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Growth, Job Matching and Unemployment in Austria

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1. Introduction

In the recent discussion in Austria's media, the issue of unemployment is dominant. In particular, the issue of a higher education level as a possibility to escape from unemployment is discussed very broadly. The empirical facts in Austria, nourishing this discussion, are that higher educated people face a lower unemployment rate compared to lower educated.

Keeping this in mind, the aim of this diploma thesis is the following. First, the explanation of the different unemployment rates of high and low educated people, and second, to find out whether economic growth or other determinants affect unemployment in a dynamic setup.

Aghion and Howitt (1994) showed by applying the Schumpeterian argument of creative destruction that growth driven by innovation can also have positive effects on unemployment. This means that economic growth can yield a higher unemployment rate. Although, after introducing some specific conditions they derived a hump-shaped unemployment curve with respect to growth, i.e. growth can have positive and negative effects on unemployment. This result is derived by using a matching function from the prevailing Equilibrium Unemployment Theory by Pissarides (2000). This function describes the allocation of unemployed workers to vacant jobs.

This diploma thesis extends the theoretic model of Aghion and Howitt (1994) in a way that two different skill levels (i.e. high and low skilled labour) are introduced. A model is derived which uses these two skill types as input for production so that a differentiated analysis is guaranteed. These extensions are necessary to answer the question if high skilled or low skilled labour suffers more from unemployment induced by growth or other factors. Furthermore, the usage of the matching function by Pissarides (2000) allows for different job matching probabilities of high and low skilled labour and therefore contributes to a possible explanation of different unemployment rates of these two sorts of labour.

To support the theory, an extensive empirical part accompanies the theoretical part. There, the analysis is geographically focused on Austria. A broad data description is followed by several estimations of matching functions subject to educational differences. The econometric method used is panel data analysis. To take educational differences into account two education groups are defined, i.e. high and low educated. Therefore, always two panels are estimated one for high and one for low educated people.

This diploma thesis is structured as follows. In chapter 2 the literature is reviewed. This is followed by the development of a theoretical model accompanied by some simulations in chapter 3. Chapter 4 sheds light on the empirical side. In the first part of the chapter the data used is described in detail. The second part deals with the results of different panel data regressions. Finally, chapter 5 provides some conclusions.

2. Literature review

In the subsequent sections I present an overview of the major literature I have used as a base for my diploma thesis. The first section contains information about growth theory and in particular endogenous growth theory. Second, the theory of the Beveridge curve and the concept of matching functions will be described. Thereafter, the link between growth and unemployment will be introduced. Additionally, the theory of these concepts will be supported by some literature dealing with the empirical causalities of growth and unemployment which are the baseline of this thesis.

2.1. Growth models

To give a short overview of growth models one has to start with the neoclassical theories. To pick out one of the first models in this category one has to mention the model developed by Solow in 1956. There, an aggregate production function with labour and capital as inputs is the main component of the model. Individuals choose whether they save money (assuming a constant saving rate) or use it for consumption which has, like the depreciation rate on capital, implications on the capital stock. The absence of scarce resources like, for example, land makes the production function homogeneous of degree one. Further assumptions are that there is full employment and population grows at a constant rate. The result of neoclassical models like this is that in the long run the positive rate of technical progress is the only element which increases output per capita. However, technical progress is exogenous, i.e. it is just a parameter which is not explained within the model and also unemployment is not part of the model since the labour market does not appear, i.e. it is implicitly assumed that full employment is prevailing (cf. Solow (1956)).

Two other models following the neoclassical theories have become very famous. The one developed by Ramsey (1928), Cass (1956) and Koopmans (1956) and the one by Diamond (1965), to mention an example for an overlapping generations model. In principle, those two models are very similar but differ from the Solow model in a way that the saving rate is modelled to be endogenous (cf. Romer (2006)).

The interesting question where technological progress comes from cannot be answered by this kind of models. Therefore economists began to think about the issue and invested time and effort to invent the so-called endogenous growth theories which I will explain in the subsequent chapter.

2.1.1. Endogenous growth models

The most popular endogenous growth models were developed by Romer (1990), Grossmann and Helpman (1991) and the one by Aghion and Howitt (1992).
These models focus on the effects of knowledge accumulation and R&D as an origin of technological progress. R&D has effects either on

- process innovation (e.g. in production sector or distribution) or
- product innovation (respectively differentiation in product quality).

Endogenous growth models are constructed that way that R&D uses and creates knowledge. Knowledge is a public good which is per definition nonrival and nonexcludable. For example, patent rights are a common method to transform knowledge in a partially excludable good which then can create monopoly rents and therefore provides incentives to innovate. Note that these monopoly rents vanish over time since usually other innovations are made and also patent rights are limited in a sense that they exclude others only for a certain period of time.

Joseph Schumpeter's ideas based on innovation and entrepreneurship play an important role (Schumpeter, 1911, chapter 2) in these models. Furthermore, some of the endogenous growth models also reflect the so-called Schumpeterian argument of creative destruction. Schumpeter described the idea of creative destruction explicitly in his book Capitalism, Socialism and Democracy (1942) as an inner recycling process of the capitalistic economical structure - a revolutionary process which destroys old structures and creates new ones. An example for this concept is according to Schumpeter the reformation of transport facilities from stagecoach to airplanes (Schumpeter, 1942, chapter 7).
An essential part of endogenous growth models is, as Schumpeter has argued, that the reason for R&D is to benefit from it in form of future profits when the technology or product leading firm can extract monopoly profits. This monopoly power improves the possibilities to appropriate resources spent in R&D which would not be the case in a

competitive setup.
On the other hand, Arrow (1962) has argued that market power reduces incentives to innovate (e.g. a monopolist would have negative incentives to further research after a successful invention because he would destroy his own monopoly profits by replacing his own invention by another (replacement effect, cf. Arrow (1962)).
However, following the argumentation of Schumpeter in a competitive market the competitors in the market always have incentives to improve their own situation by innovations.
The model of Aghion and Howitt (explained in the subsequent chapter) considers both mentioned effects but does not allow any room for unemployment in the basic model either.

2.1.2. Aghion and Howitt: A growth model with creative destruction

Aghion and Howitt (1992) published an endogenous growth model including basic ideas traced back to Joseph Schumpeter.
The idea of the model is that growth is generated by quality improving vertical innovations (i.e. innovations within a specific product group or "technology group"). These innovations are a result of research activities. The clue of new vertical innovation is that those make old technologies or products obsolete. As already mentioned, this is just another way describing creative destruction.

The economy in the model developed by Aghion and Howitt consists of L individuals, all having the same preference over time. Population values the unique consumption good in the economy discounted by the rate of time preferences which is equal to the interest rate (cf. Aghion and Howitt (1992)).
Each individual is endowed with a unit flow of labour. Furthermore, the fixed stock of labour L consists of the sum of workers employed in the manufacturing sector and researchers. The manufacturing sector is using the intermediate goods as inputs for their production function. If an invention which replaces the old intermediate good (which is used to produce the consumption good) by another whose use raises the technology parameter (which is part of the production function), the innovating firm is market leader and gains the monopoly profit until the innovation is replaced by the next innovator. Note that innovations are modelled to arrive randomly with a certain Poisson arrival rate (an overview of the Poisson process is given in Appendix A.1)(cf. Aghion and Howitt (1998)).

Research that generates growth in the technology parameter has, on the one hand, positive spillover effects like, for example, that the consumer surplus subject to the new invented intermediate good is higher than the monopoly profit which the inventor gains and that the invention offers the possibility for other researchers to begin working on the next innovations. On the other hand, there are also some negative spillover effects like the so-called business stealing effect, which describes the destruction of the monopoly profit of the former inventor who has had the leadership of the intermediate product (patent race, cf. Tirole (1988), Aghion and Howitt (1998)).
An arbitrage condition describes the relation between manufacturing products and the expected value of doing research. The expected value of doing research is the profit flow if leadership is prevailing, reduced by expected loss of losing leadership times the probability of an innovation, given that the incumbent researcher does no research. The reason for the absence of performing R&D by the incumbent researcher is that all other researchers have immediate access to the incumbent technology and therefore the value for making the next innovation is smaller (for the incumbent researcher) than for an outside researcher. (replacement effect, cf. Arrow (1962), Aghion and Howitt (1998)).
The last step is that firms in the manufacturing sector using the current innovation (actual intermediate good) maximise their profit under the assumption of being in a competitive market ($MC = MR$) (cf. Aghion and Howitt (1998)).
Analysing the model in steady state (which means that all variables grow at a constant rate, in the case of this model, that the productivity adjusted wage rates are independent of the number of innovations and therefore constant over time and that the labour stock is equally composed over time) it turns out that there exists a unique equilibrium. Since the interval of two successive innovations is supposed to be random and following a Poisson process, the time path of the final output will be a random step function. This random step function follows an exponential distribution. The average growth rate can therefore easily be computed by taking the expected values of the differences in the logs of output (cf. Aghion and Howitt (1998)).
It turns out that the average growth rate in steady state is dependent on several factors. Average growth is positively dependent on the number of researchers in steady state. Furthermore, an increase of the growth rate can be caused by an increase in the size of the labour market, a reduction of the interest rate and a decrease in market competition. Moreover, economic growth is prevailing in this model if the size of innovation increases and if R&D becomes more productive (cf. Aghion and Howitt (1998)).

2.2. Growth, job matching and unemployment

In which way does growth affect the labour market? Artur Okun was the first who proposed a correlation between unemployment and economic growth (cf. Okun (1962)). In a scatter plot where the growth rate of GDP is on the horizontal axis and the differenced unemployment rate on the vertical axis he showed that in the United States since 1960 a high output growth is typically associated with a low change in the unemployment rate. Nevertheless, the causality of the direction, i.e. if high economic growth fosters employment or high employment fosters growth cannot be answered in this setup. Furthermore, this investigation method of the relation between growth and unemployment is a static one.

In a dynamic environment there are also some reasons for a positive impact of growth on unemployment. The question whether technical progress creates or destroys jobs is not easy to answer because growth has probably a positive and a negative effect on unemployment. On the one hand, growth can create jobs in a sense that new firms come into the market or that firms in general produce more because of higher demand and therefore need more labour force. On the other hand, growth can also destroy jobs. One could argue that technical progress destroys jobs because it is labour-saving, i.e. firms substitute workers and employees for machines (capital). Or that through economic growth new technologies arise which make some workers endowed with antique qualifications redundant (cf. Aghion and Howitt (1994)).

In the next three subchapters the most important ingredients of Equilibrium Unemployment Theory are presented, mostly along the lines of Pissarides (2000), chapters 1,2,3. There, the concept of job matching and job creation will be described in detail. Thereafter, a model developed by Aghion and Howitt (1994) which combines growth and job matching is presented.

2.2.1. Matching functions

The matching function is a possibility to describe the relation between the number of jobs formed as a function of the number of workers looking for a job (unemployed), the number of firms looking for workers (job vacancies) and possibly some other variables. The reason for a need of such a device like the matching function is that *trade* in the labour market is a nontrivial economic activity, which means that one has to deal with heterogeneity, frictions and imperfect information. Firms and workers are different, uncertainty exists about timing and location of workers, and firms can just observe signals of productivity of a potential job candidate but do not know their real productivity level in advance. Another characteristic of the matching process between a worker and a firm is that it is generally uncoordinated, time consuming and costly for firms and workers (cf. Pissarides (2000)).

To go more into the technical features of the matching function, it is important to mention that it is introduced as an aggregate function as known from other macroeconomic fields (e.g. production functions). Furthermore, the matching function has no explicit microfoundations but has had empirical success and shows modelling effectiveness (cf. Pissarides (2000)).
In the model described below many firms and many workers act as atomistic competitors. Then the matching function is given by

$$mL = m(uL, vL) = m(U, V)$$

where L denotes the labour force, $u = \frac{U}{L}$ the unemployment rate, $v = \frac{V}{L}$ the vacancy rate, and m is the job matching rate. The function is assumed increasing in both arguments concave and, due to the argument that if unemployment and vacant jobs double also job matchings will double, homogeneous of degree one (cf. Pissarides (2000)).
Note that matching between unemployed and job vacancies takes place randomly at any point in time. The process that changes state of vacant jobs (vacant jobs become filled) is Poisson (a short overview about the Poisson process is given in Appendix A.1) with rate

$$\frac{m(uL, vL)}{vL} = m(\frac{u}{v}, 1) \equiv q(\theta)$$

where $\theta = \frac{v}{u}$ reflects the *tightness* of the labour market (Pissarides (2000)).
The probability of a successful match between an unemployed and a vacant job during a small time period δt is $\delta t q(\theta)$ and the mean duration of a vacant job is $\frac{1}{q(\theta)}$. Note that if the labour market becomes tighter (i.e. v increases and/or u decreases) the job-filling-rate becomes lower ($q'(\theta) \leq 0$) (Pissarides (2000)).

The process that changes state of unemployed persons (unemployed move into employment) is (by using homogeneity assumption) Poisson with rate

$$\frac{m(uL, vL)}{uL} = m(1, \frac{v}{u}) \equiv q(\frac{1}{\theta}) = \theta q(\theta)$$

Therefore, the mean duration of unemployment is $\frac{1}{\theta q(\theta)}$. One can see that unemployed workers find a job more easily if there are more vacancies relative to unemployed and, on the other hand, firms with vacant jobs find workers more easily when there are more unemployed workers relative to vacancies (Pissarides (2000)).

This very basic interpretation of the matching function does not cover issues like on-the-job search and job-to-job search, which means that only unemployed search for jobs.

Empirical research has shown that in many cases a matching function in Cobb Doulgas form fits the data well (i.e. $q(\theta) = (\frac{u}{v})^{\alpha} = (\frac{v}{u})^{-\alpha}$ and for $\theta q(\theta) = (\frac{v}{u})^{(1-\alpha)}$).

2.2.2. Beveridge curve

Wiliam H. Beveridge, a British economist in the 1940s, first identified the Beveridge curve. He pointed out a negative relation between unemployment and job vacancies. The Beveridge curve is illustrated in a scatter plot where unemployment rates are on the x-axis and vacancy rates on the y-axis (Bleakley and Fuhrer (1997)).

To derive the Beveridge curve theoretically, I continue with the theoretical part from the previous chapter 2.2.1. As already derived, the probability of vacant jobs becoming filled is $q(\theta)$ and the probability of an unemployed get employed is $\theta q(\theta)$. During a short interval of time δt, the price of work (wage) is not the only allocative mechanism because there is also a positive probability

- $1 - q(\theta)\delta t$ that a hiring firm will not find a worker and
- $1 - \theta q(\theta)\delta t$ that an unemployed will not find a job.

Note that these probabilities arise in a stochastic way and does not depend on prices. The only way that these probabilities are changed is via the labour market tightness θ (cf. Pissarides (2000)).

To specify the model completely, inflow into unemployment is set equal to the outflow out of unemployment (equilibrium condition). Furthermore, it is assumed that the flow into unemployment is caused by exogenous negative shocks (e.g. in productivity, demand, etc.) which arrive with Poisson rate λ. Job creation takes place when a firm and a job seeker form a match at a negotiated price. Both, job separation (occupied job becomes vacant) and job destruction (employed become unemployed) occurs with the same Poisson rate λ. Then, under the assumptions of no growth and no turnover in the labour force, the mean number of workers entering unemployment (during a small time interval δt) is (Pissarides (2000))

$$\lambda(1-u)L\delta t$$

and the mean number of workers leaving unemployment is (Pissarides (2000))

$$mL\delta t = u\theta q(\theta)L\delta t$$

The difference between these two flows gives the evolution of mean unemployment (Pissarides (2000))

$$\frac{\partial u}{\partial t} = \dot{u} = \lambda(1-u) - \theta q(\theta)u$$

In steady state the the mean unemployment rate is constant (Pissarides (2000))

$$\lambda(1-u) = \theta q(\theta)u \Rightarrow u = \frac{\lambda}{\lambda + \theta q(\theta)} \tag{2.1}$$

Equation 2.1, i.e. the Beveridge curve, shows that if the job-finding rate $\theta q(\theta)$ increases unemployment will decrease. The effect of a negative external shock, (λ rises), is that also unemployment will rise ($\frac{\partial u}{\partial \lambda} > 0$).

To show the Beveridge curve graphically I use the Cobb Douglas specification of the matching function from chapter 2.2.1. Since $q(\theta)$ was assumed to be $(\frac{u}{v})^{\alpha} = (\frac{v}{u})^{-\alpha}$ and $\theta q(\theta)$ was assumed to be $(\frac{v}{u})^{(1-\alpha)}$ the steady state mean unemployment can be rewritten into $\lambda(1-u) = v^{1-\alpha}u^{\alpha}$. Solving for v yields

$$v = (\lambda(1-u)u^{-\alpha})^{\frac{1}{(1-\alpha)}}$$

Figure 2.1 with parameters $\alpha = \lambda = \frac{1}{3}$ shows the expected negative relation between unemployment and vacancies in a Cobb-Douglas setup.

Equation 2.1 fully describes the Beveridge curve. For a given level of θ, the labour market tightness, and λ, the negative shock parameter, a unique equilibrium unemployment rate is defined (cf. Pissarides (2000)). Furthermore, the negative slope of the curve in a v,u space can be shown. However, since empirically the Beveridge curve shifts over time some theoretical reasons for these shifts are discussed in the next paragraphs (in the empirical section 4.2.5 we will see that in the Austrian case, shifts of the curve

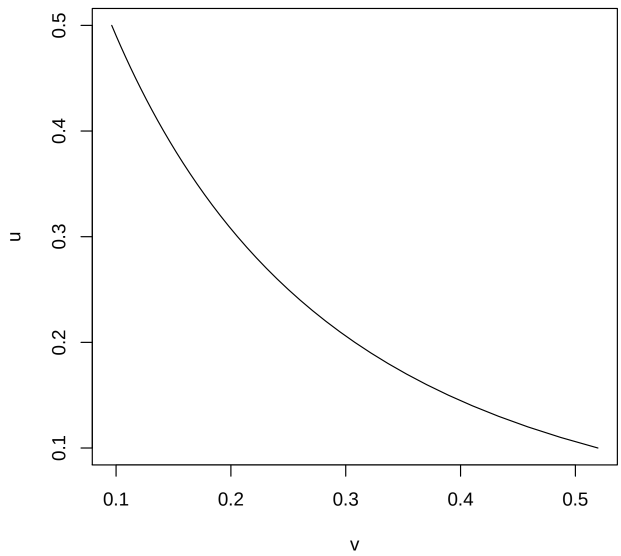

Figure 2.1.: Beveridge Curve in a Cobb-Douglas Setup, Parameters: $\alpha = \lambda = \frac{1}{3}$, Source: own calculations.

are existing, also in other countries in the EU these shifts exist (cf. Layard et al. (1991)).

One theoretical reason for an outwards shift are actions that lead to greater flows of workers and jobs. Those actions could be, for example, enormous expansions of firms or, more generally, a more flexible labour market. Results of such actions are that average job tenor is lower, turnover is higher and one needs more time for moving across firms (cf. Bleakley and Fuhrer (1997)).

Another reason for an outward shift could be a change in L (i.e. an increase in the rate of labour force growth shifts the Beveridge curve out and to the right) (cf. Bleakley and Fuhrer (1997)).

The last reason for shifts of the Beveridge curve is the job-matching process itself. Although this effect is not captured in the basic model described above. However, extending the matching function by an effectiveness parameter one can derive the following results. Lower job-matching effectiveness leads to lower outflows of unemployment. This again causes the unemployment rate to rise leading to a shift of the Bervidge curve to the right. Not only the unemployment rate is affected by a lower effectiveness also the vacancy rate increases and therefore bring an upward shift of the curve (cf. Bleakley and Fuhrer (1997)). Layard et al. (1991) argue that also a larger share of long-term unemployment reduces the search effectiveness and therefore leads to an outward shift of the Beveridge curve.

2.2.3. Job creation

The term job creation describes the situation when a firm and a worker meet and agree on an employment contract (i.e. a successful match). To describe the model as simply as possible a few assumptions are necessary. First, the economy consists only of small firms and in each firm only one job for one worker is available. Second, it is assumed that the value of a job's output is some constant $p > 0$. Last but not least, when the firm has a job vacant it has to pay some search cost, $pc > 0$ per unit of time. Obviously, the search cost is made proportional to productivity and not to wages. The reason behind this assumption is that in the long run the costs of the firm have to rise along with productivity to ensure the existence of a steady state (Pissarides (2000)).

More formally the expected profit of a vacant job can be described as (Pissarides (2000))

$$V = \frac{1}{1+r}\left[-pc + q(\theta)J + (1-q(\theta))V\right] \tag{2.2}$$

where V denotes the present-discounted value of expected profits from a vacant job and J the present-discounted value of expected profits from an occupied job. Furthermore, $q(\theta)$ denotes the job filling probability described in chapter 2.2.1 and r the interest rate. Rearranging equation 2.2 yields (Pissarides (2000))

$$rV = -pc + q(\theta)(J - V) \tag{2.3}$$

Note that an infinite horizon and perfect capital markets are assumed. Therefore, the valuation of the capital cost, rV, is equal to the rate of return on the job. One can see that the vacant job costs the search cost, pc, and yields net return, $J - V$, multiplied with the job filling probability, $q(\theta)$ (Pissarides (2000)).

In equilibrium it is assumed that $V = 0$ since all profit opportunities from new jobs are exploited yet. Thus, equation 2.3 can be stated as (Pissarides (2000))

$$J = \frac{pc}{q(\theta)} \tag{2.4}$$

Since $\frac{1}{q(\theta)}$ is the expected duration of a vacancy for an individual firm, the expected profit of a filled job can be seen as the expected costs of hiring a worker (Pissarides (2000)).

The present-discounted value of expected profits from an occupied job, J, can be expressed similar to the one of vacant jobs and therefore yields (Pissarides (2000))

$$rJ = p - w - \lambda J \tag{2.5}$$

where w is equal the cost of labour, and therefore, $p - w$ can be seen as the net return of an occupied job. λ represents the risk of an adverse shock which leads to the loss of J (Pissarides (2000)).

To derive the so-called *job creation condition* one has to substitute the J from equation 2.4 into equation 2.5 and gets (Pissarides (2000))

$$p - w - \frac{(r+\lambda)pc}{q(\theta)} = 0 \tag{2.6}$$

Note that in a case where the hiring cost, c, is equal to zero, the job creation condition will be the standard marginal productivity condition for employment in steady state, i.e. $p = w$. Figure 2.2 shows the job creation curve in a θ, w space. Obviously, through the properties of the matching function (expressed in $q(\theta)$, the job filling rate) the curve is downward sloping, i.e. a higher wage leads to a lower labour market tightness, $\theta = \frac{v}{u}$, in equilibrium (Pissarides (2000)).

To derive the equilibrium conditions one has to consider also the employees' side, i.e. wages and unemployment insurance benefit. From a technical point of view there are also two unknowns from the Beveridge curve and the job creation condition missing, i.e. the real wage rate and the interest rate to solve the system of equations. Considering the interest rate to be exogenous only the real wage rate is missing. The derivation of the wage equation is similar to the derivation of the job creation condition (for a detailed discussion see Pissarides (2000), p. 13 ff.) and is given by

$$w = (1 - \beta)z + \beta p(1 + c\theta) \tag{2.7}$$

where z denotes the unemployment insurance benefit and $\beta \in [0, 1)$ can be interpreted as a relative measure of labour's bargaining strength, i.e. β is the labour share of the total surplus that an occupied job creates (Pissarides (2000)). Furthermore, $pc\theta = \frac{pcv}{u}$ is the average hiring cost for each unemployment worker, and Pissarides (2000) showed as well that $p > z$.

The steady state equilibrium is determined by the three equations, i.e. the Beveridge curve, (equation 2.1), the job creation condition, (equation 2.6), and the wage equation, (equation 2.7). The diagram on the left side of Figure 2.2 shows the job creation condition and the wage equation in a θ, w space. One can see that these two graphs define the equilibrium level of wages and labour market tightness. The diagram on the right is based on the idea of taking the equilibrium market tightness level, θ^*, from the intersection of the two lines of the diagram on the left as a constant which is shown in the linear job creation line with slope θ^*. Therefore, the equilibrium levels of unemployment and vacancies are defined at the unique intersection with the Beveridge curve (cf. Pissarides (2000)).

In the subsequent paragraphs a short analysis of two effects of particular interests with respect to this diploma thesis, i.e. an increase in the exogenous shock parameter, λ, and an increase in productivity, p, which can be seen as the effect of technological progress and is therefore also growth related, are given.

Starting with the effects of a higher arrival rate of exogenous negative shocks one can see that the wage curve (equation 2.7) is obviously not affected, since λ does not appear. But the job creation curve is affected in a way that a higher arrival rate would shift it to the left. The consequence is a lower level of real wages and labour market tightness in equilibrium. In the Beveridge diagram (the right one in Figure 2.2) both curves are affected, i.e. the Beveridge curve shifts outwards and the job creation curve rotates down. Therefore, the unemployment rate is rising but the effect on vacancies is uncertain. To remember the definition of the Beveridge curve, where equilibrium unemployment is defined as the difference between the inflows into unemployment and the outflow out of unemployment. A higher arrival rate of productivity shocks implies a bigger flow into

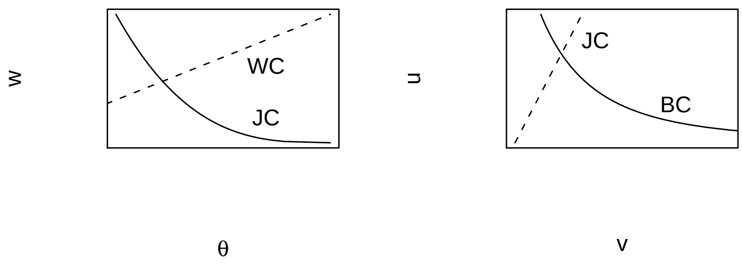

Figure 2.2.: Left diagram (θ, w space): job creation condition (JC) intersects the real wage curve (WC) and defines the equilibrium labour market tightness,(θ^*). Right diagram (v, u space): The Beveridge curve (BC) intersects the job creation condition (with the constant equilibrium labour market tightness, θ^*, on the ground). Cobb Douglas specification. Parameters: $\alpha = \lambda = \frac{1}{3}$, $c = b = z = \frac{1}{2}$, $p = 1$. Source: own calculations, Pissarides (2000).

unemployment. Therefore, the unemployment rate has to rise since it has to balance the higher inflows with the outflows (cf. Pissarides (2000)).

Last but not least an increase in the productivity parameter, p, is discussed. First, the wage curve would shift upwards and the job creation line to the right in the left diagram of Figure 2.2. But this is only the case because of the fixed unemployment benefit, $z > 0$, in the wage equation (equation 2.7). Since the unemployment benefit is independent from the real wage level wages cannot fully absorbe productivity increases, i.e. a higher productivity level leads to a higher job creation and therefore to a lower unemployment level (Pissarides (2000)). Pissarides (2000) argues that in the *long run* such a property is not desirable because, on the one hand, no balanced-growth equilibrium with constant unemployment would exist and, on the other hand, wages should fully absorb productivity changes. A solution to this property would be achieved by extending the model and setting the unemployment benefit as a function of the real wage. (i.e. setting $z = \rho w$, where ρ denotes the replacement rate, which can be seen as a policy parameter). The effect of making the unemployment benefit dependent on the real wage is an equilibrium labour market tightness which is independent of the productivity level (cf. Pissarides (2000)). Therefore, also the equilibrium unemployment and vacancy level is independent of the productivity level.

As discussed so far, the attributes of the matching function (i.e. the matching technology and the elasticities with respect to unemployment and vacancies) and the arrival rate of exogenous shocks are the only elements that influence the equilibrium unemployment rate. A model which captures the effect of economic growth on unemployment will be discussed in the next subchapter.

2.2.4. Aghion and Howitt: Growth and unemployment

The following summary of the nexus of growth and unemployment is mainly along the lines of the model by Aghion and Howitt published in 1994 respectively the dedicated chapter in their book Endogenous Growth Theory (1998).

The model of Aghion and Howitt consists of a continuum of infinitely lived individuals. Each individual owns a certain stock of x units of a fixed production factor (e.g. land) and can provide his/her labour force.
Furthermore, the individuals have all the same preferences over lifetime consumption

$$U(c) = E_0 \int_0^\infty c_t e^{-rt} dt$$

where $r > 0$ is the subjective rate of time preference (equal to the interest rate), which implies how much one values the future (i.e. if r is high then one values future consumption less) and c_t is the current consumption in period t (Aghion and Howitt (1994)).

The production side in the model is given as follows. Production of the final good takes place in so-called production units. These consist of (Aghion and Howitt (1994))

- a plant using a technology of period t
- a worker matched with the plant
- a certain amount of an input factor (in our case of land x)

Note that in this basic model capital does not play a role (Aghion and Howitt (1994)).
The cost of constructing the plant with a state of the art technology at time t is denoted by C_t. In the basic model it is assumed that the plant cannot adjust respectively update technology (Aghion and Howitt (1994)).
The output flow of a production unit is given by

$$y_s = A_t \psi(x_s - a)$$

where $a > 0$ is a so-called minimum level of the input factor (land), which represents overhead costs and ψ is a standard neoclassical production function with the following attributes

- $\psi(z) = 0, \forall z \leq 0$; no production if overhead costs cannot be covered
- $\psi' > 0$ and $\psi'' < 0$; increasing but diminishing marginal production
- $\psi'(0) = +\infty$ and $\psi'(+\infty) = 0$; the so called Inada conditions

Furthermore, A_t is defined as the productivity parameter of the production unit. But, as mentioned before, technology in a given plant cannot adjust, but the technology level itself does change over time at an exogenous rate g (Aghion and Howitt (1994)).
In steady state (all values grow at the same rate) production units eventually become unprofitable since A_t is fixed while the input price of the production unit is increasing at the economy wide growth-rate g (in steady state: $P_\tau = P_0 e^{gt}$). Therefore the production unit cannot cover overhead costs and will close down. This leads to unemployment as long as the unemployed is not matched with a new established plant (cf. Aghion and Howitt (1994)).

To get the lifetime of a production unit S, Aghion and Howitt (1994) assume that $t_0 = t + \epsilon$ is the date a plant is matched with a worker. At any time $\tau \geq t_0$ the surplus flow generated by this plant is

$$\max_{x \geq a}\{\underbrace{A_t\psi(x-a)}_{Output} - \underbrace{P_\tau x}_{Cost}\} = A_t\pi(\frac{P_\tau}{A_t})$$

Since the price, P_τ, of the input factor grows at the steady state with rate g and A_t the technology level of the firm remains constant, the unit becomes less and less profitable (Figure 2.3) until the date t_{0+S} where the production unit becomes unprofitable. From setting P^{max} equal to $\frac{p_{t0+S}}{A_t}$ one gets by taking logarithm, using steady state rate g and rearranging, the lifetime of a production unit S (Aghion and Howitt (1994)).

$$\begin{aligned}
P^{max} &= \tfrac{p_{t0+S}}{A_t} \\
P^{max} &= \tfrac{p_{t0}}{A_t} e^{gS} \\
\ln P^{max} &= \ln \tfrac{p_{t0}}{A_t} + Sg \\
S &= \frac{\ln P^{max} - \ln \frac{p_{t0}}{A_0}}{g} = \frac{\tau}{g}
\end{aligned}$$

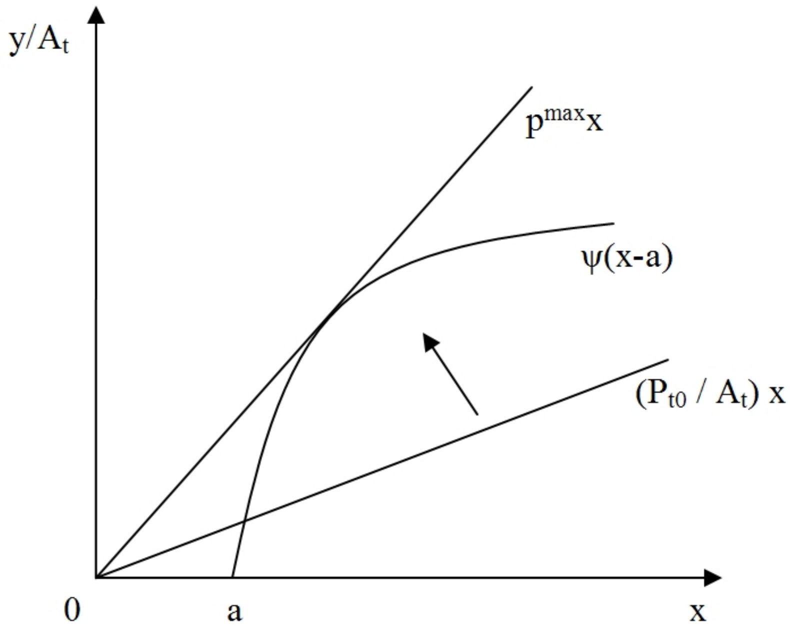

Figure 2.3.: Model of a representative firm. Source: Aghion and Howitt (1998), chapter 4.

Obviously, if the steady state growth rate is high the lifetime of a production unit becomes lower (cf. Aghion and Howitt (1994)).

To model some frictions in the labour market, i.e. taking into account that workers released do not immediately find a new job, Aghion and Howitt assumed a matching function (as described in detail in section 2.2.1).
The matching function between workers and production units is given by $m(1, v)$. In particular the referred matching function, $m(1, v)$, allocates workers to jobs and vice versa. The labour force is normalised to 1 and v denotes the mass of vacancies. It is positively dependent on vacancies, i.e. if there are more jobs vacant the chance to get matched is higher ($\frac{\partial m(1,v)}{\partial v} > 0$). On the other side the matching function is negatively dependent on the average matching, $q(v) = \frac{m(1,v)}{v}$, which reflects the *recruiting success rate* ($\frac{\partial(\frac{m(1,v)}{v})}{\partial v} < 0$) (cf. Aghion and Howitt (1994)).

Steady state unemployment ($\Delta U = 0$) is defined as inflow into unemployment equals outflow out of unemployment. Furthermore, the mass of vacancies v is assumed to be constant over time (steady state). In this model inflow into unemployment can be described as $(1 - u)\frac{1}{S}$. Since the total labour force is defined to be equal 1, $(1 - u)$ can be seen as the number of production units which currently produce, where u is the unemployment rate (and in this case also the mass of unemployment). $\frac{1}{S}$ can be seen as the frequency of production units' obsolescence. Outflow of unemployment in this model is the so-called *job finding rate* that is: $p(v) = \frac{m(1,v)}{1} = m(1, v)$ (cf. Aghion and Howitt (1994)).

By using the equilibrium condition

$$\begin{aligned} (1-u)\frac{1}{S} &= m(1,v), \text{ rearranging yields} \\ u &= 1 - Sp(v) = 1 - p(v)\frac{\tau}{g} \end{aligned} \tag{2.8}$$

Holding the mass of vacancies constant one can see that the growth rate, g, in equation 2.8 has a positive effect on unemployment (i.e. if the growth rate increases also u will increase, this is the so-called *direct creative destruction effect* of growth on unemployment). An increasing growth rate has a negative effect on production units' life time, S, and therefore a positive effect on the job destruction rate, $\frac{1}{S} = \frac{g}{\tau}$, which leads to a higher unemployment rate (cf. Aghion and Howitt (1994)).

But there is also an *indirect creative destruction effect* which works through the job creation rate, $p(v)$. To analyse this indirect effect of growth on unemployment one has to consider a further condition: the free-entry condition. Using the free-entry condition the equilibrium mass of vacancies is defined by assuming that the cost of creating a new production unit is equal to the benefit. Therefore, an increase in the growth rate, g, reduces life time of a production unit and leads to a faster decline of profits, because the price of the input factor increases faster as well (cf. Aghion and Howitt (1994)).

Another interpretation of the unemployment equation (2.8) is that if one holds S constant it also can be regarded as Beveridge curve, since unemployment is a decreasing function of the number of vacancies (Aghion and Howitt (1994), cf. chapter 2.2.2 for a detailed discussion of the Beveridge curve).

Pissarides (2000) also found a negative effect, the so-called *capitalization effect*. The logic behind this effect is that an increasing growth rate also increases the returns of building a plant and therefore more firms will be founded. The reason why this effect is not captured in this very basic model is that firms cannot adjust their technology level.

If one extends the model such that firms can adapt technology levels (which represents somehow the advantage of growth) the capitalization effect reappears (cf. Aghion and Howitt (1998), chapter 4).

The question if growth is a driving force of unemployment is not easy to answer, it depends on the parameters of the model and becomes therefore an empirical question.

2.3. The empirical side

The empiric investigations of the nexus between growth and unemployment are generally inconclusive. However, one has to pay attention to the definitions of growth and unemployment. Layard et al. (1991) argue that in the long run there is no relation between economic growth and unemployment. The most prevailing argument of denying the relation between growth and unemployment is that by simply taking a look at the unemployment data over a long period one cannot observe a trend in the data.

Therefore, I focus more on the issue concerning matching functions. There, a number of investigations have been done yet and delivered clear results. The next subchapter sheds light on the empirical findings, mostly along the lines of the survey article by Petrongolo and Pissarides (2001).

2.3.1. Job matching

One source that nourishes the idea of an existing evident matching function is the Beveridge curve explained in chapter 2.2.2. There, by equating flows in with flows out of unemployment (equilibrium condition) a negative slope is theoretically derived and is also empirically evident (cf. chapter 4.2.5, in the case of Austria). However, empirically the Beveridge curve shifts over time, especially when unemployment increases. Therefore, the Beveridge curve is not contradicting the matching function defined in chapter 2.2.1, but the evidence is indirect (cf. Petrongolo and Pissarides (2001)).

In an environment where aggregate data of unemployment, vacancies and outflow out of unemployment (or a similar proxy for matched persons) is available a direct approach to estimate the matching function is preferred. Most studies use a log linear approximation of the matching function with constant returns to scale (i.e. $\ln\left(\frac{m}{U}\right)_t = \alpha + \beta_1 \ln\left(\frac{V}{U}\right)_t$ which is an approximation of the matching function of the form $m = AV^{\beta}U^{(1-\beta)}$ or

$\ln(m_t) = \alpha + \beta_1 \ln(U_t) + \beta_2 \ln(V_t)$). Usually time trends are also included in the estimations. The estimated elasticities with respect to unemployment and vacancies depend on the dependent variable used. In principle there are three variables that come into consideration by selecting the dependent variable, i.e. outflow from unemployment, flow from unemployment to employment and the number of hires. The estimated elasticities with respect to unemployment and vacancies using outflow from unemployment as dependent variable is about 0.7 respectively 0.3.

Most of the empirical literature supports the existence of a stable aggregate matching function of a few variables that satisfy the Cobb Douglas specification with constant returns to scale (cf. Petrongolo and Pissarides (2001)).

To mention some problems of estimating a matching function one has to address some general issues occurring by dealing with aggregate data.

First, the aggregate matching function describes the flow of matches as a function of the stock of unemployment and vacancies. Due to the fact that flow variables are estimated as functions of stock conditioning variables a time aggregation problem arises. To specify the time aggregation problem one has to consider that through successful matchings the number of unemployed people and vacancies decline. Therefore, the estimates of the elasticities with respect to unemployment and vacancies are generally downward biased.
This problem can be avoided by using the method of instrumental variables estimation, where the lagged values of the number of unemployment and vacancies are usually a good instrument provided there is no serial correlation between the error term and the lagged stock variables (cf. Petrongolo and Pissarides (2001)).
Regardless, the dependent variable is mismeasured anyhow, since the measured outflow over a certain time interval does not only effect the stocks of the LHS of the estimated equation but also the outflows from inflow over the same period (cf. Petrongolo and Pissarides (2001)). Since I only use monthly data in the empirical part (cf. chapter 4.1), i.e. the shortest interval one can get, I partly avoid this problem.

The second issue is about spatial aggregation problems. Most of the empirical literature estimates the aggregate number of unemployed and vacancies across a certain space as a function of the outflow over the same space. Through this procedure it is implicitly assumed that the aggregate economy is about a single labour market. It is

ignored that there might exist a collection of spatial distinct labour markets with possibly little interaction (Petrongolo and Pissarides (2001)). Therefore, biased estimates may arise.
Since I use panel data of Austria's provinces to estimate the elasticities of the matching function I will partly avoid this problem.

3. Theory

In the theoretical part of this diploma thesis the model of Aghion and Howitt (1994) is extended to two different labour inputs, i.e. manual labour and human capital serve as inputs for production. Furthermore, some elements of the prevailing Equilibrium Unemployment Theory by Pissarides (2000) is implemented. The intention of this extension is the following. On the one hand an educational aspect is added to the model. In particular, manual labour belongs to a group with a low education level and human capital to a group with a high level. Furthermore, the impact of growth on the two different unemployment rates is of particular interest. On the other hand, the examination of other impacts which can explain different unemployment rates is essential. In the following sections the model is specified and analysed.

3.1. Consumer side

The model consists of a continuum of infinitely lived individuals. Each individual provides either human capital (H) or manual labour (M) to the labour market. Whether one provides manual labour or human capital depends on the education level of the individual. Note that this model will not evaluate the reasons of individuals behind reaching certain education levels. All individuals in the model have the same preferences over lifetime consumption, s

$$U(s) = E_0 \int_0^\infty s_t e^{-rt} dt$$

where $r > 0$ is the subjective rate of time preference (equal to the interest rate), which implies how much one values the future (i.e. if r is high then one values the future less) and s_t is the current consumption in period t. It is ignored that people who provide H might have other preferences over lifetime consumption since they have spent more time in education.

3.2. Producer side

It is assumed that all firms in the market use the same production function. Although, the technology levels can be different. Firms use so-called input bundels (I) to produce output. In those input bundles they mix labour and human capital. Furthermore, it is assumed that produced output is used for consumption.

The setup of the model is as follows. Firms observe wages of H and M that is to say w_H and w_M. They start production of the consumption good if they have found the right mix of manual labour and human capital at a price where they can make positive profits.

3.2.1. Output function of a production unit

Firms use an input bundle of manual labour (M) and human capital (H) to produce output. For simplicity, it is assumed that the input bundle is in Cobb-Douglas form (i.e. $I = f(H, M) = BH^{\delta}M^{1-\delta}$, where $\delta \in (0, 1)$ and $B > 0$). One reason of using the Cobb Douglas specification of the input bundle is that an inner solution (i.e. where both kinds of labour are used) is guaranteed. It is supposed that firms face a certain fix cost, F, and there exist an exogenous technology level A_t at time t. Note that it is assumed that firms cannot adjust respectively update technology. Cost of this input at time t is equal to $C = cI = w_H H + w_M M$.

Firms maximise profits under the assumption that ψ is a neoclassical production function with the standard properties (i.e. $\psi(z) = 0, \forall z \leq 0$, $\psi' > 0$, $\psi'' < 0$ and $\psi'(0) = +\infty$ respectively $\psi'(+\infty) = 0$).
The profit maximisation problem of a representative firm leads to

$$\begin{aligned}\max_{I \geq F}\{A_t\psi(I-F) - c_t I\} &= A_t \max_{I \geq F}\{\psi(I-F) - \frac{c_t}{A_t}I\} \\ &= A_t\{\psi'(I-F) - \frac{c_t}{A_t}\} \\ &= A_t\Pi(\frac{c_t}{A_t}) \end{aligned} \tag{3.1}$$

Since the optimal output is constant, $\Pi(\frac{c_t}{A_t})$ is a decreasing function in the cost argument c_t. Furthermore, it is assumed that there is perfect competition[1] in the market. Due to

[1] Many small firms producing a homogeneous good.

this assumption the optimization under the zero profit condition yields

$$\begin{aligned}
\max_{I \geq F}\{A_t\psi(I-F)-c_tI\} &= A_t\psi'(I-F)-c_t \stackrel{!}{=} 0 \\
\psi'(I-F) &= \frac{c_t}{A_t} \\
\psi(I-F) &= \frac{c_t}{A_t}I \qquad (3.2)
\end{aligned}$$

3.2.2. Cost minimisation of firms

As stated above, the input bundle of firms is in Cobb Douglas form. Firms minimise their total cost (i.e. they search for the least-cost combinations of inputs) subject to the input bundle. The Cobb Douglas cost function is assumed to have constant returns to scale and there is a productivity parameter, B. In the next two lines the minimisation problem is stated

$$\begin{aligned}
\min_{H,M \geq 0} C(H,M) &= w_H H + w_M M \\
\text{s.t. } f(H,M) &= BH^{\delta}M^{1-\delta} \geq I
\end{aligned}$$

Using a Lagrangian Function to solve the minimisation problem yields

$$\mathcal{L} = w_H H + w_M M + \lambda(I - BH^{\delta}M^{1-\delta})$$

$$\begin{aligned}
\text{(I)} \quad \frac{\partial \mathcal{L}}{\partial H} &= w_H - \lambda\delta\frac{f(H,M)}{H} \stackrel{!}{=} 0 \\
\rightarrow w_H H &= \lambda\delta f(H,M) \\
\text{(II)} \quad \frac{\partial \mathcal{L}}{\partial M} &= w_M - \lambda(1-\delta)\frac{f(H,M)}{M} \stackrel{!}{=} 0 \\
\rightarrow w_M M &= \lambda(1-\delta)f(H,M) \\
\text{(III)} \quad \frac{\partial \mathcal{L}}{\partial \lambda} &= I - BH^{\delta}M^{1-\delta} \\
\rightarrow I &= BH^{\delta}M^{1-\delta} \\
\text{(I), (II)} \quad \rightarrow w_H H + w_M M &= \lambda f(H,M) \\
\text{(Ia)} \quad \rightarrow H &= \frac{\lambda\delta f(H,M)}{w_H} \\
\text{(IIa)} \quad \rightarrow M &= \frac{\lambda(1-\delta)f(H,M)}{w_M}
\end{aligned}$$

plugging (Ia) and (IIa) in (III)

$$\begin{aligned}
\rightarrow I &= B\Big(\frac{\lambda\delta I}{w_H}\Big)^{\delta}\Big(\frac{\lambda(1-\delta)I}{w_M}\Big)^{(1-\delta)} \\
\rightarrow \lambda &= B^{-1}\delta^{-\delta}(1-\delta)^{-(1-\delta)}w_H^{\delta}w_M^{\beta}
\end{aligned}$$

using (I) and (II)

$$\begin{aligned}
\rightarrow C^* &= w_H H + w_M M \\
C^* &= \lambda f(H,M) = \frac{I}{B}\delta^{-\delta}(1-\delta)^{(\delta-1)}{w_H}^{\delta}{w_M}^{(1-\delta)} \\
c^* &= \frac{C^*}{I} = B^{-1}\delta^{-\delta}(1-\delta)^{(\delta-1)}{w_H}^{\delta}{w_M}^{(1-\delta)} \qquad (3.3)
\end{aligned}$$

Equation 3.3 reflects the minimised per unit cost. It is dependent on wages of human capital and manual labour and the parameters δ and B. Obviously, per unit cost and also total cost increase by an increase in the cost of human capital and/or manual labour.

3.2.3. Demand functions

To receive the demand functions for manual labour and human capital one has to take the derivatives of the total cost function with respect to the wage of the two inputs.

$$\frac{\partial C}{\partial w_H} = \frac{I}{B}\Big(\frac{\delta}{1-\delta}\Big)^{1-\delta}\Big(\frac{w_M}{w_H}\Big)^{(1-\delta)} = H^* \qquad (3.4)$$

$$\frac{\partial C}{\partial w_M} = \frac{I}{B}\Big(\frac{1-\delta}{\delta}\Big)^{\delta}\Big(\frac{w_H}{w_M}\Big)^{\delta} = M^* \qquad (3.5)$$

The analysis of the demand function using the method of comparative static yields that

- if δ rises $\rightarrow H^*$ will rise and M^* will fall
- if input cost w_H rises then demand for human capital (H^*) will fall
- if input cost w_M rises then demand for labour (M^*) will fall
- fix cost F has no influence on demand because production units will not produce anything if they do not cover at least fix cost

3.3. Evolution of costs

Generally, the evolution of the cost of the input bundle (equation 3.3) with respect to time can be seen as

$$c(t) = z(w_t^H)^\delta (w_t^M)^{(1-\delta)}$$

where $z = B^{-1}\delta^{-\delta}(1-\delta)^{(\delta-1)}$.

The question how $c(t)$ is growing can be answered easily by applying the rules of growth accounting.

$$\gamma_c(t) = \delta\gamma_H(t) + (1-\delta)\gamma_M(t) \tag{3.6}$$

where $\gamma_x = \frac{\dot{x}(t)}{x(t)}$ and $\dot{x}(t) = \frac{\mathrm{d}x(t)}{\mathrm{d}t}$. It is implicitly assumed that the growth rate of the economy is equal to the wage increase of employed people. In the subsequent paragraphs two cases of growth will be considered.

In the first case, c_t will grow at constant rate and furthermore, the rates of high and low wages grow at the same rate ($\gamma_H = \gamma_M = \gamma_c$). It follows that $\gamma_c(t) = \gamma_c$ and due to the assumption of constant growth

$$c(t) = c_0 e^{\gamma_{HM} t} \tag{3.7}$$

Obviously, these strong assumptions lead to the same results as in the model developed by Aghion and Howitt (1994) described in chapter 2.2.4.

The more interesting case is the one where it is assumed that the cost of the input bundle grow at rate, γ_c, but there might be substitution. This means that wages of both groups can grow at different rates with the only restriction of a constant growth rate (i.e. $\gamma_c(t) = \gamma_c$, but the shares of growth rates of high and low wages can vary as long as the total growth rate is constant). This aspect will be treated in the following paragraph. Using equation 3.6 and 3.7, the evolution of the cost of the input bundle with respect to time can be rewritten as follows

$$c(t) = c_0 e^{(\delta\gamma_H + (1-\delta)\gamma_M)t} \tag{3.8}$$

Obviously, both γ_H and γ_M have positive effects on the total growth rate, γ_c. But also the intensity shares (δ and $(1-\delta)$) define the growth rate. A full analysis of the effects will be given in the subsequent chapter.

3.4. Lifetime of a production unit

From setting c^{max} equal to $\frac{c_{t0+S}}{A_t}$ one gets by taking logarithm, using steady state growth rate, γ_c, and rearranging, the lifetime of a production unit S.

$$\begin{aligned} c^{max} &= \frac{c_{t0+S}}{A_t} \\ c^{max} &= \frac{c_{t0}}{A_t} e^{(\delta\gamma_H + (1-\delta)\gamma_M)S} \\ \ln c^{max} &= \ln \frac{c_{t0}}{A_t} + S(\delta\gamma_H + (1-\delta)\gamma_M) \\ S &= \frac{\ln c^{max} - \ln \frac{c_{t0}}{A_t}}{\delta\gamma_H + (1-\delta)\gamma_M} \\ S &= \frac{\tau}{\delta\gamma_H + (1-\delta)\gamma_M} \end{aligned} \tag{3.9}$$

To analyse the nominator first, an increase in τ leads to a longer lifetime of the production unit. An increase in τ can take place either through a higher level of c^{max} and/or through a lower level of $\frac{c_{t0}}{A_t}$.

The denominator depends on the parameter δ in a way that it defines the weight of the respective growth rate. Nevertheless, if the denominator rises (i.e. by an increase in growth rate of wages) the life time of a production unit declines.

3.5. Effects of growth on unemployment

To fully analyse the problem and particularly to introduce frictions in the two labour markets subject to education, I make use of the matching function by Pissarides (2000). Since there are two kinds of labour, two matching functions are used.

$$m_h = m_h(U_h, V_h) \quad \text{for high educated (human capital)} \tag{3.10}$$

$$m_l = m_l(U_l, V_l) \quad \text{for low educated (labour)} \tag{3.11}$$

where U_i defines the total mass of unemployed and V_i the total mass of vacancies for each group of $i = \{h, l\}$.
Both matching functions follow the standard assumptions (increasing, concave and having constant returns to scale).

To analyse the effects of growth on unemployment under the steady state unemploy-

ment conditions (i.e. $\Delta U_i = 0$) one has to equalise inflows into and outflows out of unemployment. A further assumption is that the number of vacancies of both groups are also equal over time (steady state).
Inflow into unemployment can be seen as $(L_i - U_i)\frac{1}{S}$, where L_i denotes the labour force of the different groups which is equal to the population in this model. $L_i - U_i$ reflects the number of production units and $\frac{1}{S}$ reflects the probability of a production units' obsolescence. Outflow of unemployment is represented by the *job finding rate* that is $p_i(U_i, V_i) = \frac{m_i(U_i,V_i)}{U_i}$.

By equating inflow and outflow one yields

$$(L_i - U_i)\frac{1}{S} = p_i(U_i, V_i) \tag{3.12}$$

Reformulating equation 3.12 gives the equations for the two different unemployment levels

$$U_i = L_i - p_i(U_i, V_i)S$$

and the respective unemployment rates by dividing by L_i

$$u_h = \frac{U_h}{L_h} = 1 - \frac{p_h(U_h, V_h)S}{L_h} = 1 - \frac{p_h(U_h, V_h)(\frac{\tau}{\delta\gamma_H + (1-\delta)\gamma_M})}{L_h} \tag{3.13}$$

$$u_l = \frac{U_l}{L_l} = 1 - \frac{p_l(U_l, V_l)S}{L_l} = 1 - \frac{p_l(U_l, V_l)(\frac{\tau}{\delta\gamma_H + (1-\delta)\gamma_M})}{L_l} \tag{3.14}$$

Equation 3.13 and 3.14 show that an increase in the labour force and an increase in the growth either of low or high wages have a positive effect on the unemployment rates. An increase in the growth rate of high (low) wages also increases unemployment rate of the low (high) educated group. On the other hand, an increase in τ and in the job finding rate let the unemployment rate decrease.

Since the two matching functions of the different education groups are probably not the same (e.g. one could find arguments that high educated match faster as they also can work in jobs with low educational requirements, etc.) the job finding rate will differ in those groups and the unemployment rates likewise (cf. chapter 3.6).

Since the economy wide growth rate is defined as $\gamma_c = \delta\gamma_H + (1 - \delta)\gamma_M$ growth of the economy has a positive effect on equilibrium unemployment. But, using the argument by Pissarides (2000), there is also a negative effect of growth on equilibrium unemployment, i.e. the so-called capitalization effect (described in chapter 2.2.4). The reason why this effect is not captured is due the assumption that firms cannot adjust the productivity level.

However, in this model economic growth influences the unemployment rate of low and high educated people in the same way. The only difference between the equilibrium unemployment rates of the two education groups is due to the possible different job matching rates and of course due to the probable different labour force size (for a numerical analysis see chapter 3.6).

3.6. Simulations

The idea of this chapter is to provide numerical results of the theory outlined above. In a first step, the production function of the firm is assumed to be Cobb Douglas (i.e. $y = A(I - F)^{\beta}$ in a given period t where $A > 0$ represents the productivity parameter, I the input bundle, F the fix cost, the parameter $\beta \in (0, 1)$ and $y = 0$ if $F \geq I$). This Cobb Douglas specification leads to a neoclassical growth function with the usual assumptions (cf. chapter 3). The minimal cost of the input bundle (also in a Cobb Douglas specification) has already been derived in chapter 3.

To find out the value of the maximum cost, this is the cost level where a firm makes zero profits, I equalise marginal cost with marginal revenue and let the total cost intersect with the production function. In mathematical form the problem can be written as follows:

$$\begin{aligned} \text{(I)} \quad y &= A(I - F)^{\beta} \\ \text{(II)} \quad C &= cI \end{aligned}$$

(III) Condition 1 (Intersection)

$$A(I - F)^{\beta} = cI$$

(IV) Condition 2 (Equal slopes of (I) and (II))

$$A\beta(I - F)^{\beta-1} = A\beta(I - F)^{\beta}(I - F)^{-1} = \beta cI(I - F)^{-1} = c$$

(IVa) Reformulating (IV)

$$I^* = \frac{F}{1-\beta}$$

If one plugs I^* into (III) and solves for c one yields the solution for c^{max}

$$c^{max} = -\frac{A(\beta-1)\left(\frac{F\beta}{1-\beta}\right)^{\beta}}{F} \tag{3.15}$$

To remember the life time function of a given production unit from chapter 3 was given by $S = \frac{\ln c^{max} - \ln \frac{c_{t0}}{A_t}}{\delta\gamma_H + (1-\delta)\gamma_M}$. At a given time, t, all unknown (i.e. c^{max} and $c_0 = c^{min}$) can be calculated. Therefore,

$$S = \frac{\ln\left(-\frac{A(\beta-1)\left(\frac{F\beta}{1-\beta}\right)^{\beta}}{F}\right) - \ln\left(\frac{zw_H^{\delta}w_M^{(1-\delta)}}{A}\right)}{\delta\gamma_H + (1-\delta)\gamma_M} \tag{3.16}$$

3.6.1. Basic model

Figure 3.1 gives a graphical overview of the model. One representative firm has decided for an optimal input bundle, I^*, and makes profit as long C_{min} has a lower slope as C_{max}. The question how fast C_{min} is growing depends on the parameter δ and on the growth rates of wages which combined is assumed to be the total growth rate in the economy. In the basic model the wage growth rates and also the wage rates of both labour types are assumed to be equal. The lifetime of a production unit with the selected parameters given in Figure 3.1 is equal to 32.96 periods.

For the analysis of the respective unemployment rates I make use of the definition of matching functions by Pissarides (2000). Furthermore, it is assumed that the matching function is in Cobb Douglas form, i.e. $m_i(U_i, V_i) = U_i^{\alpha_i} V_i^{(1-\alpha_i)}$ (cf. chapter 2.2.1). The respective job finding rate, $p_i(U_i, V_i) = \frac{m_i(U_i,V_i)}{U_i}$, can be rewritten by using the homogeneity assumption into $p_i(Ui, V_i) = (\frac{v_i}{u_i})^{(1-\alpha_i)}$ (cf. chapter 2.2.1).

Using the unemployment equations for the high and low educated groups (equation 3.13 and 3.14) and inserting the Cobb Douglas specification for the job finding rate derived above one yields

$$u_i = 1 - \frac{\left(\frac{v_i}{u_i}\right)^{(1-\alpha_i)} S}{L_i} \tag{3.17}$$

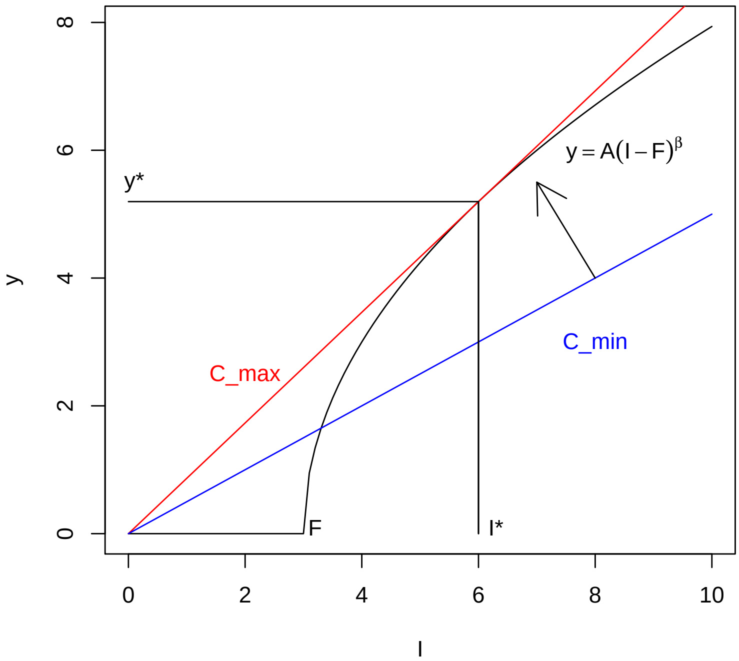

Figure 3.1.: Simulation of the model. Parameters: $\delta = \beta = \frac{1}{2}, A = F = 3, B = 2, w_H = w_M = 0.5, \gamma_H = \gamma_H = 0.05$. Source: Own calculations.

Obviously, equation 3.17 is not solvable in an algebraic way. Therefore, two cases of the properties of the vacancy rates, v_i, will be discussed.

Case 1 ($u_i = v_i$):
This very unrealistic case where the unemployment rate, $u_i = \frac{U_i}{Li}$, is equal to the vacancy rate, $v_i = \frac{V_i}{Li}$, of the two different groups implies that also the vacancies are equal to the number of unemployed. In a world without search unemployment the result of such a situation would be an unemployment rate equal to zero. To show that, through the introduction of the matching function and therefore through modelling frictions in the labour market, an unemployment rate greater than zero is expected this case is discussed. Plugging the condition $u_i = v_i$ into equation 3.17 yields

$$u_i = 1 - \frac{S}{L_i} = \frac{L_i - S}{L_i} = \frac{L_i - \frac{\tau}{g}}{L_i} \tag{3.18}$$

Obviously, the unemployment rates of both education groups are independent of α_i, the elasticity of the matching functions with respect to unemployment (and therefore also the elasticity of the matching functions with respect to vacancies, $(1 - \alpha_i)$). The only "group-individual" parameter is the size of the respective labour force, L_i. A larger size of the labour force of low educated in comparison to high educated would lead to a higher unemployment rate for low educated. Note that this only holds for the condition $L_i > S$.

Case 2 ($u_i = x_i v_i$, $x_i > 1$):
Probably the more interesting and also more realistic case where the vacancy rate is a proportion of the unemployment rate (in this case $v_i = \frac{u_i}{x_i}$) is discussed in this paragraph. Note that the restriction $x_i > 1$ is chosen because of the empirical evidence on this in Austria (cf. chapter 4.2.5). The case $x_i = 1$ was discussed in Case 1 and the case $x_i < 1$ is also feasible for all $x_i \geq \left(\frac{S}{L_i}\right)^{\frac{1}{1-\alpha_i}}$ which guarantees a non-negative unemployment rate.
However, plugging the defined u_i under the same conditions as described in Case 1 into equation 3.17 yields

$$u_i = \frac{\left(L_i \left(\frac{1}{x_i}\right)^{(\alpha_i - 1)} - S\right)\left(\frac{1}{x_i}\right)^{(1-\alpha_i)}}{L_i} = \frac{\left(L_i \left(\frac{1}{x_i}\right)^{(\alpha_i - 1)} - \frac{\tau}{g}\right)\left(\frac{1}{x_i}\right)^{(1-\alpha_i)}}{L_i} \tag{3.19}$$

To analyse the effects of a change in the size of the population of the respective groups, L_i, a change in the elasticity, α_i, and the economy wide growth rate, g, one has to take the first partial derivatives of u_i with respect to L_i, α_i and g

$$\frac{\partial u_i}{\partial L_i} = \frac{\left(\frac{1}{x_i}\right)^{(1-\alpha_i)} S}{L_i^2} > 0 \tag{3.20}$$

$$\frac{\partial u_i}{\partial \alpha_i} = \frac{\left(\frac{1}{x_i}\right)^{(1-\alpha_i)} \ln\left(\frac{1}{x_i}\right) S}{L_i} < 0 \tag{3.21}$$

$$\frac{\partial u_i}{\partial g} = \frac{\tau \left(\frac{1}{x_i}\right)^{(1-\alpha_i)}}{g^2 L_i} > 0 \tag{3.22}$$

Equation 3.20 shows the similar effect of an increase in the size of the labour force of a particular group as in Case 1, i.e. if $L_i > 0$, $S > 0$, $\alpha_i \in (0,1)$ and $x_i > 1$ the unemployment rate would increase if labour force increases.

In equation 3.21 it is shown that an increase of the elasticity parameter, α_i, has negative implications on the unemployment rate, i.e. if $L_i > 0$, $S > 0$, $\alpha \in (0,1)$ and $x_i > 1$, an increase of the elasticity of the matching function with respect to unemployment, α_i, leads to a lower level of the unemployment rate.

The effect of the growth rate, g, on unemployment (equation 3.22) remains positive as already discussed in chapter 3.5.

Figure 3.2 shows the unemployment rate as a function of x_i. One can see that the unemployment rate is rising with an increasing x_i. Furthermore, taking the $\lim x_i \to \infty$ of equation 3.19 under the assumptions of $S > 0, L_i > 0$, and $\alpha_i \in (0,1)$ yield an unemployment rate equal to one, i.e. everybody in the economy is unemployed.

3.6.2. Equal vs. different wages

This and the subsequent subchapter complete the theoretical part of this diploma thesis with some comparative static aspects in equilibrium. In Figure 3.1 the case of equal growth rates of wages and equal wage rates is demonstrated. The two effects discussed in these subchapters are in relation to the base model, with the parameters on the ground represented in Figure 3.1.

In comparison to the base model there are some good arguments why the assumption of equal wage rates does not capture the reality, i.e. high skilled which by assumption

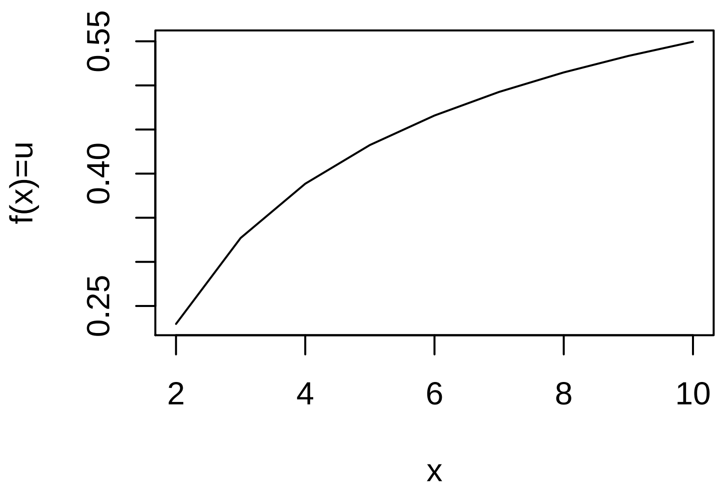

Figure 3.2.: Plot of $u = f(x_i)$, see equation 3.19. Parameters: $S = 34.09, L = S + 1, \alpha = \frac{2}{3}$. Source: Own calculations.

coincide with a high education level, have spent more time in education which generates usually no income and should therefore be compensated for the associated higher productivity with a higher wage rate. From now on it is assumed that the wage rate for high educated is higher than for low skilled labour. The question how this change in the wage rate affects the life time of a production unit is easy to answer by taking a look at the lifetime equation of a representative firm (3.16). As intuitively clear, the cost at the start of the production is higher and therefore the lifetime of a firm becomes less. Furthermore, the demand for high educated declines since wages are higher, i.e. there is a substitution effect between the two labour inputs. The shorter lifetime of a production unit however effects the unemployment rate of both educational groups in the same way, i.e. the diminished demand of high educated workers does not lead to a higher unemployment rate of high educated as u is determined by the matching function in equilibrium.

3.6.3. Equal vs. different growth rates of wages

In this ultimate subsection the model is analysed under the assumption that the wage rates of the different education groups are different and also grow at a different rate.

For simplicity, it is assumed that the wages of high educated are on a higher level and grow faster in comparison to the low educated[2]. Initially, a higher wage growth rate for high educated would lead to a higher total growth rate of the economy. Therefore, the lifetime of a firm is decreasing which also leads to higher unemployment rates of both education groups. Furthermore, the effect of the higher wage level of the high educated group goes in the same direction as described in the paragraph above and therefore also leads to higher unemployment rates. Additionally, the corresponding output elasticities of human capital and manual labour in the production function can either enforce those effects or moderate them, i.e. in a human capital augmenting environment, i.e. $\delta > \frac{1}{2}$ those effects would be reinforced.

3.7. Summary of the theoretic insights

The developed model is an extension of the model by Aghion and Howitt (1994). Two different labour inputs, i.e. human capital and manual labour which serve as inputs for the production function of a firm are used. The idea behind the modification is that the different unemployment rates of high and low skilled labour should be explained. Allowing for different matching functions for high and low skilled labour the goal of explaining the differences in their unemployment rate is achieved.

By analysing the effects on the different unemployment rates it turns out, that growth and the size of the particular labour force have a positive effect on the unemployment rates. Furthermore, the elasticity on job-matching with respect to unemployment and vacancies has a crucial impact on the different unemployment rates (a higher elasticity with respect to unemployment leads to a lower unemployment rate).

An opportunity of future investigations is the influence of the growth rate on both unemployment rates which here is the same due to the log-linear structure of the model. The introduction of differentiated sectoral structures, e.g. a skill intensive and a labour intensive sector could lead to different growth rates with differentiated effects on unemployment rates by education.

[2] This assumption is based on empirical findings. For a discussion see Haskel and Slaughter (2002) and Acemoglu (2002).

4. Empirics

The analysis of the model in the theoretical part has shown that the unemployment rates of the different education groups are positively dependent on growth rates. But in a sense that both unemployment rates are affected in the same way. This means that in the theoretic model presented economic growth does not have differentiated effects on the unemployment rates of high educated respectively low educated people. Furthermore, the theoretic model from chapter 3 suggests that the matching function has a crucial impact on the specific unemployment rates.

Therefore, in the empirical part of this diploma thesis a log linearised matching function is estimated to get estimates for the elasticities with respect to unemployment and vacancies for two types of workers. The geographical focus is on Austria. Thus, I have collected raw data for unemployment levels, job-vacancies and outflow from unemployment from Eurostat[1], Statisk Austria[2], the Austrian Employment Bureau (Arbeitsmarktservice (AMS))[3] and a platform called BALI[4], coordinated by the Federal Ministry of Labour, Social Affairs and Consumer Protection.

The estimation method used is panel data analysis for the two education groups, i.e. low and high educated, with the geographical focus on Austria's nine federal provinces.

This chapter is structured as follows. First, the econometric model is specified. This is followed by a very detailed part of data description. After giving some econometric preliminaries with respect to panel data analysis the results of different regressions are presented and finally concluded.

[1] http://ec.europa.eu/eurostat
[2] http://www.statistik.gv.at
[3] http://www.ams.or.at
[4] BALI: Beschftigung, Arbeitsmarkt, Leistungsbezieher, Informationen (http://www.dnet.at/bali)

4.1. Model specification

As I have mentioned before the geographic focus is on Austria; in particular on its nine federal provinces[5]. The matching functions from the theoretical part should be estimated. Additionally, I focus on education levels. Unfortunately, no adequate information about industry sectors was available which would have added a further interesting component of analysing unemployment.

The econometric method used is panel data analysis. This method is used to estimate elasticities of the matching functions with respect to the level of unemployed and vacancies. As dependent variable on the left hand side (LHS) logarithmic outflow of unemployment of all nine provinces is used while the logarithm of unemployment and vacancies of all nine provinces (RHS) are the explanatory variables. As described in chapter 2.3.1 a good approximation for the matching function is the log linear form of a Cobb Douglas function (i.e. $\ln(m_t) = \alpha_0 + \alpha_1 \ln(U_t) + \alpha_2 \ln(V_t)$). Formally, the panel data estimation of a particular education group can be stated as follows

$$\ln\left(Outflow_{it}\right) = \alpha + \beta X'_{it} + u_{it} \tag{4.1}$$

with $u_{it} = \mu_i + \epsilon_{it}$, and $\epsilon_{it} \sim \text{IID}(0, \sigma^2_\epsilon)$ (preliminaries of panel data estimation will given in chapter 4.3). Furthermore, the variable on the LHS is the adjusted outflow (the rule for adjustment will be discussed later in this chapter) for two education levels and all nine Austrian provinces. The matrix, X, of the RHS contains data about levels of unemployment and vacancies differentiated by provinces and the two levels of education mentioned above (for summary statistics see Table A.1 and A.2). The indices i and t denote the nine provinces and the time dimension respectively. To consider the two different education levels and in particular to get differentiated estimates for the two elasticities in scope I will always state two results one for high educated and one for low, i.e. two panels are estimated. The time dimensions of each panel is 141 since I use monthly data from January 1998 to September 2009. The cross-section dimension is 9, Austria's nine provinces.

[5] These are: Burgenland (B), Carinthia (K), Lower Austria (N), Upper Austria (O), Salzburg (S), Styria (St), Tyrol (T), Vorarlberg (V) and Vienna (W).

4.2. Data description

In the following subchapters the datasets of labour force, job vacancies and inflow into respectively outflow out of unemployment will be examined in detail. The relevant time period starts in January 1998 and ends in September 2009. The AMS and the platform BALI are providing requested data on a monthly basis while the majority of the relevant times series from Statistik Austria and Eurostat are available on a quarterly basis. I generally worked with monthly data but have calculated sometimes average yearly data for plots for an easier presentation of the data.

4.2.1. Labour force

In general labour force (L) is defined by

$$L = E + U$$

where E are employed people and U stands for unemployed people.
In Austria two measurement methods are prevailing. The Labour Force Survey concept forced by the European Union (EU-LFS) and the method of the Austrian Employment Bureau (AMS). The differences between these two methods is in the definition of E and U. In the next paragraphs I will explain the different approaches.

EU-LFS: The European Commission defines U in a way that the group of unemployed people comprise persons aged 15 to 74 who where

- without work during the reference week,
- currently available for work and
- actively seeking work.

E is defined as group of people who worked at least one hour for pay or profit during the reference week or were temporarily absent (holidays, illness, etc.) from such work. Self-employed people are also in this group (cf. European Commission (2000)).

The concept follows the recommendation of the 13th International Conference of Labour Statisticians, convened in 1982 by the International Labour Organisation (ILO).
Eurostat and Statistik Austria provides data on unemployment using the EU-LFS concept. It should be mentioned, that the EU-LFS will be executed quarterly and is based

on surveys[6].

AMS: In the measurement approach used by the Austrian Employment Bureau (AMS) all persons who are registered there as unemployed are counted to be unemployed (except for people in training schemes).
Labour force (L) comprise the sum of unemployed people (U) plus all compulsory social insured employment relationships (E) registered at the Main Association of Austrian Social Security Institutions (Hauptverband der Sozialversicherungen). Note that AMS does not count self-employed people in contrary to the EU-LFS approach, therefore L has to be smaller.

If one compares the yearly unemployment rates ($u = \frac{U}{L}$) of the two approaches (Figure 4.1) one can see that there are major differences in levels but not in changes. For September 2009 the manipulated[7] unemployment rate following the EU-LFS definition is 4.8%. By contrast, following the national definition of the AMS the unemployment rate for September 2009 is 6.4%. If one compares both timeseries (Figure 4.1) from 1998 to 2008 the difference in levels is about 2 percentage points.

For my thesis I will continue with data from AMS because the agency is as well providing outflow-of-unemployment data which I will use later on. That means that from now onwards U is defined as "number of people who are registered at the AMS" and E equals "the number of people registered at the Main Association of Austrian Social Security Institution".
As a final remark to complete this subchapter, I give a few details about self-employed people in Austria although those are not included in my definition of E, for reasons of insufficient data quality (e.g. no information about education level is available). However, the platform BALI provides the number of self-employed people in September 2009 with 414,157. This is about 5% of the total Austrian population[8]. Another aspect is that the number of self-employed has grown at a moderate level between the year 2000 and 2009 with about 1.4% growth per year.

[6] These surveys contain personal visits, telephone interviews and self-administered questionnaires.

[7] Statistik Austria is using a model to calculate unemployment rates also on a monthly base, since the EU-LFS approach is executed quarterly.

[8] cf. Statistik Austria Database; for 2nd quarter 2009 the Austrian population is equal to 8,359,197 people.

Figure 4.1.: Comparison of two approaches to calculate u-rates for Austria. Source: AMS, Eurostat.

4.2.2. Labour force subject to education

In the theoretic model I used human capital which belongs to people with high education and manual labour which belongs to people with low education as inputs for the production function. I defined high education as the group of people who have at least passed general qualification for university entrance (i.e. in the case of Austria a person which has at least passed High school (Allgemeinbildende Höhere Schule, Berufsbildende Höhere Schule or other forms that lead to the "Matura") belongs to this group). In addition, I defined low education as the group of people who have neither reached High school level nor higher education (i.e. tertiary education).

In 2008 10% of the Austrian population older than 15 years have reached a degree from university or on a comparable level. Furthermore, 14% have passed a secondary school (Allgemeinbildende Höhere Schule, Berufsbildende Höhere Schule) compared to 76% of the population older than 15 years with low education according to my definition. This group comprises persons who have passed secondary modern school (13%), apprentice examination (36%) or compulsory school (27%)) (cf. Statistik Austria (2009a)). Note that these definitions of high an low educated do not coincide with the ISCED (International Standard Classification of Education) defined by the UNESCO. The reason why I do not use the ISCED definitions is the inaccurate data quality.

In September 2009, 3,403,968 persons were registered employed at the Main Association of Austrian Social Security Institution. Assuming that the educational distribution given in the paragraph above is also valid for the employed people E[9], yields that 2,587,016 people are in a job with low education and 816,952 with high education. If one compares the numbers of September 1998 to that of September 2009 the number of employed people is 9.06% higher. The corresponding compound annual growth rate[10] yields 0.79%. Furthermore, it has to be remarked that E, the number of employed people, also has a seasonal component.

According to my definition of high and low education, in September 2009, 198,949 people with low education and 35,556 with high education were registered as unemployed. Compared to the other September values of the sample this is the highest value, both for high and low educated people. If one calculates specific unemployment rates[11] for high and low educated people using the assumption about E from above, one will find that in September 2009 the belonging rates are 7.14% for low and 4.17% for high educated persons.

Figure 4.2 shows that the number of unemployed people has a strong seasonal component (e.g. data reflect that the number of unemployed persons is higher in winter than in the rest of the year). Furthermore, looking at the log returns[12] of unemployed people, one can see that seasonal fluctuation for low educated people is higher compared to high educated persons. One reason for this could be the construction sector, which normally faces less demand in winter and where, generally, many low educated people work.

[9] This is a rather strong assumption and probably downward biased, since the base for population older than 15 is stated in Statistik Austria (2009a) with 6,952,000 persons. It can be argued that the education level of the 3,403,968 employed people is higher since those people in working life are adjusted by retired people. Since education level of earlier cohorts is lower than of the later ones, a downward biased result is very likely. Statistik Austria provides numbers for 2007 Statistik Austria (2009b) where 27.15% of the Austrian population between the age of 25 and 64 (4,560,800 people) is educated on the defined high level.

[10] $CAGR^{E}_{199809to200909} = (\frac{E_{200909}}{E_{199809}})^{\frac{1}{2009-1998}} - 1$

[11] $\frac{U_l}{L_l}$ and $\frac{U_h}{L_h}$

[12] This is a good approximation for the growth rate for small growth rates ($\log(U_t^{h,l}) - \log(U_{t-1}^{h,l}) \approx \frac{U_t^{h,l} - U_{t-1}^{h,l}}{U_{t-1}^{h,l}} = g_t^{h,l}$).

The trend component of the decomposed[13] time series shows that at the end of the year 2000 unemployment growth rates of higher educated people where higher than of lower educated persons. It could be a result of the so-called dot-com bubble with its climax in March 2000, which probably affected high skilled persons more than low skilled ones. Another characteristic of the two seasonal adjusted time series in scope is that since April 2008 the number of unemployed persons has been growing. At present the impact of the actual financial crisis, that started in 2007, on "white-collar" employees cannot be assessed since unemployment usually reacts with a certain delay, i.e. the hypothesis that high educated workers are more affected from the current financial crisis can at present neither rejected nor confirmed.

4.2.3. Labour force subject to region

In this subchapter regional differences with respect to labour force are examined. First, one can observe that the yearly unemployment rate shows huge differences across Austria's nine federal provinces (Figure 4.3). In three out of nine provinces, i.e. Burgenland (B), Carinthia (K), and Vienna (W) the yearly unemployment rate is higher than the average unemployment rate for the given period and in four, i.e. Upper Austria (O), Salzburg (S), Tyrol (T) and Vorarlberg (V) it is lower (except for Vorarlberg (V) in 2009 it is equal to the average unemployment rate). In Lower Austria (N) and Styria (St) yearly unemployment rate is close to the average rate during the respective period. It can be seen that in 2009 the unemployment rate has increased in all nine federal provinces. The highest unemployment rate was found in Carinthia (K) with 9.3% while Upper Austria (O) had the lowest with 4.9%.

The number of employed people has grown differently in Austria's provinces over the last eleven years. In Burgenland (+0.55 percentage points (ppt)), Upper Austria (+0.43 ppt) and Tyrol (+0.50 ppt) the compound annual growth rate (CAGR) between September 1998 and 2009 has been higher than for the whole country (CAGR=0.79%). On the other hand, in Vienna the labour force has been rather constant (CAGR=0.2%) within the last eleven years. In September 2009, 46% of the Viennese population is classified to be employed which is the highest level (the Austrian share is 40%) out of Austria's nine provinces while in Burgenland only 32% are working. The respective share in Upper Austria and Tyrol is slightly above the Austrian one. The share of self-employed people

[13] Fur seasonal adjustment I used the Seasonal Decomposition of Time Series by Loess (stl) procedure in R.

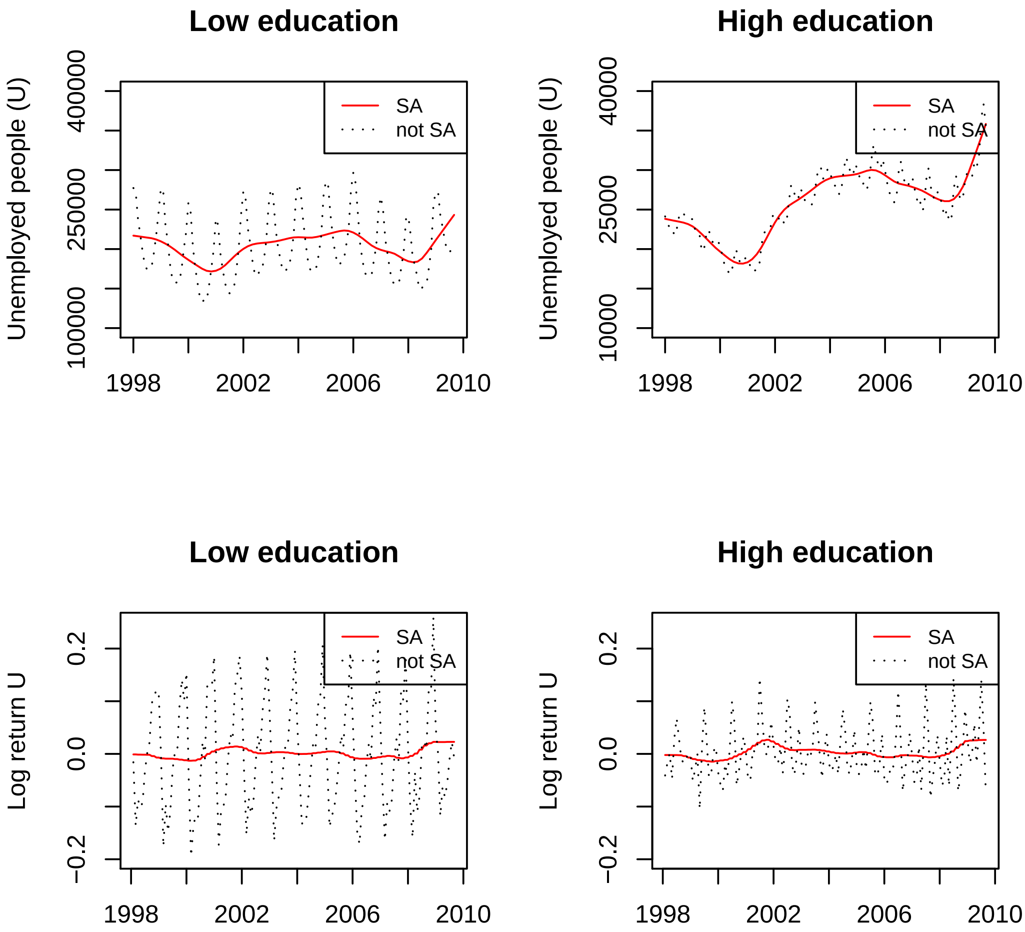

Figure 4.2.: Comparing the number of unemployed persons with high education to low education in Austria. *Note the different scale dimensions in the upper plots.* Source: AMS and own calculations.

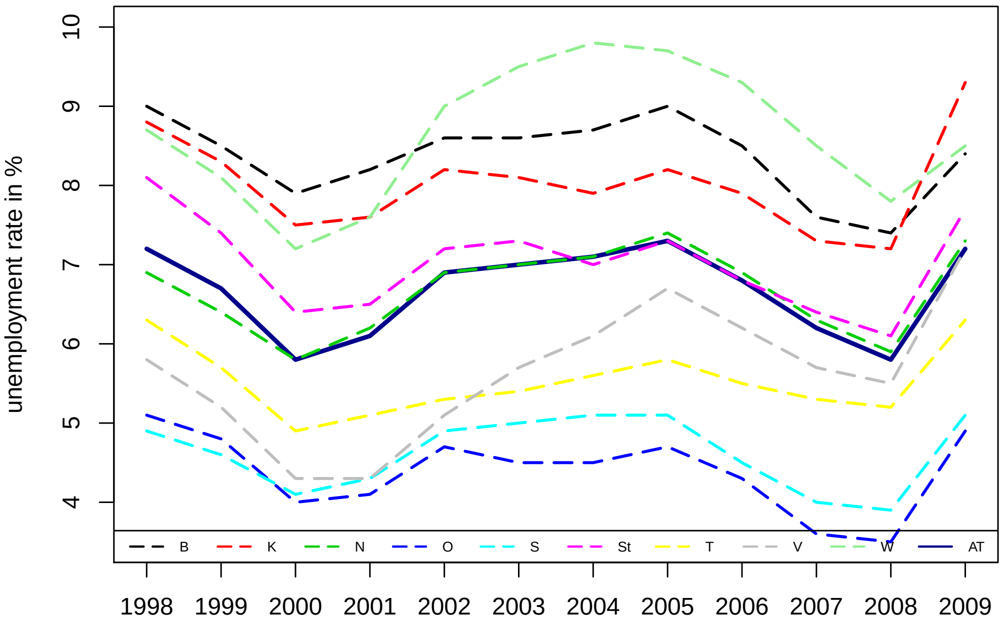

Figure 4.3.: Unemployment rates in Austria's regions. Source: BALI.

is equal to 5% in almost all provinces.

In this paragraph the education level of the Austrian population with respect to regional differences is discussed . Due to lack of more recent data I will refer to the year 2007 where, as stated in chapter 4.2.2, 72.85% of the Austrian population has education on the defined low level and 27.15% on the high level (Statistik Austria (2009b)). Only one federal province, namely Vienna, has a share above (40.43%) the average high education level. The provinces with the lowest share of high educated people in the respective group is Upper Austria (20.88)[14].

4.2.4. Job vacancies

This subchapter examines the job vacancy situation in Austria and also provides a differentiated perspective with respect to regions and education levels. Initially, I want to mention that there are some problematic aspects by using vacancy data provided by the AMS. Vacancies are probably underestimated for the following reasons. First, the reported data represent only a fraction of total vacancies since many job offers are not reported to the AMS. Second, job vacancies for high educated are probably more under-represented since there exist some hints that recruiting is prevailing through other channels (i.e. job to job search, personal networks, newspaper announcements, etc.). However, due to the absence of alternatives (e.g. data on job hires) I have to use job vacancies registered at AMS as input for my empirical study.

In September 2009 the AMS reports 26,648 job vacancies for low educated persons and 2,509 for high educated persons. Both time series also show a seasonal component. Particularly in winter there are less jobs vacant.
The ratio of job vacancies with respect to unemployment ($\frac{V_h}{U_h}$ and $\frac{V_l}{U_l}$) or in other words the labour market tightness if one considers two separated labour markets in September 2009 is 13.4% for low educated people and 7.1% for high educated. This means that in September 2009 the ratio of the vacancies with respect to the unemployment rate is higher for the low educated compared to the high skilled. The number of unemployed is 7.5 times higher than the number of vacancies in the case of the low educated and 14.1 times higher by contrast in the case of the high educated. Data shows that this has been the case for most of the time since 1998 (see Figure A.3). At this point I want to

[14] In 2007, Vienna had the highest unemployment rate (8.5%) according to the AMS definition, and Upper Austria the lowest (3.6%). This very interesting empirical finding with respect to the share of high educated persons will not be further analysed since it is not in the focus of this diploma thesis.

emphasise that higher educated people also can apply for vacancies with low education requirments and normally not the other way round. But on the other hand, one has to mention that both vacancy and unemployment rates of high educated are probably underestimated. This would be a reason of the higher labour market tightness of the low educated group compared to the high educated.

From December 2003 until April 2008 the seasonal adjusted time series of high educated job vacancies rose from 1,390 up to 2,824 (Figure 4.4). From there on, the number of job vacancies declined. In the case of job vacancies for low educated people the boost which also started at the end of 2003 was not that spectacular, but also prevailing. The decline in job vacancies also started in the first half of 2008.

Looking at the data with respect to regions, it is remarkable that the share of vacancies for high educated persons has increased almost in all nine provinces except Salzburg (which also has the lowest share in Austria). In 2008 the share was 10.1% for Austria compared to 6.3% ten years before. In some federal provinces, e.g. Vorarlberg, the share increased by 9.6 ppt.

Figure 4.5 shows the seasonal adjusted time series of total unemployed persons and the seasonal adjusted time series of total job vacancies. There is a clear relationship between the two series. In particular, the number of unemployed people is rising if vacancies are less.

4.2.5. Beveridge curve

The Beveridge curve for Austria, i.e. the combined illustration of the unemployment rate and the job vacancy rate in a scatter plot, shows that the expected negative relation (for theoretical background see section 2.2.2) can be confirmed for most of the time.

In Figure 4.6 I used average yearly data of the vacancy and unemployment rates. The negative relation proposed in chapter 2.2.2 can be confirmed. Although, it can be seen that there have been various shifts in the Beveridge curve in the last decade. For example, the Beveridge curve between 2008 and 2009 has shifted outwards in comparison to the curve during the year 2000 and 2002 (cf. theoretical reasons for shifts in section 2.2.2).

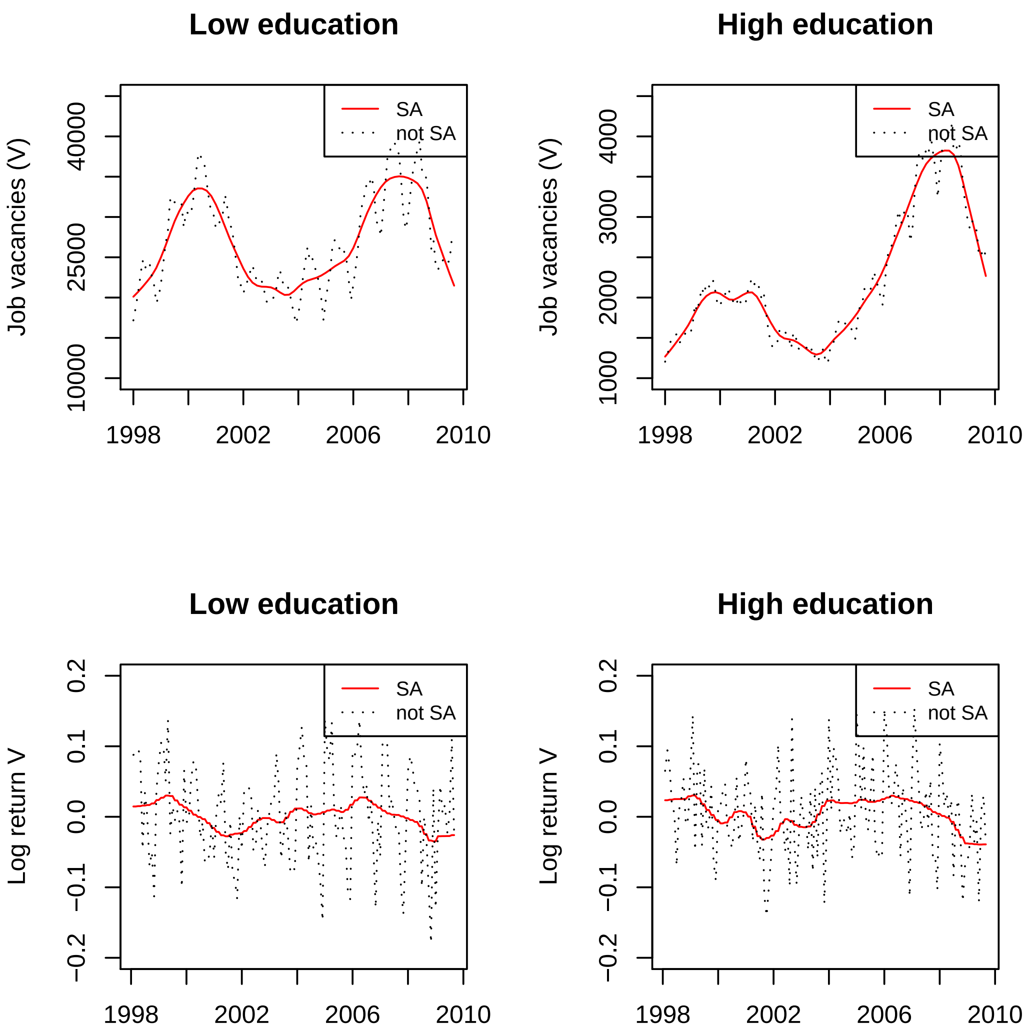

Figure 4.4.: Job vacancies for high- and low-educated persons in Austria. *Note the different scale dimensions in the upper plots.* Source: AMS and own calculations.

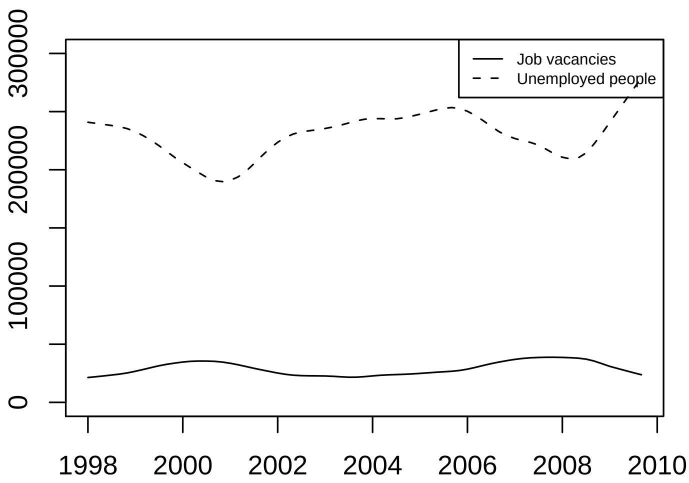

Figure 4.5.: Job vacancies vs. Unemployed people in Austria. Source: AMS, BALI.

Figure 4.7 shows two Beveridge curves with respect to education levels[15], i.e. for high and low educated persons. First, it is noteable that the scale dimensions of vacancies and unemployment rates differ gravely between those two education groups. While in the case of the low educated the rates of unemployed and vacancies are typically beyond the total vacancy and unemployment rates it is the other way round in the case of high educated. Furthermore, it is remarkable that in the case of the high educated the plot seems to be split, i.e. between 2005 and 2009 the vacancies are drastically higher compared to the period between 1998 and 2004. The Beveridge curve for the low educated has approximately the same pattern as the one of the whole economy. This seems reasonable because of the large proportion of low educated persons in Austria's population.

[15]To calculate differentiated unemployment and vacancy rates one needs also data for the respective labour force, $L_i = E_i + U_i$. Unfortunately data on employed people, E_i, is not available subject to educational levels. Therefore, it is assumed that the rates defined in chapter 4.2.2 are valid for the whole period (although it is a very strong assumption), i.e. 76% of the employed people are supposed to be low educated and 24% to be high educated. Another alternative would be to fall back to the yearly respectively quarterly EU-LFS data. Unfortunately, they use clusters of the ISCED (International Standard Classification of Education) defined by the UNESCO which do not coincide with my defined education levels. Therefore other assumtpions would have been necesary.

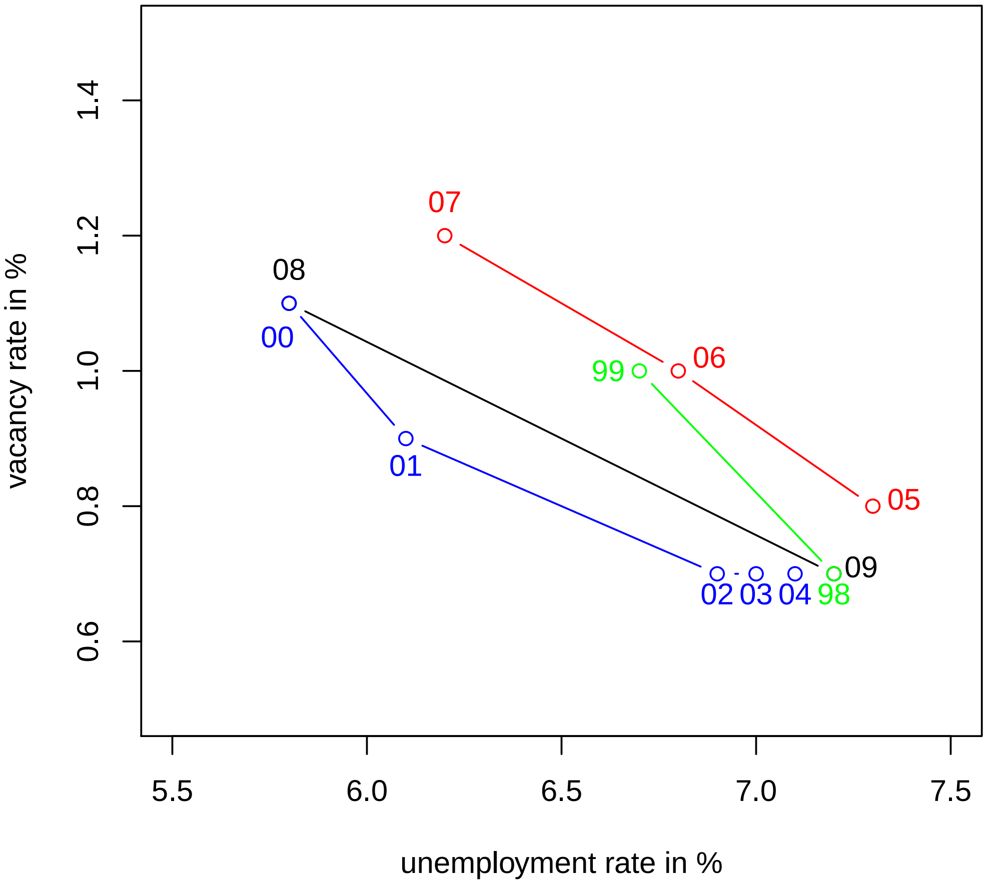

Figure 4.6.: Beveridge curve for Austria. *For simplicity only negative relations are highlighted.* Source: AMS, BALI and own calculations.

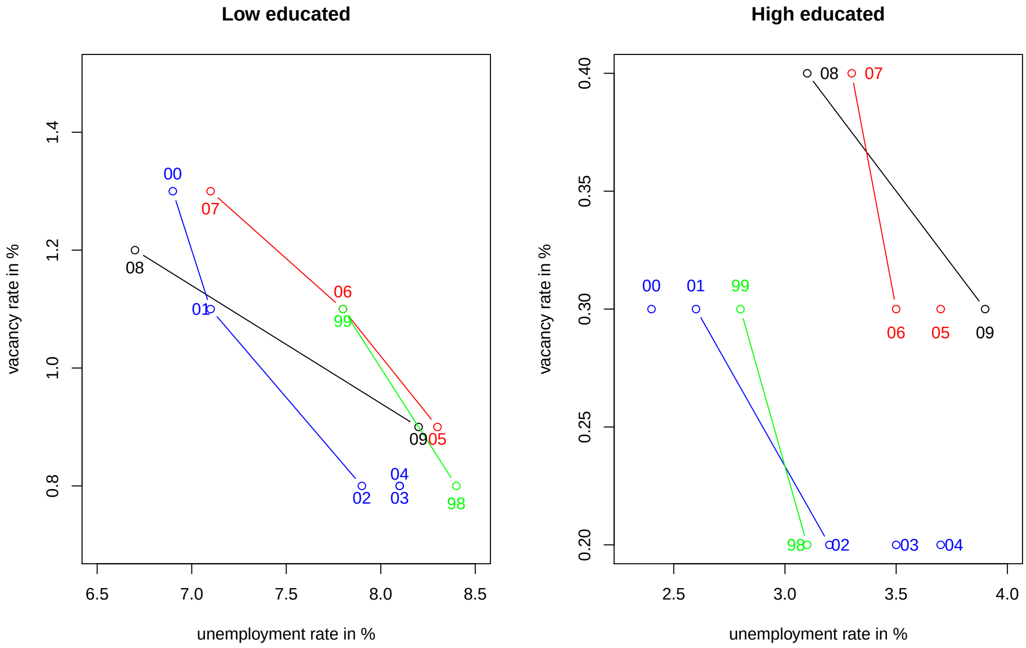

Figure 4.7.: Beveridge curves for Austria subject to education levels. *Note the different scale dimensions and that only negative relations are highlighted.* Source: AMS, BALI and own calculations.

4.2.6. Okun's law

In this short subsection the static relation between economic growth and the change in the unemployment rate described in chapter 2.2 is presented[16].
In Figure 4.8 one can see that the proposed negative relation between growth and unemployment can be justified for the Austrian case over the period 1998 to 2009. A simple OLS regression yields with the following result

$$Y = 0.51 - 0.28X$$

where Y denotes the yearly change in unemployment rates and X the yearly growth of the GDP. Furthermore, both coefficients are statistically significant at a confidence level of 99%. The standard error of the coefficient belonging to the costant is equal to 0.14 respectively equal to 0.05 of the remaining coefficient. The resulting R^2, as an indicator for the goodness of fit of the model is equal to 75.4. According to the regression a GDP growth of zero leads to a change in the unemployment rate of 0.51 points from one year to the next. Furthermore, a GDP growth of 1.84% would be necessary to keep the unemployment rate on the level of the previous period.

4.2.7. In- and outflow of unemployed

In chapter 2.2.2 the change in unemployment has been characterised as the excess of inflow into unemployment over outflow out of unemployment (cf. Pissarides (2000) and Layard et al. (1991)).

$$\Delta U = Inflow - Outflow$$

Obviously, if there is more inflow into unemployment than outflow $\Delta U > 0$.

AMS is providing data on inflows into and outflows out of unemployment for Austria. Like the majority of the labour market data also inflows and outflows have a seasonal component (Figure 4.9). Furthermore, Figure 4.9 shows that the number of inflows and outflows has slightly increased since January 1998. This is an indication for a higher job-rotation in the labour market.

[16] Note that this small analysis of this static relation should be seen as a digression since it is not a major target of this diploma thesis. Therefore, problems of standard OLS regression like omitted variables, spuriousity, causality and so on will not be discussed.

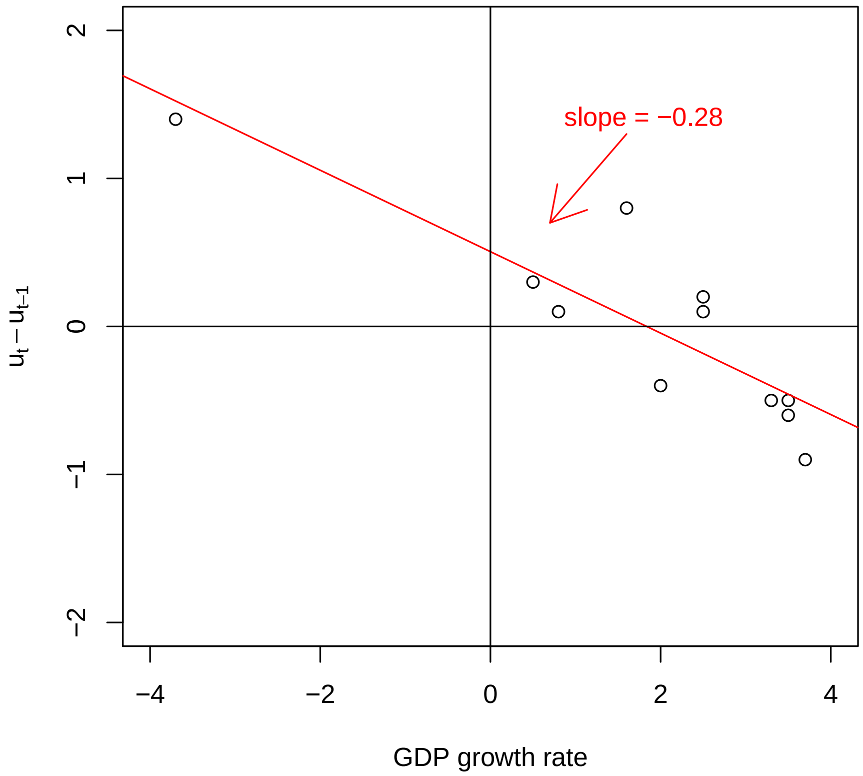

Figure 4.8.: Okun's law relation for Austria, 1998 to 2009. Source: AMS, BALI, Statistik Austria and own calculations.

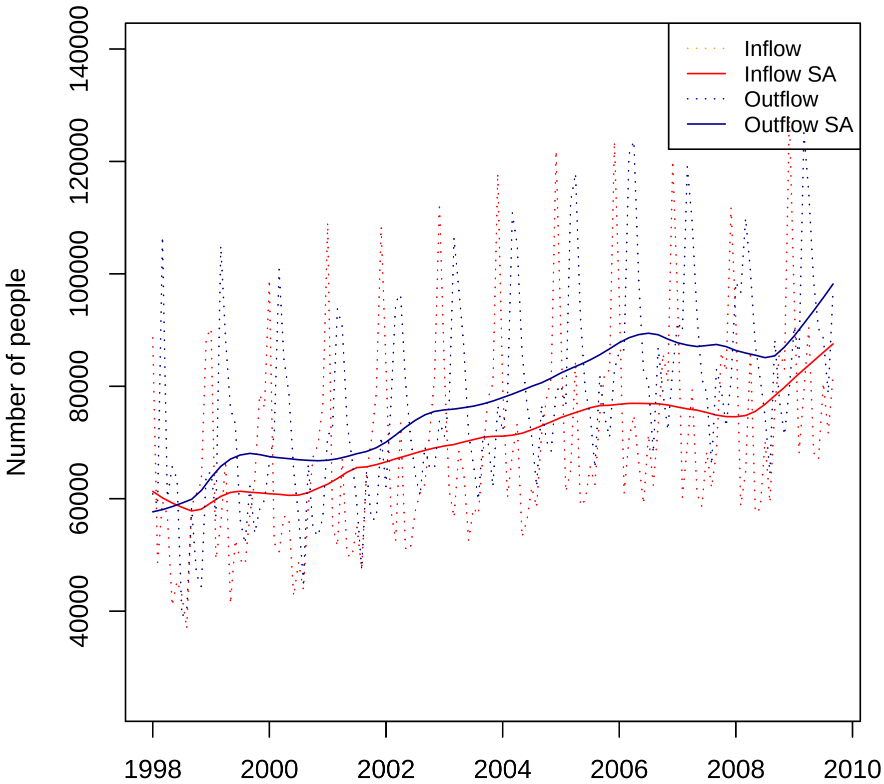

Figure 4.9.: Inflows into and Outflows out of Unemployment for Austria. Source: AMS, BALI and own calculations.

Another feature which, at first sight, seems remarkable is that in Austria outflow out of unemployment is generally higher than inflow into unemployment but the level of unemployment has risen. An explanation for this is that AMS overestimates outflow data in a sense that they count breaks in unemployment (even due to illness) in many cases[17] as outflow. However, much more important is the fact that data in Figure 4.9 reflect *all* inflows and outflows of people who are registered at the AMS. This means that AMS does not distinguish between people coming from labour force or not, respectively going back to labour force. Two examples might clarify the difficulty:

1. if school leavers do not find a job and therefore register at the AMS they are part of inflow data,

2. if unemployed are retiring they are part of the outflow data.

However, AMS is providing, on request, annual data[18] for outflow into labour force for the year 2000 to 2007 for the two different education groups. It is remarkable that in these eight years on average only 47.94% of high educated and 50.27% of low educated people flow out from unemployment into labour force. Since these data are only available on a yearly base and for the mentioned period I assume that percentages over outflows into labour force are equally distributed within a year and for the missing periods I used the fitted values of a linear forecast model[19] for the missing years respectively months.

Focusing on the regional component one observes that outflow out of unemployment data show that outflow into employment is very different among Austria's provinces. While, in 2007, in Vienna only 35.60% of high educated and 26.64% of low educated people flow out from unemployment into labour force in Tyrol 64.08% of high educated and 68.63% of low educated people flow into employment. However, between 2000 and 2007, in all nine provinces the share of outflow into employment decreased.

Unfortunately data on inflows coming from labour force were not available in a satisfying amount and quantity. Just as a remark, in 2008, 48% came from labour force, 39% from out of the labour force and 13% from educational training provided by AMS.

[17] AMS uses the so-called 28-days rule; normally a break in unemployment within 28 days will not be counted as outflow out of unemployment, but since AMS is providing data on a certain deadline and does not know if the unemployed will finish the interruption before 28 days, AMS is counting it as outflow. Unfortunately, data will not be corrected in the future.

[18] Sonderauswertung DWH-PST(12.11.2009). Many thanks to Veronika Murauer (AMS).

[19] In both cases, i.e. for high and low educated people, data show a decline in the percentage of people who flow from unemployment into employment. Although, the absolute number of people who flow into employment has increased but the the absolute number of total outlflows has risen even more.

The proportion of people who came from out of the labour force has been rather constant between 2000 and 2008 while the share of people who came from educational training has increased and percentage of people coming from the labour force has decreased.

Another problem occurred by correcting inflows in a way that the number of people flowing out of unemployment into labour force are the correct one and the following equation should be valid

$$U_{t+1} = U_t + Inflow_t - Outflow_t$$

Since in spring the percentage of switching from unemployment to employment is probably higher (the construction sector starts up again after winter break, and so on) it turned out that the approach to correct the inflow data yielded in negative values for inflows in spring.

However, the problems of missing adequate inflow data can be neglected since the aim of the empirical part of this thesis is to estimate matching functions where inflow data of unemployment does not play a role neither as dependent nor as independent variables (cf. section 4.1).

4.3. Econometric preliminaries

The econometric method used in this thesis is panel data analysis (cf. section 4.1). The structure of panel data consists of two dimensions. These are, on the one hand, a time dimension and, on the other hand, a cross section dimension. I decided to use panel data analysis since this method has some advantages (some of them are explained below) compared to others (e.g. time series).
In comparison to time series or cross section analysis, heterogeneity, which in many cases is ignored and therefore bears the risk of biased results, is reduced in panel data analysis. Panel data control for individual heterogeneity in a sense that the cross section dimension (individuals, firms, provinces, etc.) is seen as heterogenous (cf. Baltagi (1995)). Another advantage of panel data in comparison to pure time series analysis is that multicollinearity does not appear that often because much more information is available (cf. Baltagi (1995)).

In the next paragraphs I will roughly explain the prevailing estimating models with

respect to panel data.
The general linear panel model can be described as follows

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \tag{4.2}$$

where $i = 1, ..., n$ indicates the individuals (firms, countries, etc.) and $t = 1, ..., T$ the time index. Following the one-way error component model for the disturbances one can split u_{it} into $\mu_i + \epsilon_{it}$ where μ_i reflects the unobservable individual specific effect and μ_{it} the remaining disturbance. Note that μ_i is time independent, which means that it captures the individual specific effect which is not captured in the equation, and ϵ_{it} can be seen as the usual disturbance term in cross section or time series analysis (cf. Baltagi (1995)).

4.3.1. The fixed effects model (FE)

In this model the μ_i are defined to be fixed parameters and ϵ_{it} is independently and identically distributed with expectation equal to zero and variance σ^2_ϵ.
The next line formally captures the fixed effects model

$$y_{it} = \alpha + X'_{it}\beta + \mu_i + \epsilon_{it} \tag{4.3}$$

where α is fixed for all t and the error term is split as described above.
The LSDV (least square dummy variables) estimator or *within* estimator is one method to get estimates for β. There, the average from each variable in the model (4.3) is subtracted and leads to the following transformed model $y_{it} - \overline{y}_{i.} = \beta(x_{it} - \overline{x}_{i.}) + (\epsilon_{it} - \overline{\epsilon}_{i.})$
One can see that through this time demeaning procedure the individual effects are wiped out. Note that to get rid of the individual effects one can subtract the average over time or over groups which entails group respectively time effects. Performing pooled OLS on the transformed model usually leads to unbiased and consistent estimates for β if the error term is uncorrelated with the regressors (cf. Baltagi (1995), Greene (2003) and Wooldridge (2002)).

Another way of getting rid of the individual effects is to take first differences of the data (i.e. $\Delta y_{it} = y_{it} - y_{i,t-1}, \Delta X_{it} = X_{it} - X_{i,t-1}, ...$). Performing pooled OLS on the transformed model (i.e. Δy_{it} on ΔX_{it}, for $t = 2, ..., T$ and $i = 1, 2, ..., N$) is a second way to get estimates for β. The so-called first-difference estimator is in favour to the within estimator if the error term follows a random walk while the within estimator is more efficient under the assumption that the disturbances are serially uncorrelated (cf. Wooldridge (2002)).

4.3.2. The random effects model (RE)

In this model the individual effect is (contrary to the fixed effect model) considered to be randomly distributed ($\mu_i \sim \text{IID}(0, \sigma_\mu^2)$. Furthermore, μ_i is seen to be independent of ϵ_{it} and also the regressor matrix X_{it} is independent of the μ_i and ϵ_{it} (cf. Baltagi (1995)). This means that an optimal specification of the RE model would be if one draws a sample randomly from a large population. Usually the RE model is used for microeconomic studies where those assumptions are more likely to apply (cf. Baltagi (1995)).
The benefit of this kind of model (in comparison to the FE model) is that, due to the reduced number of parameters to estimate the degrees of freedom are higher. But on the other hand, there is the possibility of inconsistent estimates if the model specification is not appropriate (cf. Greene (2003) and Baltagi (1995)).

In the case of my diploma thesis I will present the results of both estimation approaches. Although, it seems that the RE model does not fit data optimally, because the regressors are not drawn randomly from a large population.

4.4. Results

In this section the results of different econometric models are presented. I worked in a "step-by-step" procedure, which means that I have started with a very basic model which I have extended gradually.

To safe space and to avoid redundant content I give a short list of common features of all following regressions presented in the subsequent sections.

- There are always two regressions differentiated by education.

- The two samples in scope contain 1269 observations each. To remember, the time dimension, t, is equal 141 months (1998 01 to 2009 09) and the cross-section dimension, i, is equal to 9 provinces.

- The dependent variable is $\ln(Outflow)$ in all regressions, although it is sometimes seasonal adjusted. Note that only outflow into employment instead of total outflow is meant.

- Standard errors in the regression tables are given in parentheses.

- Coefficients significantly different from zero at a confidence level of 99%, 95% and 90% are indicated with ***,** and *.

4.4.1. Step 1: Fixed effects model

In a first step I start with a simple panel data approach. In particular the within estimator with individual effects is used (i.e. estimating pooled OLS on the time-demeaned equation). The model can be specified as follows

$$\ln(Outflow_{it}) = \alpha + \beta_1 \ln(U_{it}) + \beta_2 (V_{it}) + \mu_i + \epsilon_{it} \tag{4.4}$$

where in a single province, i, $\alpha + \mu_i = \ln(A_i)$ and the equation for outflow can be described by $Outflow = AU^{\beta_1}V^{\beta_2}$. This equation is estimated one time for the group of high and one time for the group of low educated each with unaffected and seasonal adjusted data. The parameter β_1 and β_2 are of particular interest since they reflect the outflow-elasticities with respect to unemployment respectively vacancies.

In Table 4.1 one can see the obtained results. The elasticity of low educated with respect to unemployment is lower than for high educated in both approaches. The estimation of seasonal adjusted data shows that, in comparison to the unadjusted data, the elasticity with respect to unemployment has decreased for the group of low educated while it has increased for the other group.

The meaning of a coefficient of $\ln(U)$ equal to 0.44 is that if the number of unemployed increases by one percent, the number of outflow will increase by 0.44 percent.

The elasticities with respect to vacancies are in all cases lower than those with respect to unemployment. Furthermore, one can see that in the group of low educated the elasticity with respect to vacancies is much lower in equation 1.1.2 than in 1.1.1.

If one tests the hypothesis with a linear hypothesis test, i.e. the Wald-Test, that the sum of the estimated coefficients of $\ln(U)$ and $\ln(V)$ is equal to one (i.e. if the constant

dependent variable	**outflow low**		**outflow high**	
equation	1.1.1	1.1.2	1.2.1	1.2.2
coef[ln U]	0.44*** (0.03)	0.41*** (0.02)	0.70*** (0.03)	0.86*** (0.01)
coef[ln V]	0.37*** (0.03)	0.13*** (0.01)	0.14*** (0.01)	0.15*** (0.01)
seas. adj.	no	yes	no	yes
TSS	122.87	6.84	96.72	45.14
RSS	105.54	5.27	65.37	9.30
	Fixed effects			
Burgenland	0.75* (0.44)	2.62*** (0.23)	-0.42** (0.21)	-1.44*** (0.09)
Carinthia	1.14** (0.49)	3.27*** (0.26)	-0.12 (0.24)	-1.29*** (0.10)
L. Austria	0.83 (0.54)	3.21*** (0.28)	-0.24 (0.27)	-1.54*** (0.12)
U. Austria	0.87 (0.53)	3.29*** (0.27)	-0.08 (0.26)	-1.30*** (0.11)
Salzburg	1.07** (0.48)	3.24*** (0.25)	-0.06 (0.23)	-1.16*** (0.10)
Styria	1.06** (0.52)	3.32*** (0.27)	-0.22 (0.27)	-1.52*** (0.11)
Tyrol	1.28*** (0.49)	3.45*** (0.26)	-0.05 (0.24)	-1.19*** (0.10)
Vorarlberg	0.71 (0.45)	2.67*** (0.24)	-0.45** (0.21)	-1.46*** (0.09)
Vienna	0.51 (0.55)	2.89*** (0.29)	-0.46 (0.30)	-1.92*** (0.13)

Table 4.1.: Step 1: Fixed effects model (within).

returns to scale assumption is valid) one has to reject this hypothesis in the case of equation 1.1.1, 1.1.2 and 1.2.1. Only in equation 1.2.2 the restricted model and therefore the constant return to scale assumption can be validated.

If one takes a look at the fixed effects of the nine provinces in Table 4.1, one can see that the values for the low educated group are positive and negative for the high educated group. Although, some of them are not significant on a satisfying level (i.e. those are supposed to be zero, which implies $A_i = 1$). Negative intercepts imply a moderate influence of U and V on outflow out of unemployment (i.e. $0 < A_i < 1$). But since the intercept also catches other effects, e.g. specific regional effects or sectoral structures, etc. the interpretation of the intercept should not be overstretched.

In Table 4.1 one can see that in the group of low educated, Burgenland has the lowest intercept (only statistically significant values are taken into account), while in the group of high educated, Vorarlberg and Vienna (seasonal adjusted) are leading. This means that Burgenland, Vorarlberg and Vienna have the lowest matching technology in the respective groups.
On the other hand Tyrol shows the highest intercept in the group of low educated and Salzburg in the group of high educated.

4.4.2. Step 2: Random effects model

Table 4.2 shows the results of a random effects model. Interestingly, the values of the coefficients of $\ln(U)$ and $\ln(V)$ are approximately the same as in Step 1. All coefficients are significant on a satisfactory level except for the intercept in equation 2.2.1.

Due to the fact that the results of the two different models are roughly the same I will not go into the details of testing which model should be used. Obviously, in a fixed effect model one has the advantage that the fixed effects for the different provinces are available. In the subsequent approaches I will state both results.

4.4.3. Step 3: Including monthly dummy variables

In Table 4.3 one can see the results by including dummy variables[20] for each month (i.e. February to December; one month of the year is skipped to avoid multicollinearity). The reason of using monthly dummy variables is that so seasonal effects can be captured as

[20] A dummy variable is a binary variable which is equal to one if the property applies or zero otherwise.

dependent variable	**outflow low**		**outflow high**	
equation	2.1.1	2.1.2	2.2.1	2.2.2
intercept	1.00**	3.02***	-0.22	-1.37***
	(0.46)	(0.27)	(0.23)	(0.12)
coef[ln U]	0.43***	0.42***	0.70***	0.85***
	(0.03)	(0.02)	(0.03)	(0.01)
coef[ln V]	0.37***	0.13***	0.15***	0.15***
	(0.03)	(0.01)	(0.01)	(0.01)
seas. adj.	no	yes	no	yes
TSS	126.59	7.02	104.62	46.25
RSS	106.19	5.32	65.76	9.40

Table 4.2.: Step 2: Random effects model.

well.
In comparison to the results of Step 1 and Step 2 one can see in Table 4.3 that the introduction of dummy variable leads to lower coefficients of $\ln(U)$ for the group of low educated.

Table 4.3 shows that the season does play a role in finding a job. In comparison to January a low educated is more likely to find a job in March, April, May and June and less likely in August, October and November on average. Although, there are small differences between the random effects and the fixed effects model for the group of low educated.

In the group of high educated the results of these two methods are roughly the same. In comparison to January an average high educated is more likely to find a job in September and October. In February, April, July, August, November and December it is less likely.

One can see that in the case of low educated the seasonal pattern is more conspicuous. A comparison of the fixed effects from the seasonal adjusted data from Step 1 (equation 1.1.2 and 1.2.2) with the result of the approach with monthly dummy variables lead to slight differences in levels. However, the quantitative conclusion is rather the same, i.e. Tyrole has the highest matching technology while Burgenland and Vienna have the lowest in this approach.

dependent variable	**outflow low**		**outflow high**	
equation	3.1.1	3.1.2	3.2.1	3.2.2
model	FE	RE	FE	RE
intercept		3.12***		-0.31
		(0.47)		(0.20)
coef[ln U]	0.27***	0.29***	0.72***	0.72***
	(0.04)	(0.04)	(0.03)	(0.02)
coef[ln V]	0.25***	0.27***	0.14***	0.14***
	(0.03)	(0.02)	(0.01)	(0.01)
coef[D_Feb]	0.02	0.02	-0.12***	-0.12***
	(0.03)	(0.03)	(0.02)	(0.02)
coef[D_March]	0.45***	-0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.02)	(0.02)
coef[D_Apr]	0.34***	-0.09***	-0.09***	-0.09***
	(0.03)	(0.03)	(0.02)	(0.02)
coef[D_May]	0.21***	0.01	0.01	0.01
	(0.03)	(0.03)	(0.02)	(0.02)
coef[D_June]	0.12***	-0.04	-0.04	-0.04
	(0.04)	(0.04)	(0.02)	(0.02)
coef[D_July]	-0.04	-0.19***	-0.19***	-0.19***
	(0.04)	(0.04)	(0.02)	(0.02)
coef[D_Aug]	-0.22***	-0.27***	-0.27***	-0.27***
	(0.04)	(0.04)	(0.02)	(0.02)
coef[D_Sep]	-0.01	0.01	0.26***	0.25***
	(0.03)	(0.04)	(0.02)	(0.02)
coef[D_Oct]	-0.15***	-0.14***	0.16***	0.16***
	(0.03)	(0.03)	(0.03)	(0.03)
coef[D_Nov]	-0.15***	-0.14***	-0.08***	-0.08***
	(0.03)	(0.03)	(0.03)	(0.03)
coef[D_Dec]	0.03	0.03	-0.13***	-0.13***
	(0.03)	(0.03)	(0.03)	(0.03)
TSS	122.87	125.04	96.72	101.75
RSS	61.04	61.55	41.23	41.49

Table 4.3.: Step 3: Panel data - Fixed and Random effects model including monthly dummy variables.

4.4.4. Step 4: Lagged explanatory variables

Since outflow out of unemployment is a flow variable while the number of unemployed and vacancies is a stock variable it makes sense to lag those two variables. It is likely that the outflow of e.g. April (1.4. to 30.4.) is more dependent on the number of unemployed and vacancies of March (31.3.) than that of April (30.4.).

In Table 4.4 one can see that the coefficients of $\ln(U_{t-1})$ and $\ln(V_{t-1})$ are significant for

dependent variable	**outflow low**		**outflow high**	
equation	4.1.1	4.1.2	4.2.1	4.2.2
model	FE	RE	FE	RE
intercept		-3.05*** (0.37)		-1.87*** (0.20)
coef[ln U]$_{t-1}$	0.94*** (0.03)	0.91*** (0.02)	0.96*** (0.03)	0.93*** (0.03)
coef[ln V]$_{t-1}$	0.32*** (0.02)	0.30*** (0.02)	0.13*** (0.01)	0.13*** (0.01)
seas. adj.	no	no	no	no
TSS	122.69	124.80	96.42	101.89
RSS	59.98	60.40	44.59	45.32

Table 4.4.: Step 4: Panel data - Fixed and Random effects model with lagged explanatory variables.

both groups. Furthermore, the impact of the coefficients has increased in comparison to Step 1-3. Applying a linear hypothesis test to test the validity of the constant returns to scale assumption one has to confirm in the case of the high educated. By contrast, one finds increasing returns to scale for the group of low educated. Another aspect is that the constant has now become negative for the low educated group. More precisely, in this approach the constant of the low educated group is even more negative compared to the high educated, which is an indication for a less efficient matching.

Including monthly dummy variables to the estimation shown in Table 4.4 results yield similar coefficients for $\ln(U_{t-1})$ and $\ln(V_{t-1})$, although for the first time the coefficient of $\ln(U_{t-1})$ is slightly higher for the low educated than for the high educated.

4.4.5. Step 5: Including regional dummy variables

In a penultimate step I use the within estimator with time effects instead of individual effects and add regional dummy variables. Therefore, I define three regions (i.e. East={Burgenland, L. Austria, Vienna}, Mid={U. Austria, Salzburg, Styria} and West={Carinthia, Tyrol, Vorarlberg}). The reason for the definition of these regional clusters is that the eastern region can be seen as one labour market due to the concentration around Vienna. This argument of a single labour market is also true, although in a moderated way, for the defined middle and western region. As in Step 3, I add two out of three dummy variables to the equation. Furthermore, lagged variables of $\ln(U)$ and $\ln(V)$ are used.

The results shown in Table 4.5 indicate that the region where an unemployed lives

dependent variable	**outflow low**	**outflow high**
equation	5.1.1	5.2.1
coef[ln U]$_{t-1}$	0.53*** (0.02)	0.73*** (0.01)
coef[ln V]$_{t-1}$	0.29*** (0.02)	0.13*** (0.01)
coef[D_East]	-0.37*** (0.02)	-0.19*** (0.01)
coef[D_Mid]	-0.02 (0.02)	0.07*** (0.01)
seas. adj.	no	no
TSS	430.3	686.81
RSS	74.17	35.74

Table 4.5.: Step 5: Panel data - Fixed effects model with lagged explanatory variables and regional dummy variables.

has a significant influence on getting employed again. In comparison to the western region of Austria the influence of outflow is lower in the eastern region for high and low educated. The middle region of Austria shows a slightly positive impact in comparison to the western region on outflow for the group of high educated while for the high educated group the coefficient is not significant.

4.4.6. Step 6: Including a metropolis dummy variable

In this last step again the within estimator with time effects is used. Furthermore, a dummy variable for Vienna is included. Since Vienna is the only metropolis in Austria there are some good reasons for a different matching pattern to be found there. Table

dependent variable	**outflow low**	**outflow high**
equation	5a.1.1	5a.2.1
coef[ln U]$_{t-1}$	0.65*** (0.02)	0.84*** (0.01)
coef[ln V]$_{t-1}$	0.27*** (0.02)	0.11*** (0.01)
coef[D_Vienna]	-0.69*** (0.02)	-0.48*** (0.01)
seas. adj.	no	no
TSS	430.3	686.81
RSS	73.32	35.93

Table 4.6.: Step 6: Panel data - Fixed effects model with lagged explanatory variables and including a metropolis dummy variable.

4.6 shows the result of using a dummy variable for Vienna. The results are very similar to Step 5. It is shown that the Vienna dummy variable has a very strong impact on job matching. Another characteristic of this equation is that by applying a linear hypothesis test the constant returns to scales hypothesis cannot be rejected.

4.4.7. Summary of the regression results

To summarise the different approaches of estimating outflow elasticities with respect to unemployment and vacancies one has to mention first that the results are very similar (only statistically significant results will be discussed). The estimated elasticity with respect to unemployment is generally higher than that one with respect to vacancies. The interval of the elasticity with respect to unemployment is approximately between 0.27 and 0.44 for the low educated group between 0.53 and 0.98 by considering lagged explanatory variables and between 0.7 and 0.86 for the high educated group and between 0.73 and 0.96 respectively. On the other hand, the estimated elasticity with respect to vacancies is in a range between 0.13 and 0.37 for low educated and between 0.14 and 0.15 for high educated concerning the non lagged explanatory variable. Considering the lagged explanatory variable yields coefficients between 0.25 and 0.32 for the low educated group and in-between 0.11 and 0.13 for the high educated.

The proposed constant returns to scale assumption from the theoretical part could be rejected in some cases and in some not. The prevailing results with respect to non-lagged variables (case 1-3) of the estimations show decreasing returns to scale. On the other hand, by taking lagged explanatory variables into account, there is some evidence that the high educated group shows constant return to scale while the low educated show increasing returns to scale. The results of the empirical literature normally show constant returns to scale (cf. Petrongolo and Pissarides (2001)) but there are also studies which found opposite effects (cf. Blanchard and Diamond (1990) for an increasing return to scale example in the US labour market between 1968 and 1981).

By ignoring the intercept the results can be interpreted that way that high educated match more easily since the elasticity with respect to unemployment of the high educated group is generally higher (especially in the case with non-lagged explanatory variables) than the one of the low educated group. On the other hand the elasticity with respect to vacancies behaves the other way round. Since the absolute number of unemployed is higher compared to vacancies this conclusion can be drawn.

However, since the estimated intercept generally is not equal to zero, which would imply an additive technology level of one and therefore neglect the technological impact, one has to consider those estimates. In Step 1-3 where non-lagged explanatory variables have been used the low educated show generally a positive estimate while high educated show a negative one. Therefore, matching of low educated is multiplied by a factor greater than one and high educated with a factor lower than one. This means that in the case of the low educated the technology parameter of the matching function has a positive impact on the matching rate, and a negative one in the case of the high educated.

Using lagged explanatory variables changed the situation considerably. Low educated show a much more negative intercept compared to the high educated ones, which implies a less efficient matching function for this group.

It ought to be mentioned that there also exist other influences on job matching than the number of unemployed and vacancies. These are seasonal and regional aspects. There are particular months in the year which have a greater impact on outflow of unemployment than others.

On the other hand, there are several regions or regional clusters which have a higher influence on outflow than others. There is some evidence that regions in the western part of Austria have a higher impact on outflow out of unemployment than in eastern regions.

Last but not least, including a yearly linear time trend as it is done in other empirical studies (cf. Petrongolo and Pissarides (2001)) has lead to insignificant coefficients. The reason for this could be the relatively short time span. Therefore, it is not considered in my study.

5. Conclusion

In this diploma thesis two goals were pursued. First, an explanation of the different unemployment rates of high and low skilled labour. And second, an analysis of some impacts (e.g. growth) on the different unemployment rates.

In the theoretic part of this thesis a model by Aghion and Howitt (1994) was extended to capture these two features in scope. The extension showed that growth has a positive influence on unemployment. Although, the effect is the same for both the high and low skilled unemployed. Furthermore, it was shown that the difference in the two unemployment rates depend crucially on the matching function. This function, which is an element of the prevailing Equilibrium Unemployment Theory by Pissarides (2000), is a way to model the allocation of unemployed workers to vacant jobs. Another result of the theoretical investigation was that the size of the labour market also plays a role in defining the unemployment rates.

In the empirical part which geographically focuses on Austria it was shown that the unemployment rate for high educated has been lower than for low educated in the period between 1998 and 2009. Furthermore, the labour market where high educated compete shows a lower size, which is according to the theory a first sign of explaining the lower unemployment rate of this group. However, the more challenging part of the empirical investigation was to estimate matching functions for both education groups. The method used was panel data analysis with monthly data starting in January 1998 until September 2009 and Austria's nine provinces as cross-section dimension. The results of the different estimations were quite clear. The high educated showed, compared to the low educated, a more efficient matching pattern. Furthermore, the estimated elasticities of job matching with respect to unemployment are generally higher in this educational group while the elasticities with respect to vacancies are lower.

Summarising, one can say that combining this theoretical setup with the empirical results of Austria, higher educated compete in a smaller labour market, have a more efficient matching pattern and therefore show a smaller unemployment rate. But on the other hand, that the effects of a change in the economy wide growth rate has the same effects on both types of labour, i.e. a higher growth rate leads to higher unemployment rates of both types.

A. Appendix A

A.1. Poisson process

Poisson distribution

$$p(\lambda, k) := e^{-\lambda}\frac{\lambda^k}{k!} \qquad \forall k \in \mathbf{N} \qquad \lambda \in (0, \infty)$$

Expectation

If X is a Poisson distributed random variable, Expectation is

$$E[X] = \sum_{k=0}^{\infty} k e^{-\alpha}\frac{\lambda^k}{k!} = \lambda e^{-\lambda}\sum_{k=1}^{\infty}\frac{\lambda^{k-1}}{(k-1)!} = \lambda$$

Variance

$$Var[X] = E[X] = \lambda$$

Poisson process

The waiting time between T and X, $(X > T)$ is supposed to be a random variable with distribution:

$$F(T) \equiv \text{Prob[Event occurs bevore T]} = 1 - e^{\lambda T}$$

Therefore, the probability density function is given by:

$$f(T) = F'(T) = \lambda e^{\lambda T}$$

In a short interval between T and $T + dt$ the probability that an event will occur is approximately $\lambda e^{\lambda T} dt$. The probability between an interval $T = 0$ and dt which indicates the waiting time from now on, is approximately the probability:

$$f(0) = F'(0) = \lambda dT$$

The number of events, k, taking place over any interval of length, Δ, follow a Poisson distribution described above.

A.2. Data overview

Province		Low educated		
		Unemployed (U_l)	Outflow into Employment ($Outflow_l$)	Job Vacancies (V_l)
Burgenland	Min	4,027	542	337
	Max	12,784	3,564	1,307
	Mean	6,994	1,288	757
Carinthia (K)	Min	7,789	1,787	950
	Max	26,181	7,233	3,861
	Mean	15,420	3,691	1,939
Lower Austria (N)	Min	22,068	2,826	2,895
	Max	54,776	10,295	7,786
	Mean	34,121	5,482	5,020
Upper Austria (O)	Min	14,342	2,878	2,569
	Max	37,842	8,777	11,008
	Mean	23,187	5,055	5,977
Salzburg (S)	Min	5,198	1,523	1,499
	Max	13,372	6,081	3,683
	Mean	9,611	3,048	2,303
Styria (St)	Min	19,261	2,659	1,696
	Max	46,834	9,833	4,361
	Mean	29,635	5,397	3,072
Tyrol (T)	Min	5,748	1,733	1,468
	Max	23,912	11,720	4,589
	Mean	14,677	4,655	2,314
Vorarlberg (V)	Min	4,438	886	587
	Max	11,111	2,164	1,764
	Mean	7,561	1,373	1,054
Vienna (W)	Min	46,101	2,395	1,700
	Max	81,422	6,905	8,639
	Mean	62,260	4,919	4,598
Austria (At)	Min	132,897	19,883	16,761
	Max	296,798	55,845	39,422
	Mean	203,466	34,873	27,033

Table A.1.: Summary statistics of the variables used belonging to the low educated group. Note that the method to calculate the values of Outflow into Employment is described in chapter 4.2.7. Period: 1998 01 to 2009 09. Source: AMS, BALI, Statistik Austria and own calculations.

Province		High educated		
		Unemployed (U_h)	Outflow into Employment ($Outflow_h$)	Job Vacancies (V_h)
Burgenland	Min	400	50	24
	Max	1,107	228	120
	Mean	660	112	59
Carinthia (K)	Min	1,074	139	49
	Max	2,760	678	285
	Mean	1,696	328	134
Lower Austria (N)	Min	2,331	251	227
	Max	6,085	1,201	657
	Mean	3,795	602	393
Upper Austria (O)	Min	1,460	219	125
	Max	4,065	1,062	971
	Mean	2,229	483	425
Salzburg (S)	Min	688	119	52
	Max	1,705	474	239
	Mean	1,101	251	118
Styria (St)	Min	2,649	260	112
	Max	5,777	1,169	515
	Mean	3,770	572	259
Tyrol (T)	Min	870	133	63
	Max	2,202	699	227
	Mean	1,416	382	141
Vorarlberg (V)	Min	316	39	11
	Max	1,003	184	305
	Mean	595	119	86
Vienna (W)	Min	6,418	445	177
	Max	13,821	1,702	1,297
	Mean	10,441	1,021	603
Austria (At)	Min	16,840	1,737	1,180
	Max	38,360	7,196	4,148
	Mean	25,704	3,790	2,218

Table A.2.: Summary statistics of the variables used belonging to the high educated group. Note that the method to calculate the values of Outflow into Employment is described in chapter 4.2.7. Period: 1998 01 to 2009 09. Source: AMS, BALI, Statistik Austria and own calculations.

Province		Employed (E)	Tightness (low) ($\theta_l = \frac{\overline{V_l}}{\overline{U_l}}$)	Tightness (high) ($\theta_h = \frac{\overline{V_h}}{\overline{U_h}}$)
Burgenland	Min	72,088		
	Max	94,056	0.11	0.09
	Mean	83,964		
Carinthia (K)	Min	177,866		
	Max	222,622	0.13	0.08
	Mean	197,268		
Lower Austria (N)	Min	492,229		
	Max	580,146	0.15	0.10
	Mean	532,138		
Upper Austria (O)	Min	503,847		
	Max	622,555	0.26	0.19
	Mean	558,119		
Salzburg (S)	Min	204,789		
	Max	244,521	0.24	0.10
	Mean	221,695		
Styria (St)	Min	404,471		
	Max	490,920	0.10	0.07
	Mean	443,731		
Tyrol (T)	Min	242,964		
	Max	310,589	0.16	0.10
	Mean	276,385		
Vorarlberg (V)	Min	126,326		
	Max	149,372	0.14	0.14
	Mean	137,437		
Vienna (W)	Min	739,104		
	Max	802,328	0.07	0.06
	Mean	767,712		
Austria (At)	Min	46,101		
	Max	81,422	0.13	0.07
	Mean	62,260		

Table A.3.: Summary statistics of Employed (do not include self employed persons) and labour market tightnesses of the high and low educated group. Period: 1998 01 to 2009 09. Source: AMS, BALI, Statistik Austria and own calculations.

A.3. Abstract

The intention of this diploma thesis is to determine the causes of persistently higher unemployment rates of people with a lower education level compared to people with a higher one. Furthermore, the determinants of different unemployment rates are of particular interest, especially the impact of economic growth.

Aghion and Howitt (1994) showed in their model by applying the Schumpeterian argument of creative destruction that growth can have positive effects on unemployment. This particular model is extended by two different types of skill levels (i.e. high and low skilled labour) to guarantee a differentiated analysis. These extensions are necessary to answer the question if high skilled or low skilled workers suffer more from unemployment induced by growth or other factors. Furthermore, the implementation of two different matching functions from the prevailing Equilibrium Unemployment Theory by Pissarides (2000) allows for different job matching probabilities of high and low skilled labour and therefore contributes to a possible explanation of different unemployment rates of these two sorts of labour.

In the extended model it can be shown that growth has a positive influence on unemployment. Although, the effect is the same for both the high and low skilled unemployed. Furthermore, it is demonstrated that the difference in the two unemployment rates crucially depends on the matching function. Another result of the theoretical investigation is that the size of the labour market also plays a role in defining the unemployment rates, i.e. a larger labour market leads to a higher unemployment rate.

The empirical part, which geographically focuses on Austria, shows that in the period between 1998 and 2009 the unemployment rate of the high educated has been lower than that of the low educated . Furthermore, the labour market where high educated compete is smaller, which is according to the theory a first sign of explaining the lower unemployment rate of this group.

In the second part of the empirical investigation matching functions for both education groups are estimated. The method used is panel data analysis with monthly data starting in January 1998 until September 2009 and Austria's nine provinces as cross-section dimension. The results of the different estimations are quite clear. The high educated show compared to the low educated a more efficient matching pattern. Furthermore, the estimated elasticities of job matching with respect to unemployment are generally higher in this educational group while the elasticities with respect to vacancies are lower.

JEL codes: E24, J21, J24, O47

Keywords: Job Matching in Austria, Panel data analysis of skill differentiated matching functions in Austria, Growth and Unemployment in Austria

A.4. Abstract - German

In dieser Diplomarbeit werden die Gründe höherer Arbeitslosenraten für Personen mit niedrigerem Bildungsniveau im Vergleich zu besser Ausgebildeten erörtert. Des Weiteren werden die Determinanten, im Speziellen von Wirtschaftswachstum, der beiden unterschiedlichen Arbeitslosenraten beleuchtet.

Aghion and Howitt (1994) zeigen in ihrem Model, dass Wirtschaftswachstum auch positive Effekte auf Arbeitslosigkeit haben kann. Dabei implementieren sie die Idee der kreativen Zerstörung von Joseph Schumpeter. Die Idee dahinter ist, dass technischer Fortschritt Jobs zerstört, da neue Produkte anders hergestellt werden bzw. unterschiedliche Qualifikationen von Arbeitern benötigt werden.

Im theoretischen Teil der Diplomarbeit erweitere ich das Model von Aghion and Howitt (1994) um Bildungsfaktoren. Genau genommen werden zwei unterschiedliche Arten von Arbeit eingeführt, das sind zum einen manuelle Arbeit und zum anderen Humankapital. Manuelle Arbeit ist Leuten mit einem geringeren Bildungsniveau zugeordnet, während Humankapital von Leuten mit einer höheren Ausbildung bereitgestellt wird. Diese Erweiterung des Models ist notwendig, um die Frage zu beantworten, ob gut oder weniger gut Ausgebildete mehr von Arbeitslosigkeit betroffen sind, welche durch Wirtschaftswachstum oder andere Faktoren entstanden ist. Des Weiteren erlaubt die Implementierung von Matching-Funktionen, aus der vorherrschenden "equilibrium unemployment"- Theorie, von Pissarides (2000), unterschiedliche Job Matching-Wahrscheinlichkeiten für die zwei Arten von Arbeitern.

Im erweiterten Model kann ein positiver Einfluss von Wirtschaftswachstum auf die Arbeitslosigkeit gezeigt werden. Wenngleich sich aber der Effekt auf die Arbeitslosenraten beider Bildungsgruppen gleich auswirkt. Des Weiteren kann gezeigt werden, dass die Arbeitslosenraten sehr stark von den Matching-Funktionen abhängen. Ein weiteres Ergebnis ist, dass die Größe des Arbeitsmarktes Einfluss auf die Arbeitslosenrate ausübt.

Im empirischen Teil über Österreich wird gezeigt, dass die Arbeitslosenrate für den Zeitraum von 1998 bis 2009 für besser Ausgebildete niedriger ist als für schlechter Ausgebildete. Des Weiteren ist der Arbeitsmarkt der besser Ausgebildeten kleiner, was gemäß der entwickelten Theorie ein Anzeichen für eine niedrigere Arbeitslosenrate ist.

Im zweiten Teil der empirischen Untersuchung werden unterschiedliche Matching-Funktionen für die beiden Ausbildungsgruppen mittels Panel Daten geschätzt. Die Zeitdimension reicht von Jänner 1998 bis September 2009 und die "Cross Section-Dimension" beinhaltet Österreichs neun Bundesländer. Die Ergebnisse der Schätzungen zeigen, dass besser Ausgebildete ein effizienteres Matching-Muster aufweisen. Weiters sind die Job Matching-Elastizitäten bezüglich der Anzahl an Arbeitslosen höher in der Gruppe der besser Ausgebildeten, während die Elastizitäten bezüglich der Anzahl der freien Stellen niedriger ist.

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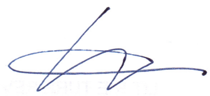
Eidesstattliche Erklärung

Ich erkläre hiermit an Eides statt, dass ich die vorliegende Arbeit selbstständig und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

Wien, im Februar 2010



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