MSc Economics

Job creation over the business cycle and the theory of poaching explored for the case of Austria.

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MSc Economics

Affidavit

I, Johanna Luise Reuter

hereby declare

that I am the sole author of the present Master's Thesis,
Job creation over the business cycle and the theory of poaching explored for the case of Austria.

50 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, 06.06.2016

Signature

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Nomenclature

AMDB Arbeitsmarktdatenbank, Austrian Social Insurance Data Set

HP Hodrick-Prescott-Filter

NACE Nomenclature Statistique des Activités Économiques dans la Communaute Europeenne, Statistical Classification of Economic Activities in the European Community

Abstract

This thesis uses Austrian social insurance data from 2000 to 2014 to analyze how job creation evolves over the business cycle. For this analysis, firms are split into quintiles according to the median monthly wage earnings of all of their employees, such that one can examine how high paying firms react to a change in the unemployment rate in comparison to low paying firms. For this purpose the net job creation rate or employment growth rate is decomposed into a hire and a separation rate, which are further split into hires from employment and hires from non-employment, likewise for the separations. This makes it possible to examine if high paying firms display stronger pro-cyclical growth, as suggested by the theory of poaching by Moscarini and Postel-Vinay (2012). Yet, results in favor of the wage ladder model cannot be found in general, only for specific samples of the dataset and when particular measures of the business cycle such as the twelve month differences in regional unemployment rates are used, is there evidence in favor of poaching. The novelty of this thesis is the monthly dataset used, which allows to more accurately distinguish between separations to employment and separations to from non-employment, likewise for hires from employment and non-employment, hence making a more detailed analysis of the theory of poaching possible.

1 Introduction

Job creation or firm growth has always been a topic of utmost importance to policy makers, since the creation of jobs and thereby the reduction of unemployment is seen as one of the main goals of economic policy provided by the government. This could be one of the reasons why firm growth has received so much attention in the literature since Gibrat (1931). Over time job creation has continuously been explored, often with a focus on its relationship to firm size. Birch (1987) came to the conclusion that small firms are contributing more to job creation than all other firms. Davis et al. (1998) concluded that the results of Birch (1987) were driven by conceptual errors and unsuitable data and found that large firms are the main creators of jobs. Comparatively less emphasis has been placed on employment growth in relation to average or median wages payed by a firm, since wages are more difficult to measure than size. Nevertheless in theory as well as to some extent in data, firm size and wages[1], which are seen as a proxy for productivity, are positively linked. In addition to investigations into the job creation process along a firm characteristic such as firm size or average wage, the job creation process over the business cycle has also been explored [eg. Davis et al. (1998)]. Yet the combination of both firm characteristics and the business cycle together as an explanation for varying paths of job creation of firms has only recently received attention by Moscarini and Postel-Vinay (2012) and Kahn and McEntarfer (2014) among others.

Empirical evidence on the influence of firm size on a firm's employment growth rate has been inconclusive. Many publications [eg. Birch (1987) or Headd (2010)] find that there is a negative relationship between employment growth, whereas others find that this negative effect is either an artifact of firm age driving the result [eg. Böheim et al. (2008)] or solely based on conceptual errors [eg. Davis et al. (1998)]. Exploring the relationship between job creation and wages instead of size, as well as including the business cycle into the analysis may provide clearer results as to which firms are the drivers of job creation.

The goal of my thesis is therefore to build on the small recent body of research, focusing on how different firms react differently to changes in the business cycle in terms of job creation. My primary goal is to look at the the patterns of job creation in relation to the business cycle at the aid of the Austrian Social Insur-

1. For a theoretical model in which this holds see Burdett and Mortensen (1998) or Moscarini and Postel-Vinay (2013), for an empirical analysis see Brown and Medoff (1989)

ance Data Set (AMDB). Additionally, I want to explore the theory of poaching in more detail, which was first proposed by Moscarini and Postel-Vinay (2013) who build upon an existing wage ladder model by Burdett and Mortensen (1998). The essence of this theory is that high paying firms, which in theory correspond one to one to large firms, are able to hire new employees no matter how low the unemployment rate might be, because they can poach workers away from lower paying firms. Low paying firms on the other hand can only increase their number of employees when the unemployment rate is high, thereby making low paying firms' growth rates counter-cyclical and those of high paying firms pro-cyclical.

I investigate this theory by exploring the impact of various measures of the business cycle, most of them based on the unemployment rate, on job creation rates of firms classified into different pay quintiles, thereby building heavily on existing empirical research by Moscarini and Postel-Vinay (2012) and Kahn and McEntarfer (2014), but with the great advantage of using a more detailed administrative monthly dataset, which is a full sample of the Austrian labor market from 2000 to 2014.

This thesis is organized as follows: section 2 reviews the existing literature. In section 3 I explain how to best measure job creation rates, which possible biases could be driving the results and how these can be overcome. In section 4 I present the theory of poaching and the methodology used for the analysis. In section 5 I focus on the dataset used as well as on the data cleaning and processing. In section 6 I show the results and section 7 provides some discussion and an outlook.

2 Literature Review

When looking at existing literature on the relationship between job creation, monthly earnings and the business cycle, apart from the very small recent literature such as Kahn and McEntarfer (2014) and Haltiwanger et al. (2015) there is very little research to build upon, unlike for the relationship between firm size and job creation, which has been explored continuously ever since the "law of proportionate effect" was proposed by Gibrat (1931) in 1931. Job creation or employment growth has often been explored together with a firm characteristic and often this firm characteristic was size, probably due to the fact that data on wage earnings within a firm is not as readily available.

2.1 Job Creation and Firm Characteristics

I begin by exploring the existing literature on job creation firm size. As mentioned, this topic has received much attention, not only theoretically by Gibrat (1931) among others, but also empirically by many such as Birch (1987) or Headd (2010) who find that small firms are the main creators of jobs and thereby the drivers of growth. This research was often used to argue for higher subsidies for the main job creating firms.

The findings of Birch (1987) were later on heavily criticized, for various reasons. Probably the most prominent example for critique agains the results of Birch (1987) are Davis et al. (1998) who themselves explore how job creation takes place in the manufacturing sector and revisite the conclusions of many on who the alleged creators of jobs are. They do so by analyzing how job creation is measured, how it is attributed to a firm, and how this firm is classified according to its size. They postulate that many of the results claiming small firms to be the engines of job creation arise due to measurement errors or unsuitable data. This calls for extra attention when measuring growth rates or classifying firms, which I deal with extensively in section 3. Therefore there is no clear result as to whether small or large firms are the drivers of job creation.

This has led many to reexamine the relationship between job creation or employment growth and firm size, but there while including extra firm characteristics. One of the important examples is firm age, which has brought up many interesting results. One recent publication, which explores firm size and age is by Haltiwanger et al. (2013). Using US data from the Business Dynamics Statistics from the Census Bureau and a non-parametric regression approach, Haltiwanger et al. (2013) first explore the effect of firm size on employment growth and find that there is a negative relationship. However this is to a large extent due to a fallacy known as the "regression to the mean fallacy", which will be explored further in section 3. When conditioning on firm age and controlling for the regression to the mean fallacy, Haltiwanger et al. (2013) find no support of the systematic relationship between firm size and employment growth. Thereby providing possible evidence for Gibrat's law, showing that even approximately 80 years after the original publication by Gibrat (1931) there is no single stand on the relationship between firm size and employment growth, even when aspects such changes over the business cycle are not considered. Another recent publication on firm age is by Böheim et al. (2009), who use a 10 percent sample of a quarterly version of the Austrian Social Insurance dataset, to analyze how jobs created by firms of different age have varying hazard rates. Using Kaplan-Meier estimates to find how many of the jobs created within new or old firms are still active after n quarters, they come to the conclusion that:

> *"jobs created by entering establishments in Austria last considerably longer than new jobs in old establishments(...)"* Böheim et al. (2009, p.19)

2.2 Job Creation and the Business Cycle

Job creation has not only been looked at in relation to firm characteristics but also in relation to the business cycle. Already in the 1990's Davis et al. (1998) explored how job creation in manufacturing firms in the USA changed over the business cycle focusing mainly on correlations of gross job creation and gross job destruction. They find that job destruction displays a stronger relationship with the business cycle than does job creation. Moscarini and Postel-Vinay (2012) revisit this issue but differentiate by firm size and adopt a more theoretical approach to studying the relationship between job creation and the business cycle. Moscarini and Postel-Vinay (2012) use quarterly data from the US Census Bureau's Business Register from 1979 to 2009 to compute growth rates of small and large firms separately. By examining correlations of the detrended difference in firm growth rates for large and small firms and detrended[2] measures of the business cycle[3] they find that

2. Using an HP filter

3. Large firms are classified to have more than 1000 employees, small firms to have less than 50 employees

> *"The differential growth rate of employment between large and small US firms is strongly negatively correlated (in deviations from trend) with the contemporaneous unemployment rate (...). Large employers on net destroy proportionally more jobs relative to small employers, when unemployment is above trend, late in and right after a typical recession, and create more when unemployment is below trend, late in a typical expansion"* Moscarini and Postel-Vinay (2012, p. 2509)

There is not only empirical research on the relationship of job creation, firm characteristics and the business cycle but also theoretical models. Concerning research on the business cycle and firm size one well known theory by Gertler and Gilchrist (1994) states that aggregate negative shocks to credit availability should have a stronger influence on small firms, i.e. small firms should experience relatively lower growth rates in times of a bust or when the unemployment rate is high. The theory explored by Moscarini and Postel-Vinay (2013), which builds on a wage ladder model developed by Burdett and Mortensen (1998), is the theory of poaching. Workers move up the wage ladder, because larger, more productive high paying firms poach them away from their current firms, which are smaller and lower paying. This model incorporates that large and high paying firms are more cyclical in their job creation patterns. Another very well known theory on how firms of varying size react differently to changes in the business cycle is almost as old as the model by Gibrat, namely the theory developed by Schumpeter (1939) which postulates that in recessions resources are reallocated to more productive firms, because in a recession the least productive firms are no longer profitable. If one then assumes that firms who are able to pay higher wages, are more productive, this theory would imply that high paying firms grow more in recessions than low paying firms which should shrink.

The contradicting view points of the above theories motivate Kahn and McEntarfer (2014) to explore these theories empirically. They do so by analyzing how firms paying varying levels of average monthly wages to their employees react differently to the unemployment rate, i.e. to fluctuations over the business cycle. Kahn and McEntarfer (2014) try to explore which theory holds in the data by regressing the aggregate employment growth rate of firms paying different monthly wages onto the unemployment rate. Their specification allows each of the five quintiles to have a different coefficient on the unemployment rate, which is a way of allowing firms paying different monthly wages to react differently to changes in the business cycle. I will present this model in more detail in section 4

Kahn and McEntarfer (2014) use Longitudinal Employer Household Dynamics program data to find that in the US large firms display much stronger and more negative reactions to increases in the unemployment rate, thereby validating the theory of poaching. I will follow this approach in order to see if the Austrian labor market displays the same effects of variations in job creation within certain types of firms over the business cycle.

Even though in the theory according to Burdett and Mortensen (1998), as well as in the dynamic version of the model by Moscarini and Postel-Vinay (2013), large firms are identical to high paying firms, this relationship might not be as clear in the data. Hence Haltiwanger et al. (2015) build on the analysis by Kahn and McEntarfer (2014) as well as the one of Moscarini and Postel-Vinay (2012). They try to identify if the reason for the stronger cyclical employment growth rate of large firms when compared to small firms is the same reason for which high paying firms show a pro-cyclical job creation behavior in comparison to low paying firms, as well as reexamine the empirical findings of Moscarini and Postel-Vinay (2012) and Kahn and McEntarfer (2014). They thereby find a pro-cyclical differential growth rate of large and small firms[4], when using the deviation of the unemployment rate from its HP trend as a measure of the business cycle, yet this is not due to poaching. Additionally, they find small firms' net employment growth rate drops more than large firms' net employment growth rate in recessions by using first differences in the unemployment rate as a measure of the business cycle[5], which is consistent with rather classic literature on job creation such as Gertler and Gilchrist (1994). Concerning low and high paying firms they find:

> *(...) evidence of a strong pro cyclical firm wage ladder. Job-to-job flows move workers up the wage distribution across firms. Such moves are highly pro cyclical. During booms we find positive net poaching yields net employment growth gains of as much as 1 percent per quarter at high wage firms and net employment losses of an equivalent amount at lower wage firms. This high pace of reallocation of workers in booms falls dramatically in contractions.* Haltiwanger et al. (2015, p.28)

Many new approaches have been used to analyze long existing theories empirically. With my thesis I want to build on these new approaches and extend

4. In the analysis by Haltiwanger et al. (2015) all time series are seasonally adjusted using the X-11 procedure

5. The first differences in the unemployment rate are correlated much higher with times of recessions, classified as such by the National Bureau of Economic Research.

them even further by exploiting a dataset which gives the immense advantage of having high frequency data on all employees. This makes it possible to examine the extent to which evidence of poaching can be found on the labor market with even more accuracy. Using the AMDB it is possible to determine for each individual who is newly hired by a firm, if she was employed before starting her new job, thereby making this job creation a result of poaching.

3 Measurement of the Firm Growth or Job Creation

In order to examine job creation in any way, it is necessary to first define job creation or firm growth in a way which causes as little bias in one direction or the other. Many ways of measuring firm growth in terms of employment growth have been proposed, especially when using these growth rates to explore the relationship of firm growth and firm size, yet all of them have certain drawbacks and advantages. The most extensive discussion of caveats can be found in "Job Creation and Destruction" by Davis et al. (1998), which presents the major biases, that seem to be the drivers of the result that small firms are the creators of growth, which can often be read about in older publications [eg. Birch (1987)]. In order to explain these possible fallacies, I will use definitions and examples proposed by Davis et al. (1998), but adapt them in order to fit my notation

Definition 1. (Gross) Job Creation at time t equals employment gains summed over all firms that expand or start up between $t-1$ and t.

Definition 2. (Gross) Job Destruction at time t equals employment losses summed over all firms that contract or shut down between $t-1$ and t.

Definition 3. Net Employment Change or Net Job Creation at time t equals the difference between employment at time t and $t-1$. The net employment change at time t also equals gross job creation minus gross job destruction.

3.1 The Size Distribution Fallacy

For this bias or fallacy to come into play, one has to first define a certain cutoff value for size, such that all firms which exhibit a size lower than this value are classified to be small, where each firm is classified at each point in time separately. I follow the example by Davis et al. (1998) to explain the fallacy. The statistic of interest is the contribution of small firms to job creation (or destruction) within a given year:

$$\frac{Small_{t+1} - Small_t}{Total_{t+1} - Total_t} \tag{1}$$

where $Total_t$, $(Small_t)$ is the total number of employees at all firms, which are classified to be small respectively.

Table 1: The Size Distribution Fallacy

	Firm 1	Firm 2	Firm 3	Small firms	Big firms	All firms
Employment in t	300	550	650	300	1200	1500
Employment in $t+1$	50	340	1210	390	1210	1600
Net change	-250	-210	560	90	10	100

Source : Davis et al. (1998)

When plugging the numbers from Table 1 into Equation 1 and using a cutoff value between small and large firms of 500, one obtains the result that small firms' contribution to net job creation is

$$\frac{390-300}{1600-1500} = 0.9$$

> *"These changes in the distribution of employment by firm size ignore the fact that firms can migrate between size categories, as shown in the three leftmost columns, resulting in a false inference about the share of job creation accounted for by small firms. (...) If one executes the typical calculation on data in the example, small business appears to contribute 90 percent to net job growth. But, as the construction of the example makes clear, this interpretation is fallacious. In the example, firm-level net job growth actually increases with firm size, an observation that can be made only by following individual employers over time (...)."* Davis et al. (1998, p. 63)

According to Davis et al. (1998) this fallacy is of special importance in times of stagnation or slow growth, when larger firms might exhibit declining employment.

3.2 The Regression Fallacy

Davis et al. (1998) describe the regression fallacy to be best described by the fact that firms which are small are more likely to grow, and firms which are large are more prone to experience a negative movement in their employment and the additional fact that transitionary movements tend to reverse themselves. Once again using a numerical example helps illustrate this bias. Firms are reclassified each year using their base year employment, for growth in $t+1$ the base year is year t, for growth in $t+2$ the base year is year $t+1$, and a cutoff value of 500.

Table 2: The Regression Fallacy according

	Firm 1	Firm 2	Firm 3	Small firms	Big firms	All firms
Employment in t	450	550	600	450	1150	1600
Employment in $t+1$	550	450	600	450	1150	1600
Employment in $t+2$	450	550	600	450	1150	1600
Growth rate in $t+1$	0.22	-0.18	0	0.22	-0.09	0
Growth rate in $t+2$	-0.18	0.22	0	0.22	-0.09	0

Source : Davis et al. (1998)

From the data in Table 2 one obtains the impression that the growth rate of small firms is much higher, than the one of large firms, yet this effect comes only from self reversing shocks to individual firms and reclassifying firms each year.

3.3 Netting Out Reality

A further problem described by Davis et al. (1998) is the one denoted as netting out reality. If one only looks at the change in employment, so the difference in employment in period t and $t+1$, not for each firm separately but only after aggregating firms into different bins, one might be driving results in a certain direction, when one then is talking about net job creation as opposed to gross job creation. Again Davis et al. (1998) use a numerical example to explain this limitation:

Table 3: Netting Out Reality

	Firm 1	Firm 2	Firm 3	Small firms	Big firms	All firms
Employment in t	300	600	600	300	1200	1500
Employment in $t+1$	350	400	800	350	1200	1550
Net change	50	-200	200	450	0	50

Source : Davis et al. (1998)

As before a cutoff value of 500 is used for small firms. With the data from Table 3 it is possible to calculate the share of small firm net job creation which is equal to:

$$\frac{50}{50} = 1$$

which gives the impression that small firms were responsible for 100 percent of all job creation. Then one can calculate the share of small firm gross job creation, which is equal to:

$$\frac{50}{50+200} = 0.2$$

This measure of small firms' contributions to job creation gives a much less favorable picture for small firms, which Davis et al. (1998) say could be the reason for results such as those by Birch (1987).

3.4 Overcoming the Fallacies and Measurements of Rates

After having discussed the possible biases, which could be driving results, it is important to state precise definitions for job creation, which are subject to as few fallacies as possible. In order to avoid the fallacies, which arise due to reclassification, both Davis et al. (1998) and Moscarini and Postel-Vinay (2012) state that the best solution is to use a panel dataset and suggest classifying firms once and for all, at the point of time in which a firm first exists. To take care of netting out reality, one simple procedure is to look at gross creation and gross destruction rates separately, so to look at only those firms which expand or start up, and then to look at only those who shrink or close down in a given time period.
These are though very basic suggestions, so it remains to find exact definitions for growth rates:

When simply measuring the growth from one period to the next, in form of a rate, the classical formula used is

$$\frac{Employment_t - Employment_{t-1}}{Employment_{t-1}} = \frac{Net\,Job\,Creation_t}{Employment_{t-1}}. \tag{2}$$

The drawbacks to the classical formulation of the growth rate according to Equation 2 are that it is not well defined for firms entering, as well as the fact that the growth rate calculated is not symmetric. By changing the denominator of Equation 2 to $Employment_t$ one could make sure that this growth rate is well defined for entrants, but not any more for exiting firms. A positive aspect to this formulation is the fact that it can also be measured by:

$$log(Employment_t) - log(Employment_{t-1}). \tag{3}$$

Yet again the growth rate according to Equation 3, which is simply the difference in logs is not well defined for entrants. Another drawback of the change in logs is the fact that when looking at gross job creation and gross job destruction separately, the rate of gross job creation minus the rate of gross job destruction does not equal the net rate of job creation.

Therefore Davis et al. (1998) propose a growth rate, which is well defined for entrants and exiting firms, symmetric and can be decomposed into gross creation and cross destruction rates:

$$\frac{Employment_t - Employment_{t-1}}{0.5 \cdot (Employment_t + Employment_{t-1})}. \tag{4}$$

This growth rate proposed by Davis et al. (1998) is symmetric between -2 and 2 and defined for all firms, independent of the firm starting-up or closing down. In addition to these properties the net job creation rate defined according to Equation 4, will exactly equal the gross job creation rate minus the gross job destruction rate. Also the employment growth rate will equal the hire minus the separation rate. For these reasons for all estimations, the growth rate is measured according to the formula proposed by Davis et al. (1998).

4 Theory and Methodology

To better understand the relatively more cyclical growth rate of large or high paying firms found by Moscarini and Postel-Vinay (2012) and Kahn and McEntarfer (2014) I will give a theoretical explanation of these results. The theory underlying this phenomenon is the theory of poaching. According to Moscarini and Postel-Vinay (2012) it is due to hiring and turnover frictions, which can be seen as a form of labor adjustment cost. The level of unemployment, or the business cycle has different effects on a firm's growth rate, depending on the size of the firm. For an intuitive explanation of this theory it is necessary to consider a labor market, in which firms compete for workers, and to acknowledge that large firms can on average pay higher wages than small firms. When one then considers fluctuations over the business cycle such that the unemployment rate is falling, it becomes harder and harder for the less productive and therefore lower paying, small firms to recruit workers, simply because the stock of unemployed persons has decreased. Large firms on the other hand are not as constrained by the low stock of unemployed workers to choose from, because they are more productive and can therefore afford to pay higher wages, which lets them poach workers away from small firms. This theory is used to explain why large in comparison to small firms grow more when the unemployment rate is low, and less when the unemployment rate is high. In order to explain the relatively smaller growth rate of large firms in periods of high unemployment, Moscarini and Postel-Vinay (2012) argue that by not being able to increase their stock of employees, small firms might have less employees than desired before the crisis. Therefore when the crisis begins, small firms do not yet want to lower their number of employees. Since large, high paying firms always have the desired number of employees, as soon as the crisis hits, they will stop their hiring efforts, thereby stopping their poaching of workers from small, low paying firms. Besides explaining the intuition of the theory of poaching and presenting empirical results, Moscarini and Postel-Vinay (2013) also adapt the wage ladder model of Burdett and Mortensen (1998), which gives the result that workers upgrade or switch their employers only to be employed with a larger firm, which is in the model also always higher paying[6]. After adapting this model to a dynamic version, numerical simulations of the model by Moscarini and Postel-Vinay (2013) give exactly the poaching results found in the data.

Kahn and McEntarfer (2014) take this theory developed by Moscarini and

6. For an empirical analysis see Brown and Medoff (1989)

Postel-Vinay (2012) further by first of all using earnings to classify firms as high or low paying, rather than using size to classify them as large or small. Second by using a matched employer-employee dataset from the Longitudinal Employer Household Dynamics program they are able to combine an analysis of worker and job flows, which allows them to examine further implications of the theory of poaching. This combination of worker and job flows is unique because not only can they define net job creation within a firm according to Definition 3, but they can also calculate the number of hires within each firm for each time period as well as the number of separations within each firm for each time period, independent of the firm experiencing changes in firm size. This is a huge advantage over the datasets originally analyzed by Davis et al. (1998), because it makes it possible to so to say measure gross job creation and gross job destruction within each firm. To not confuse notation I will define the hires and separations in the the following way:

Definition 4. Hires at time t equal the number of new employees hired within a firm between $t-1$ and t.

Definition 5. Separations at time t equal the number of employees, who were employed at a firm in $t-1$ and are not employed with this firm anymore in t.

Yet another advantage arises out of the panel dataset on employees used namely the possibility of determining whether the individual was employed or not previous to being hired by a firm and similarly whether the individual is employed or not after the separation from a firm. This leads me to the next set of definitions:

Definition 6. Hires from employment at time t equal the number of new employees hired within a firm between $t-1$ and t, who were employed with a different firm between $t-2$ and $t-1$.

Definition 7. Hires from non-employment at time t equal the number of new employees hired within a firm between $t-1$ and t, who were non-employed between $t-2$ and $t-1$.

Definition 8. Separations to employment at time t equal the number of employees who separated from a firm between $t-1$ and t, who were then employed with a different firm between t and $t+1$.

Definition 9. Separations to non-employment at time t equal the number of employees who separated from a firm between $t-1$ and t, who were then non-employed between t and $t+1$.

Definition 10. Employment growth at time t equals firm size in t minus firm size in $t-1$, when defining a firm to have size 0, whenever it does not have any employees[7].

Concerning these definitions it is important to note that they are all closely linked:

$$\textit{Hires from employment} + \textit{Hires from non-employment} = \textit{Hires}$$

$$\textit{Separations to employment} + \textit{Separations to non-employment} = \textit{Separations}$$

$$\textit{Hires - Separations} = \textit{Employment growth}$$

Once these concepts have been defined it is very helpful to go back to the definitions according to Davis et al. (1998) and see how the definitions arising from new micro data can be linked with these. First of all summing up over all firms' employment growth gives net job creation. Additionally one can divide firms into three groups according to the sign of their employment growth: those with positive employment growth, those with zero employment growth and those with negative employment growth. Summing up over all firms out of the first group, which can additionally be defined by saying that the number of hires exceeds the number of separations for this firm, gives exactly gross job creation as defined in Definition 1. Summing up over the third group, or those firm who experienced more separations than hires, yields gross job destruction from Definition 2.These connections of the definitions demonstrate the benefits of high frequency data on individuals over aggregated data on firms.

After having explained the advantages of using a linked employer-employee panel dataset, it becomes clear how Kahn and McEntarfer (2014) use this in order to further examine the theory of poaching. In addition to seeing a more cyclical growth of large or high paying firms, they predict three additional effects, which originate in the fact that a downturn limits the extent of poaching:

1. A decline in the rate of hires from employment within the high paying firms in a bust;

2. A decrease in the rate of separations to employment within the low paying firms in a bust;

7. One can also define employment growth when not assuming that a firm has size 0, whenever it has no employees, meaning that the employment growth is only defined when a firm is starting up or shutting down. By using this definition, one excludes all entries and exits of firms from the analysis, therefore I will denote this employment growth according to this definition as employment growth without entries and exits.

3. A general increase in the rate of separations within the high paying firms in a bust.

So in total Kahn and McEntarfer (2014) determine four effects which, if found in the data, would validate the theory of poaching. In order to test if these predictions hold in the data, I will partially follow the analysis of Kahn and McEntarfer (2014). The first step to their approach is to divide firms into quintiles according to their employees' monthly wage earnings and then calculate the employment growth rate for each such quintile. Then these growth rates are regressed onto the unemployment rate among other covariates, thereby allowing each quintile to have a different coefficient on the unemployment rate. Hence this specification allows high and low paying firms to react differently to changes in the business cycle and since one can not only use the growth rate but hire or separation rates as well, one can also use this specification to analyze the three additional effects predicted by Kahn and McEntarfer (2014).

In order to account for other firm characteristics which might be influencing the growth rates of firms, I will again follow Kahn and McEntarfer (2014) and include industry i and region r into the regression as explanatory variables, as well as defining region and industry specific cutoff values for the quintiles. In order for my analysis to not be subject to the regression to the mean fallacy or the size distribution fallacy, I classify firms into quintiles once and for all, first taking the median over the monthly wage earnings of all workers of the firm for each month in which the firm exists, and then again using the median to aggregate over the whole existence time of the firm. Hence by associating each firm to one region r, for the Austrian case this is a Bundesland, and an industry i, for the Austrian case one of the 26 -2008 1-digit level industries, and then for each such possible combination defining 5 quintiles, this procedure yields 765 separate industry-region-quintile combinations[8] in the Austrian dataset.

In a next step I calculate the employment growth rate among others, for each such industry-region-quintile combination F_{irq}:

$$rate_{tqir} = \frac{\sum\limits_{f \in F_{qir}} employment\_growth_{t,f}}{\sum\limits_{f \in F_{qir}} E_{t,f}}. \tag{5}$$

In this equation $E_{t,f}$ is the number of workers at firm f at time t. The indices q, i, r stand for firm quintile, industry and region (Bundesland). Therefore the

8. After data cleaning I am left with 9 regions, 17 industries and 5 quintiles

growth rate of each bin can be calculated by summing up over the employment growth of each firm in each industry-region specific quintile and then dividing by the sum over the size of all firms in this bin. Employment growth of each firm can, as explained above, be measured either including entries and exits, or excluding entries and exits.

It is also possible to work with a formula more closely related to the version by Davis et al. (1998), as displayed in Equation 4, which then leads to the following definition of the growth rate:

$$rate_{tqir} = \frac{\sum\limits_{f \in F_{qir}} employment - growth_{t,f}}{\sum\limits_{f \in F_{qir}} 0.5(E_{t,f} + E_{t-1,f})}. \tag{6}$$

The only difference in Equation 5 and Equation 6 is then that rather than summing up over the size of all firms in a bin as is done in Equation 5, in Equation 6 one sums up over the average size over two periods.

Both rates from Equation 6 and Equation 5 can be decomposed into the hire and the separation rate, where H_{tf} respectively S_{tf} are hires and separations, respectively.

$$rate_{tqir} = \frac{\sum\limits_{f = \in F_{qir}} (H_{tf} - S_{tf})}{\sum\limits_{f \in F_{qir}} 0.5(E_{t,f} + E_{t-1,f})} = \frac{\sum\limits_{f \in F_{qir}} H_{tf}}{\sum\limits_{f \in F_{qir}} 0.5(E_{t,f} + E_{t-1,f})} - \frac{\sum\limits_{f \in F_{qir}} S_{tf}}{\sum\limits_{f \in F_{qir}} 0.5(E_{t,f} + E_{t-1,f})}. \tag{7}$$

Hence Equation 7 yields the hire rate and the separation rate separately. Each of these two rates can yet again be decomposed into two rates, depending on whether the hires were from employment or from non-employment and separations were to employment or to non-employment. This additional decomposition is necessary in order analyze whether or not the model of a job ladder, or poaching, can be validated for the Austrian labor market.

After having defined all the relevant variables, the regression model is defined again in close relation to the specification of Kahn and McEntarfer (2014) in the following way:

$$rate_{tqir} = \alpha_q + \beta_q * unemp_{rt} + \gamma_i + \delta_r + I^{month} + I^{year} + \varepsilon_{tqir} \tag{8}$$

The general formulation on the left hand side of Equation 8 is due to the fact that one can interchange this for any of the possible rates discussed above. From Equation 8 it becomes clear that the growth rate$_{tqir}$ is regressed onto a dummy variable for each wage quintile thereby allowing α_q to differ for each quintile, the unemployment rate in time t and region r, which also allows β_q to differ for each quintile, as well as industry, region, month and year dummies. The vector of coefficients of interest is β_q, since this coefficient is allowed to be different for each quintile and therefore measures how firms in different wage quintiles react differently to changes in the business cycle.

As robustness checks I will use different measures of the business cycle: first of all the region-level unemployment rate, which has not been seasonally adjusted. I then take 12 month differences to achieve a seasonally adjusted region-level unemployment rate. For all regressions rate, I use standard errors which are clustered at the regional level following Kahn and McEntarfer (2014), because as they argue the regional unemployment rate varies over time and across regions, but is likely to exhibit serial correlation within a state. Concerning the region-level unemployment rate, it is defined according to the Austrian definition, rather than the EU definition, so it gives the ratio of all people registered as unemployed with the publicly funded employment agency to the labor force. As a second set of measures of the business cycle I will use a seasonally adjusted nation wide unemployment rate[9], which I use as it is, as well as its first differences and additionally its deviation from trend, which is defined using an HP filter[10]. Another measure of the business cycle could be the regional employment to population ratio. I will also include regression specifications in which I weight each observation by the number of employees in each bin i.e. the size of each bin, because this enables the coefficients to be interpreted as the impact on aggregate growth rates.

9. Source: FRED

10. using the usual smoothing parameter of 14400 for monthly data

5 Data

The dataset used is provided by the Austrian Social Insurance Agency (Hauptverband der Sozialversicherungsträger), which keeps a record of all persons who have some form of social insurance in Austria, from 01.January 2000 to 31.December 2014. It features observations on each individual, at least once per month. This means that if a person is employed with the same firm for 1 year, there will be exactly 12 observations on this individual. If an individual changes her status, which can either mean that she changes her employer or becomes unemployed, within one month, there are two observations for this individual within this given month. These observations include some personal characteristics, as well as the labour market status and if the individual is classified to be working, the "firm" identifier together with information on gross monthly earnings. Additionally the Austrian Social Insurance Agency also provides information on some "firm" characteristics such as industries[11] and regions[12].

The largest deficit which could potentially bias the results, is the fact that the unique "firm" identifier, does not as one would assume identify an actual "business" or "enterprise" but it identifies one account with a the Austrian Social Insurance Agency, from which employer social insurance contributions are payed, which can also just be one establishment, which is part of a larger enterprise. Therefore if one actual firm or enterprise pays social insurance contributions from different accounts, it will show up with multiple identifiers in the dataset, yet the dataset does not provide any possibility to link these identifiers to each other in a reliable way. This could lead to more identifiers in the dataset than firms in Austria, and also to "firms" in the the dataset being smaller. However Stiglbauer (2003), as cited by Holzl and Huber (2014) states that by reporting social insurance contributions at the enterprise level instead of at the establishment level, decreases the administrative burden for firms, thereby implying that this deficit will not be of such grave importance.

From the dataset being collected by Austrian social insurance providers, therefore an administrative data, several advantages arise: First the largest advantage

11. Data on the industry of a firm is given in a separate dataset at irregular intervals: whenever the industry of the firm changes. It is given with respect to NACE-2008 coding in 4 digit specification, I recode it into NACE-2008 1 digit specification, resulting in 21 possible industries

12. Like industry data, information is provided on the firm level whenever a change occurs. Regions are given as the 9 Austrian states (Bundesländer) as well as "ÖBB" the Austrian public railway company and "Beamten-VA", the social insurance company for civil-cervants. All firms falling into the last 2 categories are excluded

of this dataset is that by being a full sample of all people receiving social insurance, it follows all individuals over the whole time period from 2000 to 2014, conditional on them being insured in Austria.

Another virtue of this dataset, is the fact that it includes data closely related to monthly earnings of individuals in form of the social insurance contribution basis for most employees. These are top coded and only amount to the average monthly basis, if the individual under consideration was employed with one firm throughout the whole month. Therefore for the analysis of the impact of firm quality, measured as median monthly earnings within a firm, only those employees who worked full months will be used. On this note I also exclude all self-employed individuals, because they are not subject to paying mandatory social security contributions in Austria, therefore their social insurance basis is either 0 or missing or some other value, so it , but cannot be considered a regular wage in the classical sense or any other measure related to their actual income.

One disadvantage of the dataset is the lacking of information on hours worked, but an indicator "Geringfügig" partially compensates for this. The jurisdictional status of being employed "geringfügig" describes a situation in which so little hours are worked, such that the employee is completely exempt from income taxes as well as from all compulsory social insurance payments. Also the employer is exempt from paying social insurance contributions for this employee apart from occupational accident insurance payments. The restriction of being "geringfügig" is a monetary one, so in order to be classified as such one has to have earned less than 395.31 € per month in 2014. Using this indicator I exclude all individuals which classified to be "geringfügig". This might seem as problematic when then considering firm size, but the advantage for the employers if immensely reduced social insurance contributions of employees which are "geringfügig" but as soon as an employer pays more than $1.5 \cdot 395.31 = 592.97$€ to employees which are "geringfügig" this employer has to pay other social insurance contributions, which are as large as with regular employees, therefore having many such employees is not increasingly profitable for firms.

To see how the quintiles differ in Table 4 I present some summary statistics for July 2012. Already from this simple comparison of means one can clearly see that the quintiles differ to quite some extent also in terms of their size and the median earnings of their workers. The patterns for the growth-, hire- and separation-rates are readily visible, which makes an analysis of these even more interesting. In Table 5 I present similar summary statistics, only using the median instead of the mean and the interquartile range. This also shows how low paying firms are typically smaller.

Table 4: Means by Quintile,

Quintile	**Size**	**Median Earnings**	**Growth Rate**	**Hire Rate**	**Separation Rate**
1	1.683873	705.492	.0152201	.0363949	.0211748
	(2.179988)	(223.1385)	(.1742329)	(.1825341)	(.1320697)
2	3.048119	1105.931	.0190966	.0481964	.0290998
	(5.351248)	(280.467)	(.1817678)	(.2001609)	(.1496426)
3	4.52194	1463.34	.02298	.0559453	.0329653
	(9.252261)	(350.4871)	(.1810456)	(.2017921)	(.1532601)
4	7.022239	1912.779	.0251772	.0559265	.0307493
	(17.12445)	(463.3369)	(.1725031)	(.2183751)	(.1740312)
5	8.511898	2882.078	.0266469	.0479442	.0212973
	(34.54771)	(919.0035)	(.1594574)	(.1764624)	(.1158866)
Total	5.581906	1793.207	.0228761	.0502241	.027348
	(20.30338)	(934.3504)	(.1729803)	(.1973224)	(.1469831)

Standard errors in parentheses, *Source:* Own calculations using the AMDB

Table 5: Medians by Quintile

Quintile	**Size**	**Median Earnings**
1	1	692
	(1)	(297)
2	2	1098.915
	(2)	(384.25)
3	2	1481.367
	(4)	(525.0333)
4	3	1964.333
	(6)	(666.4167)
5	3	2741.375
	(7)	(1303.646)
Total	2	1614.357
	(4)	(1118.694)

Interquartile range in parentheses*Source:* Own calculations using the AMDB

5.1 Data Processing

To get from the above described dataset on individuals, to a dataset which provides information on firm size and median wage earnings of the employees with the firm at monthly frequencies, I aggregate over all individuals classified to be working at a given point in time with one firm, given by a firm identifier. This is procedure is fairly easy for the variables firm size, where it is simply necessary to count the individuals classified as working at each firm at the end of each month, as well as for median earnings. For the number of hires, I use the labor market status change variable to see if an individual has become newly employed with a firm and then again I simply aggregate over an indicator for becoming hired. For the number of separations, I check for each individual if she either transitioned to a new employer, thereby causing a separation at the old employer, or if she became unemployed thereby also causing a separation at the old employer. By proceeding in this way I am able to obtain firm size and median wage earnings as well as the number of hires and separations for each firm, but I can additionally track if hires are from employment, so being caused by firms hiring workers who were already employed with other firms, or from non-employment, so being achieved by firms hiring someone who was non-employed, the same goes for separations[13].

After having created all these firm specific variables, it is possible for me to define employment growth within one firm in several ways, the first and simplest definition being the difference in size from one month to the next according to Definition 10. This definition includes all hires happening when a new firm starts existing as well as all separations which happen at firm closure. Since if a firm ceases to exist, it simply does not show up in the dataset I have constructed, because this was done by summing up over employees of this firm. In order to incorporate this aspect of job creation into a definition, I fill up my panel dataset with a size of zero whenever a firm does not exist, and can then define employment growth the usual way. The second definition of firm growth excludes hires and separations happening due to entries or exits of firms[14].

Unfortunately as mentioned before a firm identifier does not correspond to a firm, but only an account with the social insurance agency. So even though the

13. Due to the fact that when measuring firm size and median wage I only consider those individuals who are not self-employed, I also count a firm hiring someone who was self-employed before as a job creation from non-employment. The same goes for all other measures of growth.

14. One necessary remark is that in the panel dataset on firms, which I have constructed, a firm having zero employees does not automatically mean that the firm does not exist any longer, because I excluded all self-employed individuals. Thereby the employment growth variable defined to exclude entries and exits, only refers to entries and exits in this special way and might not always correspond to the usual picture one has in mind when thinking of a starting up or closing down of a firm.

firm identifier of an employee can change in the dataset it does not mean that the labor market status variable has to reflect this by taking the value for a new employer. This problem arises because one actual firm can consist of several firm identifiers in the AMDB likewise. Yet this can also be seen as an advantage for more in depth future research, because it allows for a possibility of identifying which firm identifiers belong to the same actual firm. This task still remains very challenging and is therefore left as a possible extension to this analysis for the future.

To still be able to work with the hire and separation rates, I simply identify those firms, for whom the above described problem does not arise and use the different concepts to analyze their job creation rates[15]. These steps now identify 2 possible samples: first the full sample, yet in this sample I cannot examine hires and separations in a meaningful way because they do not sum up to employment growth, and second the reduced zero difference sample in which I exclude all observations where the above described problem arises, which then allows me to follow a more detailed analysis. Additionally for both of the samples, I can again define a subsample, which excludes entries and exits.
For increased clarity I will name the samples in the following way:

Table 6: Samples

	Sample name	Observations	Distinct firms
Full sample	FS	44,899,461	636,737
Full sample excluding entry and exit	FS no EE	42,750,046	636,737
Hires + Separations = Employment growth	ZD	41,490,310	634,255
Hires + Separations = Employment growth excluding entry and exit	ZD no EE	34,529,736	577,902

Source : Own definitions and AMDB

As explained above to aggregate I take the median over of the wage earnings of all employees at a firm in a given month, to get a monthly measure for firm pay or

15. In the panel on firms I have approximately 45 million observations, by excluding those observations for which the net job creation rate, or the difference in size is not equal to gross job creation minus gross job destruction within this firm I am left with over 38 million observations.

firm wage earnings. To classify firms once and for all, in order to prevent as much as possible of the regression fallacy and the size distribution fallacy, I aggregate again within each firm over all median monthly wages payed, to find the median wage over the total existence time of the firm. For the general specification I define industry and region (Bundesland) specific pay quintiles, and assign each firm to such a quintile. For this to be possible I need to exclude five industry[16] categories, because in some regions they have less than five observations. Also I exclude all firms which change industry or region. This way each firm can be classified into one of 765 distinct bins, arising from 17 industries, 9 regions , and 5 quintiles.

16. I exclude all firms, which fall into the NACE level 1 categories: B, D, E, U. Each of them accounts for less than 1 percent of all firms in each region.

6 Results

Since I have four possible samples, I will structure the results according to the samples, presenting the estimates for each sample separately. I will only present the coefficients β_1 to β_5, where β_1 is the coefficient for the lowest wage earnings quintile on the measure of the business cycle and β_5 the coefficient for the highest wage earnings quintile. All regressions reported are based on Equation 8 , the only differences being that in some specifications I also include the lagged rate as well as the fact that for some regressions I weight observations by the number of employees in each region-industry-quintile combination. For all regressions I use rates defined according to Equation 6 and according to Equation 7.

6.1 Full Sample

For the full sample I first use the region-level unemployment rate, as well its 12 month differences, in order to obtain a seasonally adjusted region-level unemployment rate. In order to compare different specifications, in this sample for all tables the first column is defined according to Equation 8, the second column uses weighted observations and the third includes a lagged rate as an explanatory variable.

When regarding the first specification in column 1 of Table 7 which uses the region-level unemployment rate as an explanatory variable, the results do not point in the direction of poaching. Low and high paying firms have very similar coefficients on the unemployment rate, all of which are significantly different from zero and negative, indicating that as the unemployment rate increases, all firms' growth rates decrease. Also the coefficient of the lowest quintile lies within the confidence interval of the highest quintile thereby suggesting that there is no significant difference in the reaction of low and high paying firms to the unemployment rate. The same conclusions hold when one looks at the second column of Table 7, which displays a weighted regression. Column 3 includes the lagged rate and also shows no patterns which would be in favor of poaching.

Due to the fact that the unemployment rate at the regional level is not seasonally adjusted, I take twelve month differences and repeat the estimations of Table 7. But also the specifications using the 12 month difference of the region-level unemployment rate in Table 8 yield only coefficients which are not significantly different from each other thereby also not indicating that there could be poaching behavior among Austrian firms.

Table 7: FS, growth rate dhs, region-level u-rate

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	-0.00551**	-0.00806**	-0.00388*
	(0.00155)	(0.00221)	(0.00133)
β_2	-0.00543*	-0.00785*	-0.00380*
	(0.00166)	(0.00239)	(0.00146)
β_3	-0.00544**	-0.00767*	-0.00397*
	(0.00160)	(0.00243)	(0.00141)
β_4	-0.00534*	-0.00769*	-0.00385*
	(0.00162)	(0.00250)	(0.00136)
β_5	-0.00493**	-0.00691*	-0.00366*
	(0.00134)	(0.00236)	(0.00110)
N	136935	136935	136935
R^2	0.043	0.053	0.073

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 8: FS, growth rate dhs, region-level u-rate 12 month diff

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	-0.00284	-0.00151	-0.00269
	(0.00133)	(0.00127)	(0.00134)
β_2	-0.00361	-0.00217	-0.00356
	(0.00166)	(0.00131)	(0.00170)
β_3	-0.00367*	-0.00201	-0.00362
	(0.00152)	(0.00136)	(0.00159)
β_4	-0.00387*	-0.00235	-0.00380*
	(0.00155)	(0.00164)	(0.00159)
β_5	-0.00290	-0.000923	-0.00285
	(0.00153)	(0.00212)	(0.00152)
N	136935	136935	136935
R^2	0.039	0.044	0.071

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 9: FS, growth rate dhs, u-rate seas. adj.

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	0.00633***	0.00444***	0.00543***
	(0.000741)	(0.000863)	(0.000753)
β_2	0.00505***	0.00293*	0.00426***
	(0.000750)	(0.000951)	(0.000752)
β_3	0.00573***	0.00364**	0.00484***
	(0.000860)	(0.000754)	(0.000883)
β_4	0.00550***	0.00341**	0.00462**
	(0.000939)	(0.000843)	(0.000930)
β_5	0.00689***	0.00439***	0.00574***
	(0.000915)	(0.000803)	(0.000928)
N	136935	136935	136935
R^2	0.039	0.044	0.071

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Since Austrian regions are not very large and one might say it is not the regional unemployment rate which influences firms's behavior, I will repeat all above specifications using a nation wide seasonally adjusted unemployment rate.

Surprisingly in Table 9 all coefficients on the seasonally adjusted nation wide unemployment rate are positive and significant, suggesting that as the nation wide unemployment rate increases, the growth rates of all firms increase. This could mean that it is not the nation wide unemployment rate which forces firms to adjust their employment but regional unemployment rates, or other measures of the business cycle. Additionally for all specifications in Table 9 the magnitudes of the coefficients are very similar, thereby suggesting that firms of all quintiles react in the same manner to a change in the nation wide seasonally adjusted unemployment rate. To further investigate the positive coefficients I will use first differences of this unemployment rate and estimate the regressions once more.

Like with the region-level unemployment rate, using first differences of the nation wide unemployment rate does not yield any significant coefficients for any of the specifications in Table 10, also the coefficients all lie within each others confidence intervals. As another measure of the business cycle, I use the nation wide unemployment rate's deviation from trend. This does not lead to any coefficients

Table 10: FS, growth rate dhs,first differences of u-rate seas. adj.

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	0.00327	-0.00328	0.00344
	(0.00799)	(0.00749)	(0.00789)
β_2	-0.00159	-0.00340	-0.00190
	(0.00898)	(0.00515)	(0.00974)
β_3	0.00261	0.00121	0.00297
	(0.00761)	(0.00456)	(0.00758)
β_4	-0.0102	-0.00618	-0.00868
	(0.00589)	(0.00428)	(0.00585)
β_5	-0.00595	-0.000897	-0.00523
	(0.00482)	(0.00596)	(0.00460)
N	136935	136935	136935
R^2	0.039	0.043	0.071

Standard errors in parentheses

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

Source: Own calculations using the AMDB

which are significantly different from each other either. This again shows that it is not possible to confirm the theory of poaching using this sample. Therefore one can conclude that the analysis of the full sample using many different measures of the business cycle does not give any results in favor of poaching. Neither is there clear evidence for pro- or counter-cyclical growth rates, nor is there any pattern which would lead to the conclusion that high paying firms' growth rates differ from those of low paying firms.

Table 11: FS, growth rate dhs, deviations from hp trend of u-rate seas. adj.

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	-0.0000418	0.00181	-0.000219
	(0.00133)	(0.00171)	(0.00126)
β_2	0.000465	0.000541	-0.000108
	(0.00155)	(0.00146)	(0.00146)
β_3	-0.000337	0.000591	-0.000685
	(0.00135)	(0.00128)	(0.00127)
β_4	-0.0000267	0.000392	-0.000241
	(0.00141)	(0.00132)	(0.00135)
β_5	0.000233	0.00113	-0.000124
	(0.00157)	(0.00122)	(0.00146)
N	136935	136935	136935
R^2	0.039	0.043	0.071

Standard errors in parentheses

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

Source: Own calculations using the AMDB

6.2 Full Sample Excluding Entries and Exits

For this sample I exclude all employment growth which arises due to firms entering or exiting. Like above I begin by using the region-level unemployment rate and proceed to its 12 month differences. Also the specification of each column is the same as for the full sample above.

From Table 12 it becomes clear that independent of the specification chosen, all quintiles show significant reductions in their growth rates as a reaction to an increase in the unemployment rate. Yet, when comparing the coefficients for high and low paying firms no significant difference appears, thereby also in this sample one cannot say that high paying firms show stronger pro-cyclical employment growth rates. One might have expected to see results more in line with the theory of a wage ladder model, which collapses in a bust, because excluding entries should make poaching behavior more visible. This is because one can assume that firms starting-up will hire workers, who were employed with different firms before, even though the start-ups are likely to fall into a lower quintile. This fact would then offset the effects one would usually expect to see due to poaching. Another explanation can also be found in the literature: especially young firms seem to display rather erratic behavior when in comes to employment growth [eg.

Table 12: FS no EE, growth rate dhs, region-level u-rate

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	-0.00226**	-0.00445**	-0.00178*
	(0.000642)	(0.00114)	(0.000581)
β_2	-0.00266**	-0.00510**	-0.00210**
	(0.000713)	(0.00138)	(0.000610)
β_3	-0.00314**	-0.00524**	-0.00251**
	(0.000725)	(0.00145)	(0.000662)
β_4	-0.00338**	-0.00547**	-0.00271**
	(0.000815)	(0.00156)	(0.000723)
β_5	-0.00332**	-0.00485*	-0.00269**
	(0.000691)	(0.00148)	(0.000605)
N	136935	136935	136170
R^2	0.044	0.067	0.057

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Haltiwanger et al. (2013)], thereby through excluding entries one can possibly find how low paying firms react to changes in the unemployment rate without the confounding factor of start-ups. Yet both of these aspects do not lead to significant results in favor of stronger pro-cyclical growth of high paying firms.

Table 13, in which the growth rate which excludes entries and exits, is regressed onto the 12 month difference of the region-level unemployment rate also suggests that high paying firms do not display stronger reactions to changes in the business cycle. Even though both in column 1 and column 3 the coefficients on the measure of the business cycle for low paying firms are not significantly different from zero, whereas the high paying firms have stronger and more negative coefficients, the coefficients are not significantly different from each other. Also the regression weighted by size in column 2 of Table 14 does not suggest pro-cyclical employment growth for high paying firms, because of large standard errors.

Like in the full sample in Table 14 when using the nation wide seasonally adjusted unemployment rate as a measure of the business cycle the coefficients become positive. This suggests counter-cyclical growth of all firms, yet smaller reactions of higher paying firms. This could be due to the exclusion of exits,

Table 13: FS no EE, growth rate dhs, region-level u-rate 12 month diff.

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	-0.00118	-0.0000787	-0.00112
	(0.000701)	(0.000869)	(0.000705)
β_2	-0.00194	-0.00118	-0.00192
	(0.00104)	(0.000909)	(0.00105)
β_3	-0.00259*	-0.00131	-0.00257*
	(0.00105)	(0.000942)	(0.00107)
β_4	-0.00330*	-0.00210	-0.00326*
	(0.00106)	(0.00118)	(0.00107)
β_5	-0.00267*	-0.000632	-0.00265*
	(0.00107)	(0.00177)	(0.00106)
N	136935	136935	136935
R^2	0.042	0.059	0.056

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 14: FS no EE, growth rate dhs, u-rate seas. adj.

	growth-rate-dhs	growth-rate-dhs weight=size	growth-rate-dhs lagged growth-rate
β_1	0.00572***	0.00537***	0.00531***
	(0.000632)	(0.000571)	(0.000660)
β_2	0.00381**	0.00339***	0.00374**
	(0.000970)	(0.000627)	(0.000870)
β_3	0.00299**	0.00365***	0.00302**
	(0.000817)	(0.000486)	(0.000772)
β_4	0.00295*	0.00331***	0.00302**
	(0.000929)	(0.000598)	(0.000823)
β_5	0.00368**	0.00416***	0.00355**
	(0.000957)	(0.000648)	(0.000858)
N	136935	136935	136170
R^2	0.042	0.060	0.056

Standard errors in parentheses

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

Source: Own calculations using the AMDB

which could be the driving factor behind smaller growth rates in times of economic downturn.
Concluding one can say that once one excludes entering and exiting firms the theory of stronger pro-cyclical growth rates of high paying firms still does not become more plausible.

6.3 Zero Difference Sample

In this section I only use those observations for which hires minus separations are equal to net job creation within a firm. For better visibility in each table, all columns use the same specification, yet they all are for different dependent variables.

Table 15 uses the region-level unemployment rate as a measure of the business cycle and from column 1 one can see that when the unemployment rate increases, the growth rate for firms of all quintiles will decrease. Column 2 shows that also hires will decrease as the unemployment rate increases and by looking at column 3 it becomes clear that separations increase as the unemployment rate increases, yet only significantly different from zero for the lower quintiles. This is inconsistent with the theory of poaching since one assumes that high paying firms reduce their poaching in a crisis, thereby reducing the separations which low paying firms experience due to poaching.
Table 16 shows that even though for the full sample weighting did not a have much of an influence on the results, it does for this sample. Again all quintiles' growth rates seem to react similarly to a change in the unemployment rate, yet only the high paying firms reduce their hire rates significantly as the unemployment rate increases, and only the low paying firms increase their separations. The effect of the unemployment rate on the hire rate is consistent with the effects of the job ladder model predicted by Kahn and McEntarfer (2014), but according to the theory hire rates of high paying firms should decrease more than those of low paying firms, which is not the case here. The effect on the separation rate is not in line with the theory of poaching, because as poaching becomes limited, separations of low paying firms should fall.

Table 17 again uses the employment in each bin as weights, but this time the measure of the business cycle is the 12 month difference of the region-level unemployment rate. For the growth rate both β_4 and β_5 are significant at the 10 percent level, thereby indicating that high paying firms' growth rates are pro-cyclical, whereas the the β coefficients for the lower quintiles are not significantly

Table 15: ZD, region-level u-rate

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep._rate_dhs
β_1	-0.00493**	-0.00228*	0.00265*
	(0.00111)	(0.000855)	(0.00107)
β_2	-0.00481**	-0.00230*	0.00251*
	(0.00126)	(0.000894)	(0.000873)
β_3	-0.00492**	-0.00339**	0.00153
	(0.00128)	(0.000949)	(0.000896)
β_4	-0.00517**	-0.00302*	0.00214
	(0.00121)	(0.00104)	(0.00110)
β_5	-0.00487**	-0.00273*	0.00214
	(0.000990)	(0.00112)	(0.00109)
N	136168	136168	136168
R^2	0.054	0.257	0.266

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 16: ZD, region-level u-rate, weights=size

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep._rate_dhs
β_1	-0.00829*	-0.00302	0.00528*
	(0.00280)	(0.00165)	(0.00166)
β_2	-0.00843*	-0.00315	0.00528*
	(0.00280)	(0.00157)	(0.00160)
β_3	-0.00869*	-0.00385*	0.00483*
	(0.00286)	(0.00136)	(0.00176)
β_4	-0.00901*	-0.00431**	0.00469*
	(0.00288)	(0.00128)	(0.00194)
β_5	-0.00896*	-0.00489*	0.00407
	(0.00286)	(0.00160)	(0.00197)
N	136168	136168	136168
R^2	0.077	0.294	0.362

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 17: ZD, region-level u-rate 12 month diff., weights=size

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep._rate_dhs
β_1	0.142	-0.206	-0.348**
	(0.221)	(0.168)	(0.0775)
β_2	-0.105	-0.267	-0.162*
	(0.219)	(0.161)	(0.0647)
β_3	-0.209	-0.303	-0.0940
	(0.200)	(0.152)	(0.0514)
β_4	-0.371	-0.412*	-0.0411
	(0.194)	(0.142)	(0.0567)
β_5	-0.402	-0.438*	-0.0368
	(0.188)	(0.134)	(0.0627)
N	136168	136168	136168
R^2	0.066	0.291	0.354

Standard errors in parentheses

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

Source: Own calculations using the AMDB

different from zero. Also if one performs a Wald test, in order to test whether or not β_5 is equal to β_1, one obtains the result that they are significantly different from each other at the 1 percent level. This is the first estimation which yields results one would expect under the poaching hypothesis. But column 2 Table 17 does not show that hire rates of low and high paying firms would react differently to changes in the unemployment rate, whereas column 3 again shows that separations of low paying firms decrease by more than those of high paying firms as the unemployment rate increases. Therefore only columns 1 and 3 are inline with the theory of poaching.

Table 18 uses the 1 period difference in the nation wide seasonally adjusted unemployment rate and displays somewhat similar results to Table 17: high paying firms' growth rates are pro-cyclical, whereas firms in lower than quintiles show a reaction to the business cycle variable which is not statistically significant from zero but statistically different from the coefficient for the highest quintile, according to a Wald test at the 1 percent level. Column 2 of Table 18 shows that low paying firms' hire rates increase even as the unemployment rate increases, which is also consistent with the theory of a wage ladder model, since only when the unemployment rate is high, are there enough unemployed such that low paying

Table 18: ZD, seas. adj. u-rate 1 month diff., weights=size

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep._rate_dhs
β_1	0.00401	0.0310***	0.0270**
	(0.00669)	(0.00429)	(0.00799)
β_2	-0.000483	0.0204**	0.0208**
	(0.00478)	(0.00448)	(0.00469)
β_3	-0.00122	0.0151*	0.0163***
	(0.00529)	(0.00502)	(0.00203)
β_4	-0.0110	0.00344	0.0144***
	(0.00505)	(0.00445)	(0.00144)
β_5	-0.0147**	-0.00117	0.0135***
	(0.00310)	(0.00342)	(0.000640)
N	136168	136168	136168
R^2	0.066	0.291	0.355

Standard errors in parentheses

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

Source: Own calculations using the AMDB

firms can effectively hire workers. Column 3 displays results which cannot be clearly attributed to the theory of poaching because all quintiles increase their separation rates as the unemployment rate increases.

What remains to be done is to look at the hire rate from non-employment and from employment, as well as the separation rate to non-employment and to employment. To do so in all tables following column 1 will have the hire rate as the dependent variable, column 2 the hire from employment rate, column 3 the hire from non-employment rate and likewise for the separation rate.

Using Table 19, which uses the region-level unemployment rate, the poaching pattern, can be explored in more detail. In column 1, one can see how the hire rates of high quintiles decrease significantly as the unemployment rate increases, yet again they are not significantly different from those of low paying firms. Column 2 shows results which are in favor of poaching because as the unemployment rate increases the hire rate from employment decreases for high paying firms, whereas for low paying firms in increases. These coefficients are statistically significant from each other, a Wald test giving a p-value of 0.0482. Column 3 shows no evidence of high and low paying firms displaying different behavior in terms

Table 19: ZD, region-level u-rate, weights=size, hires

	(1) hire_rate_dhs	(2) hire_e_rate_dhs	(3) hire_n_rate_dhs
β_1	-0.00302	0.0000977	-0.00311
	(0.00165)	(0.000196)	(0.00161)
β_2	-0.00315	-0.0000104	-0.00314
	(0.00157)	(0.000159)	(0.00157)
β_3	-0.00385*	-0.000258	-0.00360*
	(0.00136)	(0.000119)	(0.00142)
β_4	-0.00431**	-0.000502**	-0.00381*
	(0.00128)	(0.000136)	(0.00134)
β_5	-0.00489*	-0.000626*	-0.00427*
	(0.00160)	(0.000203)	(0.00159)
N	136168	136168	136168
R^2	0.294	0.189	0.287

Standard errors in parentheses

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

Source: Own calculations using the AMDB

of their hire from non-employment rate.

Using 12 month differences of the region-level unemployment rate as done in Table 20 leads to similar results regarding the overall hire rate, which declines significantly for high paying firms as the unemployment rate increases, yet again it is not significantly different from the coefficient for the hire rate of low paying firms. For the hire rate from employment, as seen in column 2, the poaching pattern is also not clear because both high and low paying firms adjust their hires from employment downwards as the unemployment rate increases, thereby the coefficients show no significant differences from each other. As already seen in Table 19 hires from non-employment decrease for high paying firms in times of high unemployment, yet not more than for low paying firms.

Table 21 shows how separation rates react to changes in the region-level unemployment rate. Column 1 does not show a pattern in favor of the theory of poaching, because as the unemployment rate increases one would expect high paying firms to increase their separation rate by more than low paying firms do, but here all coefficients lie within one another's confidence intervals. Also column 2 show does not show poaching clearly because as the unemployment rate rises separations to employment, so having workers poached away, should decreases

Table 20: ZD, region-level u-rate 12 month diff., weights=size, hires

	(1) hire_rate_dhs	(2) hire_e_rate_dhs	(3) hire_n_rate_dhs
β_1	-0.206	-0.0693*	-0.136
	(0.168)	(0.0294)	(0.165)
β_2	-0.267	-0.0721*	-0.195
	(0.161)	(0.0237)	(0.160)
β_3	-0.303	-0.0772**	-0.226
	(0.152)	(0.0161)	(0.152)
β_4	-0.412*	-0.0921***	-0.320
	(0.142)	(0.0136)	(0.139)
β_5	-0.438*	-0.0975***	-0.341*
	(0.134)	(0.0150)	(0.135)
N	136168	136168	136168
R^2	0.291	0.186	0.285

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 21: ZD, region-level u-rate, weights=size, separations

	(1) sep._rate_dhs	(2) sep._e_rate_dhs	(3) sep._n_rate_dhs
β_1	0.00528*	-0.0000657	0.00534**
	(0.00166)	(0.000131)	(0.00159)
β_2	0.00528*	-0.0000723	0.00535**
	(0.00160)	(0.0000983)	(0.00153)
β_3	0.00483*	-0.000235*	0.00507*
	(0.00176)	(0.0000910)	(0.00168)
β_4	0.00469*	-0.000330*	0.00502*
	(0.00194)	(0.000137)	(0.00183)
β_5	0.00407	-0.000362	0.00443*
	(0.00197)	(0.000186)	(0.00182)
N	136168	136168	136168
R^2	0.362	0.318	0.338

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 22: ZD, region-level u-rate 12 month diff., weights=size, separations

	(1) sep._rate_dhs	(2) sep._e_rate_dhs	(3) sep._n_rate_dhs
β_1	-0.348**	-0.225**	-0.123*
	(0.0775)	(0.0564)	(0.0453)
β_2	-0.162*	-0.140**	-0.0226
	(0.0647)	(0.0346)	(0.0455)
β_3	-0.0940	-0.107***	0.0133
	(0.0514)	(0.0205)	(0.0415)
β_4	-0.0411	-0.0887***	0.0476
	(0.0567)	(0.0145)	(0.0497)
β_5	-0.0368	-0.0626**	0.0257
	(0.0627)	(0.0142)	(0.0543)
N	136168	136168	136168
R^2	0.354	0.321	0.327

Standard errors in parentheses

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

Source: Own calculations using the AMDB

for low paying firms more than for high paying firms, which is not the case. Column 3 shows that for all firms separations to non-employment increase as the unemployment rate increases, which is not surprising, but does not allow for any conclusions on the theory of poaching.

I repeat the exercise using the 12 month differences of the regional unemployment rate in Table 22 and find the following results: As the unemployment rate increases separations as well as separations to employment decrease by more for low paying firms than for high paying firms. The difference between β_1 and β_5 being significant at the 1 percent level both times. This lets me conclude that poaching could be to some extent driving the results. The separations to employment also increase for high paying firms in a bust, which could be an indicator that the job ladder does not always take individuals form a low paying firm to a high paying firm, but there might be substantial movements between high paying firms as well.

Since the specifications using the 12 month differences in regional unemployment rates gave the results most in line with the theory of a wage ladder model, I repeat the estimations using this measure of the business cycle, but I include a lagged rate into the regression.

From Table 23 column 1 one can see that even when including a lagged rate the growth rate of high paying firms is pro-cyclical and it's reaction to change in the unemployment rate is significantly different from the one of firms in the lowest quintile at the 1 percent level. Columns 2, 4, and 5, therefore all columns using a hire rate show no evidence of poaching because all quintiles' hire rates behave similarly. When looking at column 3, so the changes in the separation rate, one can see that as the unemployment rate increases low paying firms separation rates decrease by more than those of high paying firms. This difference is significant at the 1 percent level. Also column 6 shows results which are in favor of poaching, because as the unemployment rate increases the separation to employment rate of low paying firms decreases. The coefficients for the separation to employment rate for the lowest and the highest quintile are significantly different from each other. Therefore one can conclude that one can some evidence in favor of poaching but only for the employment growth rate and the separation rate.

Table 24 repeats the estimations of Table 23 but instead of using the 12 month differences in the unemployment rate it uses the change in percentages from a year ago of the production of total industry. The patterns found are again very similar. All columns using some form of the hire rate show no evidence of poaching. Column 1, in which the employment growth rate is the dependent variable, shows pro-cyclical growth of high paying firms which is significantly different from that of low paying firms at the 1 percent level. Also columns 3, 6 and 7 show that as industrial production increases separation rates increase more for low paying firms than for high paying firms, which is consistent with the theory of poaching.

Concluding one can say that one can find some evidence for the theory of poaching when using this zero difference sample but only for specific measures of the unemployment rate and never when it comes to hire rates, but exclusively for separation and employment growth rates.

Table 23: ZD, region-level u-rate 12 month diff., weights=size, lagged rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	growth_rate	hire_rate	sep_rate	hire_e_rate	hire_n_rate	sep_e_rate	sep_n_rate
β_1	0.0313	-0.254	-0.199*	-0.0654*	-0.192	-0.181**	-0.0488
	(0.201)	(0.145)	(0.0653)	(0.0260)	(0.140)	(0.0509)	(0.0488)
β_2	-0.164	-0.295	-0.0853	-0.0674*	-0.233	-0.115**	0.0110
	(0.206)	(0.141)	(0.0650)	(0.0203)	(0.139)	(0.0293)	(0.0561)
β_3	-0.245	-0.316	-0.0428	-0.0723***	-0.248	-0.0888***	0.0320
	(0.195)	(0.139)	(0.0601)	(0.0143)	(0.137)	(0.0167)	(0.0562)
β_4	-0.371	-0.382*	-0.00904	-0.0846***	-0.306*	-0.0745***	0.0539
	(0.192)	(0.134)	(0.0619)	(0.0145)	(0.130)	(0.0124)	(0.0593)
β_5	-0.386	-0.388*	-0.0141	-0.0880**	-0.311*	-0.0531**	0.0311
	(0.187)	(0.130)	(0.0633)	(0.0176)	(0.128)	(0.0118)	(0.0599)
N	135402	135402	135402	135402	135402	135402	135402
R^2	0.096	0.360	0.443	0.205	0.355	0.346	0.419

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 24: ZD, ind-prod., weights=size, lagged rates

	(1) growth_rate	(2) hire_rate	(3) sep_rate	(4) hire_e_rate	(5) hire_n_rate	(6) sep_e_rate	(7) sep_n_rate
β_1	-0.000354*	0.000319*	0.000571***	0.000147*	0.000173	0.000336*	0.000273***
	(0.000130)	(0.000115)	(0.000108)	(0.0000573)	(0.000115)	(0.000104)	(0.0000311)
β_2	-0.000100	0.000344**	0.000397***	0.000147*	0.000202*	0.000228*	0.000194***
	(0.0000870)	(0.0000797)	(0.0000787)	(0.0000558)	(0.0000752)	(0.0000754)	(0.0000167)
β_3	-0.00000992	0.000321**	0.000305***	0.000144*	0.000182*	0.000179*	0.000145***
	(0.0000524)	(0.0000711)	(0.0000552)	(0.0000488)	(0.0000635)	(0.0000542)	(0.0000133)
β_4	0.0000979	0.000321***	0.000227***	0.000134**	0.000191**	0.000145**	0.0000954***
	(0.0000425)	(0.0000567)	(0.0000334)	(0.0000318)	(0.0000534)	(0.0000364)	(0.0000123)
β_5	0.000138**	0.000311***	0.000188**	0.000143**	0.000176**	0.000119*	0.0000774***
	(0.0000337)	(0.0000473)	(0.0000374)	(0.0000312)	(0.0000456)	(0.0000366)	(0.00000847)
N	135402	135402	135402	135402	135402	135402	135402
R^2	0.095	0.359	0.444	0.205	0.355	0.348	0.419

Standard errors in parentheses

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

Source: Own calculations using the AMDB

6.4 Zero Difference Sample Excluding Entries and Exits

The analysis of the section above can be repeated for a smaller sample when one excludes all entering and exiting firms, to test whether or not entries and exits are driving the results. As it has become clear from the above specifications, if at all poaching results are visible when one uses the 12 month differences of the regional unemployment rate, I will repeat the analysis in this section using only this measure of the business cycle.

Table 25 shows the growth rate, the hire rate and the separation rate as functions of the 12 month differences in the the region-level unemployment rate. Concerning the growth rate the β_5 is significantly different from β_1 using a Wald test, which indicates some poaching behavior. Yet neither for hires nor for separations does one find additional results in favor of the wage ladder model. To analyze the results more in depth I will again show results with rate from and to non-employment and employment as well.

When considering Table 26, column 1 corresponds to column 2 of Table 25 and therefore has been analyzed above. Column 2 show results in favor of poaching because hire rates from employment decrease for high paying firms, significantly more than for low paying firms, but there are no results which would point in the direction of poaching. which uses the 12 month differences in the region-level unemployment rate also shows estimates in which the coefficients for the highest quintiles are not significantly different from those for the lowest quintile, thereby one can also conclude that poaching is not driving these results.

Even though the evidence in favor of the theory of poaching is very limited, it seems to be partially plausible in this sample, which excludes entries and exits and limits the attention to only those observations in which all job flows are correctly accounted for by worker flows. Therefore I also use the change in percentages from a year ago of the production of total industry[17] in Austria as a measure of the business cycle.

Table 28 shows the coefficients of the rates, when regressing them onto the change in total industry production. The growth rate of high paying firms displays pro-cyclical behavior and its coefficient is significantly different from the one for the lowest paying quintile. This again suggests stronger pro-cyclical behavior of high than low paying firms and thereby poaching. Column 2 does not indicate any poaching behavior since all quintiles hire rates increase as industrial production

17. Source: FRED

Table 25: ZD no EE, region-level u-rate 12 month diff., weights=size

	(1)	(2)	(3)
	growth_rate_dhs	hire_rate_dhs	sep._rate_dhs
β_1	0.00212	-0.101	-0.103*
	(0.147)	(0.141)	(0.0322)
β_2	-0.0660	-0.152	-0.0858*
	(0.135)	(0.118)	(0.0260)
β_3	-0.114	-0.170	-0.0555*
	(0.125)	(0.107)	(0.0228)
β_4	-0.254	-0.275*	-0.0213
	(0.119)	(0.0926)	(0.0300)
β_5	-0.277*	-0.291**	-0.0135
	(0.112)	(0.0797)	(0.0430)
N	136168	136168	136168
R^2	0.072	0.291	0.379

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 26: ZD no EE, region-level u-rate 12 month diff., weights=size, hires

	(1)	(2)	(3)
	hire_rate_dhs	hire_e_rate_dhs	hire_n_rate_dhs
β_1	-0.101	0.0139	-0.115
	(0.141)	(0.00913)	(0.133)
β_2	-0.152	-0.0136	-0.138
	(0.118)	(0.00798)	(0.112)
β_3	-0.170	-0.0312**	-0.139
	(0.107)	(0.00678)	(0.103)
β_4	-0.275*	-0.0536***	-0.222*
	(0.0926)	(0.00633)	(0.0885)
β_5	-0.291**	-0.0576***	-0.233*
	(0.0797)	(0.00520)	(0.0794)
N	136168	136168	136168
R^2	0.291	0.294	0.282

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 27: ZD no EE, region-level u-rate 12 month diff., weights=size, sep.

	(1) sep._rate_dhs	(2) sep._e_rate_dhs	(3) sep._n_rate_dhs
β_1	-0.103*	-0.0545***	-0.0483
	(0.0322)	(0.00889)	(0.0306)
β_2	-0.0858*	-0.0531***	-0.0327
	(0.0260)	(0.00259)	(0.0252)
β_3	-0.0555*	-0.0569***	0.00132
	(0.0228)	(0.00389)	(0.0225)
β_4	-0.0213	-0.0519***	0.0307
	(0.0300)	(0.00507)	(0.0313)
β_5	-0.0135	-0.0320***	0.0185
	(0.0430)	(0.00341)	(0.0419)
N	136168	136168	136168
R^2	0.379	0.397	0.345

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 28: ZD no EE, total industry production, weights=size

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep._rate_dhs
β_1	-0.0000985	0.000187	0.000285***
	(0.0000986)	(0.000123)	(0.0000437)
β_2	-0.0000201	0.000231*	0.000251***
	(0.0000705)	(0.0000757)	(0.0000242)
β_3	0.0000291	0.000209**	0.000180***
	(0.0000426)	(0.0000590)	(0.0000252)
β_4	0.000142**	0.000228**	0.0000853**
	(0.0000352)	(0.0000556)	(0.0000235)
β_5	0.000152***	0.000175***	0.0000236
	(0.0000241)	(0.0000329)	(0.0000158)
N	136168	136168	136168
R^2	0.072	0.291	0.379

Standard errors in parentheses

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

Source: Own calculations using the AMDB

Table 29: ZD no EE, region-level u-rate 12 month diff., weights=size, lagged rate

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep._rate_dhs
β_1	-0.0545	-0.138	-0.0556
	(0.130)	(0.110)	(0.0275)
β_2	-0.105	-0.176	-0.0481
	(0.123)	(0.0973)	(0.0302)
β_3	-0.143	-0.189	-0.0306
	(0.119)	(0.0918)	(0.0309)
β_4	-0.247	-0.253*	-0.00928
	(0.115)	(0.0841)	(0.0336)
β_5	-0.256*	-0.254*	-0.0117
	(0.111)	(0.0761)	(0.0394)
N	135402	135402	135402
R^2	0.114	0.378	0.470

Standard errors in parentheses

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

Source: Own calculations using the AMDB

increases. Column 3 possibly suggests poaching because as industrial production decreases so do the separation rates of the lower paying firms.

One can then also include a lagged rate as another robustness check into the regression with the 12 month differences of the region-level unemployment rate. If one does this all results suggesting possible poaching disappear, because the coefficients for the lowest and the highest quintile are not significantly different from each other. Therefore one can conclude that even if the sample is chosen which shows the results most in favor of the wage ladder model and the theory of poaching as soon as small part of the specification are changed, the estimated coefficients do not support the theory any longer in this sample.

7 Conclusion

After regressing different measures of growth rates, hire rates, and separation rates onto various measures of the business cycle, there is no clear evidence for poaching. Recall that according to Kahn and McEntarfer (2014) there should be in total four implications of the job ladder model:

- A decrease in the growth rate of high paying firms in a bust;
- A decline in the rate of hires from employment within the high paying firms in a bust;
- A decrease in the rate of separations to employment within the low paying firms in a bust;
- A general increase in the rate of separations within the high paying firms in a bust.

Only some of these effects can be found in the Austrian data and only under very specific sample selection as well as only for very specific measures of the business cycle. For none of the specifications can all of them be found to hold at the same time.

The theory of poaching is, if at all visible, when one chooses the sample denoted as the zero difference sample, which consists only of the observations in which all job flows are exactly accounted for by workers flows, i.e. hires minus separations equals employment growth. For this sample one can find stronger pro-cyclical employment growth of high paying firms and stronger decreases in the separation rates of low paying firms as the unemployment rate rises. Yet, these results rely heavily on the measure of the business cycle chosen and are found when one uses 12 month differences in the regional unemployment rates. Also the zero difference sample excluding exit and entry shows some results in line with the theory of poaching. This is possibly due to the fact that excluding entries and exits makes it easier to find results consistent with poaching because one can assume that firms starting up will hire workers, who were employed with different firms before, even though the start-ups are likely to fall into a low paying quintile. This fact would then offset the effects one would usually expect to see due to poaching. Another explanation can also be found in the literature: especially young firms seem to display rather erratic behavior when in comes to employment growth [eg.Haltiwanger et al. (2013)]. Yet even when excluding exits and entries and limiting the analysis to the zero difference sample, including a lagged rate as an explanatory variable lets all effects in line with the theory of poaching disappear. Also results concerning the hire rate from employment as well as the separation to employment are hard to find independent of the specification.

I conclude that the theory of poaching is not generally valid in the Austrian labor market. Higher paying firms only show stronger pro-cyclical behavior than lower paying firms in some of the cases. In most of these specifications also the separation rate, as well as the separation to employment rate show stronger reactions for low paying firms. Yet, decompositions of the hire rate and the hire rate itself do not show any reactions to changes in the business cycle over different specifications, which would support a wage ladder model as proposed by Moscarini and Postel-Vinay (2013) and Burdett and Mortensen (1998). This model claims that workers move up the wage ladder, because larger, more productive high paying firms poach them away from their current firms, which are smaller and lower paying. This is why, if this model is supported by the data, high paying firms are more cyclical in their job creation patterns than low paying firms. Yet, the data also does not support the theory developed by Schumpeter (1939) which postulates that in recessions resources are reallocated to more productive firms, because in a recession the least productive firms are no longer profitable. This theory would then imply that in a recession low paying firms, which are seen as firms of low productivity would experience more negative employment growth. However, the Austrian data also does not support this theory since one does not find substantial differences between employment growth rates of high paying and employment growth rates of low paying firms.

An important question which arises from these findings is why for the US labor market several researchers such as Haltiwanger et al. (2015) or Kahn and McEntarfer (2014) were able to find strong evidence in favor of a job ladder model which collapses in times of economic downturn. This is presumably not due to differences in the measures of the business cycle chosen, because for the Austrian data for various measures based on unemployment rates such as the region-level unemployment rate, its twelve month differences, a seasonally adjusted nation wide unemployment rate, its first differences and its deviation from HP trend no systematic pattern consistent with the theory of poaching emerges. Also, when using a different measure of the business cycle namely the percentage change from a year ago in the industrial production index, only some of the results are consistent with the theory of paoching.

A possible answer to this question is the fact that earlier studies [eg. Haltiwanger et al. (2015) or Kahn and McEntarfer (2014)] had to rely on quarterly data, which makes for instance the analysis of separations to unemployment very difficult, because in order to be considered a separation to unemployment an individual has to be unemployed for a full quarter. This could be causing large differences in categorizations of separations and hires, thereby greatly influencing the results. Therefore an interesting extension of the analysis of job creation over the business cycle, would be to use different classifications of worker flows concerning the minimum duration of non-employment necessary to be classified as a separation to non-employment or a hire from non-employment.

Concluding one must say that for Austria, using the AMDB, a clear pattern in support of a wage ladder model, which collapses in times of high unemployment and therefore a theory of poaching can only be found in very specific cases.

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A Data Appendix

This section presents relevant additional information on the data used:

To show how the different measures of the business cycle behave, I plot some of them.

Figure 1: Region-level Unemployment rate
Source AMS

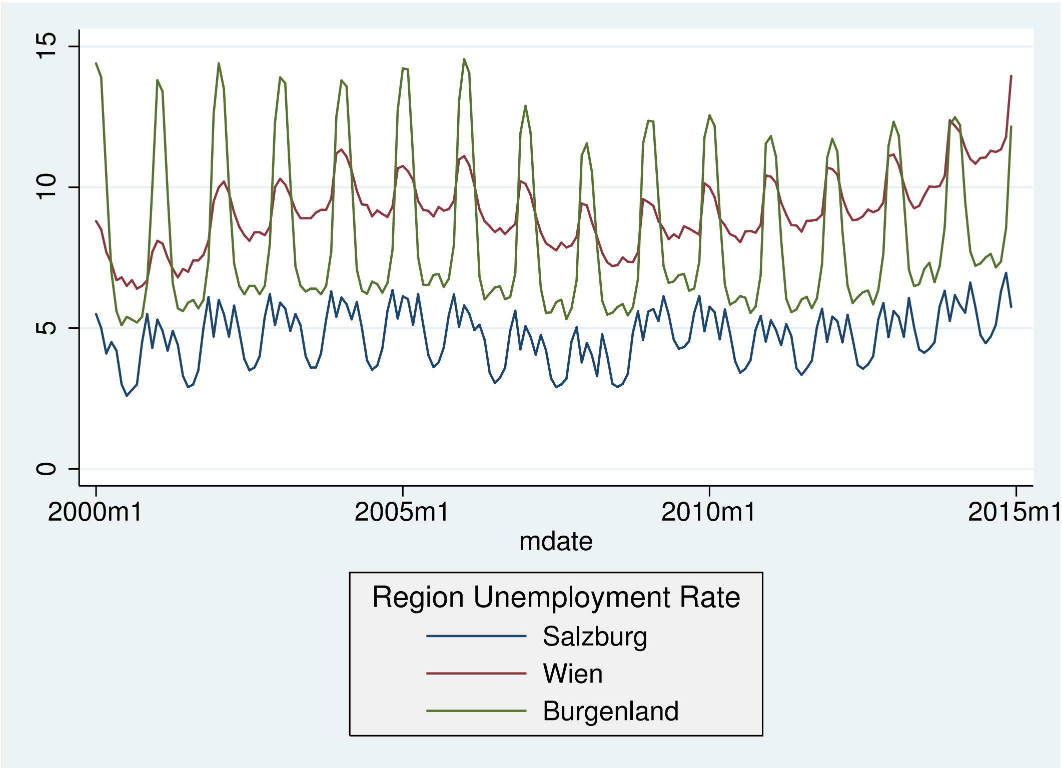


Table 30: NACE - Classificiations

NACE	Industry
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, Gas, Steam and Air Conditioning Supply
E	Water Supply; Sewerage, Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
H	Transportation and Storage
I	Accommodation and Food Service Activities
J	Information and Communication
K	Finacial and Insurance Activities
L	Real Estate Activities
M	Professional, Scientific and Technical Activities
N	Administrative and Support Service Activities
O	Public Administration and Defense; Compulsory Social Security
P	Education
Q	Human Health and Social Work Activities
R	Arts, Entertainment and Recreation
S	Other Service Activities
T	Activities of Households as Employers; Undifferentiated Goods- and Services- Producing Activities of Households for own use
U	Activities of Extraterritorial Organizations and Bodies

Source: Eurostat

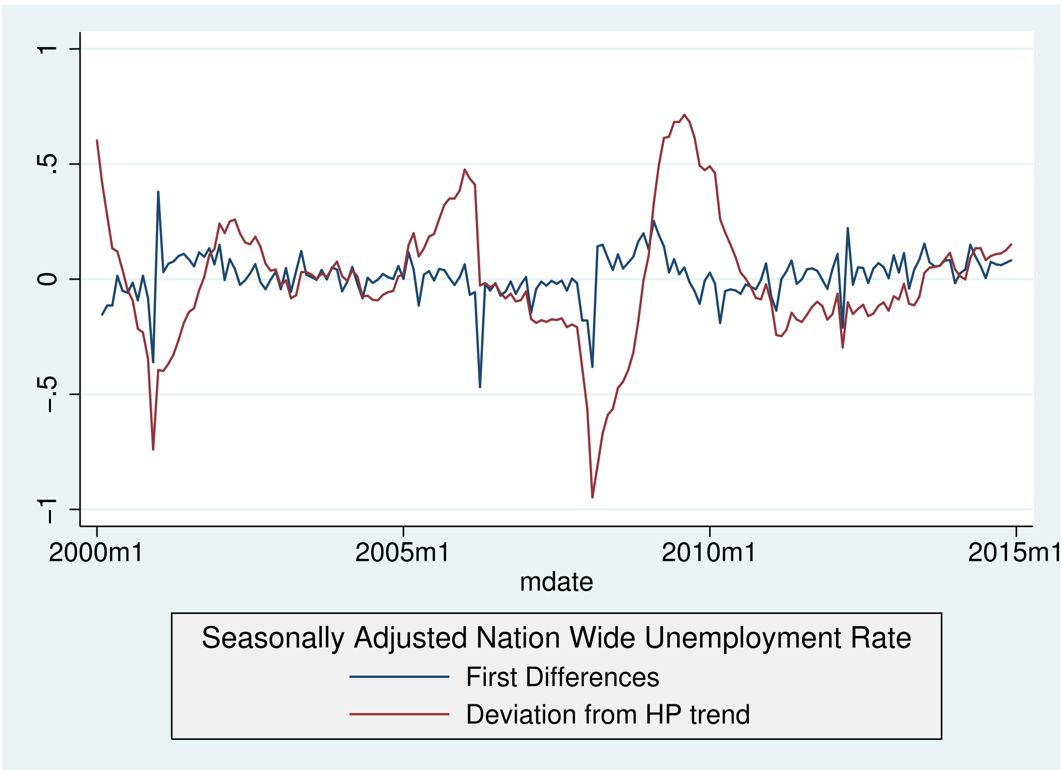
Table 31: Regions - Bundesländer

Numbering	Region
1	Burgenland
2	Kärnten
3	Niederöesterreich
4	Oberöesterreich
5	Salzburg
6	Steiermark
7	Tirol
8	Vorarlberg
9	Wien

Source: Own definitions

Figure 2: Regional Unemployment rate, 12 month differences
Source AMS, FRED

Figure 3: Nation wide Unemployment rate, deviations
Source FRED



B Results Appendix

For the sake of completion I will include not only the estimations of β_q but the full regression output for Table 17, Table 20 and Table 22.

Table 32: Full Specification for Table 17

	(1) growth_rate_dhs	(2) hire_rate_dhs	(3) sep_rate_dhs
1.quintc.u_rate_bl_12_diff	0.142	-0.206	-0.348**
	(0.221)	(0.168)	(0.0775)
2.quintc.u_rate_bl_12_diff	-0.105	-0.267	-0.162*
	(0.219)	(0.161)	(0.0647)
3.quintc.u_rate_bl_12_diff	-0.209	-0.303	-0.0940
	(0.200)	(0.152)	(0.0514)
4.quintc.u_rate_bl_12_diff	-0.371	-0.412*	-0.0411
	(0.194)	(0.142)	(0.0567)
5.quintc.u_rate_bl_12_diff	-0.402	-0.438*	-0.0368
	(0.188)	(0.134)	(0.0627)
2.quint	-0.00261*	-0.00614**	-0.00352**
	(0.000811)	(0.00165)	(0.000935)
3.quint	-0.00304*	-0.0102**	-0.00721**
	(0.00121)	(0.00265)	(0.00168)
4.quint	-0.00158	-0.0132*	-0.0116**
	(0.00208)	(0.00461)	(0.00278)
5.quint	-0.000462	-0.0215**	-0.0210***
	(0.00283)	(0.00639)	(0.00381)
2.bl_1	0.00331***	0.0122***	0.00890***
	(0.000295)	(0.000805)	(0.000539)
3.bl_1	-0.00296***	-0.00545***	-0.00249***
	(0.000416)	(0.000478)	(0.000137)
4.bl_1	-0.00215***	-0.00499***	-0.00284***
	(0.000408)	(0.000686)	(0.000344)
5.bl_1	0.00643***	0.00828***	0.00185*
	(0.000701)	(0.00135)	(0.000689)
6.bl_1	-0.00162***	-0.000387	0.00123**
	(0.0000876)	(0.000289)	(0.000245)
7.bl_1	0.0114***	0.0235***	0.0121***
	(0.00161)	(0.00289)	(0.00131)
8.bl_1	0.00232***	0.00209*	-0.000231
	(0.000436)	(0.000886)	(0.000494)
9.bl_1	-0.00337***	-0.00473***	-0.00137*
	(0.000466)	(0.000567)	(0.000592)
3.Nace_1	-0.0459***	-0.167***	-0.121***
	(0.00412)	(0.0166)	(0.0145)
6.Nace_1	-0.0333***	-0.131***	-0.0973***
	(0.00411)	(0.0167)	(0.0146)
7.Nace_1	-0.0429***	-0.164***	-0.121***
	(0.00410)	(0.0169)	(0.0146)
8.Nace_1	-0.0411***	-0.141***	-0.100***
	(0.00415)	(0.0167)	(0.0148)
9.Nace_1	-0.00597	-0.0626	-0.0566*
	(0.0143)	(0.0351)	(0.0224)
10.Nace_1	-0.0373***	-0.155***	-0.118***
	(0.00412)	(0.0172)	(0.0150)
11.Nace_1	-0.0455***	-0.173***	-0.127***
	(0.00441)	(0.0170)	(0.0144)

12.Nace_1	-0.0416***	-0.163***	-0.122***
	(0.00431)	(0.0172)	(0.0148)
13.Nace_1	-0.0393***	-0.159***	-0.120***
	(0.00420)	(0.0175)	(0.0152)
14.Nace_1	-0.0341***	-0.113***	-0.0790***
	(0.00420)	(0.0166)	(0.0149)
15.Nace_1	-0.0463***	-0.172***	-0.126***
	(0.00434)	(0.0168)	(0.0141)
16.Nace_1	-0.0233*	-0.125**	-0.102***
	(0.00965)	(0.0267)	(0.0186)
17.Nace_1	-0.0433***	-0.167***	-0.124***
	(0.00414)	(0.0172)	(0.0151)
18.Nace_1	-0.0274**	-0.125***	-0.0974***
	(0.00562)	(0.0177)	(0.0152)
19.Nace_1	-0.0428***	-0.159***	-0.117***
	(0.00414)	(0.0175)	(0.0151)
20.Nace_1	-0.0397***	-0.163***	-0.123***
	(0.00448)	(0.0178)	(0.0150)
2.month	0.00601*	-0.00551*	-0.0115***
	(0.00242)	(0.00185)	(0.00116)
3.month	0.0232**	0.0149*	-0.00827**
	(0.00617)	(0.00507)	(0.00240)
4.month	0.0138	0.0121*	-0.00170
	(0.00633)	(0.00468)	(0.00651)
5.month	0.0139*	0.00633	-0.00761
	(0.00520)	(0.00725)	(0.00372)
6.month	0.0142	0.00125	-0.0130***
	(0.00730)	(0.00710)	(0.00129)
7.month	0.0187**	0.0117*	-0.00704***
	(0.00525)	(0.00462)	(0.00121)
8.month	-0.00396*	-0.00508*	-0.00113
	(0.00134)	(0.00205)	(0.00138)
9.month	-0.00247	0.00140	0.00387
	(0.00330)	(0.00131)	(0.00297)
10.month	-0.0100*	-0.00661*	0.00341
	(0.00336)	(0.00202)	(0.00488)
11.month	-0.00733**	-0.00873	-0.00140
	(0.00171)	(0.00439)	(0.00291)
12.month	0.0126	0.0228	0.0102*
	(0.0265)	(0.0275)	(0.00340)
2001.year	0.00809*	0.00464	-0.00345**
	(0.00350)	(0.00295)	(0.000805)
2002.year	0.00947*	0.00399	-0.00548***
	(0.00359)	(0.00295)	(0.000818)
2003.year	0.00910**	0.00156	-0.00754***
	(0.00262)	(0.00230)	(0.000669)
2004.year	0.00909*	0.00163	-0.00746***
	(0.00273)	(0.00249)	(0.000748)
2005.year	0.0103**	0.00224	-0.00809***
	(0.00301)	(0.00289)	(0.000904)
2006.year	-0.0262***	-0.0378***	-0.0115***
	(0.00331)	(0.00251)	(0.00128)
2007.year	0.00754***	0.000558	-0.00698***
	(0.00140)	(0.00180)	(0.000937)
2008.year	0.00778**	0.00168	-0.00610***
	(0.00205)	(0.00203)	(0.000910)
2009.year	0.0119	0.00687	-0.00501**

	(0.00539)	(0.00464)	(0.00142)
2010.year	0.00850**	0.00171	-0.00679***
	(0.00184)	(0.00181)	(0.000936)
2011.year	0.00918**	0.00300	-0.00618***
	(0.00212)	(0.00197)	(0.000859)
2012.year	0.0103*	0.00447	-0.00586**
	(0.00349)	(0.00303)	(0.00120)
2013.year	0.00973*	0.00500	-0.00473**
	(0.00366)	(0.00326)	(0.00117)
2014.year	0.00680	-0.00324	-0.0100***
	(0.00360)	(0.00301)	(0.00115)
_cons	0.0382**	0.202***	0.164***
	(0.00985)	(0.0226)	(0.0158)
N	136168	136168	136168
R^2	0.066	0.291	0.354

Table 33: Full Specification of Table 20

	(1) hire_rate_dhs	(2) hire_e_rate_dhs	(3) hire_n_rate_dhs
1.quintc.u_rate_bl_12_diff	-0.206	-0.0693*	-0.136
	(0.168)	(0.0294)	(0.165)
2.quintc.u_rate_bl_12_diff	-0.267	-0.0721*	-0.195
	(0.161)	(0.0237)	(0.160)
3.quintc.u_rate_bl_12_diff	-0.303	-0.0772**	-0.226
	(0.152)	(0.0161)	(0.152)
4.quintc.u_rate_bl_12_diff	-0.412*	-0.0921***	-0.320
	(0.142)	(0.0136)	(0.139)
5.quintc.u_rate_bl_12_diff	-0.438*	-0.0975***	-0.341*
	(0.134)	(0.0150)	(0.135)
2.quint	-0.00614**	-0.00143***	-0.00471*
	(0.00165)	(0.000268)	(0.00144)
3.quint	-0.0102**	-0.00203**	-0.00822**
	(0.00265)	(0.000419)	(0.00229)
4.quint	-0.0132*	-0.00281**	-0.0104*
	(0.00461)	(0.000792)	(0.00390)
5.quint	-0.0215**	-0.00319*	-0.0183**
	(0.00639)	(0.00116)	(0.00533)
2.bl_1	0.0122***	0.000681***	0.0115***
	(0.000805)	(0.0000394)	(0.000786)
3.bl_1	-0.00545***	0.000101	-0.00555***
	(0.000478)	(0.0000495)	(0.000502)
4.bl_1	-0.00499***	0.000967***	-0.00596***
	(0.000686)	(0.0000579)	(0.000699)
5.bl_1	0.00828***	0.00119***	0.00709***
	(0.00135)	(0.0000369)	(0.00133)
6.bl_1	-0.000387	0.000627***	-0.00101**
	(0.000289)	(0.0000638)	(0.000291)
7.bl_1	0.0235***	0.00201***	0.0215***
	(0.00289)	(0.0000527)	(0.00286)
8.bl_1	0.00209*	0.00106***	0.00103
	(0.000886)	(0.0000419)	(0.000879)
9.bl_1	-0.00473***	0.00221***	-0.00694***
	(0.000567)	(0.000158)	(0.000593)
3.Nace_1	-0.167***	-0.0103***	-0.157***
	(0.0166)	(0.00142)	(0.0160)

6.Nace_1	-0.131***	-0.00643*	-0.124***
	(0.0167)	(0.00202)	(0.0157)
7.Nace_1	-0.164***	-0.00881***	-0.155***
	(0.0169)	(0.00141)	(0.0164)
8.Nace_1	-0.141***	-0.00182	-0.140***
	(0.0167)	(0.00132)	(0.0161)
9.Nace_1	-0.0626	-0.00186	-0.0607
	(0.0351)	(0.00162)	(0.0349)
10.Nace_1	-0.155***	-0.00499**	-0.150***
	(0.0172)	(0.00146)	(0.0167)
11.Nace_1	-0.173***	-0.0109***	-0.162***
	(0.0170)	(0.00163)	(0.0163)
12.Nace_1	-0.163***	-0.00875***	-0.155***
	(0.0172)	(0.00142)	(0.0169)
13.Nace_1	-0.159***	-0.00669**	-0.153***
	(0.0175)	(0.00158)	(0.0169)
14.Nace_1	-0.113***	-0.000352	-0.113***
	(0.0166)	(0.00165)	(0.0160)
15.Nace_1	-0.172***	-0.0116***	-0.161***
	(0.0168)	(0.00224)	(0.0159)
16.Nace_1	-0.125**	-0.00188	-0.123**
	(0.0267)	(0.00207)	(0.0252)
17.Nace_1	-0.167***	-0.00952***	-0.158***
	(0.0172)	(0.00154)	(0.0166)
18.Nace_1	-0.125***	-0.00262	-0.122***
	(0.0177)	(0.00151)	(0.0171)
19.Nace_1	-0.159***	-0.00871***	-0.151***
	(0.0175)	(0.00143)	(0.0169)
20.Nace_1	-0.163***	-0.00826**	-0.154***
	(0.0178)	(0.00190)	(0.0168)
2.month	-0.00551*	-0.00630***	0.000790
	(0.00185)	(0.000819)	(0.00126)
3.month	0.0149*	-0.00547***	0.0204**
	(0.00507)	(0.000882)	(0.00429)
4.month	0.0121*	-0.00362*	0.0157**
	(0.00468)	(0.00110)	(0.00366)
5.month	0.00633	-0.00437**	0.0107
	(0.00725)	(0.00115)	(0.00643)
6.month	0.00125	-0.00567***	0.00692
	(0.00710)	(0.00101)	(0.00662)
7.month	0.0117*	-0.00475***	0.0164**
	(0.00462)	(0.000877)	(0.00419)
8.month	-0.00508*	-0.00599***	0.000909
	(0.00205)	(0.000941)	(0.00168)
9.month	0.00140	-0.00373**	0.00513**
	(0.00131)	(0.000767)	(0.00103)
10.month	-0.00661*	-0.00345**	-0.00316
	(0.00202)	(0.000790)	(0.00202)
11.month	-0.00873	-0.00585***	-0.00288
	(0.00439)	(0.000920)	(0.00405)
12.month	0.0228	-0.00629**	0.0291
	(0.0275)	(0.00180)	(0.0259)
2001.year	0.00464	0.00115	0.00349
	(0.00295)	(0.000550)	(0.00300)
2002.year	0.00399	-0.000431	0.00442
	(0.00295)	(0.000297)	(0.00290)
2003.year	0.00156	-0.00127**	0.00283

	(0.00230)	(0.000270)	(0.00221)
2004.year	0.00163	-0.00128**	0.00291
	(0.00249)	(0.000335)	(0.00236)
2005.year	0.00224	-0.00134*	0.00358
	(0.00289)	(0.000450)	(0.00262)
2006.year	-0.0378***	-0.00279***	-0.0350***
	(0.00251)	(0.000446)	(0.00257)
2007.year	0.000558	-0.000757	0.00132
	(0.00180)	(0.000377)	(0.00149)
2008.year	0.00168	-0.000191	0.00187
	(0.00203)	(0.000311)	(0.00185)
2009.year	0.00687	0.0000983	0.00677
	(0.00464)	(0.000867)	(0.00429)
2010.year	0.00171	-0.00139**	0.00310
	(0.00181)	(0.000354)	(0.00162)
2011.year	0.00300	-0.00117**	0.00416
	(0.00197)	(0.000330)	(0.00181)
2012.year	0.00447	-0.00149*	0.00596
	(0.00303)	(0.000487)	(0.00282)
2013.year	0.00500	-0.00124	0.00623
	(0.00326)	(0.000559)	(0.00297)
2014.year	-0.00324	-0.00371***	0.000466
	(0.00301)	(0.000472)	(0.00289)
_cons	0.202***	0.0236***	0.178***
	(0.0226)	(0.00189)	(0.0221)
N	136168	136168	136168
R^2	0.291	0.186	0.285

Table 34: Full Specification of Table 22

	(1) fire_rate_dhs	(2) sep_e_rate_dhs	(3) sep_n_rate_dhs
1.quintc.u_rate_bl_12_diff	-0.348**	-0.225**	-0.123*
	(0.0775)	(0.0564)	(0.0453)
2.quintc.u_rate_bl_12_diff	-0.162*	-0.140**	-0.0226
	(0.0647)	(0.0346)	(0.0455)
3.quintc.u_rate_bl_12_diff	-0.0940	-0.107***	0.0133
	(0.0514)	(0.0205)	(0.0415)
4.quintc.u_rate_bl_12_diff	-0.0411	-0.0887***	0.0476
	(0.0567)	(0.0145)	(0.0497)
5.quintc.u_rate_bl_12_diff	-0.0368	-0.0626**	0.0257
	(0.0627)	(0.0142)	(0.0543)
2.quint	-0.00352**	-0.000948**	-0.00258**
	(0.000935)	(0.000248)	(0.000740)
3.quint	-0.00721**	-0.00169**	-0.00552**
	(0.00168)	(0.000422)	(0.00133)
4.quint	-0.0116**	-0.00263**	-0.00901**
	(0.00278)	(0.000657)	(0.00219)
5.quint	-0.0210***	-0.00420**	-0.0168***
	(0.00381)	(0.000899)	(0.00298)
2.bl_1	0.00890***	0.000806***	0.00809***
	(0.000539)	(0.0000483)	(0.000511)
3.bl_1	-0.00249***	0.000260***	-0.00275***
	(0.000137)	(0.0000507)	(0.000135)
4.bl_1	-0.00284***	0.000720***	-0.00356***
	(0.000344)	(0.0000451)	(0.000350)

5.bl_1	0.00185*	0.000807***	0.00104
	(0.000689)	(0.0000452)	(0.000663)
6.bl_1	0.00123**	0.000881***	0.000351
	(0.000245)	(0.0000467)	(0.000228)
7.bl_1	0.0121***	0.00145***	0.0106***
	(0.00131)	(0.0000572)	(0.00128)
8.bl_1	-0.000231	0.000504***	-0.000734
	(0.000494)	(0.0000428)	(0.000467)
9.bl_1	-0.00137*	0.00172***	-0.00308***
	(0.000592)	(0.000142)	(0.000502)
3.Nace_1	-0.121***	-0.00713***	-0.114***
	(0.0145)	(0.00112)	(0.0136)
6.Nace_1	-0.0973***	-0.00433*	-0.0930***
	(0.0146)	(0.00149)	(0.0134)
7.Nace_1	-0.121***	-0.00648***	-0.114***
	(0.0146)	(0.00110)	(0.0138)
8.Nace_1	-0.100***	-0.000724	-0.0996***
	(0.0148)	(0.00113)	(0.0138)
9.Nace_1	-0.0566*	-0.000392	-0.0562*
	(0.0224)	(0.00132)	(0.0216)
10.Nace_1	-0.118***	-0.00516**	-0.113***
	(0.0150)	(0.00115)	(0.0141)
11.Nace_1	-0.127***	-0.00810***	-0.119***
	(0.0144)	(0.00115)	(0.0135)
12.Nace_1	-0.122***	-0.00727***	-0.114***
	(0.0148)	(0.00110)	(0.0139)
13.Nace_1	-0.120***	-0.00565**	-0.115***
	(0.0152)	(0.00123)	(0.0142)
14.Nace_1	-0.0790***	0.00180	-0.0808***
	(0.0149)	(0.00141)	(0.0138)
15.Nace_1	-0.126***	-0.00870***	-0.117***
	(0.0141)	(0.00124)	(0.0131)
16.Nace_1	-0.102***	-0.00371*	-0.0982***
	(0.0186)	(0.00120)	(0.0176)
17.Nace_1	-0.124***	-0.00652***	-0.117***
	(0.0151)	(0.00116)	(0.0142)
18.Nace_1	-0.0974***	-0.00372*	-0.0937***
	(0.0152)	(0.00124)	(0.0143)
19.Nace_1	-0.117***	-0.00605***	-0.111***
	(0.0151)	(0.00110)	(0.0143)
20.Nace_1	-0.123***	-0.00762***	-0.115***
	(0.0150)	(0.00119)	(0.0141)
2.month	-0.0115***	-0.00234**	-0.00918***
	(0.00116)	(0.000581)	(0.00128)
3.month	-0.00827**	-0.00189*	-0.00638*
	(0.00240)	(0.000581)	(0.00250)
4.month	-0.00170	-0.00105	-0.000650
	(0.00651)	(0.000615)	(0.00638)
5.month	-0.00761	-0.000639	-0.00697
	(0.00372)	(0.000678)	(0.00361)
6.month	-0.0130***	-0.00168*	-0.0113***
	(0.00129)	(0.000660)	(0.00148)
7.month	-0.00704***	-0.00140*	-0.00564**
	(0.00121)	(0.000602)	(0.00131)
8.month	-0.00113	-0.00166*	0.000535
	(0.00138)	(0.000661)	(0.00111)
9.month	0.00387	-0.000170	0.00404

	(0.00297)	(0.000543)	(0.00297)
10.month	0.00341	-0.000786	0.00420
	(0.00488)	(0.000502)	(0.00487)
11.month	-0.00140	-0.00148*	0.0000872
	(0.00291)	(0.000612)	(0.00274)
12.month	0.0102*	-0.00235*	0.0126**
	(0.00340)	(0.000987)	(0.00292)
2001.year	-0.00345**	-0.000405	-0.00305***
	(0.000805)	(0.000569)	(0.000495)
2002.year	-0.00548***	-0.00213***	-0.00335***
	(0.000818)	(0.000300)	(0.000663)
2003.year	-0.00754***	-0.00306***	-0.00448***
	(0.000669)	(0.000331)	(0.000494)
2004.year	-0.00746***	-0.00306***	-0.00440***
	(0.000748)	(0.000338)	(0.000537)
2005.year	-0.00809***	-0.00316***	-0.00493***
	(0.000904)	(0.000456)	(0.000600)
2006.year	-0.0115***	-0.00415***	-0.00739***
	(0.00128)	(0.000464)	(0.000858)
2007.year	-0.00698***	-0.00270***	-0.00428***
	(0.000937)	(0.000454)	(0.000528)
2008.year	-0.00610***	-0.00225***	-0.00385***
	(0.000910)	(0.000387)	(0.000619)
2009.year	-0.00501**	-0.00195**	-0.00306*
	(0.00142)	(0.000511)	(0.00119)
2010.year	-0.00679***	-0.00300***	-0.00380***
	(0.000936)	(0.000355)	(0.000644)
2011.year	-0.00618***	-0.00268***	-0.00351***
	(0.000859)	(0.000324)	(0.000596)
2012.year	-0.00586**	-0.00332***	-0.00253*
	(0.00120)	(0.000439)	(0.000924)
2013.year	-0.00473**	-0.00230***	-0.00243*
	(0.00117)	(0.000398)	(0.000920)
2014.year	-0.0100***	-0.00379***	-0.00625***
	(0.00115)	(0.000331)	(0.000872)
_cons	0.164***	0.0168***	0.147***
	(0.0158)	(0.00159)	(0.0150)
N	136168	136168	136168
R^2	0.354	0.321	0.327

C Code and Data processing

In this section I will report the important parts of my code and explain the steps involved. Since I start with separate data files for each year and then repeat steps for each year before appending the relevant datasets in order to not increase file size by too much, I only report code for one year.

In a first step I explain how I construct firm size:

```
/*First I keep only those individuals classified to be working, I also delete the self employed.*/

keep if (AM == "FU" | AM == "FB" | AM == "FL" /*
*/ | AM == "FA" | AM == "FF" | AM == "FS" | AM == "BE" | AM == "LE" | AM == "AA" /*
*/ | AM == "FD" | AM == "SO" )

/*here I keep only those people who earn more than approx. 400 euro*/
```

```
keep if (GB == "NO")

/*Since the data file possibly has more than one observation per person per month*/
/* since here I am simply counting the employed at a given point in time,*/
/* namely the end of each month (STICHTAG), I can simply */
/*get rid of all those who are not employed anymore at the STICHTAG*/

/*Here I drop those observations*/
drop if ENDDAT < STICHTAG

/*The next lines count for each firm (BENR) the number of individuals (PENR) at each STICHTAG*/

levelsof STICHTAG, local(levels)
foreach i of local levels {
preserve
collapse (count) SIZE=PENR if STICHTAG==‘i’, by(BENR)
qui gen long DATE=‘i’
display "‘i’"
if ‘i’>‘Stichtag-min’ {
append using firm_size_00
save firm_size_00, replace
}
else if ‘i’>‘Stichtag-max’ {
display "error"
}
else {
save firm_size_00, replace
}
restore
}
```

For median earnings within a firm I proceed in the same way with the only addition that I also exclude those individuals, who were not employed for a full month, and then I also change the way of collapsing

```
 /*Here I collapse over AVG_BMG which is the earnings variable for the individual*/

levelsof STICHTAG, local(levels)
foreach i of local levels {
preserve
collapse (median) PAY=AVG_BMG if STICHTAG==‘i’, by(BENR)
qui gen long DATE=‘i’
display "‘i’"
if ‘i’>‘SMin’ {
append using firm_pay_00
save firm_pay_00, replace
}
else if ‘i’>‘SMax’ {
display "error"
}
else {
save firm_pay_00, replace
}
restore
}
```

I then append the files for each year, in order to have one file for firm size, and one for median monthly earnings within a firm. Then using the size file I construct 2 growth rates:

```
 use full_firm_size
 gen empl_growth_3 = D.Size
 save full_firm_size_filled_panel, replace
tsfill, full
/*the last line fills up the panel such that it is balanced.*/
/*for the second definition of growth including entries and exits I do the following*/
by BENR: replace Size = 0 if (Size == . & Size[_n-1] != 0 & Size[_n-1]!= .)
```

```
by BENR: replace Size = 0 if (Size == . & Size[_n+1] != 0 & Size[_n+1]!= .)
gen empl_growth_6 = D.Size
```

I then use the file on median monthly earnings as well as additional data on firm characteristics to build industry-region specific quintiles.

```
encode(nace_1), gen(Nace_1)
save full_firm_pay_quintiles_bl_nace_2, replace

/*I drop those industries where I have too few observations*/
drop if Nace_1 == 2
drop if Nace_1 == 4
drop if Nace_1 == 5
drop if Nace_1 == 21
drop if bl1 == "0"
drop if bl1 == "Beamten-VA"
drop if bl1 == "ÖBB"

levelsof Nace_1, local(levels)
foreach i of local levels {
xtile quint_Wien_‘i’ = PAY if (bl1 == "Wien" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_OÖ_‘i’ = PAY if (bl1 == "OÖ" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_NÖ_‘i’ = PAY if (bl1 == "NÖ" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_Sbg_‘i’ = PAY if (bl1 == "Sbg" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_Bgld_‘i’ = PAY if (bl1 == "Bgld" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_Ktn_‘i’ = PAY if (bl1 == "Ktn" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_Stmk_‘i’ = PAY if (bl1 == "Stmk" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_Tirol_‘i’ = PAY if (bl1 == "Tirol" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
xtile quint_Vbg_‘i’ = PAY if (bl1 == "Vbg" & Nace_1 == ‘i’ & bl_n_change==0), nquantiles(5)
}

/*Now we can actually merge the quintile variables
we only needed them defined for each Bundesland seperately*/

gen quint = .
levelsof Nace_1, local(levels)
foreach i of local levels {
replace quint = quint_Wien_‘i’ if (bl1 == "Wien" & Nace_1 == ‘i’)
replace quint = quint_OÖ_‘i’ if (bl1 == "OÖ" & Nace_1 == ‘i’)
replace quint = quint_NÖ_‘i’ if (bl1 == "NÖ" & Nace_1 == ‘i’)
replace quint = quint_Sbg_‘i’ if (bl1 == "Sbg" &  Nace_1 == ‘i’)
replace quint = quint_Tirol_‘i’ if (bl1 == "Tirol" &  Nace_1 == ‘i’)
replace quint = quint_Ktn_‘i’ if (bl1 == "Ktn" &  Nace_1 == ‘i’)
replace quint = quint_Stmk_‘i’ if (bl1 == "Stmk" & Nace_1 == ‘i’)
replace quint = quint_Bgld_‘i’ if (bl1 == "Bgld" & Nace_1 == ‘i’)
replace quint = quint_Vbg_‘i’ if (bl1 == "Vbg" &  Nace_1 == ‘i’)
}
save, replace
```

I then merge the file on size and the file on median monthly earnings as well as the files on hires, hires from employment, hires from non-employment, separations, separations to employment and separations to non-employment.
For hires and separations I use the change in the labor market status variable AM CHANGE. When defining hires I again only keep the individuals who are classified to be working and then proceed in the following way.

```
keep if (AM_CHANGE == "ALNU" | AM_CHANGE == "ALGU"/*
*/ | AM_CHANGE == "QUUB" | AM_CHANGE == "KGUB" | AM_CHANGE == "REUB" /*
*/ | AM_CHANGE == "PZUB" | AM_CHANGE == "GBUB" | AM_CHANGE == "XOUB" /*
*/ | AM_CHANGE == "SBUB"  | AM_CHANGE == "NDG*" | AM_CHANGE == "NEW*")

/*then like before I sum up over all individuals for each firm for each STICHTAG*/
/*notice that by deleting all individuals who were not hired I will have
 a missing value whenever no hire happens
  when I then merge the hire file with for example the size file*/

foreach i of local levels {
```

```
preserve
collapse (count) HIRE=PENR if STICHTAG==`i', by(BENR)
qui gen long DATE=`i'
display "`i'"
if `i'>`SMin' {
append using firm_hire_00
save firm_hire_00, replace
}
else if `i'>`SMax' {
display "error"
}
else {
save firm_hire_00, replace
}
restore
}
/*For hires from employment I only keep those with the status change variable new employer*/
keep if ( AM_CHANGE == "NDG*")
/*and then sum up again the same way as before*/
/*notice that all employees who had less than 7 days between 2 jobs*/
/* will receive this status change variable entry*/

/*For hires from non-employment I simply subtract hires from employment from total hires*/
```

For the separations this procedure is more complicated, because when one observes the separation in the labor market status change variable, the firm identifier has already changed, or does not show up anymore. Here it is essential that I begin with the file for 2013 and 2014 and save all observations, in which a separation happens in January into an extra data file, which I then merge with the file from the year before. Then I define a variable separations according to the following procedure, over which I then aggregate.

```
gen fire = 0

by PENR: replace fire = 1 if (AM_CHANGE[_n+1] == "UBSB" /*
*/ |AM_CHANGE[_n+1] == "NDG*" |AM_CHANGE[_n+1] == "NUAL" /*
*/ |AM_CHANGE[_n+1] == "GUAL" |AM_CHANGE[_n+1] == "UBQU" /*
*/ |AM_CHANGE[_n+1] == "UBKG" |AM_CHANGE[_n+1] == "UBRE" /*
*/ |AM_CHANGE[_n+1] == "UBPZ" |AM_CHANGE[_n+1] == "UBGB" /*
*/ |AM_CHANGE[_n+1] =="UBXO")


foreach i of local levels {
preserve
collapse (sum) fire if STICHTAG==`i', by(BENR)
qui gen long DATE=`i'
display "`i'"
if `i'>`SM' {
append using firm_fire_01
save firm_fire_01, replace
}
else if `i'>`SMax' {
display "error"
}
else {
save firm_fire_01, replace
}
restore

}
```

Like for hires, I proceed in the same way for separations from employment adapting the code to only pick up those separations which are to to employment, thereby having the labor market status change variable equal to new employer. Then I define separations to non-employment as separations minus separations to employment.

After having done this for all years, I can merge the data sets on size, hires and separations with the one including the wage earnings quintiles. I then define an ID variable consisting of a region, and industry and a quintile. To then get growth rates for each such quintile I aggregate in the following way first over size, then over employment growth, hires, separations etc.:

```
egen ID = concat(bl1 nace_1 quint), punct(,)
encode ID, gen(ID2)

levelsof ID2, local(levels)
foreach i of local levels {
preserve
collapse (sum) Size if ID2== ‘i’, by(mdate)
gen ID2 = ‘i’
if ‘i’ == 1  {
save quint_size_bl_nace_quint, replace
}
else {
append using quint_size_bl_nace_quint
save quint_size_bl_nace_quint, replace
}
restore
}
```

Once I have aggregated over all necessary variables, I merge the resulting files and calculate the growth rates as proposed by Davis et al. (1998) and merge the resulting data file with the necessary measures of the business cycle.

```
by ID2: gen growth_rate_3_dhs =( employment_growth_3/(0.5*(Size - l.Size)))
```

I can then estimate the following regressions

```
regress growth_rate_dhs (i.quint)#c.u_rate_bl_12_diff i.quint i.bl_1 i.Nace_1 i.month i.year
[aweight=Size], vce(cluster bl_1)

regress hire_rate_dhs (i.quint)#c.u_rate_bl_12_diff i.quint i.bl_1 i.Nace_1 i.month i.year
[aweight=Size], vce(cluster bl_1)

regress fire_rate_dhs (i.quint)#c.u_rate_bl_12_diff i.quint i.bl_1 i.Nace_1 i.month i.year
[aweight=Size], vce(cluster bl_1)
```