Equation (5) specifies that the duration of spell j belonging to individual i is exponentially distributed with a rate which is defined in (4). The rate depends on the individual fixed effect and on the covariates. Note that the exponential transformation in (4) guarantees that the rate of the exponential distribution is positive.

$$\mu \sim \mathcal{N}(0, 10) \tag{1}$$

$$\sigma \sim \text{Cauchy}(0, 5) \tag{2}$$

$$\log(\lambda_i) \sim \mathcal{N}(\mu, \sigma) \tag{3}$$

$$r_{ji} = \exp(\log(\lambda_i) + Z_i\beta_z + X_{ji}\beta_x) \tag{4}$$

$$d_{ji} \sim \text{Exponential}(r_{ji}) \tag{5}$$

There are three explanatory variables which are of particular interest. The first one is an indicator for whether the current spell occurred after the individual's first occupational switch. This could be of interest, since I start observing individuals at a very young age and it is plausible that, when young, people experiment with different occupations before they decide which career path to choose. By including this indicator I intend to capture whether individuals who switched occupations sometime in the past face better or worse employment prospects. The other two variables of interest reflect the decision made by the individual while in a spell. Recall that the only possibilities are to change occupations, return to the previous employer, or change employers but stay in the same occupation. The latter option is the omitted category and for each of the other two I include an indicator.

What these variables seek to capture is how changing occupations relates to job finding rates. Controlling for them allows me to check if the main conclusion in Schmillen and Möller (2012) is consistent with the data I am using. Their conclusion was that, at least for the upper tails of the lifetime unemployment distribution, one's first occupation is a significant determinant of lifetime unemployment, even if one switches occupations later in life. In other words, those who make an "unlucky" first occupational choice cannot reduce their lifetime unemployment only by changing their profession.

An important qualification is in order. The specification of the model does not allow for any causal interpretation. Rather, the conclusions drawn from the model are to be seen as the result of a data description exercise, uncovering some of the existing patterns present in the data. It would be wrong to conclude from the results of this model that occupation changes cause a change in spell duration, since the converse may also be true. It is conceivable that the duration of the current spell of an individual motivates him to opt for an occupation switch.

Beside the above mentioned covariates, which are of primary interest, I further condition on the occupation held before the spell, on whether the spell began during a recession, on race, years of education, marital status, age, and geographic region. Note that except for race, all other variables are spell-specific. The number of years of education is standardized by subtracting the mean and dividing by the standard deviation in order to improve convergence.

The model is implemented in the Stan language for statistical modeling (Stan Development Team 2016). The estimates are obtained by means of a Markov Chain Monte Carlo method, run with four Markov chains, each having 1000 iterations. Half of the iterations in each chain serve as warm-up, leaving a total of 2000 estimates for each parameter. Model diagnostics indicate that the chains mix well and that sampling is efficient.[13] The full Stan output can be found in Appendix A.

5.1 Results

Table 5 summarizes the regression results. The first two columns show the posterior mean and standard deviation for each parameter, whereas the last two columns represent the interval which contains 95% of the estimated parameter values. I interpret a parameter to be significantly different from zero if this interval does not contain the value zero. Note that despite similarities in the wording, the latter concepts do not refer to the frequentist definitions of a 95% confidence interval and of statistical significance. When interpreting the coefficients it is important to keep in mind that the dependent variable of this regression is the job finding rate (or the rate at which nonemployment is exited from).

The first two parameters in Table 5 are the mean and standard deviation of the individual fixed effect. The second block of coefficients is of special interest. It appears that having switched occupations at least once in the past is significantly positively related to the job finding rate. One possible explanation could be that after experimenting with different occupations, one has found the occupation which is best suited to one's skills, which in turn can lead to improved employment opportunities. It is interesting to see that the coefficient on switching occupations immediately after the spell is significantly negative. The decision to change occupations while in a spell appears to be associated with longer spell duration and lower job finding rates. It is noteworthy that these two coefficients have opposite signs. Both represent occupation changes, but at a different time relative to the spell. In the longer run, having changed occupations once is associated with a higher job finding rate, whereas the spell immediately preceding an occupation switch has a lower exit rate.

[13] The potential scale reduction factor `Rhat` is close to 1 for all parameters. The number of effective draws from the posterior distribution corrected for autocorrelation, `n_eff`, exceeds a third of the post-warm-up draws in all but two isolated cases. For details see Appendix A.

Table 5: Regression results

	Mean	Std. dev.	2.5%	97.5%
μ	−3.211	0.059	−3.327	−3.099
σ	0.510	0.016	0.479	0.540
Spell after first occ. switch	0.142	0.029	0.087	0.197
Switch occ. after spell	−0.139	0.028	−0.194	−0.086
Return to previous employer	0.694	0.026	0.640	0.743
Managers/ professionals	0.087	0.041	0.006	0.168
Clerical/ retail sales	0.064	0.043	−0.019	0.145
Production/ craft	0.157	0.066	0.031	0.281
Machine operators	0.117	0.044	0.030	0.200
Transport/ construction/ mining/ farm	0.064	0.033	0.002	0.130
Spell began during recession	−0.175	0.025	−0.226	−0.125
White	0.217	0.045	0.131	0.307
Education	0.084	0.017	0.052	0.116
Married	0.151	0.028	0.096	0.205
Age 25-35	−0.052	0.026	−0.103	0.000
Age 36-45	−0.353	0.036	−0.425	−0.283
Age 46-55	−0.341	0.049	−0.437	−0.247
Northeast	0.065	0.043	−0.021	0.150
South	0.078	0.038	0.001	0.153
West	0.114	0.042	0.029	0.193

Source: Own calculations using the NLSY79

The coefficient on returning to the previous employer shows that such spells are exited from at a higher rate. Those who are recalled therefore appear to experience shorter spells. When interpreting the last two parameters in the second block, it is important to keep in mind that the omitted outcome corresponds to remaining in the same occupation but changing only employers, which captures the intermediate amount of change one can undertake. One extreme is to change both occupation and employer, which is worse than only changing employers. The other extreme is to change neither occupation, nor employers, which is better than changing only employers. What this appears to imply is that spells delimiting a change in one's employment relationship are longer than those followed by no change.

The third block of parameters shown in Table 5 corresponds to the indicators for the occupation held before the spell. The omitted category is the one containing low-skill service occupations. It is apparent that except for clerical occupations, all other occupations are followed by significantly shorter spells. Unsurprisingly, spells starting during a recession take longer to exit from.

The final parameter block also reveals some interesting results. Being white is significantly positively related to one's job-finding rate, as is education, meaning that more years of education at spell onset are associated with a shorter spell duration. Being married at the beginning of the spell is likewise positively related to the job finding rate. The coefficients on the age indicators are also noteworthy. It appears that those between 25 and 35 years of age have about the same job finding rates as the comparison group aged between 18 and 24 years, whereas all those above 35 have significantly lower job finding rates.

6 Model checking

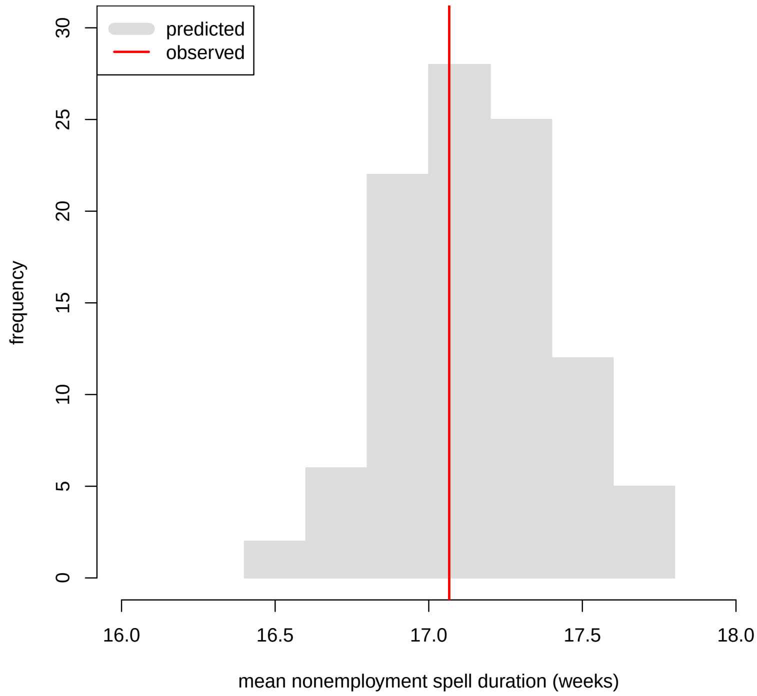
One advantage of using Bayesian methods is that this framework allows for assessing the quality of the fit obtained from a model in a way that captures both parameter uncertainty and sampling variation. Having obtained a posterior distribution for all model parameters, one can draw parameter estimates from it and use them to simulate data, which can then be compared to the observed data. In this section I define several quantities which I compute for both the simulated and the observed data in order to assess how well the simulated quantities match the observed ones. For more details on how to do posterior predictive checks, see for instance Rubin (1981, 1984) and Chapter 6 in Gelman et al. (2014). The general idea behind the posterior predictive checks done in this section is to draw 100 times from the posterior distribution of the parameters and simulate for each draw an array of spell durations.

Before proceeding, some notation needs to be introduced. Let N denote the number of individuals and n_i the number of spells of individual i. Let M denote the total number of spells, i.e. $M = \sum_{i=1}^{N} n_i$. Running the model resulted in 2000 estimates for each parameter. I randomly generate 100 numbers between 1 and 2000 and for each such number I extract the corresponding estimates for each parameter. In other words, I draw 100 times from the posterior distribution of each parameter. A superscript of k on a parameter means that it is the k-th draw from that parameter's posterior distribution. A hat above a quantity indicates that it stems from the model and not from the data.

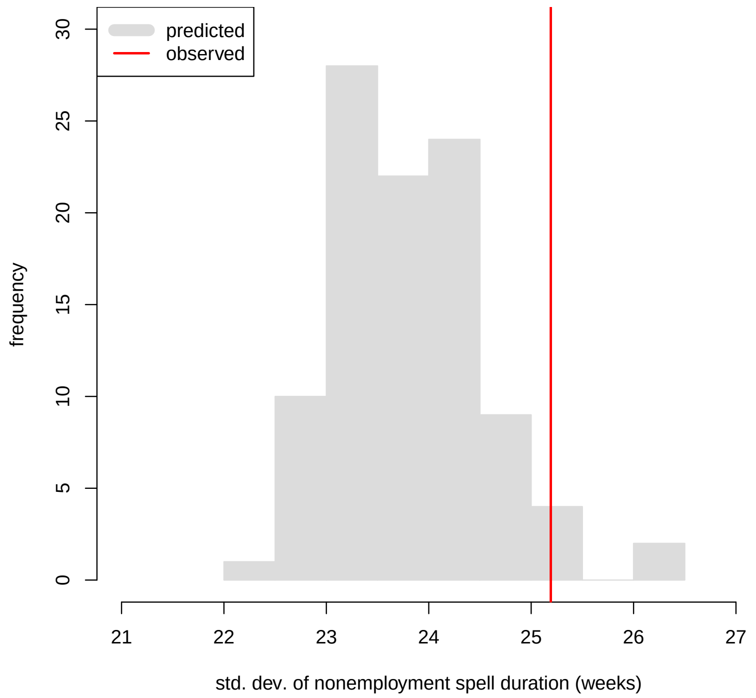
For each draw I simulate an array of spell durations as follows:

$$\hat{r}_{ji}^{k} = \exp(\log(\hat{\lambda}_i^k) + Z_i\hat{\beta}_z^k + X_{si}\hat{\beta}_x^k)$$
$$\hat{d}_{ji}^{k} \sim \text{Exponential}(\hat{r}_{ji}^{k})$$

where $k \in \{1, ..., 100\}, i \in \{1, ..., N\}, j \in \{1, ..., n_i\}$. $\hat{d}_{ji}^{k}$ represents the predicted duration of the j-th spell of individual i using the k-th draw from the posterior



(a) mean



(b) standard deviation

Figure 3: Mean and standard deviation of nonemployment spell duration

distribution of the parameters.

6.1 Mean and standard deviation of spell duration

To obtain the mean and standard deviation over all predicted durations, for each $k \in \{1, ..., 100\}$ I compute:

$$\hat{m}^k = \frac{1}{M} \sum_{i=1}^{N} \sum_{j=1}^{n_i} \hat{d}_{ji}^k$$

$$\hat{s}^k = \sqrt{\frac{1}{M} \sum_{i=1}^{N} \sum_{j=1}^{n_i} (\hat{d}_{ji}^k - \hat{m}^k)^2}$$

Figure 3a shows the resulting histogram of $\hat{m}^k$ and the actual mean spell duration from the data (represented by the red line). It appears that the model accurately predicts this quantity. Similarly, Figure 3b shows how $\hat{s}^k$ is distributed compared to the observed standard deviation of all observed durations. It appears that, according to the model, the standard deviation of all durations is concentrated around smaller values than the observed standard deviation. This means that spell duration is more dispersed in the data than the model would predict.

6.2 Individual-specific mean and standard deviation of spell duration

Similar to the procedure outlined above, I now compute for each $k \in \{1, ..., 100\}$ and $i \in \{1, ..., N\}$ the individual-specific mean and standard deviation:

$$\hat{m}_i^k = \frac{1}{n_i} \sum_{j=1}^{n_i} \hat{d}_{ji}^k$$

$$\hat{s}_i^k = \sqrt{\frac{1}{n_i} \sum_{j=1}^{n_i} (\hat{d}_{ji}^k - \hat{m}_i^k)^2}$$

Figure 4 compares the distribution of $\hat{m}_i^k$ and $\hat{s}_i^k$ to their empirical counterparts. The histogram in the background belongs to the observed individual-specific mean and standard deviation. The black line is the density plot corresponding to the observed individual mean and standard deviation, whereas each blue line is the density plot of $\hat{m}_i^k$ (in the upper panel) and $\hat{s}_i^k$ (in the lower panel) for a fixed k. From Figure 4a it can be seen that the distribution of the individual-specific mean is matched quite well by the model. However, the same cannot be said about the individual-specific standard deviation, which is shown in Figure 4b. It is quite apparent that the densities resulting from the model assign more weight to smaller values than is the case in the data. The upper tails can be seen to be thicker in the data than what the model would predict. What can be concluded from the lower panels of Figure 3 and Figure 4 is that both the pooled and the individual-specific variation in duration are underestimated by the model.

6.3 Fraction of career spent nonemployed

Yet another statistic of interest, which was not explicitly targeted in the model, is the share of an individual's career when he was nonemployed, denoted by $nonemp_i$. This quantity is obtained by summing over the length of all spell durations an individual experienced and dividing by the total amount of time that this individual is observed for, which I define to be his career and denote by c_i. For each $k \in \{1, ..., 100\}$ and $i \in \{1, ..., N\}$ I compute:

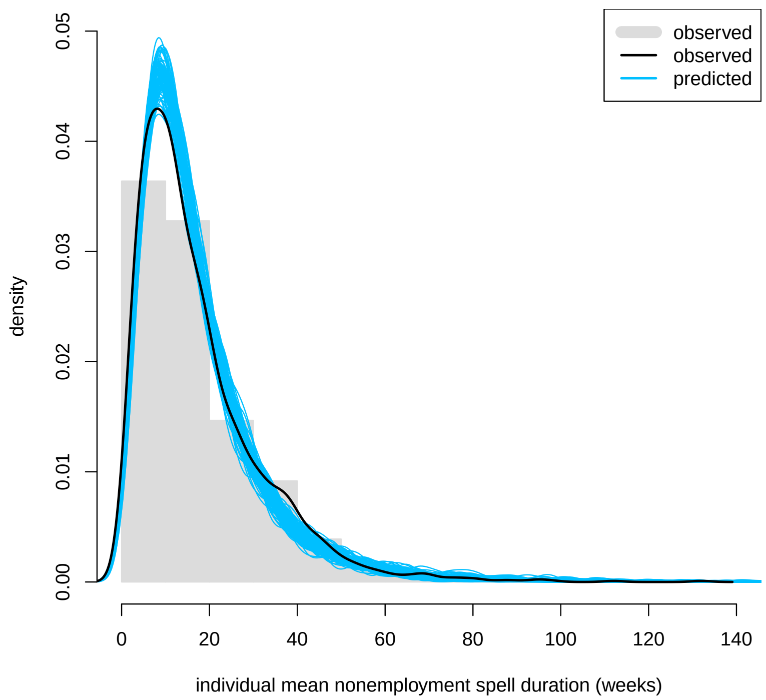
$$\widehat{nonemp}_i^k = \frac{1}{c_i} \sum_{j=1}^{n_i} \hat{d}_{ji}^k \tag{6}$$

The distribution of $\widehat{nonemp}_i^k$ is shown in Figure 5, which displays percentages for ease of exposition. It appears that the model puts more weight on smaller relative amounts of lifetime nonemployment than is the case in the data.

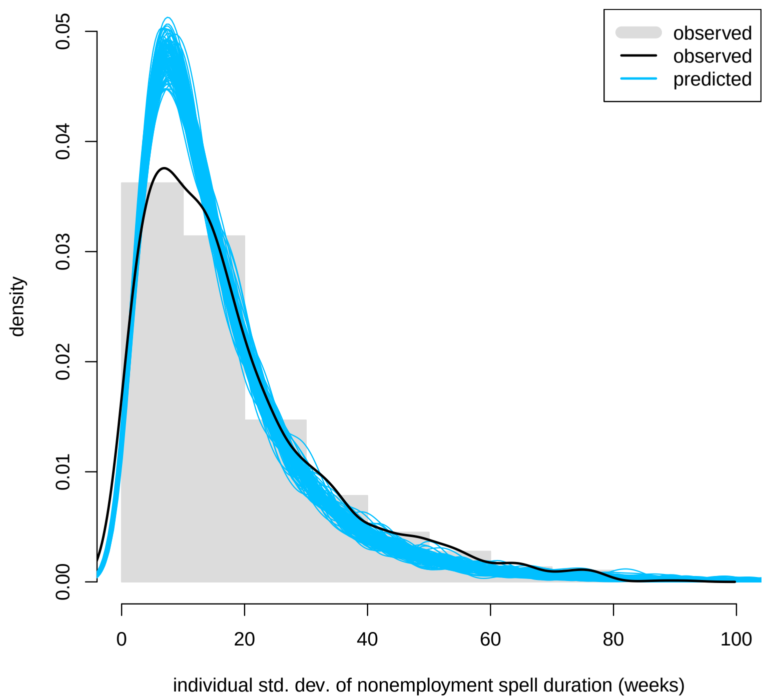
Since occupational decisions are of special interest to this thesis, it is worth asking how well the model matches the relation between the fraction of lifetime nonemployment experienced by an individual and how often this individual has changed occupations. I define two ways of measuring the number of times an individual has changed occupations. The first one is obtained by counting how often an individual found employment in an occupation in which he had no previous experience. I categorize individuals by the number of switches they experienced, denoted by l. Let N_l be the number of individuals with l occupation switches and S_l the set of individuals with l occupation switches. For each value of l and for each $k \in \{1, ..., 100\}$ I compute:

$$m\_\widehat{nonemp}_l^k = \frac{1}{N_l} \sum_{i \in S_l} \widehat{nonemp}_i^k \tag{7}$$

where $\widehat{nonemp}_i^k$ was defined in (6).



(a) mean



(b) standard deviation

Figure 4: Individual-specific mean and standard deviation of nonemployment spell duration

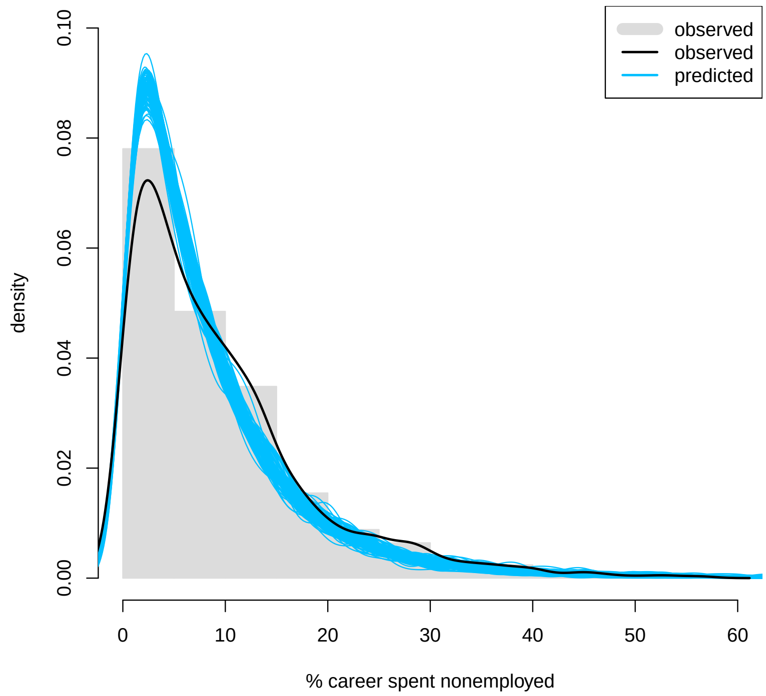
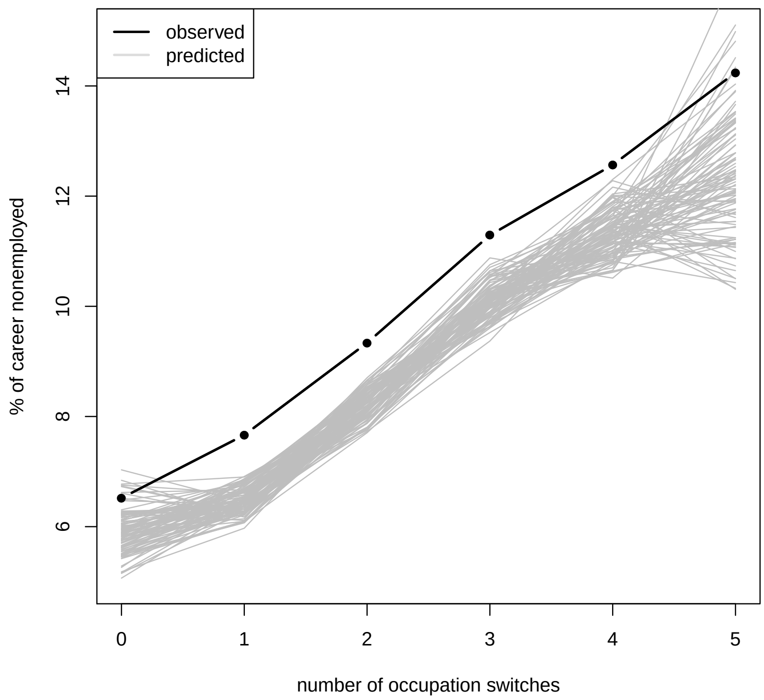


Figure 5: Percent of career spent nonemployed

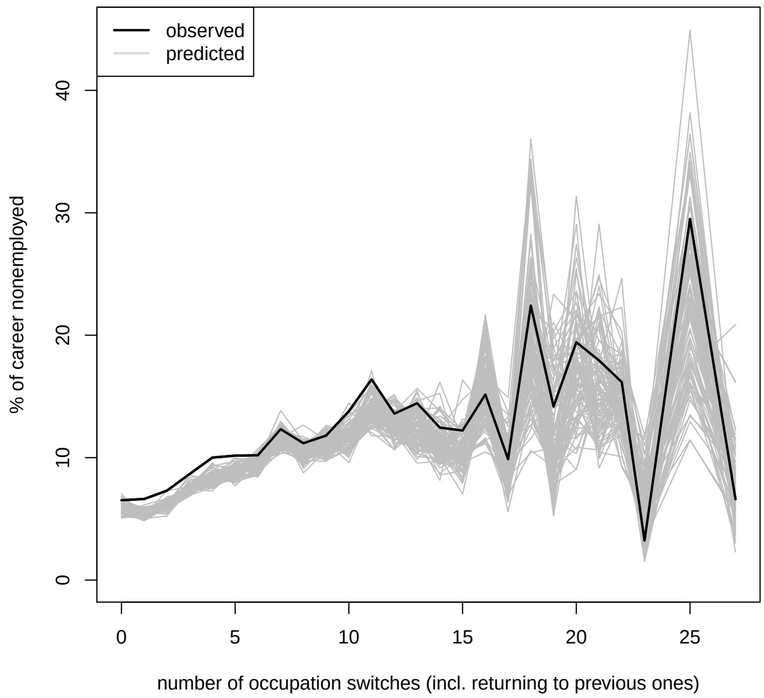
The black line in Figure 6a depicts the observed fraction of lifetime nonemployment by the number of occupation changes, which exhibits a clear increasing trend. Each grey line is the predicted fraction of lifetime nonemployment for a given simulation. The model matches qualitatively the observed positive relationship between the fraction of lifetime nonemployment and the frequency of transitions into completely new occupations. Quantitatively however, the predicted amounts of nonemployment lie persistently below the amount observed in the data.

Part of the answer lies in Figure 5, which depicts the observed and predicted distribution of lifetime nonemployment. As already mentioned, the upper tails are thicker in the actual data than in the simulations from the model. It is nevertheless remarkable that lifetime nonemployment is still underestimated even after splitting individuals into groups according to their occupational mobility. This points to the existence of different aspects, not captured by the controls included in the model, driving individuals in all occupational mobility groups to spend a longer total time without a job.

There are several aspects which could play a role in the discrepancy between the model and the data. First, the spells originating from individuals enrolled in school are usually long, and highly educated persons change occupations less



(a) new occupations



(b) all occupations

Figure 6: Percent of career spent nonemployed by number of occupation switches

often, as was seen in Table 3. It could be that the long education spells drive individuals' observed lifetime nonemployment upwards causing the mismatch between the model and the data. Furthermore, individual characteristics such as health and having children, which could influence labor market outcomes, are not controlled for in the model. The NLSY79 contains information on school enrollment, health, and children, so the analysis could be extended by accounting for these factors.

For robustness, I define a second measure for the number of occupation switches experienced by and individual. This measure counts how often the individual moves to a different occupation, irrespective of whether he has held the target occupation in the past or not. The average fraction of lifetime nonemployment is computed analogously to (7). The result is shown in Figure 6b. For this measure, the model does an overall better job at matching the corresponding amount of lifetime nonemployment observed in the data, but for few occupation changes it still slightly underestimates the fraction of one's career spent jobless.

7 Conclusion

This thesis has analyzed the relationship between occupational mobility and the distribution of nonemployment duration. The key feature of the present empirical model is that it takes into account all nonemployment spells experienced by an individual throughout his labor market career. An important finding is that the timing of the decision to change occupations matters when it comes to jobless spells duration. Those spells which immediately precede an occupation change take longer to exit from. On the other hand, spells beginning after one's first occupation change have shorter durations. This could indicate that changing occupations is associated with long-term advantages in reemployment opportunities, even if in the short run the spells separating an occupation change take longer.

Posterior predictive checks reveal a recurring feature of the empirical model used in this thesis. The model appears to underestimate the dispersion of nonemployment duration which is observed in the data. The within-individual standard deviation as well as the standard deviation of the pooled durations is higher in the data than the model would predict. Another quantity which is imperfectly matched by the model is the fraction of the labor market career spent jobless. This points to the presence of a high degree of individual heterogeneity, which is not captured by the observable characteristics presently controlled for in the model.

Finding the source of the dispersion in nonemployment durations can serve as a direction for future research. There is room for improving the present model by using readily available data from the NLSY79. School enrollment, health, and the age of one's children are two potentially relevant aspects in determining labor market outcomes and could help account for more of the variation in jobless duration. However, a more fundamental extension of the present analysis would design a mechanism which allows causal inferences to be made. One way this could be achieved is by finding appropriate instruments to deal with the endogeneity of occupation decisions to past labor market experiences, especially jobless episodes. Alternatively, one could develop a structural model where decisions are made by optimizing agents.

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A Stan output

```
Inference for Stan model: model.
4 chains, each with iter=1000; warmup=500; thin=1;
post-warmup draws per chain=500, total post-warmup draws=2000.

                   mean se_mean    sd   2.5%  97.5% n_eff  Rhat
mu               -3.211   0.002 0.059 -3.327 -3.099   631 1.001
sigma             0.510   0.001 0.016  0.479  0.540   610 1.006
beta_Z[1]         0.217   0.002 0.045  0.131  0.307   539 1.005
beta_X[1]         0.142   0.001 0.029  0.087  0.197  1312 1.003
beta_X[2]        -0.139   0.001 0.028 -0.194 -0.086  1418 0.999
beta_X[3]         0.694   0.001 0.026  0.640  0.743  1358 1.000
beta_X[4]         0.087   0.001 0.041  0.006  0.168   941 1.003
beta_X[5]         0.064   0.001 0.043 -0.019  0.145  1080 1.003
beta_X[6]         0.157   0.002 0.066  0.031  0.281  1220 1.001
beta_X[7]         0.117   0.001 0.044  0.030  0.200  1075 1.001
beta_X[8]         0.064   0.001 0.033  0.002  0.130   963 1.002
beta_X[9]         0.084   0.001 0.017  0.052  0.116   674 1.003
beta_X[10]        0.151   0.001 0.028  0.096  0.205  1242 0.999
beta_X[11]       -0.052   0.001 0.026 -0.103  0.000  1215 1.003
beta_X[12]       -0.353   0.001 0.036 -0.425 -0.283  1386 1.001
beta_X[13]       -0.341   0.001 0.049 -0.437 -0.247  2000 1.000
beta_X[14]        0.065   0.002 0.043 -0.021  0.150   758 0.999
beta_X[15]        0.078   0.002 0.038  0.001  0.153   584 1.001
beta_X[16]        0.114   0.002 0.042  0.029  0.193   720 1.002
beta_X[17]       -0.175   0.001 0.025 -0.226 -0.125  2000 1.001
log_lambda[10]   -2.499   0.007 0.299 -3.138 -1.924  2000 0.999
log_lambda[100]  -3.554   0.009 0.388 -4.340 -2.803  2000 0.999
log_lambda[1000] -3.233   0.006 0.290 -3.848 -2.706  2000 0.999

Samples were drawn using NUTS(diag_e) at Fri May 27 11:33:00 2016.
For each parameter, n_eff is a crude measure of effective sample size,
and Rhat is the potential scale reduction factor on split chains (at
convergence, Rhat=1).
```

Note: Only three fixed effect coefficients are shown for brevity, but convergence and sampling efficiency are as good for all other fixed effects coefficients.