Die approbierte Originalversion dieser Diplom-/Masterarbeit ist in der Hauptbibliothek der Technischen Universität Wien aufgestellt und zugänglich.
http://www.ub.tuwien.ac.at

The approved original version of this diploma or master thesis is available at the main library of the Vienna University of Technology.
http://www.ub.tuwien.ac.at/eng

MSc Economics

The Impact of Labour Force Histories on Future Employment

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

supervised by
Tamás Papp

Emma McKeown
1527528

Vienna, 12 June 2017

MSc Economics

Affidavit

I, Emma McKeown

hereby declare

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

The Impact of Labour Force Histories on Future Employment

26 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.

Vienna, 12.06.2017

Signature

Contents

List of Figures

List of Tables

Abstract

Using Austrian social insurance data from 1997 to 2015, this paper extends existing research into labour market histories, which indicated that breaking down the working histories of individuals gave further insight into how past employment status would affect future employment. With 5-month panels taken from the Austrian Labour Market Database, the employment histories were decomposed into five main categories: employment; unemployment; childcare/parental leave; minor employment; and other insured non-employment. One main finding shows that being out of the labour force, a category which is less attached to the labour force than the unemployed, was in fact a good measure for future employment in 1997. However, since then this effect has fallen dramatically. Another outcome indicates that if an individual is on parental leave, the likelihood of gaining employment started low in 1997 and has also experienced a steep decline. In addition, results seem to demonstrate that, while past employment has a not unexpected large effect on future employment, that it too has fallen alongside other factors, indicating that job finding rates have fallen for all individuals since 1997. The advantage of this paper is the depth and breadth of the dataset, which allows for a more detailed analysis of individual histories.

1 Introduction

Recent research has concluded that, unlike previous works, Hall (1970) which considered unemployment and out of the labour force (OLF) as arbitrary distinctions of the non-employed, the two categories are in fact behaviourally distinct, Flinn and Heckman (1983) and Elsby et al. (2010). This means that they can be separated and analysed in order to determine if these differences manifest themselves in job finding rates. As a result, the majority of the literature covering transition rates from non-employment into employment has overwhelmingly focused on those who are considered unemployed, rather than those considered to be out of the labour force.

Evidently, the history of an individual in the employment market will have an impact of their future employment, a subject which has been tackled in various ways, most notably by Kudlyak and Lange (2014). The approach of this paper was to break down the labour force status histories into four months of employment and non-employment, where the third month was non-employment followed by a fourth month of employment. The category of non-employment was further broken down into unemployment and out of the labour force (OLF). They found that job finding rates differed significantly between the groups, which could not be accounted for using one-month histories or survey questions related to non-employment status. As expected, findings indicated that those with a spell of recent employment was the best indicator for future employment. Surprisingly, if a person considered themselves to be OLF during the three months previous to employment, this did not necessarily reduce their job finding rates as much as would be expected, given that these individuals considered themselves to be not actively looking for work. Among the OLF, information on recent employment from the LFS history explained four times more variation in the employment transition rate than the respondents' reported desire and reason for not looking for work.

It should be noted that in that paper, the database used is the Current Population Survey (CPS), which is survey based, as opposed to the administrative nature of the one used in this paper, which reports if a benefit was received and for what purpose. This means that, in the CPS, the labels of unemployment and out of the labour force reflect self-determined search behaviour. While one expects overlap between the two concepts, this is not guaranteed and as a result, comparisons are made with this in mind.

Using similar ideas to those of Kudlyak and Lange (2014), this paper attempts to break down the labour force histories of individuals comprising the Austrian labour market in an attempt show which groups are least likely to transition into employment. This is achieved by sorting the non-employed into different categories of non-employment, with the expectation that those who are classified as unemployed, i.e. are currently seeking and are available for work, will transition most readily into employment, whereas those who are classified in other terms will have varying degrees of success, most likely lower than those in unemployment, which is used as a baseline.

Findings suggest that this is indeed the case but that this large effect diminishes significantly from 1997 to 2015. In addition, an interesting group were those classified to be taking parental leave, as they were the least likely group to return to employment. Notably, all categories had a significantly lower effect in 2015 than in 1997.

Using these results, it would be pertinent to learn more about those who are in the childcare category. Determining why those on parental leave are so much less likely to gain employment afterwards could induce policy that would encourage this group to rejoin the labour market. The overall drop in influence is also of interest, as it suggests a lower job-finding rate across non-employed. This adds to existing literature that attempts to discover the reasons behind recent, low transition rates and target them to decrease unemployment.

This paper is ordered in the following manner: section 2 explains the set-up and classification of the database, leading into section 3, which sets out the methodology and main results. Section 4 and section 5 present analysis of the results and a conclusion, with an outlook to possible future applications and manipulations of the data.

2 Data Description

2.1 Data Set

The Arbeitsmarktdatenbank (Austrian Labour Market Database or AMDB) contains over two million individuals and their labour market histories from 1971 to 2016, as documented by insurance companies. A 1% subsample was taken from the original database for the purpose of this paper, such that there was only information for 205,402 individuals. Each individual is equipped with several distinct sets of information, on which two were concentrated: person spells and AMP spells[1]. Person spells contains birth year, nationality, gender, death date and the interval over which their history was processed. AMP spells contains each recorded interval of employment status. Each separate spell is counted as unique, such that a person may be classified as an employee for an interval of time, be unclassified for an interval as short as a single day, and then become reclassified as an employee, which would be counted as two spells of employment.

The AMP spells do not necessarily cover every day of an individual's life, and can be as short as one day, with gaps of up to several years in some cases. Checking the data, some people had too many spells to be considered realistic in an average working lifetime. In order to find if these people were statistically relevant, 100 spells as a limit was chosen, a number that was high but not impossibly so, and thus the percentage of these people which made up the total was found. The number of people who had spells over 100 amounted to only 1.15% of the reduced database, so in calculations these results were not considered to be an issue. This was instead assumed to be an irregular method in which a company would record employment data and, for the purposes of this paper, these could be incorporated easily into the results.

2.2 Handling the Data

Once the data had been reduced to a subsample, the first step is to restrict the individuals to those with labour force histories which are of most interest. In an attempt to limit the unwanted effects of education, military service, and retirement, only those aged between 25 and 55 are included. The next step is to determine which categories are the most common and therefore the most likely to yield interesting results. Both the raw number of spells and their percentage

[1] AMP = Arbeitsmarktpositionen, i.e. Labour Market Positions

of total spells of the 23 categories are analysed from 1972 to 2015, with the first and last years of the entire dataset (i.e. 1971 and 2016) removed, since they were found to be incomplete. The results of this can be seen in Table 1, which shows that several categories dominate the labour market.

Using figures from Table 1, the categories are grouped by size and plotted, in order to create a visual representation of the development of each of the spells over time. From these graphs, it is very clear to see several patterns emerge. One such pattern is that, once the "Childcare" categories are introduced in 2001, "Parental Leave" is dropped almost entirely in the years following this, leading one to speculate that these terms are synonymous. It is also of interest to note that many of the categories were not introduced until significantly after 1972, with several not appearing at all until as late as the early 2000s.

These plots can be seen in Figures 1 through 4, where, as a rule of thumb, anything less than 1% is considered irrelevant for the purpose of this paper.

One outcome of this year-on-year breakdown is the removal of the five categories in Table 2, which were deemed unimportant both as a percentage of the entire time frame and on a year-by-year basis. In addition, although "Farmer" and "Civil Servant" make up 2.4% and 3.8% of the total, the theory in this paper was not developed for explaining job finding and losing for these categories, but rather the private sector, so these are also subsequently dropped. While "Other Insured Time" comprises a large percentage, since this category is not well-defined in the database and accompanying literature, it is not of interest and is dropped.

"Other Insured Non-Employment" (OINE) is a more difficult category to assess, as it makes up a a large percentage of the overall labour market but is not clearly unemployment or employment. Thus, leading from the accompanying literature, this is deemed to be out of the labour force (OLF) for the purposes of interpretation.

Table 1: Spell Type Share 1972:2015

Spell Type	Quantity	Percentage
Employee	496918289	32.9%
Retired	413988425	27.4%
Other Insured Time	212979928	14.1%
Self Employed	65465281	4.3%
Civil Servant	56816077	3.8%
Unemployed No Benefits	48808669	3.2%
Other Insured Non-Employment	43920982	2.9%
Minor Employment	42977471	2.8%
Unemployed Mixed Benefits	40708684	2.7%
Farmer	35768487	2.4%
(Total Childcare)	(24750274)	(1.8)%
Apprenticeship	18146051	1.2%
Childcare Allowance Active	8935184	0.6%
Childcare Allowance Inactive	6853160	0.5%
Service Contract	3109043	0.2%
Military	3077916	0.2%
Maternity Active	2924793	0.2%
Parental Leave Active	2626283	0.2%
Parental Leave Inactive	2517323	0.2%
Education	2505584	0.2%
Other Employment	1288175	0.1%
Maternity Inactive	893531	0.1%
Transition Allowance	375081	0%
Rehabilitation	341911	0%

The six forms of non-employment pertaining to raising children are: childcare, parental leave and maternity leave, all either inactive or active. This distinction between active and inactive is considered to be arbitrary for our purposes, as an individual is in a distinct category from employment or unemployment, thus could not be definitively sorted into another group. These six spell types have varying sizes, with none standing out as a clear choice to assume an overall 'childcare' category (see Table 3). However, in graphical form (see Figure 1 and 2), they can be seen to oppose each other, implying that these categories are interchangeable

Table 2: Smallest Spell Types: Maximum Share 1972-2015

Spell Type	Max. Percentage: 1972-2015
Education	0.5%
Service Contract	0.3%
Other Employment	0.1%
Transition Allowance	0.04%
Rehabilitation	0.03%

Table 3: Forms of Childcare: Maximum Share 1972-2015

Spell Type	Max. Percentage: 1972-2015
Childcare Allowance Active	1.2%
Childcare Allowance Inactive	0.9%
Maternity Active	0.3%
Maternity Inactive	0.1%
Parental Leave Active	0.8%
Parental Leave Inactive	1.5%

Table 4: Forms of Childcare: Relative Proportion

Spell Type	Proportion
Childcare Allowance Active	36.1%
Childcare Allowance Inactive	27.7%
Maternity Active	11.8%
Maternity Inactive	3.6%
Parental Leave Active	10.6%
Parental Leave Inactive	10.2%

for the insurance firms that are recording the data. This leads to all six categories being merged into a single category, i.e. "Childcare", which would then account for 1.8% of the total employment statuses.

It is also of interest to note the relative size of the categories of childcare (Table 4). Here it can be seen than, although "Childcare Allowance" dominates, the other categories are not small enough to discount, hence the decision to merge them.

Some of the categories are removed from further calculations for being uninteresting for a study into private-sector employment (see above) and then several more categories are collected together to create fewer, more general groups, which are more easily identified with existing literature. This entailed organising five groups: employment, unemployment, childcare, minor employment and other insured non-employment. Employment consists of "Employee" and "Self-Employed", unemployment is "Unemployed No Benefits" and "Unemployed Mixed", childcare is comprised of the six categories mentioned above, and the other two contain just one category each, both of which are eponymous. Table 5 shows the relative proportions of these five categories.

Since several candidates have more than one person spell, often as a result either of a change of nationality or due to the construction of the database, simply the first personal spell of each candidate was taken, since a candidate cannot

Table 5: Categories of Interest: Relative Proportion

Category	Proportion
Unemployment	8.0%
Childcare	0.1%
Minor Employment	3.1%
Other Insured Non-Employment	4.3%
Employment	79.5%

change their year of birth, and changes in gender are negligible, leaving the relevant data intact.

3 Results and Analysis

The aim of the regression is to find what impact being in one of the four categories of unemployment, childcare, minor employment, and other insured non-employment at the start of the year has on gaining employment in the following months. To achieve this, a model which allows for binary output is necessary, i.e. if someone was employed or not. Hence, a logit model is implemented.

3.1 Regression

Using these categories, a logit model is run using employment in April and May of a given year as the dependent variable. This is then turned into a binary column vector, with a 1 indicating that a person was employed during that time and a 0 indicating that they were not. The independent variables are unemployment, childcare, other insured non-employment, and minor employment, which are all taken from January through to March of that same year. Since all categories are mutually exclusive, unemployment is dropped and is used as a baseline with which the other three categories are compared. The aim of this is to find the significance of each of the other regressors' comparative likelihood on becoming employed after the first three months of a year. The independent variables were also represented as binary column vectors, meaning that a 1 represented an individual being, for example, unemployed, and a 0 indicating that they are not.

For this, the following formulae were implemented:

- First regression:

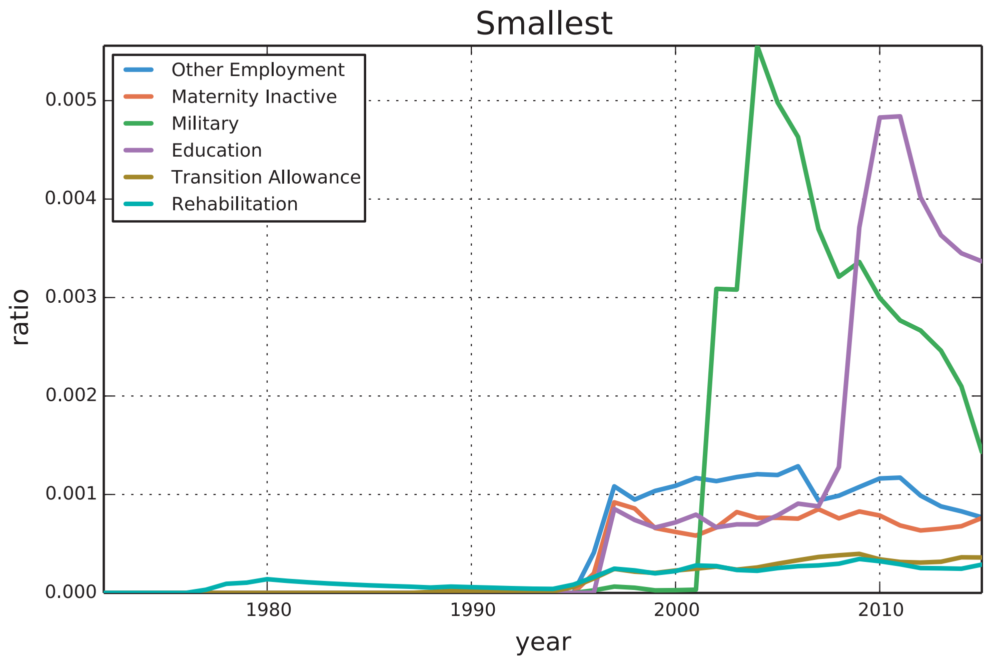

Figure 1: Spell Type Share 1972-2015: 0% to 0.2%

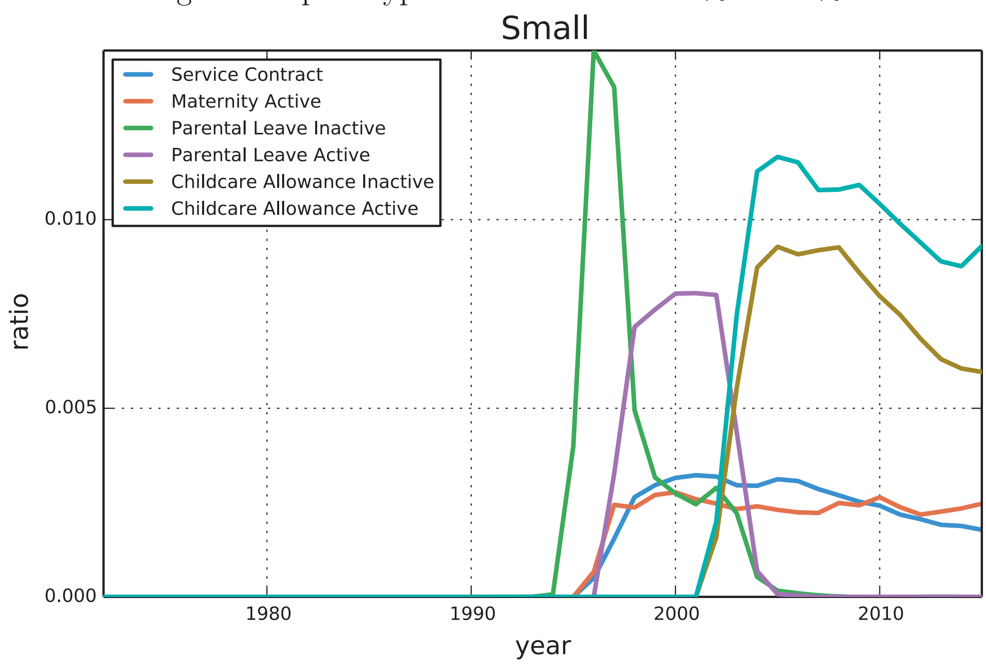

Figure 2: Spell Type Share 1972-2015: 0.2% to 0.6%

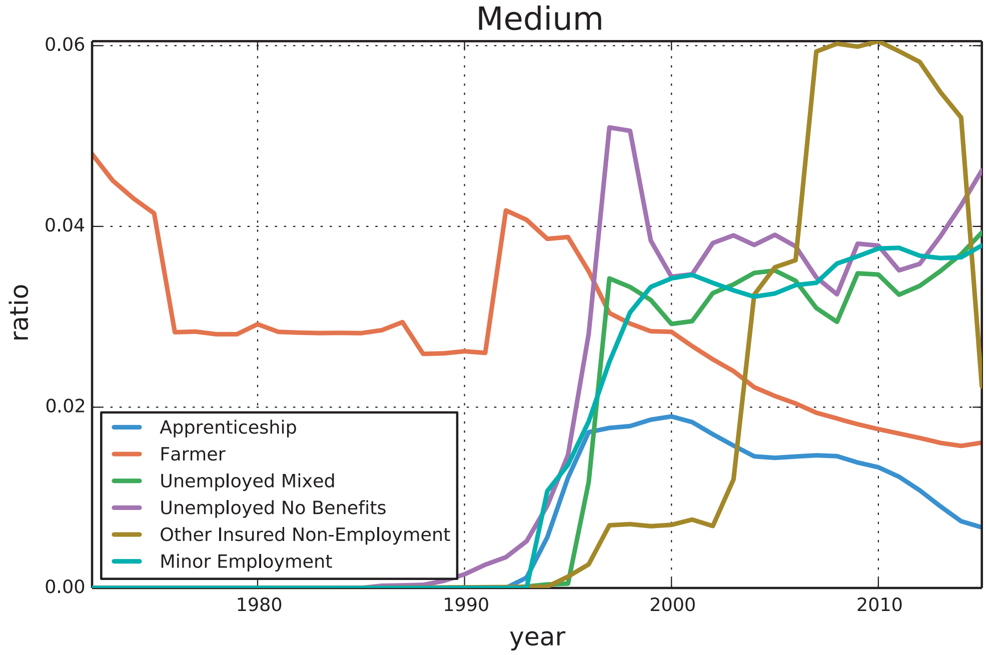

Figure 3: Spell Type Share 1972-2015: 0.6% to 3.2%

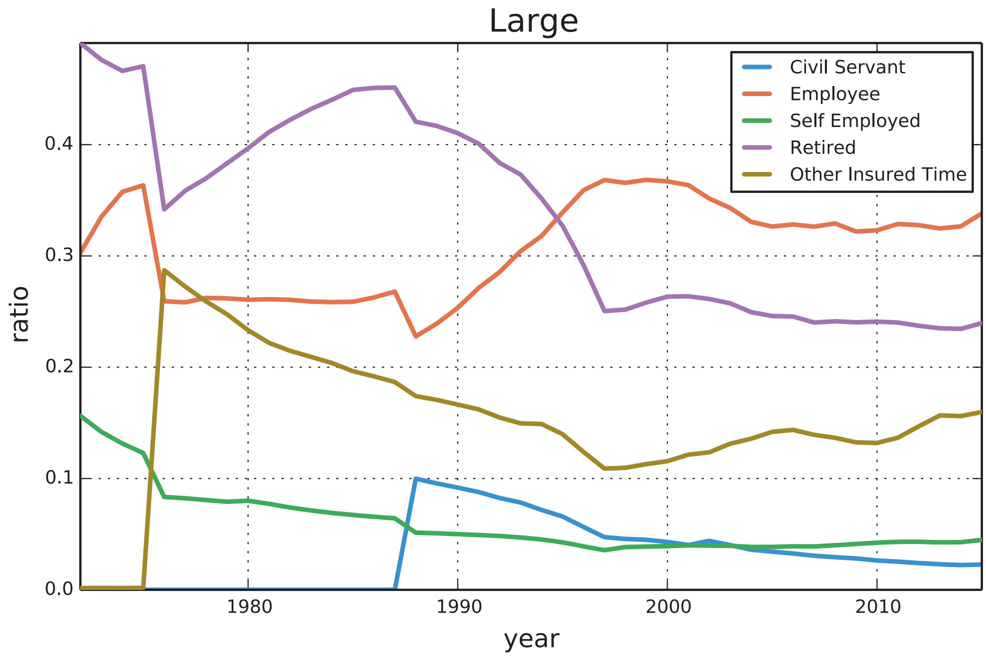

Figure 4: Spell Type Share 1972-2015: 3.2% to 32.9%

$$logit(probability(employment)) = 1 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_t$$

- Second regression:

$$logit(probability(employment)) = 1 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t$$

- Third regression:

$$logit(probability(employment)) = 1 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_5 X_{5t} + \varepsilon_t$$

$X_{1t} = childcare$
$X_{2t} = minor\ employment$
$X_{3t} = other\ insured\ non - employment$
$X_{4t} = past\ employment$
$X_{5t} = female$

3.2 Results

Each regression refers to a figure for the full time period and to a table with the 1997, 2015 and overall coefficients.

3.2.1 Non-Employment Regression

The first regression is initially run with the minimum number of days required for an individual to be counted in a category set at only 1 (i.e. days >0). The results can be seen in Table 6 and Figure 5.

The regression is then run with the minimum number of days required to be in a category set at 2 (i.e. days >1), can be seen in Table 7 and Figure 6.

3.2.2 Regression plus Employment

Now employment is added in as a regressor, using an additional binary column with employment from January to March for each year from 1997 to 2015.

The new regression, with the minimum number of days required to be in a category set at 1 can be seen in Table 8 and Figure 7.

This same regression, with the minimum number of days required to be in a category set at 2, can be seen in Table 9 and Figure 8.

3.2.3 Regression plus Gender

Now gender was introduced as the fifth regressor, using the same binary column. However, since no genders were updated across the length of the time period, this column remained the same year-by-year. In order to gain an accurate insight into the effect of this regressor, the percentage of women in the database used was calculated and found to be 47.5%.

The regression with days >0, produces the results in Table 10 and Figure 9.

The regression with days >1 produces Table 11 and Figure 10.

Table 6: Coefficients for Days >0: 1997, 2015, Total

	(1) Employment 1997	(2) Employment 2015	(3) Employment 1997:2015
intercept	-0.922***	0.462***	-0.115***
	(0.007)	(0.007)	(0.001)
childcare	-1.286***	-2.123***	-1.622***
	(0.060)	(0.043)	(0.010)
minor	0.310***	-0.718***	-0.570***
	(0.049)	(0.029)	(0.007)
OINE	0.668***	-1.403***	-0.268***
	(0.051)	(0.032)	(0.007)

Standard errors in parentheses

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

Table 7: Coefficients for Days >1: 1997, 2015, Total

	(1) Employment 1997	(2) Employment 2015	(3) Employment 1997:2015
intercept	-0.925***	0.458***	-0.119***
	(0.007)	(0.007)	(0.002)
childcare	-1.299***	-2.123***	-1.632***
	(0.061)	(0.043)	(0.010)
minor	0.151***	-0.733***	-0.583***
	(0.043)	(0.029)	(0.008)
OINE	0.734***	-1.466***	-0.297***
	(0.048)	(0.029)	(0.007)

Standard errors in parentheses

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

3.3 Findings

The first two regressions, with three regressors, yield the coefficient transformations found in Table 12.

This results in the following outcomes:

- Childcare produces an interesting result, as it presents with a considerably weaker effect than expected, much lower than the other two regressors and, by extension, unemployment. It is worth noting that the effect also falls substantially and has an decreasing effect on the likelihood of eventual employment. There are also two clear negative jumps in likelihood: in 1999 and 2003.
- Minor unemployment starts with a likelihood over 50% in 1997, increases slightly until 2000 but then falls steeply to just over a third of its initial

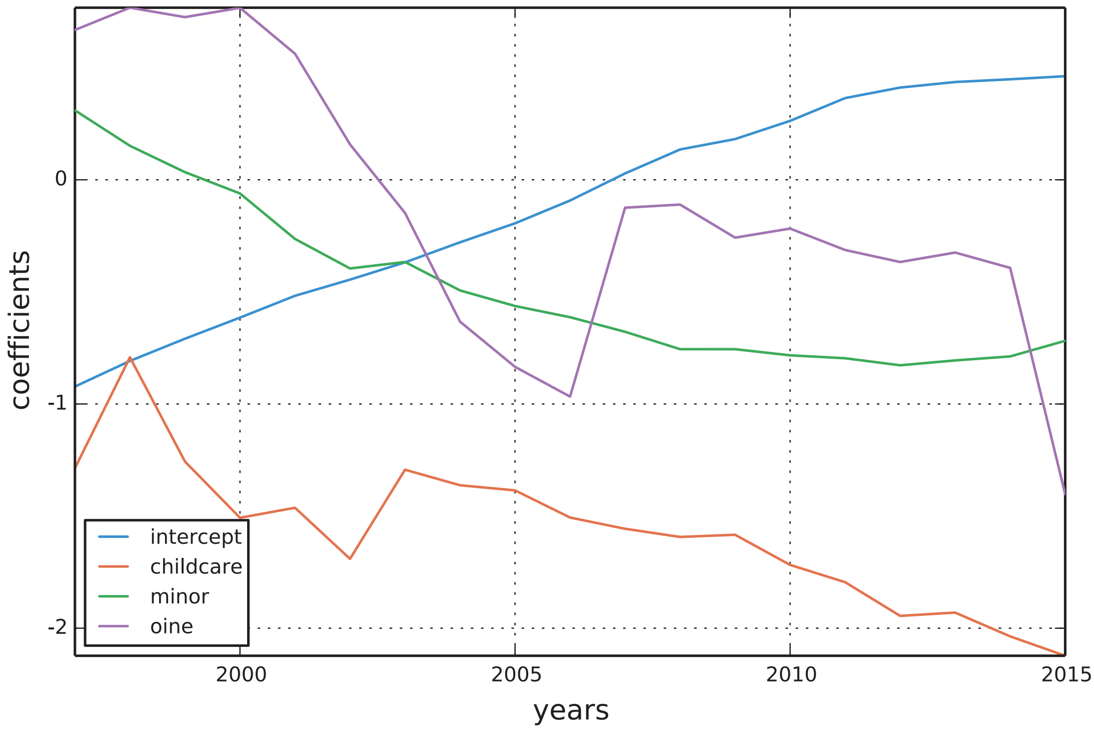

Figure 5: Regression for Days >0: 1997-2015

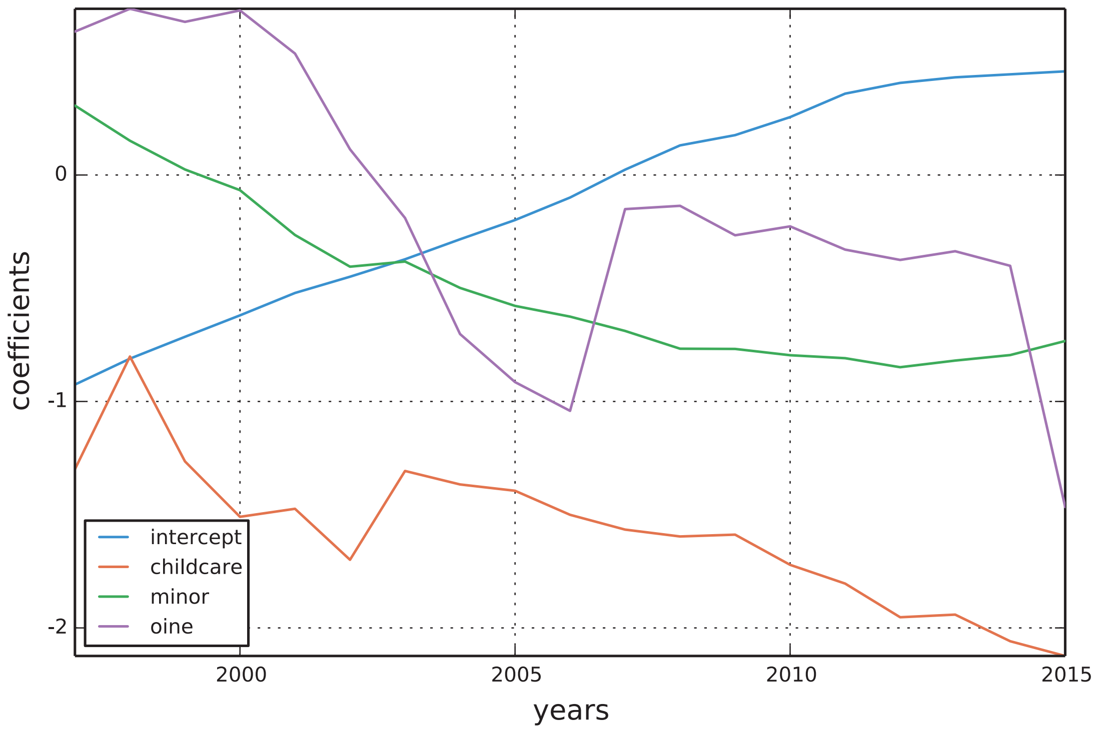

Figure 6: Regression for Days >1: 1997-2015

Table 8: Coefficients for Days >0 with Employment: 1997, 2015, Total

	(1) Employment 1997	(2) Employment 2015	(3) Employment 1997:2015
intercept	-1.983***	-1.107***	-0.238***
	(0.022)	(0.020)	(0.004)
childcare	-2.320***	-2.274***	-1.951***
	(0.104)	(0.084)	(0.019)
minor	0.922***	0.285***	0.294***
	(0.125)	(0.065)	(0.018)
OINE	-1.676***	-2.228***	-1.315***
	(0.091)	(0.067)	(0.013)
employment	7.042***	6.478***	6.838***
	(0.041)	(0.036)	(0.009)

Standard errors in parentheses

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

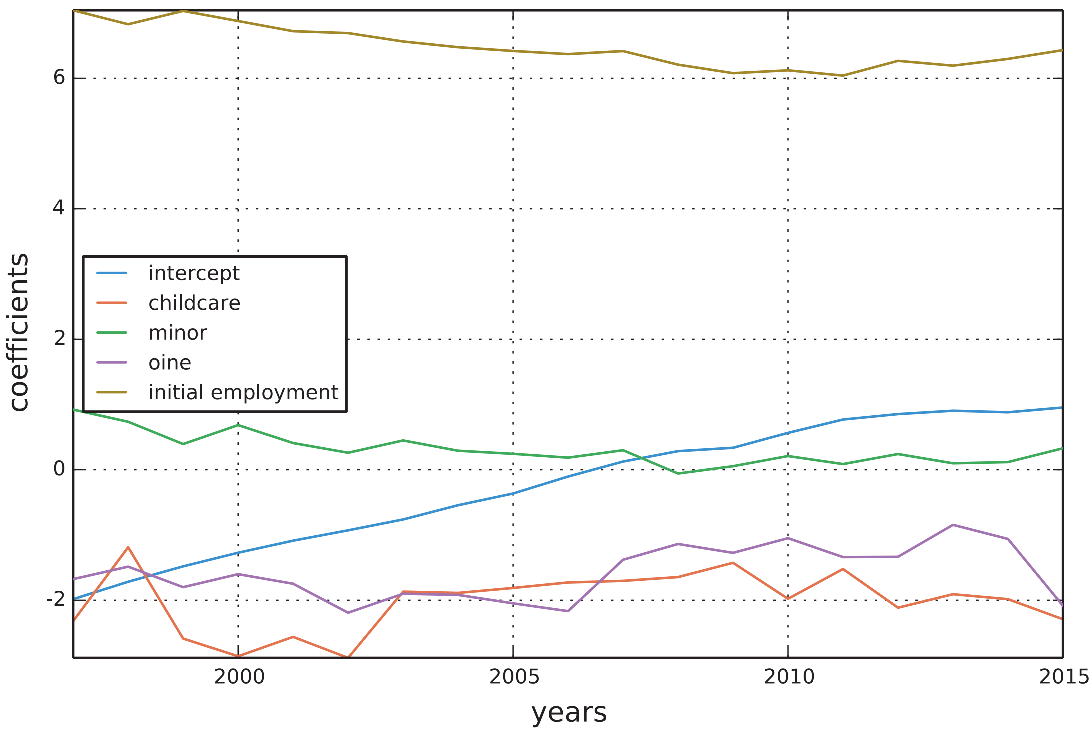

Figure 7: Regression with Past Employment for Days >0: 1997-2015

Table 9: Coefficients for Days >1 with Employment: 1997, 2015, Total

	(1) Employment 1997	(2) Employment 2015	(3) Employment 1997:2015
intercept	-1.998***	0.943***	-0.251***
	(0.022)	(0.017)	(0.004)
childcare	-2.263***	-2.224***	-1.924***
	(0.106)	(0.084)	(0.020)
minor	0.952***	0.308***	0.320***
	(0.126)	(0.066)	(0.018)
OINE	-1.500***	-2.003***	-1.202***
	(0.100)	(0.067)	(0.014)
employment	7.032***	6.418***	6.826**
	(0.041)	(0.035)	(0.009)

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

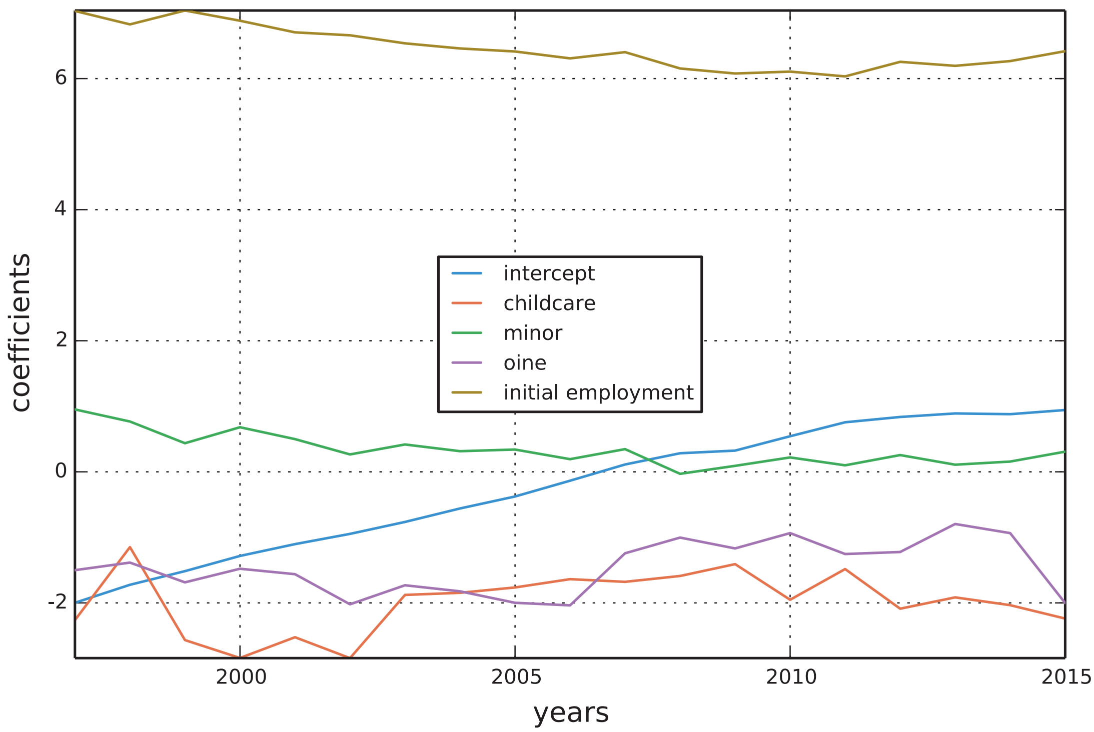

Figure 8: Regression with Past Employment for Days >1: 1997-2015

Table 10: Coefficients for Days >0 with Gender: 1997, 2015, Total

	(1)	(2)	(3)
	Employment 1997	Employment 2015	Employment 1997:2015
intercept	-0.925***	0.465***	-0.054***
	(0.007)	(0.007)	(0.002)
childcare	-1.151***	-2.147***	-1.559***
	(0.061)	(0.044)	(0.011)
minor	0.348***	-0.603***	-0.552***
	(0.049)	(0.029)	(0.007)
OINE	0.672***	-1.304***	-0.274***
	(0.051)	(0.033)	(0.007)
female	-0.252***	-0.055***	-0.127***
	(0.014)	(0.014)	(0.003)

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

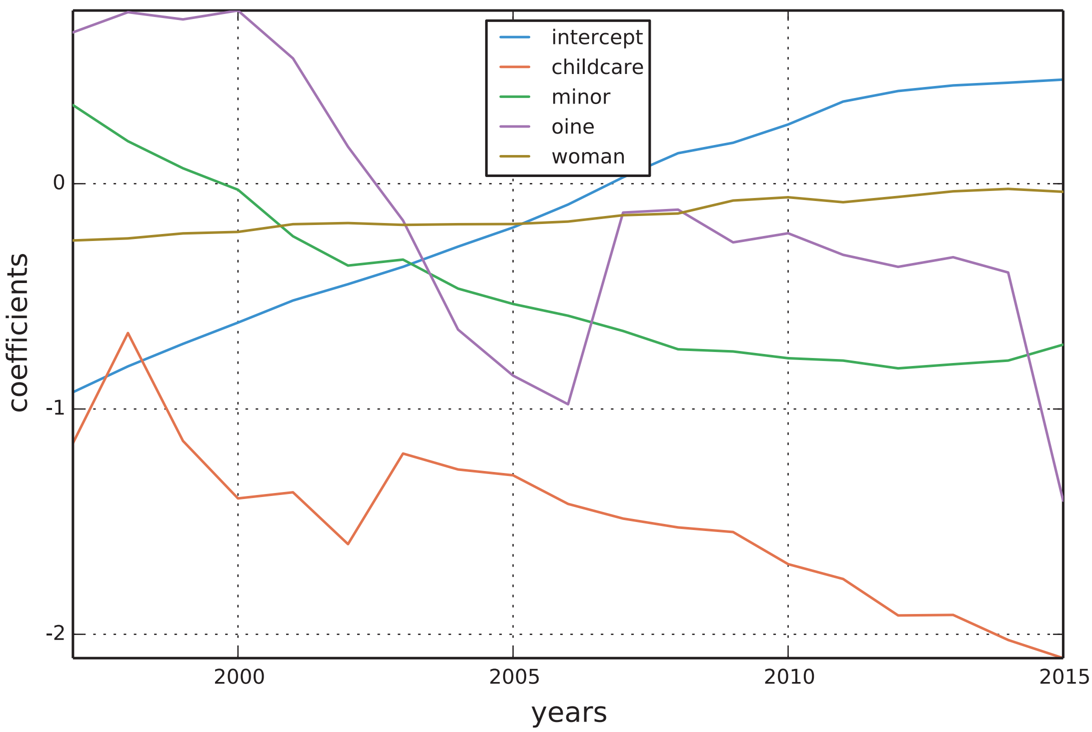

Figure 9: Regression with Gender for Days >0: 1997-2015

Table 11: Coefficients for Days >1 with Gender: 1997, 2015, Total

	(1) Employment 1997	(2) Employment 2015	(3) Employment 1997:2015
intercept	-0.929***	0.458***	-0.059***
	(0.007)	(0.007)	(0.002)
childcare	-1.164***	-2.106***	-1.568***
	(0.062)	(0.044)	(0.011)
minor	0.346***	-0.729***	-0.564***
	(0.050)	(0.023)	(0.008)
OINE	0.638***	-1.470***	-0.303**
	(0.053)	(0.033)	(0.007)
female	-0.253***	-0.038***	-0.127***
	(0.015)	(0.014)	(0.003)

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

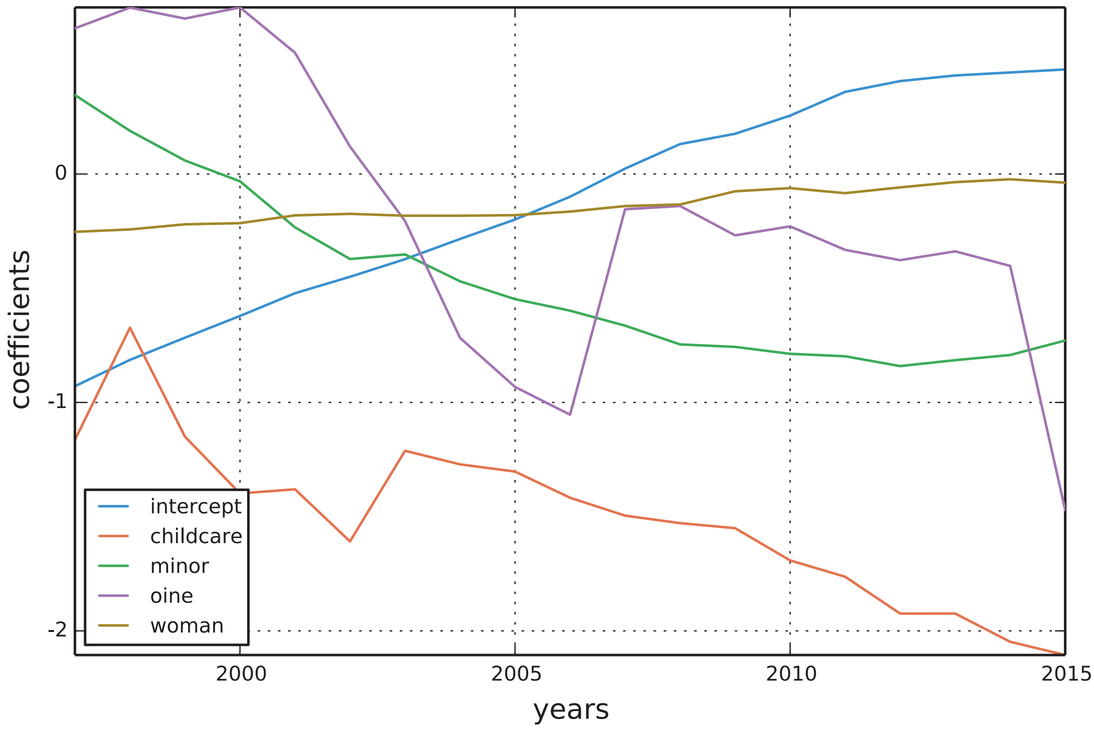

Figure 10: Regression with Gender for Days >1: 1997-2015

Table 12: Transformed Coefficients for Basic Regressors

	Employment 1997	Employment 2015	Employment 1997:2015
childcare	0.217	0.107	0.165
minor	0.577	0.328	0.361
OINE	0.661	0.197	0.433

Table 13: Transformed Coefficients with Employment

	Employment 1997	Employment 2015	Employment 1997:2015
childcare	0.090	0.093	0.124
minor	0.715	0.571	0.573
OINE	0.158	0.097	0.212
employment	0.999	0.998	0.999

value by the end of the period. However, using Figure 5, the untransformed coefficient can be seen to turn slightly upwards after 2012.

- Other insured non-employment (OINE) starts with a larger effect than minor unemployment in 1997 but rapidly falls, creating a significant gap between probabilities in the two categories by 2015 (see Table 12). In both Figure 5 and Figure 6, it is interesting to note that there is a large increase in 2007, which sustains until 2014.

The second two regressions, with four regressors including past employment, yields the transformed coefficients as found in Table 13.

This leads to the following:

- The new regressor of employment in the three months leading up to employment in April and May was unsurprisingly strong. However, even that has fallen since 1997, although this is marginal.
- Childcare is much lower than before, with just 9.4% chance of employment, a figure which experiences some volatility during the time period but at 2015 is almost level with its starting probability.
- Minor employment enjoys a boost and, while its influence also falls, this is by a much smaller margin than the previous regression.
- Other insured non-employment (OINE) has the most drastic change, falling to just 15.8% chance of attaining a job in 1997 from 66.1%. This category exhibits signs of increasing its influence during the Great Recession but falls sharply in 2015.

The third and final regression, with four regressors including gender, produced only small changes from the three regressor model, as can be seen in Table 14. Setting gender to female reveals a job-finding probability consistently under 50%.

For all three sets of regressions, changing the amount of days an individual spent in a category in order to be counted as such made little difference to the

Table 14: Transformed Coefficients with Gender

	Employment 1997	Employment 2015	Employment 1997:2015
childcare	0.240	0.105	0.174
minor	0.586	0.354	0.365
OINE	0.662	0.213	0.432
female	0.437	0.486	0.468

overall effect.

One can see that when employment is added as a regressor, it has a high probability of leading to an individual's future employment and has a marked effect on the others. On the other hand, adding gender made little difference to the progression of the other regressors.

It is of interest to note, and is unsurprising, that women are more likely to become employed in 2015 than in 1997, an effect which increase in an almost linear fashion, Figure 9 and Figure 10.

The effect of past employment on future employment decreases slightly over the time period, Figure7 and Figure 8. This would indicate that full-time employment overall is becoming a less likely outcome for any type of non-employment. Additionally, by adding another strong regressor it is clear to see that the other regressors experience polarising effects.

3.4 Reasons for the Data

3.4.1 Childcare

Childcare has actually reduced the chances of becoming employed, despite policy changes for parental leave improving steadily since 1996 (CES 2014). This is also strange considering that Austria's childcare costs are relatively low compared with other countries, at just 16.8%, with an OECD average of 18.6%. It may be explained by the gender pay gap in Austria, which was "one of the highest gender pay gaps in the OECD" in 2015. In 2012, the same group published a study showing pay gap of 23%, one of the highest in the EU, with the average at 16.4%.

Using data from Eurostat and the OECD, the PwC Women In Work Index showed that from 2000 to 2015, Austria had fallen from 13th to 22nd place out of 33 countries in their ongoing study, which takes pay gap, unemployment rates for women and labour force participation rates for women into account. This lack of support for women in the workplace may explain this negative effect, as well as the lowest job-finding rate in the non-employment categories, at just 17.4% (Table 18).

Here, it is important to note that childcare is the smallest of the non-employment categories, as seen in Table 17. Despite this, there remains a strong effect, which supposes that there may be a stronger pattern, which could be explored further with a larger sample size.

3.4.2 Minor Employment

Minor employment has an increasingly small effect, which may be due to an increase in part time workers, who are therefore not returning to full-time employment. This is supported by a 2015 OECD study on inequality, which shows that minor unemployment in Austria has increased and that the share of temporary staff that become permanent was only 30% from 2008 to 2011, as well as this paper which shows an overall transition rate of just 36.1% from 1997 to 2015 (Table 18). This increase in the number of people engaging in minor employment may be explained by households heading towards a dual-breadwinner status, a trend seen in the OECD's 2015 Survey of Austria.

This group represents just under a fifth of the groups chosen to represent non-employment but consistently produces the highest standard errors, leading one to believe that this group is not as homogeneous as other groups in its behaviour. Minor employment is a diverse group, as many are forced to choose part-time jobs during recessions, changing the composition considerably. During recessions, minor employment is taken up by many highly-skilled individuals, who are more likely to gain employment, see Krueger, Cramer and Cho (2014). This can be seen in Figure 5 through Figure 10, where minor unemployment experiences a slowing down of its increasingly negative effect around 2008 and even turns upwards towards the end of the time period.

Since these are predominantly new workers, rather than previously full-time employed, they are heavily affected by the introduction of employment as a regressor, since traditionally these jobs have been dominant. However, with the introduction of more jobs which fit this "minor employment" criteria, this category does comparatively well against unemployment in the first and third regression.

3.4.3 Other Insured Non-Employment

During a recession, the composition of a group such as OINE changes significantly, as workers are laid-off from their jobs and the job market now contains much more highly-skilled individuals. These individuals are perhaps simply waiting for an opportunity to either rejoin their previous firm or to gain employment from strong contacts found through previous employment (Hall 1983). This increase in talent can be seen though a sharp spike in likelihood of employment, see Figure 5 after the market crash in 2007, returning to its previous low level after 2014.

Since OINE is viewed here as OLF, its decreasing effect may be linked to unemployment rates. If OINE is considered to contain the individuals who have been unemployed for a long time and have therefore stopped looking or who have become discouraged, it can be seen to some extent as an extension of those who are merely "unemployed". The unemployment rate started at 9% in 1997 and rose to 10.5% by January of 2015, which would imply that the number in the OINE category would increase as well. The data suggests that higher current unemployment rates have a negative effect on future employment, a common link found in the literature. The unemployment rate is closely linked with the GDP, which has stagnated in Austria since 2008.

Shimer (1998) posited that the U.S. unemployment had fared poorly due to an aging population, the effects of which can be seen as recently as the Great Recession according to Krueger (2016), Hall (2016). Using field data on population demographics (see Table 15), it can be seen that nearly one fifth of Austria's population is over 65 years old in 2015, which is significantly higher than 1997 population, which was 15% (see Table 16). Working population has decreased from 68% of the population to 67.2% in 2015.

Unemployment is the largest non-employment category, as can be seen in Table 17, which explains at least part of its strong effect on employment and, by extension, OINE.

OINE comprises over a quarter of the non-employed but still experiences some of the least change across all the regressors over time. Augmenting the administrative AMDB database with a self-reported one, such as the CPS, would be beneficial in determining the attitude to employment of the individuals in this group. Since this group has a high raw job-finding rate but a comparatively

Table 15: Age Structure of Austria 1997

Age Group	Percentage	Male	Female
0-14 years	17%	717,989	681,897
15-64 years	68%	2,777,525	2,703,296
65+ years	15%	464,802	786,996
Total Population: 8,132,505			

Source: CIA World Factbook

Table 16: Age Structure of Austria 2015

Age Group	Percentage	Male	Female
0-14 years	13.6%	573,146	546,596
15-64 years	67.2%	2,771,206	2,754,759
65+ years	19.2%	670,75	906,605
Total Population: 8,223,062			

Source: CIA World Factbook

Table 17: Relative Proportions of Non-Employment Categories

Category	Proportion
Unemployment	48.0%
Childcare	7.4%
Minor Employment	18.4%
Other Insured Non-Employment	26.2%

Table 18: Raw Job Finding Rates

Category	Job Finding Rate
Unemployment	50.5%
Childcare	17.4%
Minor Employment	36.1%
Other Insured Non-Employment	47.0%

muted effect on future employment, exploring this facet could benefit from closer examination.

3.4.4 Past Employment and Gender

While these were not the main focus of this paper, it is clear to see that they also have relative effects on future employment. Overall higher unemployment rates have risen, which may both cause and be caused by those who are currently employed being less likely to retain their jobs. This may also have stemmed from an increasing mechanisation of the work force in Austria.

As for gender, this is heavily discussed in section 3.4.1, with the broad consensus that women's working conditions are improving in Austria but still have some flaws which must be addressed in order to increase the likelihood of women gaining full-time employment.

4 Comparison to the Literature

For all three sets of regressions, it can be seen that, with unemployment as a baseline, other insured non-employment clearly experiences an increasingly negative path. It is interesting to note in the first and third sets of regressions that, in the Great Recession, the probability of the OINE transitioning to employment increased significantly in comparison to unemployment, although it has fallen again noticeably since 2014. These dates correspond to a stagnation of GDP since 2008, which correlates with the findings of Krueger, Cramer and Cho (2014). They show that the long-term unemployed are more insulated from negative effects of macroeconomic activity than short-term and that the long-term unemployed are much more likely leave the labour force and become classified as out of the labour force (OLF) than the short-term unemployed. For the purposes of comparison with this paper, OINE can be seen as an expected outcome for the long-term unemployed and unemployed can be viewed as short-term unemployed.

On of the aims of this paper was to show that the composition of the non-employed accounted for the future prospects of employment for those groups. This technique can be seen in Barnichon and Figura (2013), which presented a composition effect, taking into account how close a person was to the labour market and therefore, how likely they were to gain employment. They noticed that those in employment were increasingly more likely to gain future employment than those considered to be unemployed or marginally attached to the workforce. They also studied demographics, such as age, sex and education, and found, similar to this paper, that labour force attachment declined somewhat more for women than for men.

It has been seen in Hall (2016), that other components which comprise the labour market may capture unutilised labour more than unemployment does, which may partially explain the overall decrease in the likelihood of employment. One aspect of that paper does not hold for Austria: reduced productivity, as Austria's productivity rates have increased steadily and cyclically since 1997, except a setback after the 2008 crisis. However, technology may be a factor. One study showed that while Austria's industry-based R&D as a percentage of its GDP was above the average among developed countries, the study indicted a need for Austria to "facilitate mobility between vocational/technical and academic studies" (OECD 1997).

It seems counter-intuitive that OINE has such a relatively strong attachment to the labour force, considering its apparent standing as "unemployed and not currently looking for a job", if one were to make comparisons with similar categories in other works, such as the CPS used in Kudlyak and Lange (2016). However, using the idea that those who are not actively looking for work may still find employment, as in Coles and Smith (1998) and Hall (1983) "waiting at the airport", it can be theorised that an individual may have expected to become re-employed after a lay-off or otherwise reasonably expect to become employed again after a period of non-employment.

5 Conclusion

By breaking down the work histories of those who transition into employment after non-employment, it is clear that these groups have large variances in the likelihood of this transition occurring. This is as follows:

- childcare has the smallest impact on future employment, in comparison to those considered unemployed. This may indicate a lack of support for women to return to the workplace, as supported by women having a lower job-finding probability;
- minor employment has a moderate but shrinking effect against unemployment, which may be explained partially by an increase in part-time workers and part-time jobs that don't seek to compete for the same positions;
- other insured non-employment (out of the labour force) has a similar but less pronounced effect to unemployment, which can be understood as a group that is less willing to look for employment than the unemployed, excepting recessions;
- gender plays a smaller role in job-finding prospects now than 20 years ago but is still a prevalent force in today's labour market.

All non-employment groups experiencing an overall drop in job-finding probabilities indicates a greater problem surrounding transitions into employment. This may be in part due to an increase in unemployment of 1.6pp from 1997 to 2015 and stagnation of the Austrian GDP since 2008.

In summary, further research into the driving force behind higher unemployment rates can, to some extent, be shown to have a dependence on the exact nature of non-employment. Looking forward, it would be of interest to explore the demographics of these groups, especially with respect to childcare and minor employment, in order to find out whether further patterns emerge, in order to introduce policy that can more accurately reduce unemployment rates.

References

[1] Barnichon Regis, Figura Andrew (2013) Declining labor force attachment and downward trends in unemployment and participation. Barcelona Graduate School of Economics, Working Paper No. 14-18.

[2] CES (2014): Parental leave entitlements: Historical perspective (around 1870 - 2014). https://www.cesifo-group.de/ifoHome/facts/DICE/Social-Policy/Family/Work-Family-Balance/parental-leave-entitlements-historical-perspective/fileBinary/parental-leave-entitlements-historical-perspective.pdf - accessed 11 May 2017.

[3] CIA (2017): The World Factbook. https://www.cia.gov/library/publications/the-world-factbook/fields/2010.html – accessed on: 15 May 2017.

[4] Coles Melvyn, Smith Eric (1998) Marketplaces and Matching. International Economic Review, Vol. 39, No. 1, pp. 239-54

[5] Elsby Michael W., Hobijn Bart, and Aysegul Sahin (2010) The labor market in the Great Recession. NBER Working Paper, No. 15979.

[6] Flinn Christopher J., Heckman James J. (1983) Are Unemployment and Out of the Labor Force Behaviorally Distinct Labor Force States? Journal of Labor Economics, Vol. 1, No. 1, pp. 28-42.

[7] Hall Robert E. (1970): Why is the unemployment rate so high at full employment? Brookings Papers on Economic Activity, Vol. 1970, No. 3, pp. 369-410.

[8] Hall Robert E. (1983) Is Unemployment a Macroeconomic Problem? The American Economic Review, Vol. 73, No. 2, pp. 219-222.

[9] Hall Robert E. (2016) Why Has the Unemployment Rate Fared Better than GDP Growth? Draft for the Boston Federal Reserve's conference, "The Elusive 'Great Recovery': Causes and Implications for Future Business Cycle Dynamics".

[10] Krueger Alan B. (2016). Where have all the workers gone? https://www.bostonfed.org/-/media/Documents/economic/conf/great-recovery-2016/AlanB-Krueger.pdf - accessed on: 2 April 2017.

[11] Krueger Alan B., Cramer Judd and Cho David (2014) Are the Long-Term Unemployed on the Margins of the Labor Market? Brookings Papers on Economic Activity, Vol. 2014, No. 1, pp. 229-299.

[12] Kudlyak Marianna, Lange Fabian (2014): Measuring Heterogeneity in Job Finding Rates Among the Nonemployed Using Labor Force Status Histories.

FRB Richmond, Working Paper No. 14-18.

[13] OECD (2016): Gender pay gap statistics. http://ec.europa.eu/justice/genderequality/files/gender_pay_gap/2016/gpg_country_factsheet_at_2016_en.pdf - accessed on: 10 May 2017.

[14] OECD (2015): In It Together: Why Less Inequality Benefits All. OECD Publishing, Paris.

[15] OECD (2015): OECD Economic Surveys: AUSTRIA. https://www.oecd.org/eco/surveys/Austria-2015-overview.pdf – accessed on: 3 May 2017.

[16] OECD (1997): Technology, Productivity and Job Creation: Best Policy Practices. https://www.oecd.org/sti/ind/2759012.pdf – accessed on: 3 May 2017.

[17] PwC (2017): PwC Women In Work Index: Closing the gender pay gap. https://www.pwc.at/publikationen/verschiedenes/women-in-work2017.pdf – accessed on: 15 May 2017.

[18] Shimer Robert (1998) Why is the U.S. Unemployment Rate So Much Lower? NBER macroeconomics annual Vol. 13, No. 1, pp. 11-61.

[19] Trading Economics (2017): Austria Productivity. https://tradingeconomics.com/austria/productivity – accessed on: 15 April 2017.

A Data Appendix

This section presents relevant additional information on the data used:

Table 19: Regression with Days >0: 1997-2015

	intercept	(1) childcare	(2) minor	(3) OINE
Total	-0.114***	-1.622***	-0.570***	-0.267***
	(0.001)	(0.010)	(0.007)	(0.006)
1997	-0.922***	-1.286***	0.309***	0.668***
	(0.007)	(0.060)	(0.049)	(0.051)
1998	-0.808***	-0.791***	0.151***	0.767***
	(0.006)	(0.050)	(0.042)	(0.046)
1999	-0.708***	-1.256***	0.034	0.725***
	(0.006)	(0.063)	(0.039)	(0.046)
2000	-0.614***	-1.507***	-0.061	0.766***
	(0.006)	(0.065)	(0.037)	(0.045)
2001	-0.517***	-1.462***	-0.263***	0.562***
	(0.006)	(0.062)	(0.036)	(0.043)
2002	-0.445***	-1.690***	-0.395***	0.157***
	(0.006)	(0.064)	(0.036)	(0.046)
2003	-0.368***	-1.293***	-0.366***	-0.147***
	(0.006)	(0.044)	(0.035)	(0.040)
2004	-0.278***	-1.362***	-0.493***	-0.632***
	(0.006)	(0.041)	(0.034)	(0.036)
2005	-0.194***	-1.385***	-0.563***	-0.834***
	(0.006)	(0.038)	(0.033)	(0.034)
2006	-0.092***	-1.506***	-0.612***	-0.967***
	(0.006)	(0.038)	(0.032)	(0.033)
2007	0.028***	-1.556***	-0.677***	-0.124***
	(0.006)	(0.038)	(0.031)	(0.025)
2008	0.135***	-1.592***	-0.755***	-0.110***
	(0.006)	(0.037)	(0.029)	(0.024)
2009	0.181***	-1.583***	-0.755***	-0.258***
	(0.006)	(0.036)	(0.028)	(0.023)
2010	0.262***	-1.717***	-0.782***	-0.217***
	(0.006)	(0.037)	(0.027)	(0.023)
2011	0.364***	-1.794***	-0.796***	-0.313***
	(0.006)	(0.037)	(0.027)	(0.023)
2012	0.411***	-1.945***	-0.827***	-0.366***
	(0.006)	(0.040)	(0.027)	(0.023)
2013	0.436***	-1.930***	-0.805***	-0.324***
	(0.006)	(0.040)	(0.028)	(0.022)
2014	0.448***	-2.036***	-0.787***	-0.392***
	(0.006)	(0.042)	(0.028)	(0.022)
2015	0.461***	-2.122***	-0.718***	-1.402***
	(0.006)	(0.043)	(0.028)	(0.032)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Regression with Days >1: 1997-2015

	intercept	(1) childcare	(2) minor	(3) OINE
Total	-0.119***	-1.631***	-0.583***	-0.297***
	(0.001)	(0.010)	(0.007)	(0.006)
1997	-0.925***	-1.299***	0.306***	0.633***
	(0.007)	(0.060)	(0.049)	(0.052)
1998	-0.810***	-0.801***	0.151***	0.734***
	(0.006)	(0.050)	(0.043)	(0.048)
1999	-0.714***	-1.264***	0.024	0.676***
	(0.006)	(0.064)	(0.039)	(0.048)
2000	-0.619***	-1.509***	-0.066	0.726***
	(0.006)	(0.066)	(0.037)	(0.046)
2001	-0.520***	-1.473***	-0.264***	0.536***
	(0.006)	(0.063)	(0.036)	(0.045)
2002	-0.449***	-1.699***	-0.404***	0.113*
	(0.006)	(0.065)	(0.036)	(0.048)
2003	-0.372***	-1.306***	-0.382***	-0.189***
	(0.006)	(0.044)	(0.036)	(0.042)
2004	-0.283***	-1.366***	-0.498***	-0.702***
	(0.006)	(0.041)	(0.035)	(0.038)
2005	-0.198***	-1.394***	-0.577***	-0.914***
	(0.006)	(0.039)	(0.033)	(0.035)
2006	-0.099***	-1.500***	-0.625***	-1.041***
	(0.006)	(0.038)	(0.032)	(0.035)
2007	0.023***	-1.565***	-0.688***	-0.150***
	(0.006)	(0.038)	(0.031)	(0.025)
2008	0.130***	-1.596***	-0.767***	-0.136***
	(0.006)	(0.037)	(0.029)	(0.024)
2009	0.176***	-1.588***	-0.768***	-0.266***
	(0.006)	(0.036)	(0.028)	(0.024)
2010	0.255***	-1.721***	-0.795***	-0.226***
	(0.006)	(0.037)	(0.028)	(0.023)
2011	0.359***	-1.804***	-0.808***	-0.329***
	(0.006)	(0.037)	(0.027)	(0.023)
2012	0.406***	-1.952***	-0.848***	-0.375***
	(0.006)	(0.040)	(0.028)	(0.023)
2013	0.431***	-1.941***	-0.819***	-0.336***
	(0.006)	(0.040)	(0.028)	(0.022)
2014	0.444***	-2.058***	-0.795***	-0.400***
	(0.006)	(0.042)	(0.028)	(0.022)
2015	0.457***	-2.123***	-0.733***	-1.466***
	(0.006)	(0.043)	(0.028)	(0.033)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Regression with Days >0 (incl. employment): 1997-2015

		(1)	(2)	(3)	(4)
	intercept	childcare	minor	OINE	employment
Total	-0.238***	-1.951***	0.293***	-1.315***	6.838***
	(0.003)	(0.019)	(0.017)	(0.013)	(0.008)
1997	-1.983***	-2.320***	0.921***	-1.676***	7.042***
	(0.021)	(0.104)	(0.124)	(0.091)	(0.041)
1998	-1.717***	-1.188***	0.735***	-1.485***	6.828***
	(0.020)	(0.113)	(0.107)	(0.083)	(0.038)
1999	-1.480***	-2.587***	0.393***	-1.799***	7.032***
	(0.019)	(0.106)	(0.104)	(0.082)	(0.040)
2000	-1.271***	-2.858***	0.684***	-1.600***	6.877***
	(0.018)	(0.101)	(0.089)	(0.080)	(0.038)
2001	-1.087***	-2.561***	0.409***	-1.747***	6.721***
	(0.018)	(0.102)	(0.088)	(0.073)	(0.037)
2002	-0.928***	-2.883***	0.260**	-2.191***	6.692***
	(0.017)	(0.097)	(0.088)	(0.072)	(0.036)
2003	-0.762***	-1.868***	0.448***	-1.900***	6.563***
	(0.017)	(0.086)	(0.082)	(0.072)	(0.035)
2004	-0.543***	-1.888***	0.291***	-1.918***	6.476***
	(0.016)	(0.080)	(0.080)	(0.069)	(0.034)
2005	-0.364***	-1.812***	0.243**	-2.047***	6.418***
	(0.016)	(0.078)	(0.075)	(0.064)	(0.034)
2006	-0.104***	-1.728***	0.185**	-2.167***	6.370***
	(0.016)	(0.080)	(0.071)	(0.062)	(0.034)
2007	0.125***	-1.703***	0.299***	-1.379***	6.416***
	(0.016)	(0.081)	(0.069)	(0.054)	(0.034)
2008	0.284***	-1.645***	-0.058	-1.138***	6.208***
	(0.015)	(0.076)	(0.067)	(0.051)	(0.032)
2009	0.336***	-1.426***	0.054	-1.273***	6.078***
	(0.015)	(0.074)	(0.063)	(0.048)	(0.031)
2010	0.565***	-1.978***	0.209***	-1.049***	6.121***
	(0.015)	(0.071)	(0.059)	(0.051)	(0.032)
2011	0.769***	-1.521***	0.086	-1.338***	6.041***
	(0.015)	(0.077)	(0.059)	(0.047)	(0.031)
2012	0.852***	-2.114***	0.240***	-1.334***	6.267***
	(0.016)	(0.077)	(0.061)	(0.049)	(0.033)
2013	0.904***	-1.908***	0.098	-0.844***	6.193***
	(0.016)	(0.081)	(0.063)	(0.052)	(0.032)
2014	0.880***	-1.983***	0.117	-1.060***	6.296***
	(0.016)	(0.084)	(0.065)	(0.050)	(0.033)
2015	0.953***	-2.291***	0.328***	-2.085***	6.431***
	(0.017)	(0.083)	(0.065)	(0.064)	(0.035)

Standard errors in parentheses

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

Table 22: Regression with Days >1 (incl. employment): 1997-2015

	intercept	(1) childcare	(2) minor	(3) OINE	(4) employment
Total	-0.250***	-1.924***	0.320***	-1.202***	6.825***
	(0.003)	(0.019)	(0.017)	(0.013)	(0.008)
1997	-1.998***	-2.262***	0.952***	-1.500***	7.031***
	(0.021)	(0.106)	(0.126)	(0.099)	(0.041)
1998	-1.723***	-1.148***	0.767***	-1.384***	6.826***
	(0.020)	(0.114)	(0.108)	(0.088)	(0.038)
1999	-1.515***	-2.567***	0.436***	-1.686***	7.038***
	(0.020)	(0.107)	(0.105)	(0.087)	(0.040)
2000	-1.283***	-2.840***	0.680***	-1.478***	6.882***
	(0.018)	(0.102)	(0.091)	(0.087)	(0.038)
2001	-1.103***	-2.523***	0.499***	-1.561***	6.705***
	(0.018)	(0.102)	(0.088)	(0.080)	(0.036)
2002	-0.946***	-2.842***	0.265**	-2.021***	6.660***
	(0.017)	(0.098)	(0.089)	(0.079)	(0.036)
2003	-0.764***	-1.878***	0.417***	-1.730***	6.537***
	(0.017)	(0.086)	(0.083)	(0.078)	(0.035)
2004	-0.559***	-1.845***	0.314***	-1.823***	6.459***
	(0.016)	(0.081)	(0.080)	(0.073)	(0.034)
2005	-0.376***	-1.764***	0.339***	-1.998***	6.413***
	(0.016)	(0.079)	(0.075)	(0.067)	(0.034)
2006	-0.135***	-1.637***	0.193**	-2.037***	6.308***
	(0.015)	(0.080)	(0.072)	(0.065)	(0.033)
2007	0.111***	-1.678***	0.346***	-1.242***	6.403***
	(0.016)	(0.081)	(0.069)	(0.057)	(0.034)
2008	0.283***	-1.589***	-0.030	-1.003***	6.154***
	(0.015)	(0.076)	(0.067)	(0.053)	(0.032)
2009	0.323***	-1.408***	0.091	-1.168***	6.077***
	(0.015)	(0.075)	(0.063)	(0.049)	(0.031)
2010	0.542***	-1.952***	0.219***	-0.934***	6.106***
	(0.015)	(0.071)	(0.060)	(0.052)	(0.032)
2011	0.755***	-1.483***	0.099	-1.254***	6.033***
	(0.015)	(0.078)	(0.059)	(0.048)	(0.031)
2012	0.836***	-2.088***	0.255***	-1.223***	6.255***
	(0.016)	(0.078)	(0.061)	(0.051)	(0.033)
2013	0.890***	-1.915***	0.108***	-0.795***	6.194***
	(0.016)	(0.081)	(0.063)	(0.053)	(0.032)
2014	0.879***	-2.034***	0.156	-0.935***	6.266***
	(0.016)	(0.083)	(0.065)	(0.052)	(0.033)
2015	0.942***	-2.239***	0.307*	-2.003***	6.418***
	(0.017)	(0.084)	(0.065)	(0.067)	(0.035)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Regression with Days >0 (incl. gender): 1997-2015

	intercept	(1) childcare	(2) minor	(3) OINE	(4) female
Total	-0.054***	-1.559***	-0.551***	-0.273***	-0.126***
	(0.002)	(0.010)	(0.007)	(0.006)	(0.003)
1997	-0.925***	-1.151***	0.348***	0.671***	-0.252***
	(0.007)	(0.060)	(0.049)	(0.051)	(0.014)
1998	-0.810***	-0.662***	0.188***	0.761***	-0.242***
	(0.006)	(0.050)	(0.042)	(0.046)	(0.014)
1999	-0.710***	-1.141***	0.068	0.729***	-0.220***
	(0.006)	(0.064)	(0.039)	(0.047)	(0.013)
2000	-0.616***	-1.396***	-0.026	0.768***	-0.214***
	(0.006)	(0.066)	(0.037)	(0.045)	(0.013)
2001	-0.518***	-1.369***	-0.233***	0.556***	-0.179***
	(0.006)	(0.063)	(0.036)	(0.043)	(0.013)
2002	-0.446***	-1.599***	-0.363***	0.164*	-0.174***
	(0.006)	(0.065)	(0.036)	(0.046)	(0.013)
2003	-0.368***	-1.197***	-0.336***	-0.163***	-0.182***
	(0.006)	(0.044)	(0.035)	(0.040)	(0.013)
2004	-0.279***	-1.268***	-0.465***	-0.647***	-0.179***
	(0.006)	(0.041)	(0.034)	(0.037)	(0.013)
2005	-0.194***	-1.294***	-0.533***	-0.851***	-0.179***
	(0.006)	(0.039)	(0.033)	(0.034)	(0.013)
2006	-0.092***	-1.421***	-0.585***	-0.978***	-0.168***
	(0.006)	(0.039)	(0.032)	(0.033)	(0.013)
2007	0.028***	-1.486***	-0.653***	-0.128***	-0.139***
	(0.006)	(0.039)	(0.031)	(0.025)	(0.013)
2008	0.135***	-1.525***	-0.734***	-0.115***	-0.132***
	(0.006)	(0.037)	(0.029)	(0.024)	(0.013)
2009	0.181***	-1.546***	-0.744***	-0.260***	-0.074***
	(0.006)	(0.036)	(0.028)	(0.023)	(0.013)
2010	0.262***	-1.688***	-0.774***	-0.219***	-0.060***
	(0.006)	(0.037)	(0.027)	(0.023)	(0.013)
2011	0.364***	-1.754***	-0.785***	-0.315***	-0.082***
	(0.006)	(0.038)	(0.027)	(0.023)	(0.013)
2012	0.411***	-1.916***	-0.819***	-0.369***	-0.058***
	(0.006)	(0.040)	(0.027)	(0.023)	(0.013)
2013	0.436***	-1.913***	-0.801***	-0.326***	-0.033
	(0.006)	(0.041)	(0.028)	(0.022)	(0.013)
2014	0.448***	-2.025***	-0.784***	-0.394***	-0.023
	(0.006)	(0.043)	(0.028)	(0.022)	(0.013)
2015	0.461***	-2.105***	-0.714***	-1.406***	-0.035**
	(0.006)	(0.043)	(0.028)	(0.032)	(0.013)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Regression with Days >1 (incl. gender): 1997-2015

	intercept	(1) childcare	(2) minor	(3) OINE	(4) female
Total	-0.058***	-1.567***	-0.564***	-0.302***	-0.127***
	(0.002)	(0.010)	(0.007)	(0.006)	(0.003)
1997	-0.928***	-1.163***	0.345***	0.637***	-0.253***
	(0.007)	(0.061)	(0.049)	(0.052)	(0.014)
1998	-0.813***	-0.672***	0.189***	0.728***	-0.242***
	(0.006)	(0.051)	(0.043)	(0.048)	(0.014)
1999	-0.716***	-1.149***	0.059	0.680***	-0.220***
	(0.006)	(0.064)	(0.040)	(0.048)	(0.013)
2000	-0.621***	-1.398***	-0.031	0.729***	-0.215***
	(0.006)	(0.066)	(0.037)	(0.046)	(0.013)
2001	-0.521***	-1.380***	-0.233***	0.531***	-0.180***
	(0.006)	(0.063)	(0.037)	(0.045)	(0.013)
2002	-0.449***	-1.608***	-0.372***	0.120*	-0.174***
	(0.006)	(0.065)	(0.036)	(0.048)	(0.013)
2003	-0.372***	-1.211***	-0.352***	-0.205***	-0.182***
	(0.006)	(0.045)	(0.036)	(0.042)	(0.013)
2004	-0.284***	-1.270***	-0.469***	-0.717***	-0.182***
	(0.006)	(0.041)	(0.035)	(0.038)	(0.013)
2005	-0.199***	-1.302***	-0.547***	-0.932***	-0.180***
	(0.006)	(0.039)	(0.034)	(0.036)	(0.013)
2006	-0.099***	-1.417***	-0.598***	-1.053***	-0.164***
	(0.006)	(0.039)	(0.032)	(0.035)	(0.013)
2007	0.023***	-1.495***	-0.663***	-0.154***	-0.140***
	(0.006)	(0.039)	(0.031)	(0.025)	(0.013)
2008	0.131***	-1.528***	-0.745***	-0.140***	-0.133***
	(0.006)	(0.037)	(0.029)	(0.024)	(0.013)
2009	0.176***	-1.550***	-0.756***	-0.268***	-0.075***
	(0.006)	(0.036)	(0.028)	(0.024)	(0.013)
2010	0.255***	-1.691***	-0.787***	-0.229***	-0.061***
	(0.006)	(0.037)	(0.028)	(0.023)	(0.013)
2011	0.359***	-1.763***	-0.797***	-0.332***	-0.083***
	(0.006)	(0.038)	(0.027)	(0.023)	(0.013)
2012	0.406***	-1.924***	-0.840***	-0.377***	-0.058***
	(0.006)	(0.040)	(0.028)	(0.023)	(0.013)
2013	0.431***	-1.924***	-0.814***	-0.338***	-0.035**
	(0.006)	(0.041)	(0.028)	(0.022)	(0.013)
2014	0.444***	-2.047***	-0.792***	-0.402***	-0.023
	(0.006)	(0.043)	(0.028)	(0.022)	(0.013)
2015	0.457***	-2.105***	-0.728***	-1.470***	-0.037*
	(0.006)	(0.043)	(0.028)	(0.033)	(0.013)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: Raw Job Finding Rates by Category (%): 1997-2015

	unemployment	childcare	minor	OINE
1997	54.0	10.4	33.4	42.6
1998	53.5	17.4	33.2	47.2
1999	55.2	12.6	32.7	48.2
2000	57.5	11.1	32.7	51.9
2001	55.6	12.3	30.8	49.8
2002	52.5	10.7	29.8	41.7
2003	51.4	16.2	31.5	37.0
2004	50.5	16.9	31.3	28.5
2005	49.4	18.0	31.6	26.4
2006	50.5	18.0	32.9	26.1
2007	50.6	18.6	34.3	48.5
2008	53.0	19.8	35.1	51.7
2009	48.8	20.9	36.5	49.8
2010	50.5	20.1	37.8	53.1
2011	51.6	20.4	39.8	53.3
2012	50.1	18.8	40.0	53.5
2013	47.8	19.3	41.1	54.9
2014	45.0	17.9	42.2	53.7
2015	42.3	17.5	43.9	29.7

Table 26: German to English Translation of AMP Spell Types

German Label	English Translation
Beamte	Civil Servant
Lehre	Apprenticeship
Arbeiter/Angestellte	Employee
Sonstige Beschäftigung	Other Employment
Freie Dienstverträge	Service Contract
Landwirte (inkl. Mithelfende)	Farmer
Selbständige	Self-Employed
Vorgemerkte Arbeitslose mit Leistungsbezug	Unemployed Mixed Benefits
Vorgemerkte Arbeitslose ohne Leistungsbezug	Unemployed No Benefits
Wochengeld mit aufrechtem Dienstverhältnis	Maternity Active
Wochengeld ohne aufrechtes Dienstverhältnis	Maternity Inactive
Elternkarenz mit aufrechtem Dienstverhältnis	Parental Leave Active
Elternkarenz ohne aufrechtem Dienstverhältnis	Parental Leave Inactive
Kinderbetreuungsgeld mit aufrechtem Dienstverhältnis	Childcare Allowance Active
Kinderbetreuungsgeld ohne aufrechtem Dienstverhältnis	Childcare Allowance Inactive
Präsenzdienst	Military
Erwerbspension/Rente	Retirement
Ausbildung (gemeldet bzw. Meldelücken bis zum 25. Lebensjahr vor erster Erwerbstätigkeit)	Education
Sonstige gesicherte erwerbsferne Position	Other Insured Non-Employment
Geringfügige Beschäftigung	Minor Employment
Sonstige Versicherungszeiten	Other Insured Time
Reha 66 (Übergangsgeldbezug)	Transition Allowance
Reha 68 (Rehabilitationszeit)	Rehabilitation