Institut für Höhere Studien
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Continuing Education Center

MSc Economics

Unemployment In Austria: Job Losing and Job Finding

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

supervised by

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Affidavit

I, Stefan Girstmair

hereby declare

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

Unemployment In Austria: Job Losing and Job FInding

39 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 Austrian administrative data to analyze the evolution of the unemployment rate and the associated job losing and job finding probabilities. Following a recent paper by Hornstein (2012), the rates are split up between short- and long term unemployment to further identify movements in the Austrian labor market. I use a logistic regression model with seasonal dummy variables to estimate the transition probabilities between employment and unemployment. In alignment with Hornstein (2012), the results indicate that the job losing rate increases in recessions while the job finding rate decreases. Moreover, the job total finding probability has a downwards trend over the observed period. A further interesting result, following the literature, is the increase of long-term unemployed as a share of the overall unemployment pool during recessions.

1 Introduction

The labor market and the movement of individuals between its different states, i.e. employment, unemployment, and out of labor force, has always been a major research topic in economics. This thesis builds on Hornstein (2012) in the way that it investigates these movements and their probabilities of occurring. Contrary to Hornstein, who uses the survey based CPS dataset, here administrative data for the Austrian labor market is used. Hornstein bases his research on the influential paper by Shimer (2012), which accounts for the volatility of unemployment with a model of homogeneous unemployed and using short-term U.S. data. Hornstein (2012) on the other hand introduces a model of heterogeneous unemployed, in which unemployment spells with a duration of up to 26 weeks, or six months, are called short-term unemployment, and all unemployment spells longer than 26 weeks are long-term. I will stick to this definition of short- and long-term unemployment, even though in Austria the official definition is that people count as long-term unemployed if the unemployment spell lasts longer than one year.[1] In this thesis what Hornstein calls the unemployment exit rate (or probability) I call the job finding rate, meaning that people must be unemployed at any given time to be able to search for a new job and therefore exit unemployment. The classification into short- and long-term job finding rates will follows the duration of the unemployment spell of these individuals. Again the threshold between short- and long-term job finding is 26 weeks. Similarly, what Hornstein calls the unemployment entry probability I will call job losing rate. Here people must be in an employment spell, lose their job and hence enter the unemployment pool. For the job losing I only calculate the total probability for people to enter the unemployment pool and then the probability for those who have already entered unemployment to become long-term, longer than 26 weeks, unemployed. Hornstein (2012) finds that variations in the exit rate from unemployment can quantitatively explain the comovement between the unemployment rate and the share of long-term unemployed. However, it cannot account quantitatively for differences in the overall duration distribution of the unemployed. This comes from the observed negative duration dependence of the unemployed, revealing that the exit rates decline with the duration of the unemployment spell. Machin and Manning (1999) pro-

[1] http://www.ams.at/ueber-ams/medien/arbeitsmarktdaten/fachbegriffe

pose two explanations for the aforementioned observed negative duration dependence. First, the true duration dependence which indicates a decreasing exit probability with the length of the unemployment, i.e. a transition from short- to long-term unemployment. Second, unobserved heterogeneity, meaning, unemployed are already different in terms of the job finding rate at the time they enter the unemployment pool. Personal rates, therefore, are not changing but the overall exit rate changes over time due to the composition of all unemployed. These definitions are not mutually exclusive. This is important, as a major concern is the extent with which duration dependence shows differences in characteristics of unemployed with different spell lengths or if it applies in the same way to unemployed with the same characteristics. Hence it is not really easy to identify whether true duration dependence or unobserved heterogeneity causes the effect without making strong assumptions about the functional form of the baseline hazard and the distribution of unobserved heterogeneity (Machin and Manning (1999)). Hornstein (2012) finds that the evolution of unemployment duration can be well described by unobserved heterogeneity where short-term unemployed are five times as likely to exit unemployment as long-term unemployed. This follows because the transition from short- to long-term is very small compared to short-term to unemployment (short-term job finding).
The purpose of this thesis is to express the job finding and job losing rates for Austria using the Austrian Social Security Database, using the 15 years between 2000 and 2014. The many different spell types are aggregated to just three, namely Employed, Unemployed, and Rest. In the subsample I use, there are approximately 2 million spells from 200 000 individuals. To process the data I work with the programming language Julia. The econometric model applied to calculate the job finding and job losing probabilities is a logistic regression model with the independent variables duration, gender, age, nationality, and month of the spell. Additionally, a monthly dummy variable model is imposed to derive yearly rates without seasonality.

Similar to Hornstein (2012) I find that most (91%) of the unemployment spells are of short-term (less than 26 weeks). The remaining 9% are long-term, meaning just one tenth are longer than 26 weeks but the mean share of long-term unemployed in the total unemployment rate is on average 44%. This share also increases in recessions, compared to the share of short-term unemployed. Calculating the probabilities with the logistic regression model I find that for job losing the duration of the unemployment spell increases the probability of entering unemployment, while gender (being female), nationality (being non Austrian citizen) and age (being older) reduces it. For the job finding probability all coefficients decrease this rate, therefore being female, Austrian, older and longer unemployed makes it less likely to enter employment again. Hornstein (2012) shows that for the U.S. long-term unemployment entries have a share of 10 to 20 percent, whereas I calculate an average share of 7% for Austria. For the 15 years covered in this thesis, I show that the share of long-term entries into unemployment increases in recessions which explains the increase of long-term unemployed in the share of total unemployment during these periods. The short- and long-term unemployment entry shares are derived by assuming unobserved heterogeneity, this is not the case for the job losing rate. The total as well as the long-term job losing probability show a comovement with the unemployment rate and hence increase in times of recessions and decrease otherwise. The long-term job losing probability gives the likelihood for those people that already lost their job and entered unemployment to become long-term unemployed (longer than 26 weeks). Total and short-term job finding decrease in recessions and show a negative trend between 2000 and 2014. This could have multiple causes and implications of which one would be if this trend is not offset by an according negative trend in the job losing rate the unemployment rate must show an increasing trend. I show that this is the case for Austria. Therefore, I demonstrate that job finding has a major influence on the unemployment rate which is one of the main findings from Hornstein (2012) and Shimer (2012).

The present thesis is structured as follows: In section 2, I start by describing the ASSD dataset and how I had to process this raw data in order to be able to derive the unemployment rate, job finding, and job losing probabilities. In section 3, I introduce the reduced-form model which is used to calculate the job finding and job losing rates. Section 4 demonstrates the results and part 5 concludes.

2 Data

In this section, I explain the dataset used for the present thesis. Further, the processing and manipulations on that given dataset, which were needed in order to calculate economically meaningful probabilities, are explained. The dataset used is the Austrian Social Security Database (ASSD) provided by the Main Association of Austrian Social Security Institutions (Hauptverband der Sozialversicherungsträger).

The time period this dataset covers starts on January 1, 1997 and ends on September 30, 2015. Because of this time constraint my calculations focus on the years from 2000 until 2014. Consequently 15 years are covered. In this period the dataset matches firm-worker data of all people in Austria having some form of social insurance. For each individual in the dataset the whole labor market history is recorded, meaning that all changes, plus time intervals, and employers for all people in the sample are contained. For instance, if an individual is unemployed for two years and then finds a job for just three weeks, and gets an education after that, it is shown in this dataset on daily rates. The main advantage of using the ASSD dataset is that it does not just offer survey information of a small number of individuals, but observes all insured people in Austria. Therefore, when using the ASSD for observations of the Austrian labor market reliable outcomes can be expected. One drawback, which I will explain in detail in the next section, is the problem with overlaps in the different spells. A majority of the given spells have overlaps. This makes calculations harder, but can be solved.

According to Zweimüller et al. (2009) in the decentralized Austrian social security system there are 23 insurers offering health, accident and pension insurance. Some of them provide both or all three of these insurances. The Main Association of Austrian Social Security Institutions collects the data of those 23 insurance providers and collects them in the ASSD with more than 200 types of spells.

The ASSD, being an administrative dataset, has an advantage over other datasets, such as unemployment surveys or freely available unemployment data from organizations like Eurostat and FRED. through the structure and organization it is, after some coding, much finer and I think better to calculate interesting labor market rates and probabilities. Using survey based datasets, like the CPS, which Hornstein (2012) and Shimer (2012), do there is no chance in getting to the level of precision an administrative dataset like the ASSD can give you from day on day observations. Moreover, the pure sample size is one of the major benefits of the ASSD dataset which most non-administrative datasets cannot offer.

In addition to the ASSD dataset I use openly accessible FRED [2] data, putting my calculations into perspective and introducing a level of comparison into this thesis. To achieve this, I process recession and unemployment data. The first will be included in all plots to get an idea of the Austrian economy and its developments between 2000 and 2014 (OECD based Recession Indicators for Austria from the Period following the Peak through the Trough (AUTRECD)). The latter is used in Figures 1 and 5 to compare my calculations using the ASSD dataset and accessible data from FRED. The definition of the recession data on the FRED homepage reads as follows: it is composed of dummy variables which take on the value 1 in a recession period and 0 in an expansionary period. Both start on the first day of the respective time interval and end on the last.

This recession data helps interpreting different results of this thesis such as the job losing probability calculated in section 4.3. Here, the intuitive interpretation would be that this rate increases in times of an economic recession. As can be seen from the definition above, the recession data is based on daily observations. However, in this thesis yearly data from this series is used, therefore there cannot be a prefect fit of the original series to the plots shown here. But it should be used as a guidance and make interpretation easier. The unemployment rate is used to clarify the calculated rate from my data to check its validity (section 4.1). Here, the seasonally adjusted registered unemployment rate for Austria in percent is used. Again, but here from monthly rates, this thesis uses yearly rates and thus will not perform perfectly. The beginning of each year is used from the recession and unemployment data. This will introduce a small but negligible bias for interpretations.

[2] https://fred.stlouisfed.org/series/AUTRECD

Figure 1:

FRED: Unemployment Rate With Recession Indicator

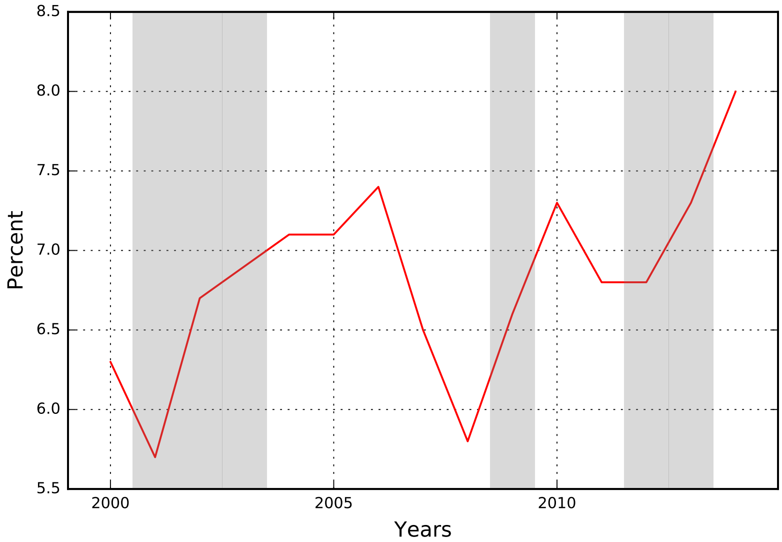


Figure 1 shows three recessions in Austria between 2000 and 2014. One period is from December 2000 until October 2003. This recession is the longest in Austria in the time observed. The second recession lasted from April 2008 to August 2009. And the last recession from June 2011 to March 2013.

2.1 Data Preparation

This thesis uses a randomized and representative subsample[3] of the full ASSD database in order to keep processing time short. To work with this data I use the programming language Julia. This subset has the size of 204 401 different individuals which comprise a total of 2 088 392 labor market spells. This number arises after converting the different spells to new ones which will be explained later. Before aggregating and processing the data there are 3 068 620 spells. Therefore, the benefit of sample size is still given.

This subsample provides me with two main individual based information sets: first, with person spell information like gender, year of birth, year of death, nationality and the interval of observation; second, with the labor market specific spells. Of the latter, there are 30 types in this subsample, from over two hundred in the whole ASSD

[3] I would like to thank Tamás Papp for providing me with this subsample

database.[4] Out of those 204 401 individuals, there are 103 089 men and 101 312 women. Hence, the share of men and women is almost equal with slightly more men. The sample includes 122 035 Austrian citizens and 82 366 individuals of different nationalities. Table 5 shows the shares and numbers after aggregation. In order to get from this raw data to an economically meaningful classification, I create three different labor market types: employed, unemployed, and rest (out of labor force).

Table 1: Shares of New Groups

	Number of spells before aggregation	Shares before aggregation
Employed	1 258 792	0.41
Unemployed	1 072 201	0.35
Rest	737 627	0.24
	Number of spells after aggregation	Shares after aggregation
Employed	990 909	0.47
Unemployed	585 351	0.28
Rest	512 132	0.25

Employed: Employee, Minor employment, Other employment, Self employment, Service Contract (990 909 spells, 1 258 792 before aggregation)

[4] Zweimüller et al. (2009) provide a full list of those spells plus the classification of nationalities and propose a way of regrouping

Table 2: Employed

	Number of spells	Shares
Employee	880 919	0.70
Minor employed	318 876	0.25
Self employment	32 821	0.03
Serviced contract	21 417	0.02
Other employment	4 759	0.004

Unemployed: Unemployed mixed, Unemployed no benefits (585 351 spells, 1 072 201 before aggregation)

Table 3: Unemployed

	Number of spells	Shares
Unemployed mixed	525 559	0.49
Unemployed no benefits	546 642	0.51

Rest: Apprenticeship, Civil servant, Child care allowance active, Child care allowance inactive, Parental leave active, Parental leave inactive, Maternity active, Maternity inactive, Education, Farmer, Military, No data, Other insured nonemployed, Other insured time, Rehabilitation, Retired, Spell dict, Transition allowance, DLU, FBU, Birth, Data gap, Death (512 132 spells, 737 627 before aggregation)

Table 4: Rest

	Number of spells	Shares
Other insured nonemployed	296 223	0.40
Other insured time	161 898	0.22
Retired	110 792	0.15
Civil servant	32 489	0.05
Apprenticeship	25 088	0.03
Military	22 279	0.03
Maternity active	19 820	0.026
Child care allowance active	15 624	0.021
Child care allowance inactive	11 277	0.015
Farmer	10 923	0.014
Education	8 399	0.011
Maternity inactive	7 052	0.009
Parental leave Inactive	5 343	0.007
Parental leave active	5 272	0.007
Transition Aallowance	2 138	0.002
Rehabilitation	1 210	0.001

One major problem with the aggregated groups is that there are plenty of spell overlaps in the personal history of individuals, both for same and different spell types. After combining the data into three groups, a related problem could an overlap between an employment spell and an unemployment spell which makes calculation impossible. Therefore, it is necessary to introduce a hierarchy: when an overlapping problem in the data occurs, the time of the overlap will be counted as an employment spell. This is an important step as one of the main goals of this thesis is to calculate the transition probabilities between employment and unemployment. The main goal of this thesis is to do research on movements between employment and unemployment. Thus if there still are overlaps after cleaning the data, the employment spell dominates the unemployment and rest spells. The rest (meaning the out of labor force group) is of not interest right now and therefore overlaps between unemployment and rest are of no concern.[5]

There were not just overlaps between different spell types, but mostly between the same spell types. As shown in Table 3, the number of the two separate unemployment spells were pretty much equal with 525 559 and 546 642. But after aggregating those that were overlapping, the new unemployed group includes 585 351 spells, indicating that almost all of them did overlap. There were similar but not so dramatic results for employed and rest (Tables 2 and 4). The spell types with no spells in the subsample are not included in Table 4. Therefore, No data, Spell dict, DLU, FBU, Birth, Data gap, and Death have no spells and are of no interest for this thesis.

Thus, cleaning and aggregating the data results in the earlier mentioned numbers for the three remaining spells: Employed (990 909), Unemployed (585 351), and Rest (512 132). The transition of theses numbers is shown in Table 1. My focus lies on unemployment and specifically the difference between short-term and long-term unemployment. Consequently, it is important to get an idea of the distribution of the unemployment spells that are in the sample. Once more, the threshold for long-term is 26 weeks or 6 months, following Hornstein (2012).

Figure 2:

Duration Unemployment Up To Three Years

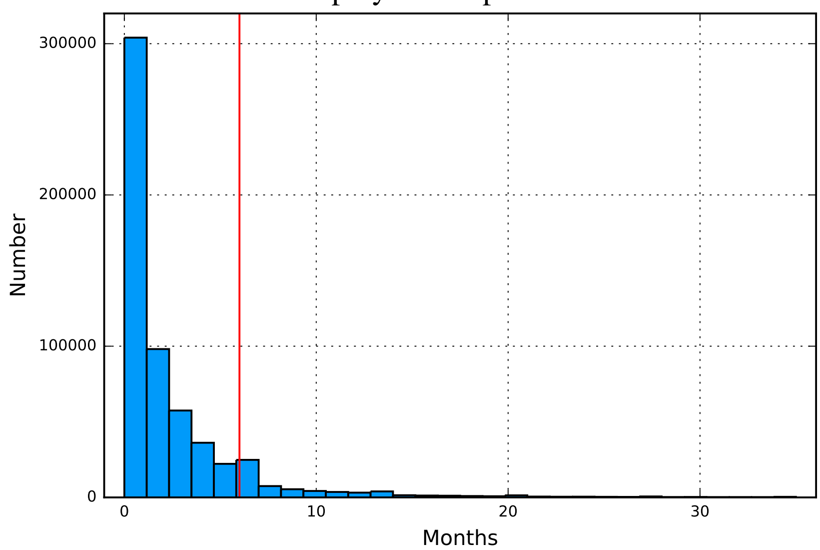


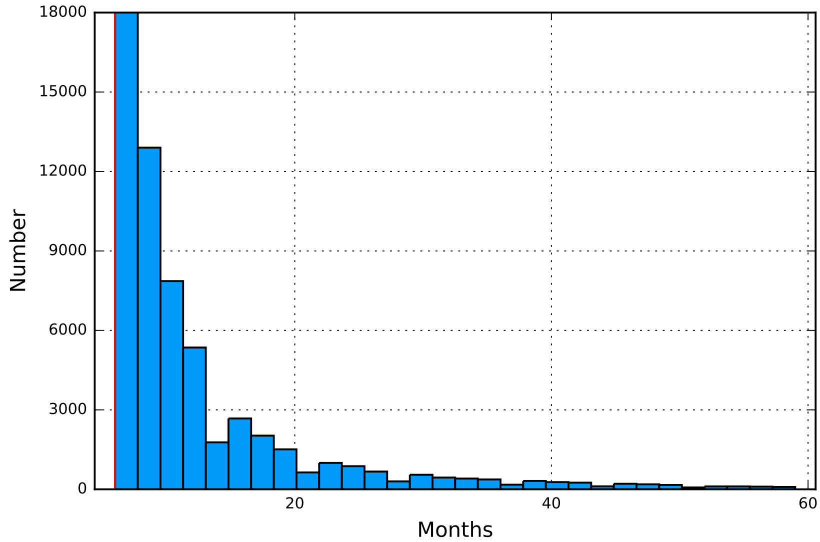
Figure 2 shows this distribution of the unemployment duration from zero to 36

[5]This could be part of future research and refinement of the subsample

months. The red line displays the threshold for long-term unemployment. The finding that, in general, unemployment is of short duration, goes hand in hand with the literature. Out of the 585 351 total unemployment spells 532 867 are of short duration, i.e. less than 26 weeks. This makes 91% of all unemployment spells short-term. In contrast, there are 52 484 long-term spells adding up to 9% of all unemployment spells. Figure 3 shows that the number of spells longer than 6 months becomes very small, compared to the number of short-term spells, with just a couple of thousand and or even hundred spells.

Figure 3:

Duration Unemployment Long-Term To 60 Months



Hornstein (2012) calculates an average duration for short term unemployed of less than one month, whereas in my sample I get a mean duration of 1.6 months which means that in Austria people are unemployed for longer compared to the U.S.. This was to be expected as unemployment in the U.S. is known to be shorter compared to Europe (Kuhn and Jung (2012)). The average duration of long-term unemployment in Austria is around 15 months and thus much longer compared to 7 months in the U.S..

Calculating the unemployment rate from the data is a purely algebraic exercise. The calculated unemployment rate can be seen in Figure 5, where I compare it to the unemployment rate from FRED. As the job finding and job losing probabilities are calculated for years, the unemployment rate will also be calculated on yearly rates. I check through all spells to see if an individual is unemployed in a specific year and then sum all spells up and divide by all individuals in this year.

$$\text{unemploymnet rate}_i = \frac{\text{Unemployed}_i}{\text{Employed}_i + \text{Unemployed}_i + \text{Rest}_i} \text{ where i are the years 2000-2014}$$

This is possible as I am working with administrative data and since all people having some kind of unemployment insurance through the state, either with or without benefits, are included.

The dependent variable needed to calculate the job finding probability is derived by for-looping through all spells, which became possible by cleaning the data. In a first step, I check if someone is unemployed at a specific date. This could be any day in the whole sample as it is on daily rates, I use the first day of every month. In the second step, for those who are unemployed, and a second date, one month later, I can see which people have left unemployment and moved into employment. This procedure yields a vector with 0s for all individuals who did not find a job and 1s for all who did. For the short-term rate, only those who were unemployed for up to six months are considered. For the long-term, only those with an unemployment duration of at least 26 weeks count. The calculated vector for the dependent variable will be used to calculate the job finding probability with the logistic regression model explained in the following section. To get the predicted variable for the job losing probability, an analogous method is used. In a first step, all individuals in the sample who are employed in a given month are collected. Next, it is examined who lost their job and thus is unemployed at a different date in the sample period. Once more, the second date is one month later and the output is a vector with 0s for people not losing their job and 1s for those who did and are unemployed at the second date. In this case, to follow the conceptual negative duration dependence, i.e. either true duration dependence or unobserved heterogeneity, the long-term rate is calculated differently. For each month, all who already lost their job are taken into account. From there, it is checked which of those were still unemployed six months later with no employment spells in-between. Thus, a new vector of 0s and 1s is obtained, where 1 refers to people still unemployed after six months, and 0 for not unemployed. This vector is needed for a new logistic regression to receive the probability for already unemployed people to become long-term unemployed.

3 Model

In this chapter, I explain which model is used to measure the job finding and job losing probabilities. Furthermore, I calculate the unemployment rate to compare the validity of my findings to a generally available dataset (FRED) as explained in section 2. Moreover, I use a seasonal dummy variable model in order to calculate yearly probabilities based on monthly data without seasonality. This is necessary as the data is not seasonally adjusted and the goal of this thesis is to clarify the movement of different labor market variables such as the job finding and job losing rates.

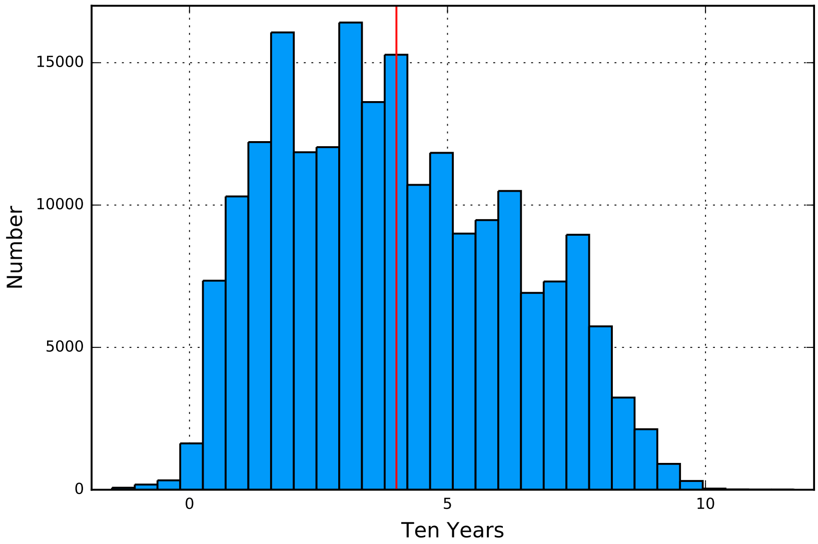
I derive the probabilities by using a logistic regression model. As my variables of interest are either 0s or 1s, explained in the previous section, this is a suitable approach. For the job finding probability my dependent variable takes on the value 1 if the person found a job in a given month, conditional on being unemployed, and 0 otherwise. For the job losing probability it takes on 1 if a person lost her job, conditional on being employed, and 0 otherwise. My predictors are:

Duration: Duration of the unemployment spell in months. This holds for people leaving unemployment but also for those entering it, i.e. the influence of the length of the coming unemployment spell for individuals losing their job is taken into account. Figures 2 and 3 show the distribution of the unemployment spells in the sample.

Gender: Gender of the individual is a binary variable with 1 for female and 0 for male. Table 5 shows the details fo the gender distribution.

Age: The age of the individual is given by $\frac{Years}{10}$ for easier interpretation of its effect, e.g. a 45-year-old person is accounted for as 4.5. Figure 4 shows the age distribution for the sample in2000 the starting year of observation.

Figure 4: Age Distribution



Nationality: Zweimüller et al. (2009) p.43 give a full list of the nationalities. For my research, I divide all individuals into two groups, Austrian citizens (1) and non-Austrian citizens (0). This is done to receive measurable sample sizes of these two classes. Table 5 shows the numbers for this sample.

Table 5: Gender and Nationanlity

	Number of Spells	Shares
Gender:		
Men	103 089	0.504
Women	101 312	0.496
Nationality:		
Austrian Citizens	122 035	0.597
Non Austrian Citizens	82 366	0.403

MonthIn: This variable is the number of the month in which the regression was derived. As explained in section 2.1, the dependent variable is always calculated for one specific month. MonthIn accounts for this and gives a vector with numbers of the month. This is important for creating the seasonal dummy variables. For example, for the regression output in April this variable will make a vector with just fours.

Combining these predictors yields the logistic model:

$$Pr(Y_j = 1) = logit^{-1}(\alpha + \gamma_1 Duration_j + \gamma_2 Age_j + \gamma_3 Gender_j + \gamma_4 Nationality_j) = \frac{exp(\alpha+\gamma_1 Duration_j+\gamma_2 Age_j+\gamma_3 Gender_j+\gamma_4 Nationality_j)}{1+exp(\alpha+\gamma_1 Duration_j+\gamma_2 Age_j+\gamma_3 Gender_j+\gamma_4 Nationality_j)}$$

Where Y either is the job finding or job losing binary variable for every observation that can be considered at each time of estimation, i.e. someone has to be unemployed in order to find a job. Following Gelman and Hill (2006), the next step is to center the input variables around their mean. This will decrease the calculations necessary to interpret the coefficients after doing the regression. Without centering the inputs, interpreting a coefficient like duration would have to assume all other coefficients at zero, including the variable age which does not make sense as age cannot be zero in the sample. Therefore, after centering, coefficients will be interpreted at their data averages. The centered inputs follow this scheme: $c.Duration_j = Duration_j - mean(Duration)$. I do not fully scale the variables, which would be done by including the standard deviation into the scaling too, because I still want to be able to interpret them on their original scales like months for duration and 10 years for age (Gelman and Hill (2006) p.93). The binary variables have also been centered. This yields their marginal contributions as the centered variables show the proportion of 1s in the sample, i.e. the proportion of women and Austrians in this thesis.

The variable MonthIn is not centered as it is used to derive a deterministic seasonal dummy model. This simple econometric model has been used many times, e.g. by Thomas and Wallis (1971), Barsky and Miron (1989), and is easily explained by Wooldridge (2015). In the present case, the seasonal frequency is 12 for monthly dummy variables. In each period t exactly one of those dummy variables is equal to 1 and all other are 0.

$$S_t = \begin{cases} \eta_1, & \text{if } t = January \\ . & \\ . & \\ . & \\ \eta_{12}, & \text{if } t = December \end{cases}$$

$=\sum_{i=1}^{12} \eta_i D_{it}$

It is necessary to exclude one of the monthly dummy variables in order to keep the intercept and not have a collinearity problem. Hence, I can write the seasonal model, for now omitting the other explanatory variables, as $S_t = \alpha + \sum_{i=1}^{s-1} \beta_i D_{it}$, where the intercept $\alpha = \eta_s$ is the period which was not included. And the other coefficients $\beta_i = \eta_i - \eta_s$ can be interpreted as the difference between the seasonal component and the omitted period.[6] Combining the logistic regression model with the seasonal dummy variable model yields the final regression model used in this thesis, where j are the observed individuals and t the months of the month the observation:

$$Pr(Y_j = 1) =$$

$$logit^{-1}(\alpha + \gamma_1 Duration_j + \gamma_2 Age_j + \gamma_3 Gender_j + \gamma_4 Nationality_j + \sum_{i=1}^{s-1} \beta_i D_{it}) =$$
$$\frac{exp(\alpha + \gamma_1 Duration_j + \gamma_2 Age_j + \gamma_3 Gender_j + \gamma_4 Nationality_j + \sum_{i=1}^{s-1} \beta_i D_{it})}{1 + exp(\alpha + \gamma_1 Duration_j + \gamma_2 Age_j + \gamma_3 Gender_j + \gamma_4 Nationality_j + \sum_{i=1}^{s-1} \beta_i D_{it})}$$

The total job finding rate is derived with this logistic regression model by taking all unemployed individuals in every observed period into account. This procedure can be split up by the duration of the unemployment spell in order to receive either the short- or the long-term job finding probability. The total job losing probability is calculated analogously by accounting for all employed people in the period to get the likelihood of switching into unemployment. To not make any conceptual mistakes by either only considering true duration dependence or unobserved heterogeneity for the

[6] http://www.ssc.wisc.edu/ bhansen/390/390Lecture14.pdf

long-term job losing probability, I only calculate the probability for individuals who just entered the unemployment pool to become long-term unemployed. In order to better understand the data in the next section I assume unobserved heterogeneity, i.e. that unemployed already differ in their job finding rates when they enter unemployment (Machin and Manning (1999)). This is possible because of the administrative dataset used and the fact that it is observable from when someone enters unemployment how long the spell will be. For this short- and long-term lob losing rates plus their shares are calculated.

Now I display the unemployment rate calculated from the data to show its validity (Figure 5). Comparing to data openly accessible, I find that the subsample used produces quite a good representation with the unemployment rate varying in level but not in movement. As there are quite a few different international definitions of the unemployment rate, which all differ in the level, this is negligible for this thesis (Sorrentino (2000)). Here, the unemployment rate is calculated by dividing the number of unemployed by the number of all other people in the economy for every year from 2000 to 2014.

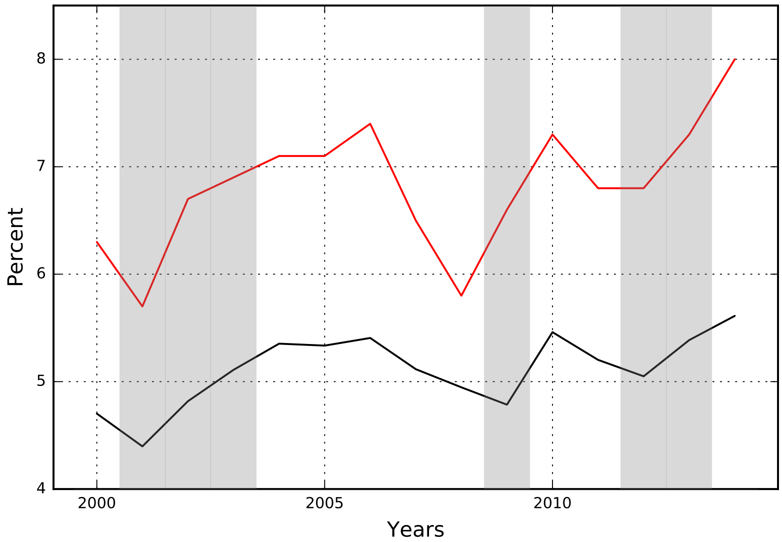
$$\text{unemployment rate for all people} = \frac{\text{Unemployed}}{\text{Employed}+\text{Unemployed}+\text{Rest}}$$

I also derived the rate by dividing by the labor force only (employed plus unemployed), which results in the same evolution but a much higher unemployment rate, around 10% (Figure 17).

$$\text{unemployment rate for the labor force} = \frac{\text{Unemployed}}{\text{Employed}+\text{Unemployed}}$$

Figure 5:

Calculated Unmeployment Rate (black) vs. FRED Unemployment Rate (red)



4 Results

In this section I present my results and put them in perspective by comparing to the findings of Hornstein (2012). The first part consists of the analysis of the unemployment rate and its partition into short-term (less than 26 weeks) and long-term rate. Additionally, the shares of those rates over the sample period as well as the comovement of the unemployment rate and the share of long term unemployed is examined. In the second part I show one of the regression outputs for the job finding rate and one for the job losing rate and explain how it can be interpreted based on the model developed in chapter 3. Finally, the job losing and job finding rates are shown. There, emphasis is put again on the difference in the evolution of long-term versus short-term rate.

4.1 Unemployment

Figures 6 and 7 show that the short- and long-term unemployment rates follow a similar path to the total calculated rate from Figure 5. Both show an upwards trend over the sample period with their highest values in the last recorded year. Splitting this total rate into short- and long-term unemployment shares (Figures 8 and 9), it becomes clear that the share of long-term unemployed increases dramatically in every recession while the share of short-term unemployed decreases. This counter movement is not surprising

Figure 6:

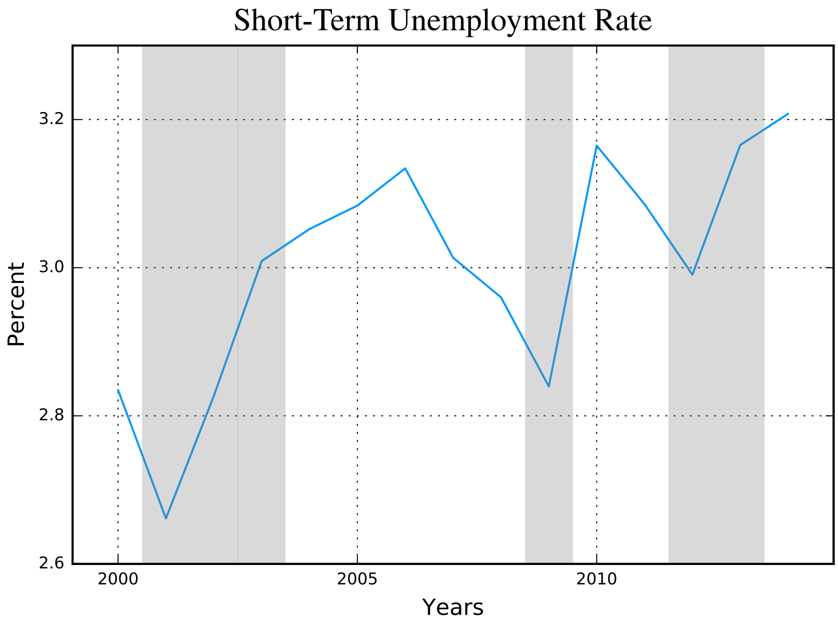


Figure 7:

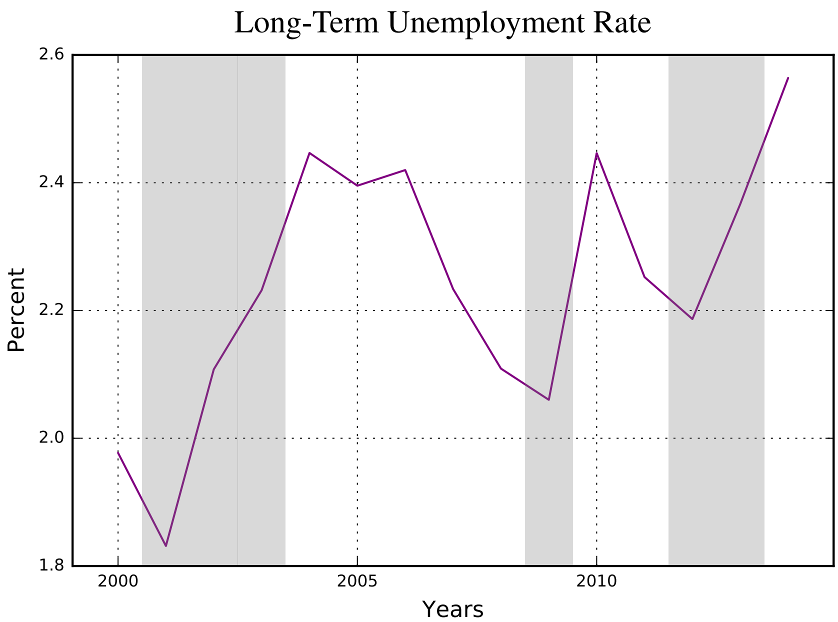


Figure 8:

Share Of Short-Term Unemployed

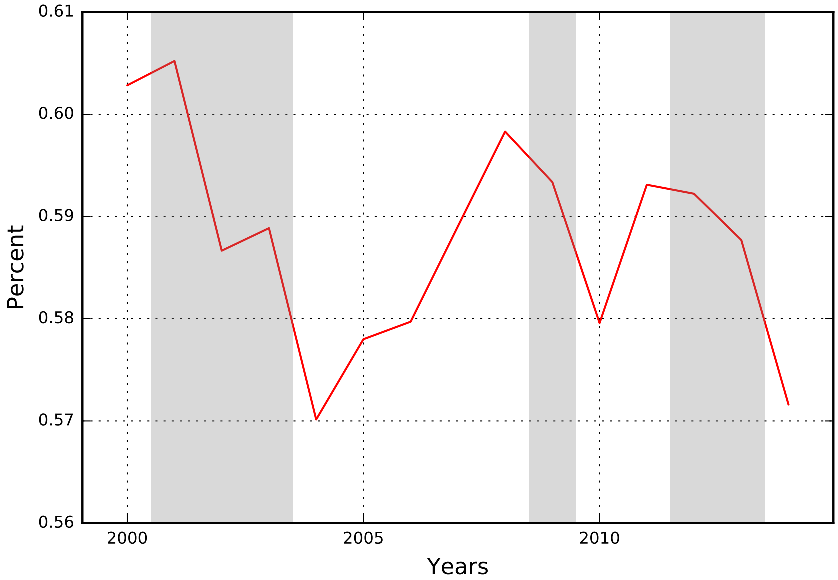
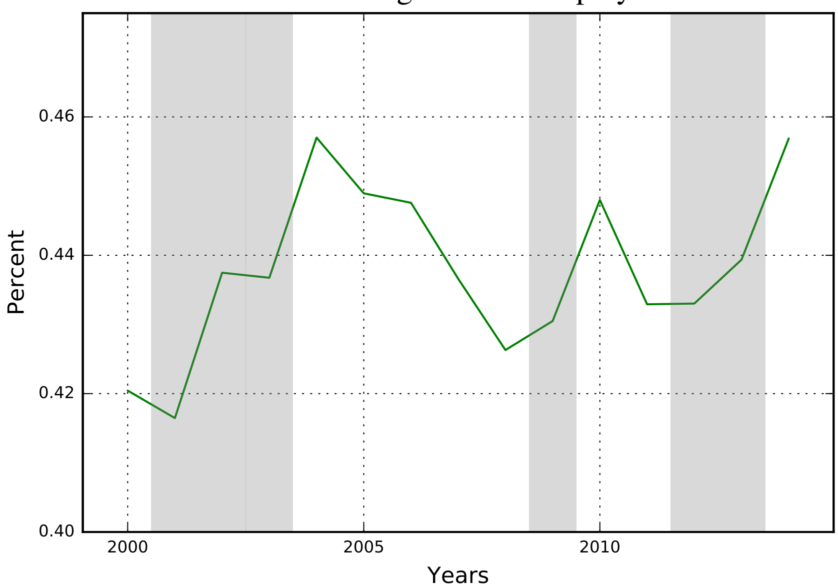


Figure 9:

Share Of Long-Term Unemployed



as those two combined must amount to the total unemployment rate.

The shares are defined and calculated as follows:

$$\text{Share of short-term unemployed} = \frac{\text{Unemployment Spells} \leqslant 26\ \text{Weeks}}{\text{All Unemployment Spells}}$$

$$\text{Share of long-term unemployed} = \frac{\text{Unemployment Spells} > 26\ \text{Weeks}}{\text{All Unemployment Spells}}$$

Hornstein (2012) and many others come to the same conclusion: in a time of recession, the share of long-term unemployed increases and decreases in ‘normal’ times, which indicates a comovement with the unemployment rate. Consequently long-term shares act countercyclical and short-term shares, therefore, procyclical. In section 2, I show that long-term unemployment accounts for only 9% of all unemployment spells. Long-term unemployed have such a big share in total unemployment because it is weighted by duration. For example, during the recession in the early 2000s, long-term unemployed had a share of almost 46% of the unemployment rate. Over the whole sample period (2000-2014), the long-term unemployed have a mean share of approximately 44%, while the short-term unemployes have a mean share of 59%. Hornstein (2012) finds that this correlation does not necessarily imply that the long-term unemployed are different from the rest of the unemployed. Even when assuming that all unemployed are identical in their chances of leaving unemployment, the unemployment rate and the share of long-term unemployed will be positively correlated. Negative duration dependence is observed, which means that job finding rates decline for longer unemployment spells. Hence the share of unemployment changes during recessions as more individuals with longer lasting spells enter the unemployment pool.

4.2 Regression Output

Below, I show the logistic regression output for the job losing and job finding probabilities for the year 2000 and explain how they can be interpreted (Tables 6 and 7). Here, the total probabilities are calculated and their predicted probability for every year will be graphed in the next section. Starting with the job losing probability, the **constant** can be read as follows (when all other variables are at their data averages):

Pr(Job-Losing) = logit^{-1}(-4.32599) = 0.0130 = 1.3% in January 2000

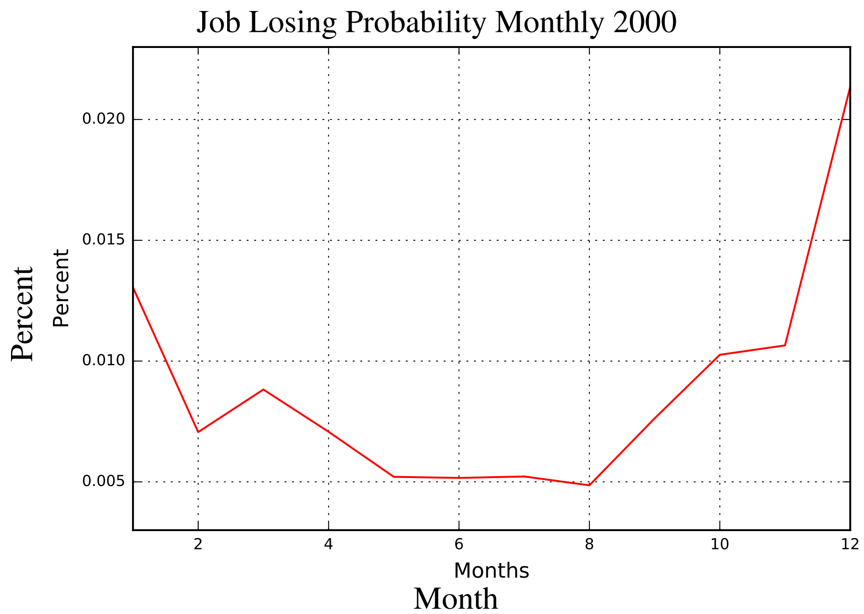
This is due to the fact that the influence of the omitted months is captured in the intercept. Having centered the data, the 'divided by 4 rule' (Gelman and Hill (2006) p.82) can be used to quickly interpret the coefficients in terms of probabilistic changes. This is due to the fact that the logistic curve is steepest at the center where $\alpha + \beta x = 0$ and logit $^{-1}(\alpha + \beta x) = 0.5$. The slope of the logistic function is maximized at this point attaining the value $\beta e^0/(1 + e^0)^2 = \beta/4$. Hence, $\beta/4$ is the maximal difference in Pr(y=1), which corresponds to a unit difference in x. Therefore, it can be used as a rule of convenience to receive an upper bound of the predicted difference, which is best approximated at the center of the logistic curve. Thus, centering introduces this rule.

Coefficient for Duration: This is the coefficient for duration of the unemployment spell on the logistic scale if all other variables are at their mean values. To get this in a probabilistic manner, dividing by 4 yields: $\frac{0.0149}{4}$ = 0.003725 = 0.37$\%$. Hence, for all other variables at their averages, the longer someone will be unemployed after losing the job will increase the probability of losing it by 0.37$\%$. The time unit used here is months, hence for every month the unemployment spell will last longer after the job loss the probability of losing the job increases by 0.37$\%$.

Coefficient for Age: This is the coefficient value for age of the people in the sample when all other variables are at their averages. On the probability scale this yields by the divided by 4 rule $\frac{-0.2555}{4}$ = -0.063875 = -6.39$\%$, that each ten years in age lead to a negative difference in the probability of losing the job, and transitioning into the unemployment pool, by -6.4$\%$. Meaning that older people tend to lose their job less likely.

Coefficient for Gender: The coefficient for the binary variable gender will bring a positive difference to the probability of losing a job ($\frac{-0.3149}{4}$ = -0.078725 = -7.8$\%$) (all other variables at their sample averages). The negative sign indicates that women, in general, lose their job less likely. This does not say anything about the employment of women compared to men, just that women, when in a job, lose it with a lower probability.

Figure 10:



Coefficient for Nationality: The coefficient for nationality has a negative sign for the year 2000. Or, in other words, non-Austrian citizens have a higher risk of losing their jobs. The specific number for 2000 is $\frac{-0.2385}{4}$ = -0.059625 = -5.9$\%$. Once more, this yields the proportion and marginal effect of Austrians in the sample.

Coefficients for Months: As explained in section 3, the interpretation for the monthly dummy coefficients is $\beta_i = \eta_i - \eta_s$, where η_s is the intercept of the regression. Hence, the other 11 dummy variables can also be read on the logistic scale, when all other variables are at their data averages. Figure 10 shows the evolution of the job losing probability in the different months of the year 2000. Clearly, the job losing probability is lowest in summer and increases again coming closer to the winter months. Job losing follows this seasonal pattern in many economies, e.g. in the construction sector, but also others. Fujita and Moscarini (2013) find that temporary layoff is highest in winter months for many sectors like manufacturing, construction, and retail, which could explain this phenomenon.

Statistical significance: The last important thing to check from the regression output in Table 6 is the statistical significance of the various coefficients. There are two ways to do this. Following Hill et al. (2008), we consider a coefficient to be statistically significant if it is two standard errors away from zero. This means it is very unlikely that the signs of the coefficients change and therefore also commute their meanings. In this dataset all values, including the monthly dummies, indeed are two standard errors away from zero and therefore are significant. The second way is by checking the p-values from the regression output. Table 6 clearly shows for the job losing probability in the year 2000 all coefficients are statistically significant on a 0.1% significance level.

Table 6:
Job Losing Probability 2000

	Coef. Est	Coef. SE
Int	-4.3259***	0.0348
Duration	0.0149***	0.0006
Age	-0.2555***	0.0113
Gender	-0.3149***	0.0245
Nationality	-0.2385***	0.0282
M 2	-0.6203***	0.0581
M 3	-0.3956***	0.0541
M 4	-0.6183***	0.0578
M 5	-0.9263***	0.0639
M 6	-0.9352***	0.0638
M 7	-0.9236***	0.0634
M 8	-0.9966***	0.0642
M 9	-0.5424***	0.0557
M 10	-0.2432***	0.0514
M 11	-0.2056***	0.0509
M 12	0.5010***	0.0436

Table 7:
Job Finding Probability 2000

	Coef. Est	Coef. SE
Int	-4.876***	0.0693
Duration	-0.3328***	0.0057
Age	-0.0739***	0.0109
Gender	-0.2065***	0.02568
Nationality	-0.03426	0.0294
M 2	0.2710***	0.0551
M 3	0.3924***	0.0536
M 4	0.0914	0.0555
M 5	-0.1540**	0.0578
M 6	-0.7304***	0.0631
M 7	-0.9998***	0.0671
M 8	-1.2179***	0.0702
M 9	-1.2727***	0.0706
M 10	-1.2280***	0.0698
M 11	-0.8837***	0.0657
M 12	-0.1038	0.0574

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Following in the same manner, the output of the logistic regression for the job finding rate (Table 7) is interpreted. For the **intercept**, the probability of finding a job in January, conditional on being unemployed (all other variables at their data means) is as follows:

Pr(Job-Finding)=logit^{-1}(-4.87685) = 0.0075 = 0.75$\%$ in January

Coefficient for Duration: This is the coefficient for duration on the logistic scale if all other variables are at their mean values. To get this in a probabilistic manner, dividing by 4 yields: $\frac{-0.3328}{4}$ = -0.0832 = -8.3$\%$. Hence, for all other variables at their averages, the longer someone is unemployed the smaller the probability of finding a new job. For each additional month an individual is unemployed the probability decreases by 8.3$\%$. This is exactly what is needed to describe the movement and contribution of long-term unemployed to the unemployment rate. Even though there are only very little long-term unemployment spells, they make up a huge share of the unemployment rate.

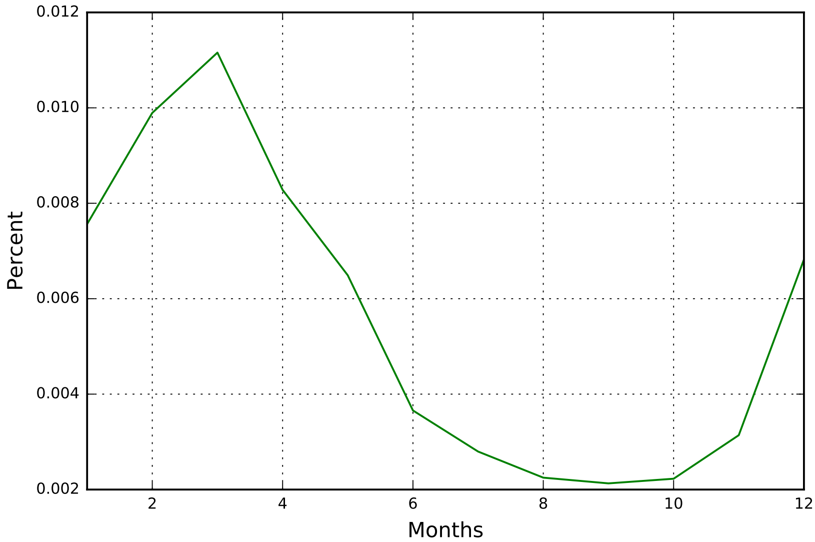
Coefficient for Age: This is the coefficient value for age of the people in the sample when all other variables are at their averages. On the probability scale this yields by the divided by 4 rule $\frac{-0.0739}{4}$ = -0.018475 = -1.84$\%$, i.e. each additional ten years in age lead to a negative difference in the probability of finding a job by -6.4$\%$. This makes sense as older people tend have longer in their unemployment spells. The older an individual is, the harder it becomes to reenter employment and the job market, once unemployed.

Coefficient for Gender: The coefficient for the variable gender is binary. All other variables at their sample averages will bring a negative difference to the probability of finding a job ($\frac{-0.2065}{4}$ = -0.051625 = -5.1$\%$). The negative sign of the coefficient goes hand in hand with what was shown for the job losing probability as it is more difficult for women to find a job once they are unemployed.In other words, it is harder for women to exit unemployment.

Coefficient for Nationality: As for the job losing probability, here the coefficient for nationality also has a negative sign for the year 2000. Consequently, Austrians have a lower probability of finding a job once they are unemployed. Combined with the result for the job losing probability this suggests that Austrian citizens are less likely to lose their job but it is harder to find a new job when they already are unemployed. This could also be due to the difference in the share of Austrians to non-Austrians in the sample or even a discrepancy in education.

Figure 11:

Job Finding Probability Monthly 2000



Coefficients for Months: Similar to the interpretation of the monthly dummy coefficients coming from the regression output of the job losing probability, here they can also be understood as the job finding probabilities for each month (all other variables at their averages). The likelihoods come from the formula $\beta_i = \eta_i - \eta_s$, where η_s again is the intercept. Based on Figure 11, we know that the pure job finding probability in the year 2000 has a spike in spring, then decreases during summer and increases again close to the winter months.

Statistical significance: Again the statistical significance has to be checked in order to get a better picture of the regression. Table 7 shows that all coefficients but Nationality, M4, and, M12 are again highly significant. This could also be the reason why interpreting the Nationality coefficient is difficult, as one would expect it to be positive.

The evolution of the coefficients can be seen in the Appendix where I include all regression outputs for the 15 years covered and also display their movements in graphs. For the job losing probability the intercept (= the probability for January) experiences a steady decreasing trend with increases in the recession periods (Figure 25). The impact of duration does stay very consistent over the first years with a slight and steady increase in the last years from 0.015 to 0.022. It looks like it increases in recessions as well (Figure 26). The age coefficient moves between -0.24 and -0.28 and the interesting thing is the spike in the year 2007 (Figure 27). The gender coefficient decreases in times of recession from -0.33 to -0.44 but moves back to to the previous values and faces a slight downwards trend (Figure 28). The coefficient for nationality decreases during recessions and also has a negative trend over the sample period (Figure 29).
For the job finding probability, the intercept decreases in recessions but starts to increase again during recessions (Figure 30). The coefficient for duration decreases in times of recessions which means it becomes less likely to find a job in recessions the longer someone is unemployed (Figure 31). The coefficient for age has the highest fluctuations. In the beginning of the sample it has a value of -0,028 and increases in the following years to 0.029, so it basically flips signs which means it has an increasing trend and changes meaning. This could mean that it became easier for older people to reenter employment during the sample period (Figure 32). Gender on the other hand decreases over the sample period. Starting around -0.11 it constantly decreases to about -0.3, indicating that it became harder for women to find a job during the 15 years observed (Figure 33). The last coefficient for the job finding rate is nationality. It increases constantly between 2000 and 2014 from about 0.057 to 0.084 with small decreases during recessions, indicating that in general it became easier for Austrians to find a job but during a recession it was harder (Figure 34).

4.3 Job Losing

In this section I show the results for the job losing probability calculated from the ASSD dataset. Job losing refers to people being in an employment spell who transition into unemployment in the observed period (in this thesis always months). The total job losing probability is calculated referring to all job losses, i.e. for all individuals who lost their jobs in the given period. From there, taking all the individuals who moved into unemployment, the long-term job losing rate is derived by doing another logistic regression on them and checking who is still unemployed after six months. Therefore, the long-term job losing rate shows the probability that someone who is freshly unemployed will still be unemployed six months later, without having been employed in the meantime. The probabilities for each year are calculated with the logistic regression model explained in section 3 and interpreted according to subsection 4.2. All regressions for the total rate are contained in the appendix, as in this section focus is put on the evolution of the job losing probabilities in the sample period.

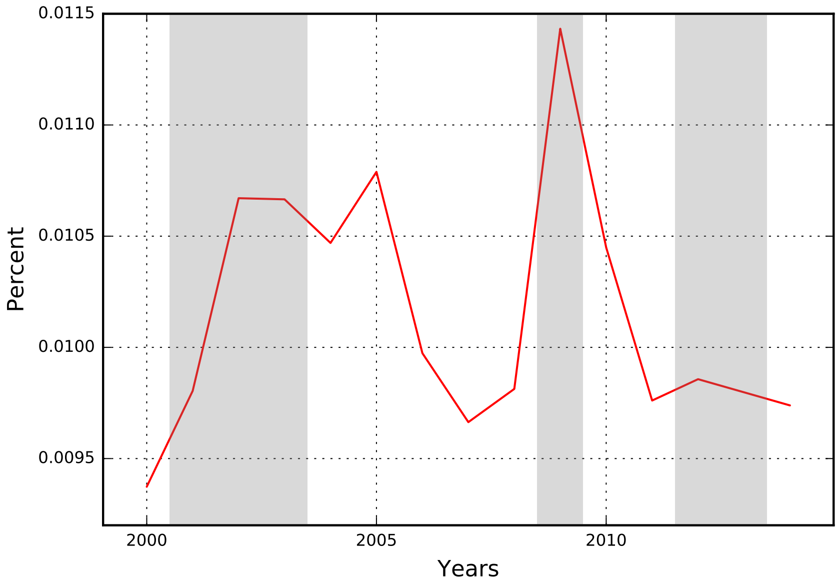
For this part I consider the length of the unemployment spell for individuals freshly entering unemployment. This is done to get a better picture of the data and its composition and also to calculate the shares of the different durations (short- and long-term) in the unemployment entries. Meaning that I assume unobserved heterogeneity for all people, i.e. that unemployed are already different in terms of the job finding rate at the time they enter the unemployment pool and therefore, it is given how long the unemployment duration will be (Machin and Manning (1999)). This can be done through the administrative dataset used and hence for all individuals that enter unemployment it is visible how long they stay unemployed. Thus, it can be seen how many people with either short- or long-term unemployment duration enter the unemployment pool. Therefore, short-term refers to people losing their job and entering unemployment for up to 26 weeks and long-term to those unemployed for more than 26 weeks. Here, I only consider the length of the unemployment spell after a job loss, contrary to the calculated long-term job losing probability where I calculate the probability for individuals already unemployed to enter long-term, longer than 6 month, unemployment. This is a strong theoretical assumption. To separate these from the long-term job losing probability I refer to those with unobserved heterogeneity as long- and short-term unemployment entries and not job losses. As for the unemployment rate, the inflows into unemployment come mainly from short-term duration spells, as short-term contributes on average 93% with a range from 91.5-94.5%. Long-term unemployment entries contribute on average 7% with a range between 5.5% and 8.5%. Hornstein (2012) calculates a 10 to 20 percent share of long-term unemployed to the total unemployment inflows. This would suggest that Austria, compared to the United States, has a smaller number of long-term inflows to the pool of unemployed. The figures for these share movements are shown in the appendix (Figures 18 and 19). Figure 19 underlines the finding from the previous section that during recessions the share of long-term unemployed increases. Here, it becomes clear that the unemployment entry share for long-term spells also increases in recessions. Hence the share of short-term unemployment entries decreases in a recession. This does not mean that total short-term entries cannot increase in a recession as shown below.

Figure 12:

Long-Term Job Losing Probability

Figure 13:

Total Job Losing Probability



The probability of losing a job and entering the unemployment pool increases in recessions and therefore also shows a comovement with the unemployment rate as shown in Figures 12 and 13 . In an economic recession the probability of losing the job increases, so more people become unemployed with a higher probability, and therefore the unemployment rate increases. The total job losing rate seems to follow a slightly different path to the long-term rate, even though it is very similar. In the 2007 recession, the total probability of losing a job increases much more compared to the long-term probability. Otherwise the probability to become long-term unemployed once unemployed increases more in the other two recessions.

The probability for a person who lost her job to become long-term unemployed starts with an average value of 5% for the year 2000. This means that the likelihood for a person who already moved into unemployment to become a long-term unemployed, longer than six months, was 5%. This probability increases in just four years to 6.8%, which corresponds to a 36% increase in just a few years. This value is also the highest in the observed time, even in the 2007 recession the maximal value is 5.9%. Figure 12 also shows that the probability rapidly decreases after each recession. It reached its minimum in the year 2012 shortly before it started to increase again in the recession, where the probability of becoming long-term unemployed once unemployed was 5%. After that it increased by 26% in just two years.

Finally, the total job losing probability in Figure 13 clearly follows a similar trend to the long-term job losing rate. Hence, the probability of becoming unemployed increases during recessions and decreases otherwise. It starts at 0.9% in 2000, peaks in the year 2005 with a 1.07% likelihood and before it cools down between 2005 and 2007. It skyrockets until 2009 where it has its maximum with 1.14% and increased around 17% in just two years. Furthermore, there is no trend to be seen in the overall job losing rate in the observed interval.

As already seen with the regression output and in Figure 10, the job losing probability is lowest during the summer months and highest in winter. Fujita and Moscarini (2013) find that this comes from the increase in temporary layoffs in the winter months, not only in the construction sector but also in manufacturing and retail. Hence, my derivations support the literature that job losings are lowest in summer.

4.4 Job Finding

Similar to the last section, in this chapter I show the outcomes for the job finding probabilities of the ASSD dataset. The job finding probability is calculated with the same logistic regression used for the job losing rates. The yearly probabilities come from monthly data and again cover the period between 2000 and 2014. Job finding, as the name suggests, refers to all people who are unemployed in a month, find a job within this month and are therefore employed in the next month. Short-term job finding refers to all people who found a job and were unemployment with a spell duration of less than 26 weeks or 6 months. For long-term job finding on the other hand someone has to be unemployed for at least 6 months before finding a new job.

Once again the majority of job findings comes from the short-term unemployed, which goes hand in hand with what Hornstein (2012) and Shimer (2012) find. Short-term exits from unemployment take an average share of total exits of approximately 86%. It ranges from 84% to 89% over the sample period. Long-term unemployment on the other hand averages at 14% and has its lowest share shortly before the crisis of 2007 hit Austria. From then on it increased to 16% in just a few years. Again the plots for this are attached in the appendix (Figures 20 and 21). The share of long-term job finding increases during recessions, following the unemployment rate. In section 4.3 I have shown that in recessions more people lose their job and stay unemployed for at least 6 months. The increasing share of long-term job finding could mean that for short-term unemployed with a duration of up to 26 weeks finding a job becomes more difficult compared to long-term unemployed. Therefore, the share of the former decreases in recessions. This indicates that during recessions more people lose their jobs and those stay in unemployment for maximal 26 weeks and so their share increases compared to long-term unemployed.

The shares are defined and calculated as follows:

$$\text{Short-term job finding share} = \frac{\text{\# of unemployed finding a job with a duration of} \leqslant 26 \text{ weeks in unemployment}}{\text{\# of all unmeployed finding a job}}$$

$$\text{Long-term job finding share} = \frac{\text{\# of unemployed finding a job with a durations of} > 26 \text{ weeks in unemployment}}{\text{\# of all unmeployed finding a job}}$$

Figure 14:

Short-Term Job Finding Probability

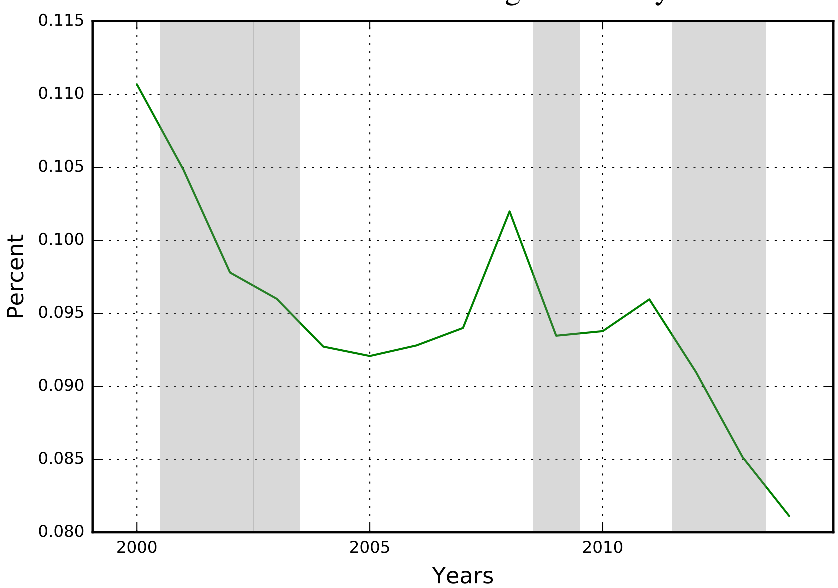


Figure 15:

Long-Term Job Finding Probability

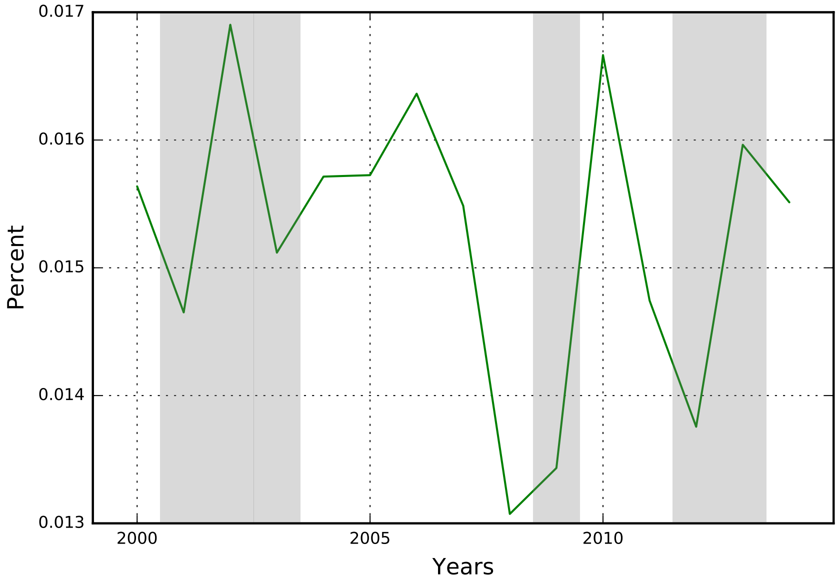
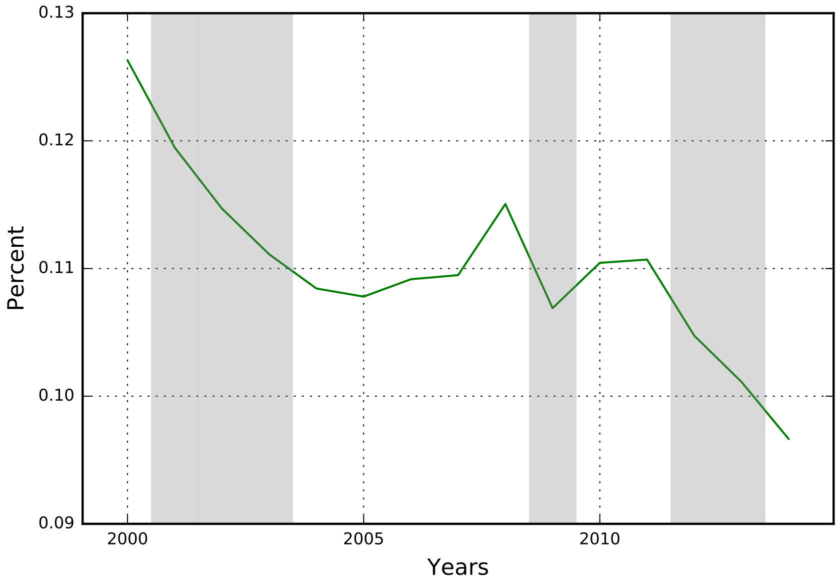


Figure 16:

Total Job Finding Probability



Figures 14 and 15 show the development of the job finding rates in Austria from 2000 to 2014. Contrary to the job losing probability from the previous section, here the short-term outflows from unemployment follow a different path compared to their long-term counterparts. The short-term rate pursues the intuitive track. The probability for finding a job, conditional on being unemployed for less than 26 weeks, decreases in times of a recession and increases otherwise. This means that the short-term job finding probability is procyclical. From early 2000, the possibility short-term unemployed finding a job decreased from approximately 11% to less than 9.2% in the year 2005. This corresponds to a 20% decrease in just five years. After 2005 the short-term job finding probability increased again until 2008 where it had a value of 10%. Subsequently it fell to just 8.1% with a small constant period around 2010. This shows that in the time between 2000 and 2014 the likelihood of finding a job for people who are unemployed for less than 6.5 months decreased by 25%. This corresponds to a noticeable descending trend for this rate.

The long-term job finding rate on the other hand seems to follow a path that is less clear. It seems that long-term unemployed start to experience a decrease in their job finding rate even before recessions take place. They do find jobs during and after recession times, it just takes longer. Furthermore, compared to the short-term and total rates, the long-term job finding probability does not show a negative trend over the sample period.

Similar to the job losing rate from the previous section, the total job finding probability has almost the same track as the short-term job finding probability. Again, this comes form the fact that the short-term probability has an average share of 86%. The total decrease in the 15 years covered is approximately 30%, so it follows the short-term likelihood with this decreasing trend.

What is really interesting about the short-term and total job finding probability is their downwards trend in the sample period. Over 15 years, the likelihood of finding a job, once unemployed, has steadily decreased.[7] This would suggest an upwards trend for the unemployment rate, if there were no structural changes in that time that forced this decrease in the job finding probability. The calculated unemployment rate from the ASSD dataset does indeed show an upwards trend in the sample period. Figure 5 shows this increasing trend. Thus, the effect of the negative trend in the job finding probability can be seen in the actual unemployment rate.

Another interesting aspect of the job finding rate is that they clearly share the same movement as shown in Figures 11 and 22. This suggesting that the job finding probability has a much higher influence on the unemployment rate compared to the job

[7] This can have different reasons and could be part of future research

losing probability. Hornstein (2012) and Shimer (2012) come to the same conclusion. So one of the main findings of Hornstein can also be validated for the Austrian economy with a much finer dataset, the ASSD. Together with the fact that the total job finding probability is decreasing over the time covered, this is the explanation why, therefore, the unemployment rate has to increase as a counterforce. The job finding rate has a large impact on the unemployment rate and this can be seen in this case as well. The same still holds true when comparing the two plots for the year 2014, though it seems that the influence slightly decreases. Figures 23 and 24 in the appendix make this clear.

5 Conclusion

In this thesis I derive some of the findings from Hornstein (2012), and for that focus on the unemployment rate movement, the job finding and job losing probabilities. The time of observation is between 2000 and 2014. The main topic is the division of the calculated probabilities into short-term, lasting up to 26 weeks, and long-term rates. A subsample of the administrative ASSD dataset is used to receive finer and more precise outcomes. A logistic regression model for yearly rates, based on monthly terms and a seasonal dummy variable model was used. I get the following findings for the Austrian labor market.

The short- and long-term unemployment rates follow the movement of the total unemployment rate. However, the share of long-term unemployment displays a comovement with the unemployment rate therefore increases in recessions and decreases in 'normal' times. Short-term shares follow a reciprocal path. From all unemployment spells long-term only accounts for approximately 9% and has a peak share of almost 46%.

Observing the output of the logistic regressions for job losings in the year 2000, I find that the longer someone will be unemployed after losing the job, the higher the likelihood for losing the job. Meanwhile, older people and females tend to be less likely to lose their jobs, non-Austrian citizens are more likely. Over a year it can also be seen that during summer the probability is smallest, while in winter it is high. The probability of becoming long-term unemployed once unemployed follows a similar path, i.e. during recessions more people become not only unemployed but also long-term unemployed.

For the job finding rate I find that people with longer unemployment spells have a lower probability of exiting unemployment. The same holds true for older people and women. The coefficient for nationality is counterintuitive and it is the only insignificant one: Austrians have a lower probability of finding a job. This could be because of the differences in the shares of Austrians to non-Austrians. Through the year 2000, the job finding rate first increases in spring, then decreases over the summer, and increases again in autumn.

Unemployment entry comes mainly from short-term spells with an average of 93%, whereas long-term entries have an average of 7%. Hornstein (2012) finds an average

10-20 percent share of long-term job losings. Therefore, it can be concluded that in Austria there are less long-term unemployment entries. I have already shown that during a recession the share of long-term unemployed increases. Assuming unobserved heterogeneity I show that the share of long-term unemployment entries increases in recessions while short-term entries decrease. Both the total and long-term probabilities follow the unemployment movement through the cycle.

Job finding is similar to unemployment in the sense that the majority of it comes from short-term job finding, about 86%. Total and short-term job finding rates decrease in recession and increase in 'normal' times. An interesting finding is that this unemployment exit rate seems to have a negative trend over the sample period, which would suggest a steady increase in the unemployment rate. I show that this is the case with the calculated unemployment rate. Further, I find that during the year job finding and the unemployment rate follow a similar path, indicating a strong influence of the job finding probability on the unemployment rate. This is one of the main findings from Hornstein (2012) and Shimer (2012).

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6 Appendix

6.1 Figures

Figure 17:

Caluclated Unmeployment Rate 2 (Black) vs. FRED Unemployment Rate (Red) 2:

Unemployed divided by the labor force

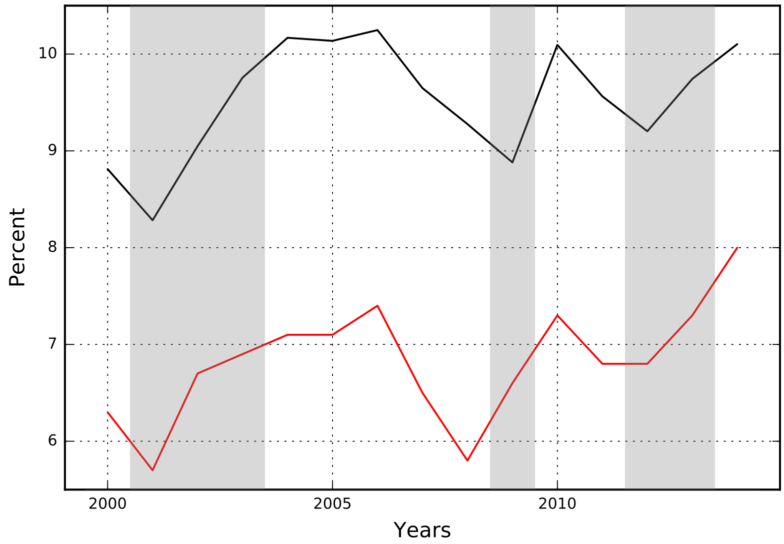


Figure 18:

Share of Short-Term Entries into Unemployment

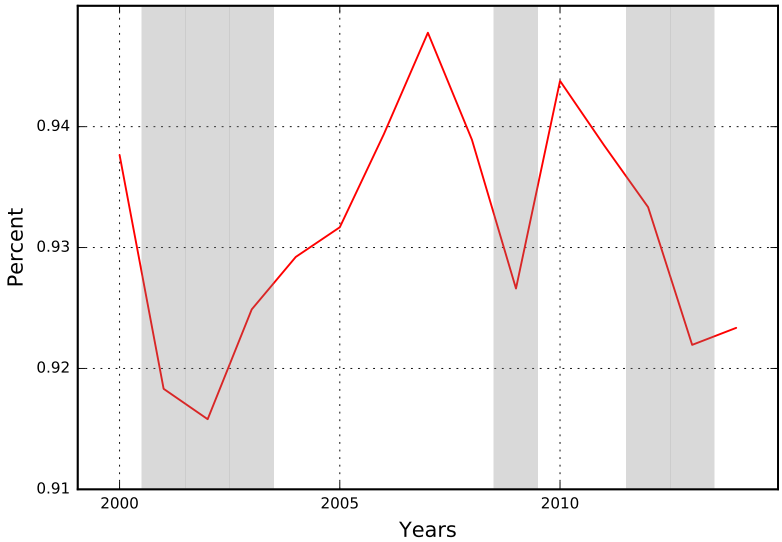


Figure 19:

Share of Long-Term Entries into Unemployment

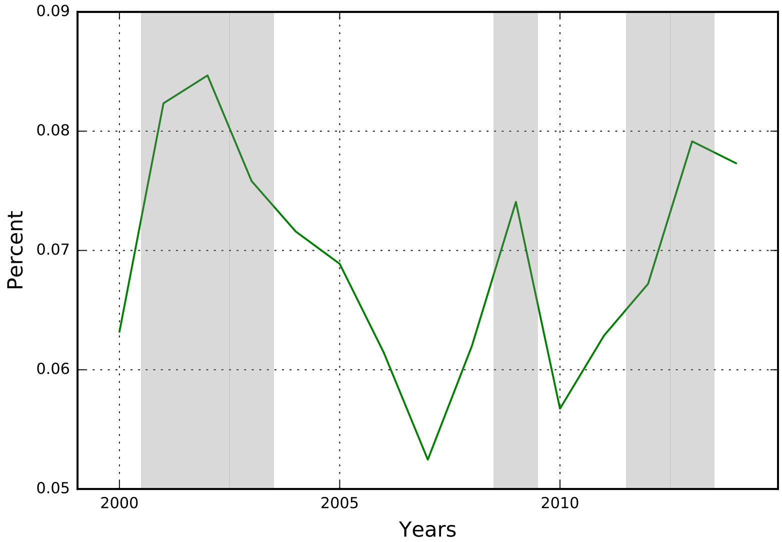


Figure 20:

Share of Short-Term in Job Finding

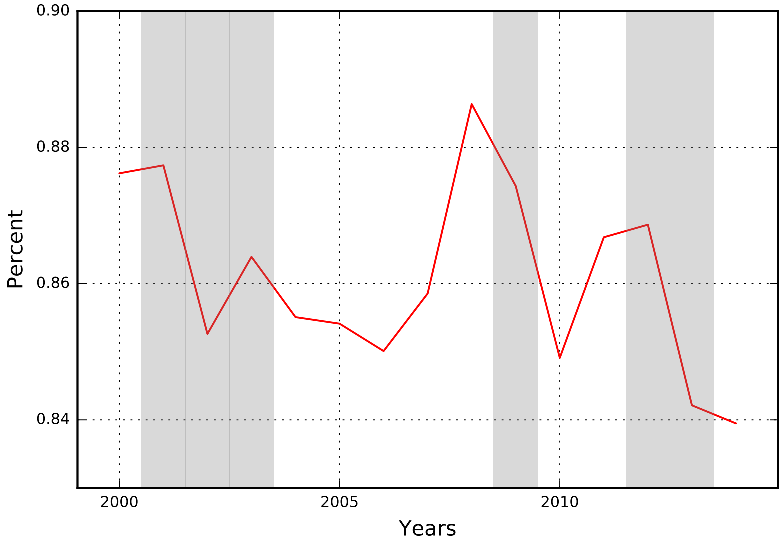


Figure 21:

Share of Long-Term in Job Finding

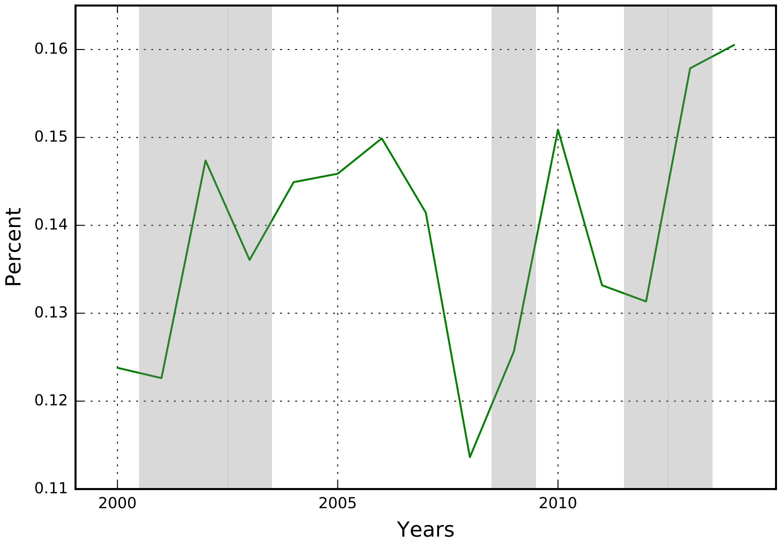


Figure 22:

Unemployment Rate 2000

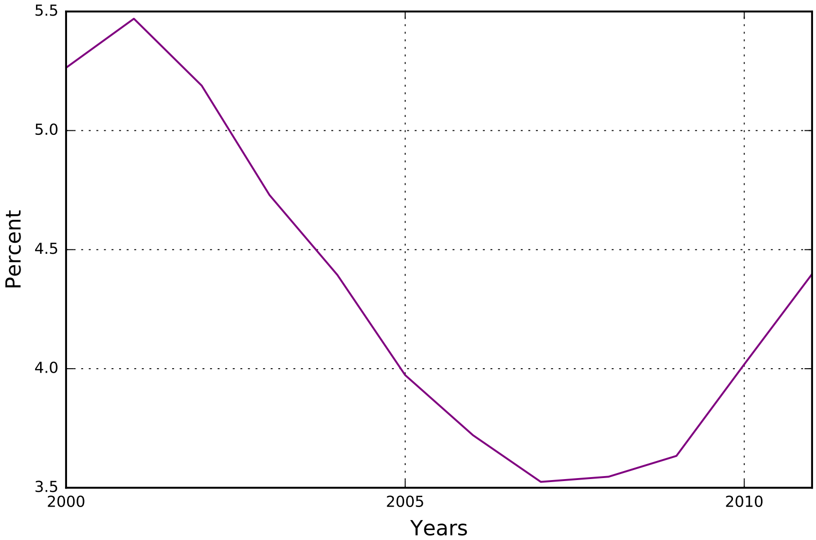


Figure 23:

Job Finding Probability Months 2014

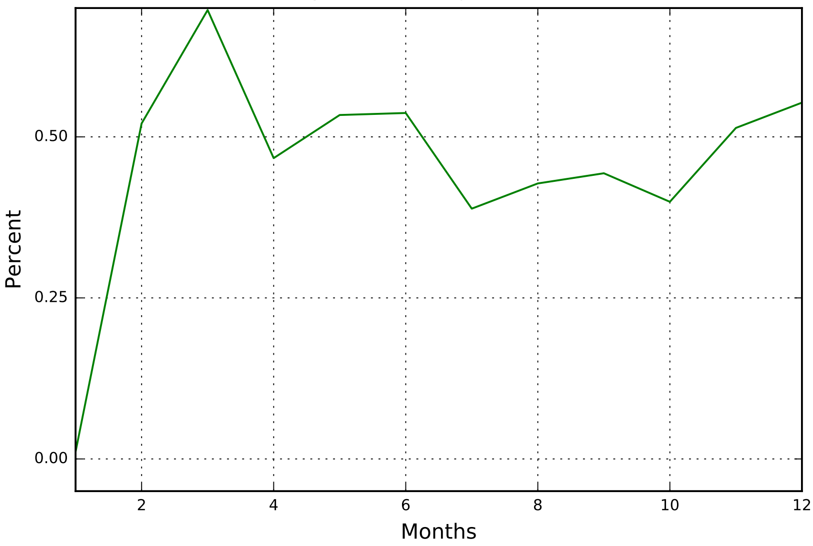


Figure 24:

Unemployment Rate 2014

Figure 25:

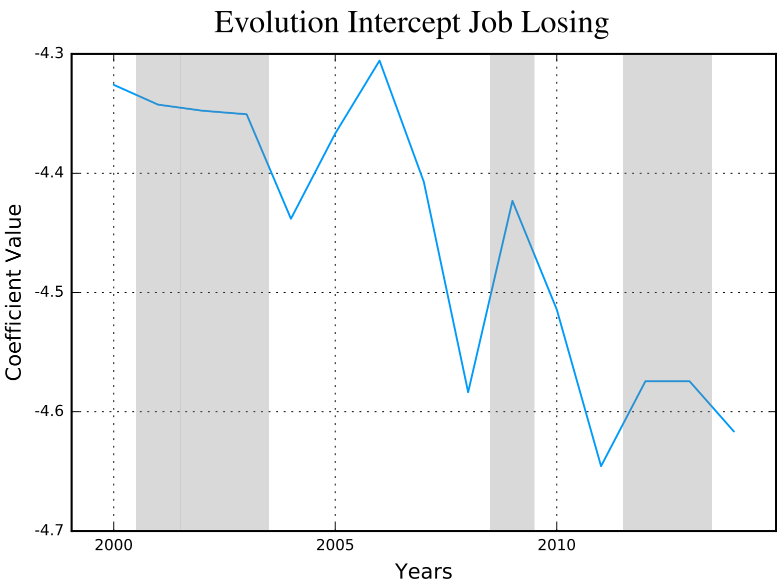


Figure 26:

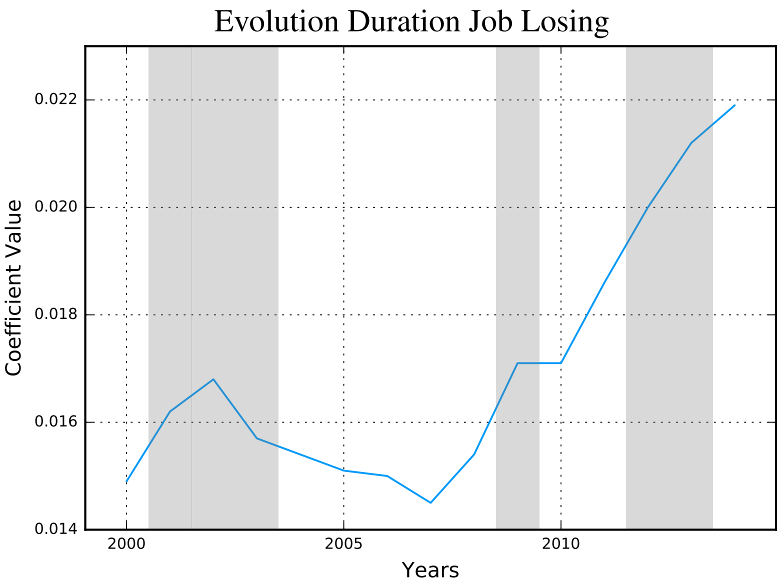


Figure 27:

Evolution Age Job Losing

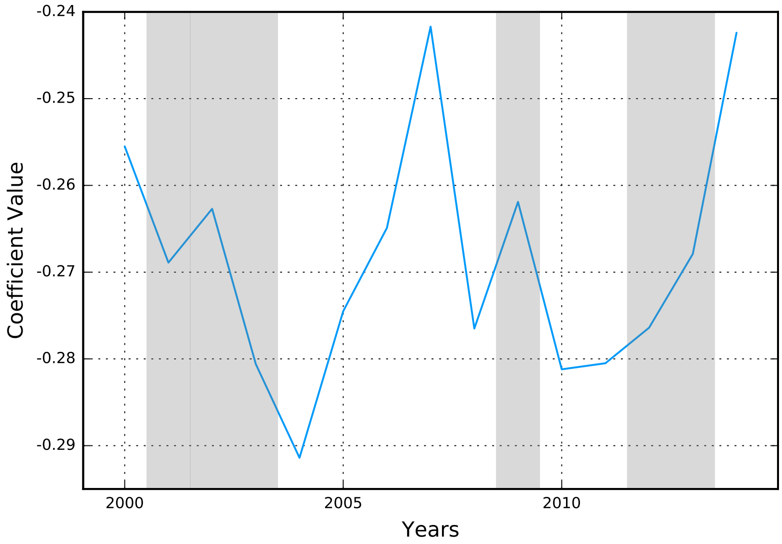


Figure 28:

Evolution Gender Job Losing

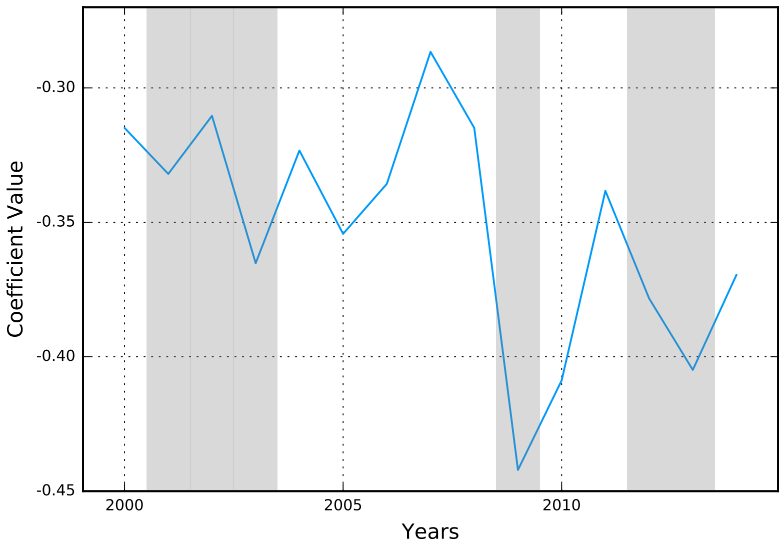


Figure 29:

Evolution Nationality Job Losing

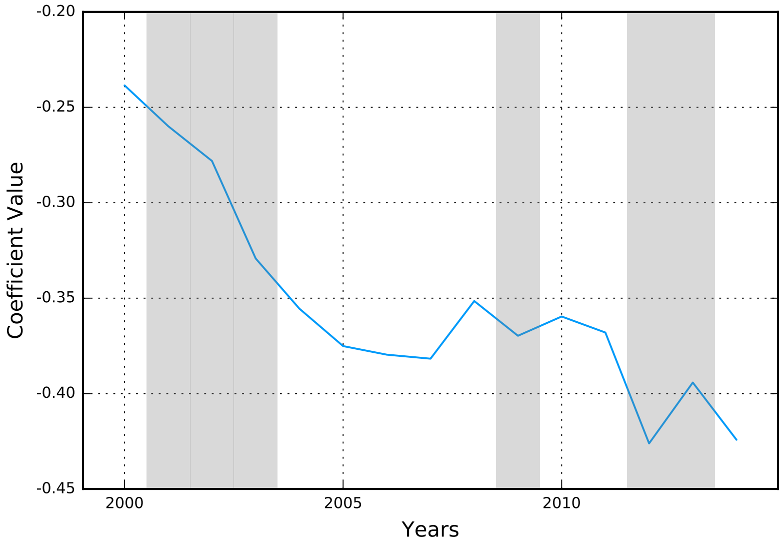


Figure 30:

Evolution Intercept Job Finding

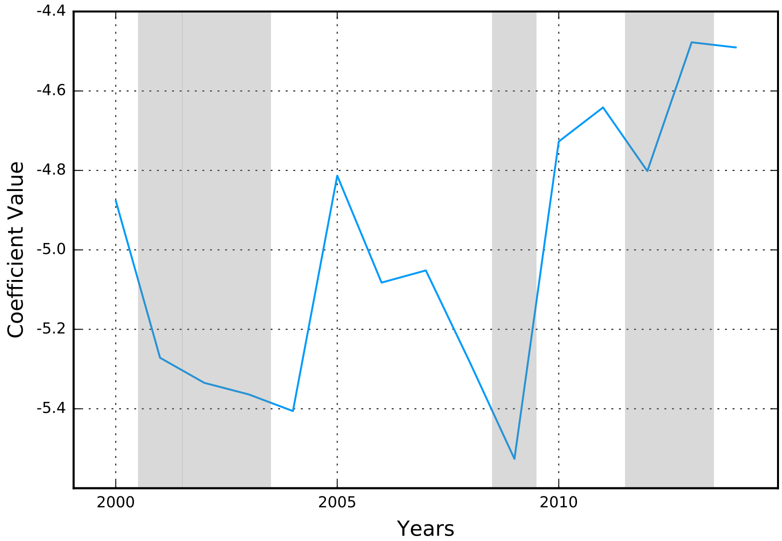


Figure 31:

Evolution Duration Job Finding

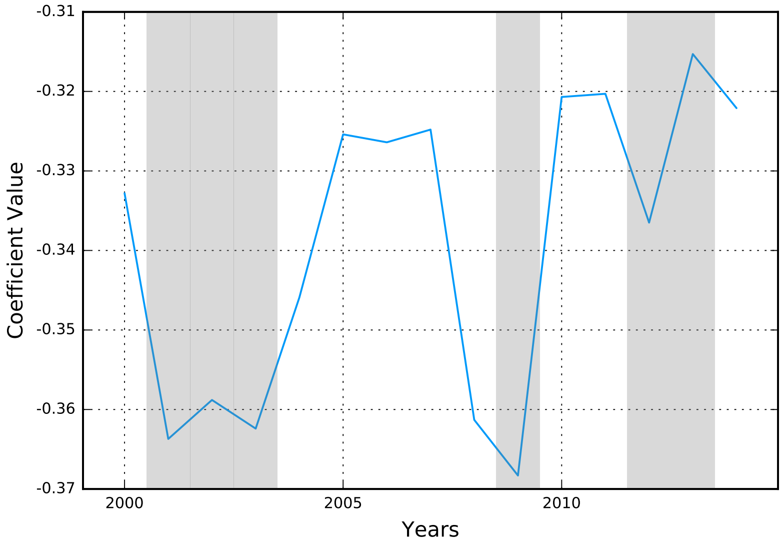


Figure 32:

Evolution Age Job Finding

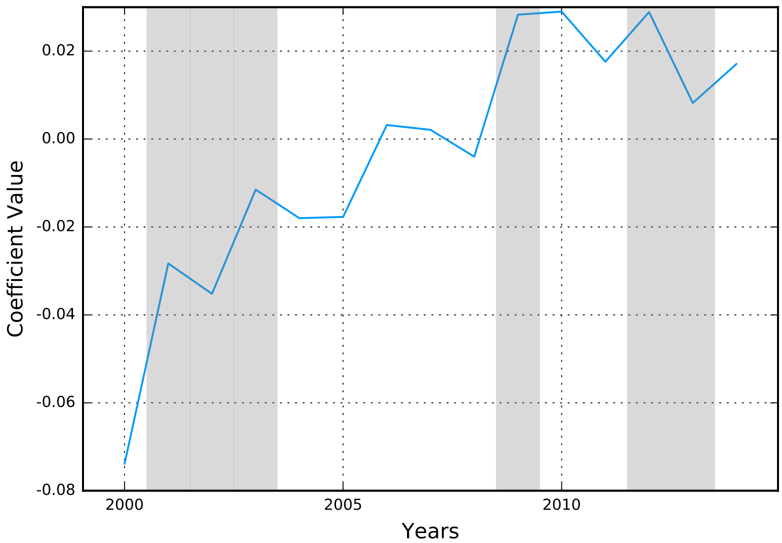


Figure 33:

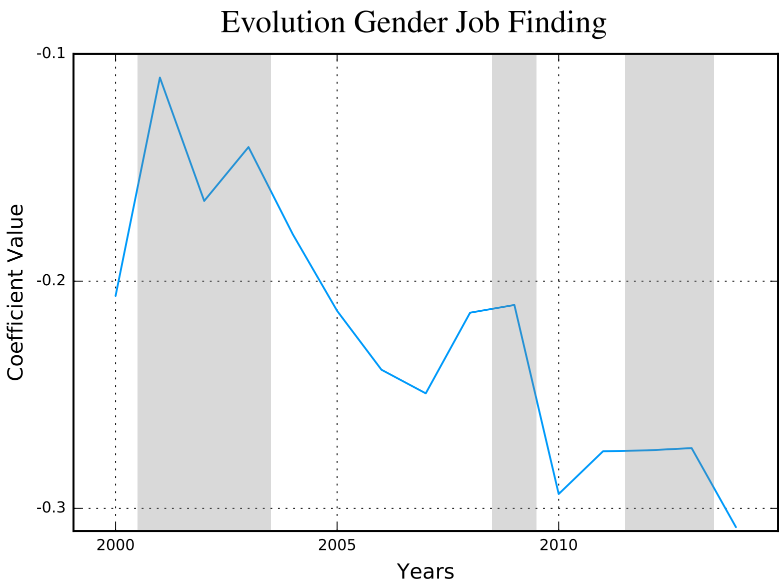
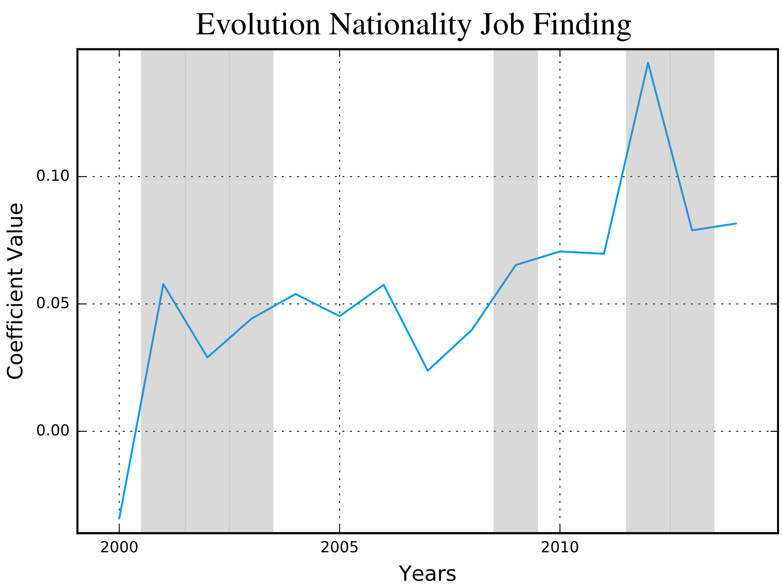


Figure 34:



6.2 Tables

Table 8:

Job Losing Probability 2001

	Coef. Est	Coef. SE
Int	-4.3425	0.0344
Duration	0.0162	0.0005
Age	-0.2689	0.0108
Gender	-0.3320	0.0237
Nationality	-0.2599	0.0269
M 2	-0.7585	0.0602
M 3	-0.4884	0.0551
M 4	-0.3528	0.0529
M 5	-0.8688	0.0621
M 6	-0.9046	0.0625
M 7	-0.8603	0.0615
M 8	-0.9291	0.0622
M 9	-0.4146	0.0533
M 10	-0.1747	0.0499
M 11	-0.0593	0.0487
M 12	0.5400	0.0430

Table 9:

Job Finding Probability 2001

	Coef. Est	Coef. SE
Int	-5.2716	0.0736
Duration	-0.3637	0.0060
Age	-0.0283	0.0109
Gender	-0.1104	0.0257
Nationality	0.0578	0.0292
M 2	0.2461	0.0581
M 3	0.4746	0.0550
M 4	0.2602	0.0561
M 5	0.0630	0.0578
M 6	-0.6303	0.0642
M 7	-0.7967	0.0660
M 8	-1.3196	0.0722
M 9	-0.7981	0.0653
M 10	-1.3647	0.0734
M 11	-0.5838	0.0636
M 12	0.0407	0.0575

Table 10:

Job Losing Probability 2002

	Coef. Est	Coef. SE
Int	-4.3476	0.0343
Duration	0.0168	0.0005
Age	-0.2627	0.0102
Gender	-0.3104	0.0225
Nationality	-0.2781	0.0253
M 2	-0.6573	0.0580
M 3	-0.5039	0.0551
M 4	-0.0851	0.0490
M 5	-0.8532	0.0615
M 6	-0.7422	0.0591
M 7	-0.6459	0.0569
M 8	-0.7022	0.0576
M 9	-0.3949	0.0529
M 10	-0.0260	0.0480
M 11	-0.1001	0.0490
M 12	0.6377	0.0422

Table 11:

Job Finding Probability 2002

	Coef. Est	Coef. SE
Int	-5.3348	0.0693
Duration	-0.3588	0.0056
Age	-0.0352	0.0102
Gender	-0.1647	0.0246
Nationality	0.0290	0.0276
M 2	0.3325	0.0572
M 3	0.6561	0.0541
M 4	0.4695	0.0553
M 5	0.0287	0.0579
M 6	-0.0867	0.0596
M 7	-0.7301	0.0662
M 8	-1.1608	0.0718
M 9	-0.4166	0.0619
M 10	-1.1632	0.0705
M 11	-0.5405	0.0634
M 12	0.0793	0.0571

Table 12:

Job Losing Probability 2003

	Coef. Est	Coef. SE
Int	-4.3506	0.0340
Duration	0.0157	0.0005
Age	-0.2806	0.0101
Gender	-0.3652	0.0225
Nationality	-0.3292	0.0247
M 2	-0.6618	0.0576
M 3	-0.3298	0.0520
M 4	-0.3777	0.0524
M 5	-0.7351	0.0586
M 6	-0.7359	0.0584
M 7	-0.7052	0.0574
M 8	-0.7965	0.0589
M 9	-0.3218	0.0512
M 10	-0.0494	0.0477
M 11	-0.0762	0.0482
M 12	0.6362	0.0417

Table 13:

Job Finding Probability 2003

	Coef. Est	Coef. SE
Int	-5.3638	0.0671
Duration	-0.3624	0.0055
Age	-0.0115	0.0100
Gender	-0.1410	0.0241
Nationality	0.0442	0.0268
M 2	0.1275	0.0575
M 3	0.9677	0.0509
M 4	-0.0275	0.0575
M 5	-0.1223	0.0578
M 6	-0.2193	0.0584
M 7	-0.8995	0.0653
M 8	-0.8389	0.0647
M 9	-0.7638	0.0640
M 10	-1.1326	0.0681
M 11	-0.4976	0.0611
M 12	-0.0506	0.0567

Table 14:

Job Losing Probability 2004

	Coef. Est	Coef. SE
Int	-4.4382	0.0352
Duration	0.0154	0.0005
Age	-0.2914	0.0100
Gender	-0.3233	0.0224
Nationality	-0.3555	0.0244
M 2	-0.6024	0.0586
M 3	-0.3151	0.0534
M 4	-0.0806	0.0501
M 5	-0.7250	0.0604
M 6	-0.6946	0.0594
M 7	-0.6469	0.0583
M 8	-0.6558	0.0583
M 9	-0.2415	0.0517
M 10	-0.1193	0.0503
M 11	0.0144	0.0488
M 12	0.7127	0.0426

Table 15:

Job Finding Probability 2004

	Coef. Est	Coef. SE
Int	-5.4058	0.0667
Duration	-0.3459	0.0052
Age	-0.0180	0.0097
Gender	-0.1794	0.0238
Nationality	0.0539	0.0259
M 2	0.5809	0.0538
M 3	0.6455	0.0521
M 4	0.3533	0.0544
M 5	0.2692	0.0548
M 6	-0.3055	0.0599
M 7	-0.7935	0.0653
M 8	-0.5347	0.0625
M 9	-0.6709	0.0637
M 10	-0.9303	0.0673
M 11	-0.4119	0.0606
M 12	0.2380	0.0559

Table 16:

Job Losing Probability 2005

	Coef. Est	Coef. SE
Int	-4.3667	0.0337
Duration	0.0151	0.0005
Age	-0.2745	0.0097
Gender	-0.3543	0.0220
Nationality	-0.3751	0.0235
M 2	-0.4974	0.0541
M 3	-0.3964	0.0524
M 4	-0.0883	0.0481
M 5	-0.7374	0.0580
M 6	-0.6713	0.0564
M 7	-0.6932	0.0567
M 8	-0.7804	0.0579
M 9	-0.3388	0.0509
M 10	-0.1545	0.0485
M 11	-0.0579	0.0475
M 12	0.6437	0.0412

Table 17:

Job Finding Probability 2005

	Coef. Est	Coef. SE
Int	-4.8132	0.0603
Duration	-0.3254	0.0050
Age	-0.0177	0.0094
Gender	-0.2131	0.0233
Nationality	0.0452	0.0248
M 2	-0.2377	0.05428
M 3	0.3998	0.0484
M 4	0.1691	0.0501
M 5	-0.1858	0.0522
M 6	-0.6498	0.0570
M 7	-0.8309	0.0593
M 8	-1.0651	0.0621
M 9	-0.9857	0.0604
M 10	-1.0465	0.0614
M 11	-0.6622	0.0569
M 12	-0.2533	0.0531

Table 18:

Job Losing Probability 2006

	Coef. Est	Coef. SE
Int	-4.3056	0.0324
Duration	0.0150	0.0006
Age	-0.2649	0.0098
Gender	-0.3357	0.0225
Nationality	-0.3796	0.0238
M 2	-0.6806	0.0551
M 3	-0.4251	0.0507
M 4	-0.3828	0.0500
M 5	-0.7964	0.0568
M 6	-0.7987	0.0565
M 7	-0.9335	0.0590
M 8	-0.8542	0.0569
M 9	-0.5201	0.0514
M 10	-0.2911	0.0483
M 11	-0.2369	0.0477
M 12	0.49181	0.0406

Table 19:

Job Finding Probability 2006

	Coef. Est	Coef. SE
Int	-5.0824	0.0632
Duration	-0.3264	0.0050
Age	0.0032	0.0093
Gender	-0.2390	0.0233
Nationality	0.0575	0.0246
M 2	0.2242	0.0522
M 3	0.4032	0.0502
M 4	0.3607	0.0502
M 5	0.0971	0.0527
M 6	-0.5823	0.0584
M 7	-0.5530	0.0586
M 8	-0.9778	0.0633
M 9	-0.9410	0.0622
M 10	-0.7980	0.0614
M 11	-0.5704	0.0586
M 12	-0.0163	0.0537

Table 20:

Job Losing Probability 2007

	Coef. Est	Coef. SE
Int	-4.4073	0.0336
Duration	0.0145	0.0006
Age	-0.2417	0.0097
Gender	-0.2866	0.0224
Nationality	-0.3817	0.0237
M 2	-0.6340	0.0564
M 3	-0.3697	0.0519
M 4	-0.1947	0.0494
M 5	-0.8599	0.0604
M 6	-0.7955	0.0588
M 7	-0.7184	0.0573
M 8	-0.6975	0.0564
M 9	-0.4301	0.0523
M 10	-0.1855	0.0488
M 11	-0.0361	0.0472
M 12	0.5095	0.0421

Table 21:

Job Finding Probability 2007

	Coef. Est	Coef. SE
Int	-5.0518	0.0655
Duration	-0.3248	0.0052
Age	0.0021	0.0094
Gender	-0.2494	0.0236
Nationality	0.0238	0.0250
M 2	0.2663	0.0508
M 3	0.3113	0.0502
M 4	0.1243	0.0513
M 5	0.0346	0.0524
M 6	-0.4449	0.0567
M 7	-0.6844	0.0594
M 8	-1.1738	0.0652
M 9	-0.6673	0.0580
M 10	-1.0845	0.0639
M 11	-0.7155	0.0589
M 12	-0.2525	0.0540

Table 22:

Job Losing Probability 2008

	Coef. Est	Coef. SE
Int	-4.5836	0.0360
Duration	0.0154	0.0006
Age	-0.2765	0.0095
Gender	-0.3149	0.0220
Nationality	-0.3515	0.0232
M 2	-0.5657	0.05904
M 3	-0.1988	0.0530
M 4	-0.0724	0.0510
M 5	-0.7297	0.0618
M 6	-0.5578	0.0583
M 7	-0.4958	0.0569
M 8	-0.6269	0.0591
M 9	-0.1919	0.0523
M 10	0.0760	0.0490
M 11	0.0628	0.0494
M 12	0.8274	0.0428

Table 23:

Job Finding Probability 2008

	Coef. Est	Coef. SE
Int	-5.2846	0.0702
Duration	-0.3613	0.0057
Age	-0.0040	0.0096
Gender	-0.2139	0.0239
Nationality	0.0398	0.0250
M 2	0.0006	0.0510
M 3	0.2844	0.0479
M 4	-0.5779	0.0545
M 5	-0.5993	0.0543
M 6	-0.6079	0.0547
M 7	-1.4341	0.0633
M 8	-1.3691	0.0622
M 9	-1.3119	0.06120
M 10	-1.4393	0.064
M 11	-0.7553	0.0558
M 12	-0.5319	0.0539

Table 24:

Job Losing Probability 2009

	Coef. Est	Coef. SE
Int	-4.4232	0.0329
Duration	0.0171	0.0005
Age	-0.2619	0.0088
Gender	-0.4421	0.0207
Nationality	-0.3697	0.0214
M 2	-0.2953	0.0499
M 3	-0.1224	0.04760
M 4	-0.0450	0.0465
M 5	-0.5443	0.0536
M 6	-0.5095	0.0528
M 7	-0.4540	0.0518
M 8	-0.6026	0.0541
M 9	-0.2449	0.0488
M 10	-0.0853	0.0468
M 11	-0.1185	0.0474
M 12	0.7257	0.0399

Table 25:

Job Finding Probability 2009

	Coef. Est	Coef. SE
Int	-5.5262	0.0674
Duration	-0.3683	0.0054
Age	0.0283	0.0091
Gender	-0.2105	0.0229
Nationality	0.0653	0.0237
M 2	-0.0347	0.0551
M 3	0.8529	0.0487
M 4	0.0379	0.0535
M 5	0.1013	0.0530
M 6	-0.0335	0.0544
M 7	-0.4934	0.0590
M 8	-0.3502	0.0568
M 9	-0.4015	0.0574
M 10	-0.8721	0.0628
M 11	-0.2000	0.0554
M 12	0.0061	0.0540

Table 26:

Job Losing Probability 2010

	Coef. Est	Coef. SE
Int	-4.5142	0.0344
Duration	0.0171	0.0006
Age	-0.2812	0.0092
Gender	-0.4088	0.0214
Nationality	-0.3596	0.0221
M 2	-0.3674	0.0531
M 3	-0.3290	0.0524
M 4	0.0259	0.0476
M 5	-0.5957	0.0566
M 6	-0.5466	0.0555
M 7	-0.4293	0.0535
M 8	-0.5815	0.0558
M 9	-0.2973	0.0514
M 10	-0.1208	0.0491
M 11	-0.0652	0.0486
M 12	0.7962	0.0411

Table 27:

Job Finding Probability 2010

	Coef. Est	Coef. SE
Int	-4.7273	0.0574
Duration	-0.3207	0.0048
Age	0.0290	0.00891
Gender	-0.2937	0.0224
Nationality	0.0706	0.0230
M 2	0.0886	0.0490
M 3	0.4114	0.0465
M 4	0.0098	0.0493
M 5	0.0409	0.0495
M 6	-0.3968	0.0529
M 7	-0.8100	0.0575
M 8	-0.7232	0.0559
M 9	-0.7867	0.0564
M 10	-1.0144	0.0599
M 11	-0.5083	0.0539
M 12	-0.2347	0.0518

Table 28:

Job Losing Probability 2011

	Coef. Est	Coef. SE
Int	-4.6456	0.0363
Duration	0.0186	0.0006
Age	-0.2805	0.0093
Gender	-0.3383	0.0217
Nationality	-0.3680	0.0224
M 2	-0.3511	0.0558
M 3	-0.0936	0.0519
M 4	-0.1199	0.0522
M 5	-0.5409	0.0588
M 6	-0.4615	0.0571
M 7	-0.4857	0.0575
M 8	-0.4376	0.0564
M 9	-0.1519	0.0523
M 10	-0.0024	0.0505
M 11	0.1205	0.0491
M 12	0.8403	0.0431

Table 29:

Job Finding Probability 2011

	Coef. Est	Coef. SE
Int	-4.6415	0.0594
Duration	-0.3203	0.0051
Age	0.0176	0.0092
Gender	-0.2749	0.0229
Nationality	0.0697	0.0236
M 2	0.0058	0.0491
M 3	0.2896	0.0466
M 4	-0.2921	0.0509
M 5	-0.2863	0.0508
M 6	-0.5134	0.0536
M 7	-0.8882	0.0577
M 8	-0.9555	0.0582
M 9	-0.9919	0.0581
M 10	-0.9054	0.0578
M 11	-0.5851	0.0543
M 12	-0.3233	0.0519

Table 30:

Job Losing Probability 2012

	Coef. Est	Coef. SE
Int	-4.5745	0.0347
Duration	0.0200	0.0006
Age	-0.2764	0.0092
Gender	-0.3783	0.0216
Nationality	-0.4261	0.0220
M 2	-0.4191	0.0543
M 3	-0.3310	0.0529
M 4	-0.0397	0.0489
M 5	-0.6454	0.0581
M 6	-0.5260	0.0557
M 7	-0.4694	0.0548
M 8	-0.5503	0.0559
M 9	-0.2590	0.0516
M 10	0.0058	0.0482
M 11	-0.0050	0.0484
M 12	0.7439	0.0419

Table 31:

Job Finding Probability 2012

	Coef. Est	Coef. SE
Int	-4.8017	0.0607
Duration	-0.3365	0.0052
Age	0.0289	0.0093
Gender	-0.2745	0.0232
Nationality	0.1447	0.0238
M 2	-0.1100	0.0520
M 3	0.4246	0.0475
M 4	0.0361	0.0504
M 5	-0.0302	0.0512
M 6	-0.5333	0.0559
M 7	-0.7073	0.0575
M 8	-1.0945	0.0626
M 9	-0.4842	0.0548
M 10	-0.9839	0.0615
M 11	-0.6808	0.0580
M 12	-0.0762	0.0520

Table 32:

Job Losing Probability 2013

	Coef. Est	Coef. SE
Int	-4.5745	0.0347
Duration	0.0212	0.0006
Age	-0.2679	0.00932
Gender	-0.4049	0.0218
Nationality	-0.3942	0.0222
M 2	-0.3464	0.0533
M 3	-0.3768	0.0537
M 4	-0.0125	0.0487
M 5	-0.7963	0.0611
M 6	-0.5422	0.0561
M 7	-0.3968	0.0536
M 8	-0.5869	0.0566
M 9	-0.2361	0.0514
M 10	0.0007	0.0483
M 11	-0.0553	0.0491
M 12	0.7451	0.0419

Table 33:

Job Finding Probability 2013

	Coef. Est	Coef. SE
Int	-4.4775	0.0550
Duration	-0.3153	0.0048
Age	0.0082	0.0092
Gender	-0.2735	0.02282
Nationality	0.0789	0.0232
M 2	-0.0351	0.0516
M 3	0.3635	0.0485
M 4	0.3441	0.0487
M 5	0.0106	0.05152
M 6	-0.1519	0.0531
M 7	-0.7017	0.0593
M 8	-0.8550	0.0612
M 9	-0.3407	0.0547
M 10	-0.7944	0.0614
M 11	-0.5007	0.0575
M 12	0.0867	0.0514

Table 34:

Job Losing Probability 2014

	Coef. Est	Coef. SE
Int	-4.6166	0.0355
Duration	0.0219	0.0006
Age	-0.2424	0.0092
Gender	-0.3695	0.0217
Nationality	-0.4242	0.0221
M 2	-0.3991	0.0555
M 3	-0.0759	0.0507
M 4	-0.1186	0.0511
M 5	-0.5943	0.0586
M 6	-0.4023	0.0552
M 7	-0.4623	0.0560
M 8	-0.4900	0.0564
M 9	-0.1879	0.0519
M 10	0.0417	0.0490
M 11	-0.0341	0.0501
M 12	0.7736	0.0427

Table 35:

Job Finding Probability 2014

	Coef. Est	Coef. SE
Int	-4.4905	0.0536
Duration	-0.3221	0.0047
Age	0.0171	0.0092
Gender	-0.3083	0.0229
Nationality	0.0816	0.0232
M 2	0.0943	0.0521
M 3	0.8437	0.0471
M 4	-0.1211	0.0541
M 5	0.1471	0.0523
M 6	0.1596	0.0525
M 7	-0.4422	0.0595
M 8	-0.2801	0.0571
M 9	-0.2158	0.0566
M 10	-0.3976	0.0599
M 11	0.0666	0.0548
M 12	0.2245	0.0536