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„Austria's Potential Output: An Alternative Approach. Okun's Method Revisited"

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Abstract

In this thesis an alternative approach to estimate potential output is presented and implemented for Austria. The starting point is a critique on certain approaches, such as wide spread production function models, which produce results close to a moving average of GDP. Alternatively I present an approach building on Okun's method (Okun, 1962), which was updated by Fontanari, Palumbo and Salvatori (2020). Considering that Austria faced at least two different labor market regimes since the 1950s, Okun's law is estimated significantly. Resulting potential output estimates show a stable under utilization of capacity since the early 1980s. Additionally a decomposition of real output into hourly labor productivity, hours worked per employee, the employment rate, the labor force participation rate and population growth is performed. The decomposition is used to calculate a benchmark case of potential output, i.e. predicting GDP if demand was high ever since 1976. Results show that real GDP is close to the benchmark case, however working hours are distributed more evenly in the hypothetical high demand regime.

Kurzfassung

In der vorliegenden Arbeit wird ein alternativer Ansatz in der Schätzung des Produktionspotenzials präsentiert und auf Österreich angewandt. Den Ausgangspunkt bildet die Kritik an bestimmten Schätzansätzen, beispielsweise an den weit verbreiteten Produktionsfunktions Modellen, welche Resultate liefern die nahe an einem gleitenden Durchschnitt des BIP liegen. Dem entgegen wird ein Ansatz präsentiert der auf Okuns Methode (Okun, 1962) beruht und von Fontanari, Palumbo and Salvatori (2020) erweitert wurde. Bezugnehmend darauf, dass Österreichs Wirtschaft seit den 1950ern zumindest zwei verschiedene Arbeitsmarktregime erlebte, wird Okuns Gesetz signifikant geschätzt. Die sich daraus ergebenden Schätzer des Produktionspotenzials zeigen eine stabile Unterauslastung der Produktionskapazitäten seit den frühen 1980ern. Darüber hinaus wird eine Zerlegung der realen Wirtschaftsleistung in stündliche Arbeitsproduktivität, Arbeitsstunden pro beschäftigter Person, die Beschäftigungsrate, die Erwerbsquote und das Bevölkerungswachstum vorgenommen. Diese Zerlegung wird genutzt, um einen Referenzwert des Produktionspotenzials zu berechnen. Konkret ist der Referenzwert eine Prognose des BIP unter der Annahme, dass seit 1976 stets hohe Nachfrage herrschte. Es zeigt sich, dass die reale Wirtschaftsleistung nahe am Referenzwert liegt, jedoch die Arbeitszeit im hypothetischen Fall der hohen Nachfrage gleicher verteilt ist.

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1. Introduction

The Corona crisis hit the world's economy by surprise and the tremendous aftermath will determine politics around the globe for years. On one hand governments have to face social and economic problems, on the other hand they have to handle budget deficits, arising from expansive fiscal policies. Regarding this situation it is clear that business cycle analysis and hence analysis of potential output (PO) and output gaps will be highly important in the political debates of the following years, including the one of Austria. And hence again it is important to think about the estimation of PO and it's issues.

Recalling the experience from the great depression 2009 and what followed, public debt will play a key role in the ongoing economic crisis in the *Economic and Monetary Union* (EMU). Obviously the example of Greece and other periphery countries in the EMU showed that the EU fiscal rules once applied have great influence on national politics. And moreover the public debt crisis showed that technical details have a huge influence on austerity politics. Heimberger, Huber and Kapeller (2020) showed that fiscal regulations in the EMU highly depend on structural deficits calculated by the *European Commission* (EC) and hence the underlying estimation method of PO.

In contrast a growing literature points out that common procedures of estimating PO suffer from serious theoretical problems as well as great differences of future and current PO estimates (see Fontanari, Palumbo and Salvatori, 2020; Fatas, 2019; Coibion, Gorodnichenko and Ulate, 2018; Heimberger and Kapeller, 2017; Lenza and Jarociński, 2016; Ball, 2014). One aspect I try to solve in this thesis is the pro cyclical behavior of many PO estimates, which usually does not come with argumentation about causes of build up and losses of production capacity. Another issue I try to solve is that there is no reason why stable under utilization of production capacity, especial labor, should not appear, still conventional models prevent this situation by construction. A third aspect I try to solve is that even though the core of many models is capable of describing above mentioned facts correct, the outer part or the input variables are such that these problems still arise. This is in particular true for the EC's PO model (Havik et al., 2014) and the notion of the non-accelerating wage rate of unemployment (NAWRU), which shows some similarities to a moving average of unemployment.

The aim of my thesis is to provide an alternative procedure to calculate the Austrian PO. Therefore I use the method established by Okun (1962) and extended by Fontanari, Palumbo and Salvatori (2020). The basic idea is to estimate Okun's law and use the coefficient of the GDP growth rate to calculate PO. In chapter 2 I give a quick overview of commonly used PO estimates and their predictions for Austria. Moreover I formulate a short critique on these procedures and introduce the adapted Okun's method. I describe used data, the model selection process in detail, intermediate results and do a pseudo forecast in chapter 3. Chapter 4 is devoted to the *High Demand Potential Path* (HDPP), I introduce the concept and discuss intermediate results. In chapter 5 I present results linked to both the adapted Okun's method and the HDPP framework and discuss limitations and extensions of the overall framework. Chapter 6 recaps the thesis and concludes.

2. What is Potential Output?

What could an economy produce if production capacity was fully utilized? This question can be answered quiet differently. Not only estimation procedures differ, but also fundamental assumptions about the term full utilization. Before an alternative estimation procedure is presented some general topics of PO need to be clarified.

2.1. Common Approaches to Potential Output

Usually PO is defined as output that would be feasible, if all production factors were fully utilized, hence it is a supply side measure. Still often production factors and production functions are not known or poorly measured, at least on an aggregate level. Therefore all PO measures are based on assumptions what full utilization of production factors is. And these again are founded in theoretical beliefs about the business cycle, diverging tremendously across different schools. A good overview of different concepts of Potential output is given by Hauptmeier et al. (2009) and Horn, Logeay and Tober (2007).

Without diving too deep into history of economic thought it is important to mention two concepts of the business cycles previous to a more concrete examination of PO estimates. The first one is the interest rate gap described by Wicksell (see Hauptmeier et al., 2009, pt. 10 ff). Wicksell finds a gap between a natural rate of interest, which equalizes savings and supply and the money interest rate. Wicksell believed that if the natural rate of interest changed because of an external shocks, the market forces the money interest rate to adjust, such that both rates eventually equal. It was also Wicksell who came up with the image of the rocking horse representing the business cycle. If the horse is pushed it begins to sway, independent of the character of the stick pushing it and after some time it stops moving, if no further impulse is given. This characterization of the economy, i.e. oscillating around a stable situation and getting pushed along the way, influenced beliefs about shocks and their interactions, as well as business cycle analysis significantly.

The other concept is the idea of effective demand by Keynes, which in contrast to the Wicksellian view allows aggregate demand to be lower than PO, even if external shocks are absent (see Hauptmeier et al., 2009, pt. 18 ff). Moreover Keynes believed that the regular situation of the economy is one where aggregate demand does not match PO. Hence there usually is a need for interventions by the government through fiscal policy. Both Wicksell's and Keynes' view on the business cycle can be found in numerical analysis of PO still. However the modeling approach and the results do not match the same dogma always.

Taking a closer look at estimation procedures one can distinguish at least two fundamentally different approaches. On one hand defining potential as a (moving) average of economic variables, on the other hand using (arbitrary) measures for full employment of resources. It is noteworthy that the first approach is only compatible with the Wicksellian view of the business cycle and PO.

Univariate filters, e.g. Hodrick-Prescott filters, directly define potential output as an average of real output. Other methods are based on smoothed paths of other variables

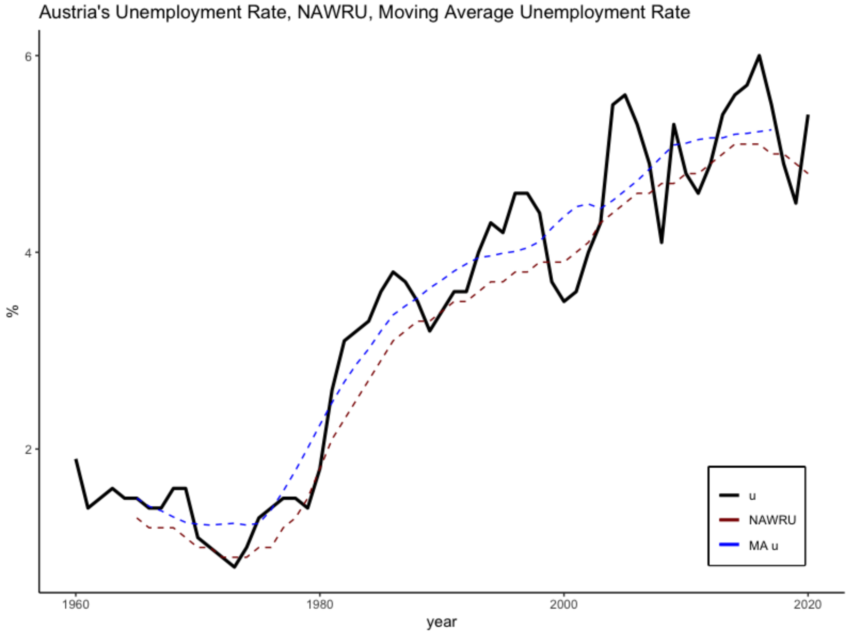

Figure 2.1.: Unemployment rates according to the ILO definition, 2021 EC NAWRU estimate and a two sided 11 year moving average of the unemployment rate. Own calculation, AMECO (see appendix A.1).

assembled to an economic model of potential output. E.g. the NAWRU estimate by the EC, used in a production function model, is a complex measure with several exogenous input variables, such as unemployment benefits, inflation and a wage mark up (Havik et al., 2014), however the resulting NAWRU estimate roughly seems like a down shifted moving average of the unemployment rate, see figure 2.1. But if all inputs to the core model, i.e. a Cobb-Douglas production function, are smoothed versions of the actual production factors, PO estimates will roughly be smoothed versions of real output.

Other measures of full employment seem to be somewhat less common. This might be due to measurement problems or the need for strict assumptions over economic variables. One example is the approach of Shaikh and Moudud (2004) who define PO as the part of output that co-varies with the capital stock. An other example is the approach of Okun (1962), who estimates the elasticity of unemployment rates with respect to output growth and defines PO as output which would be necessary to reach a target level of unemployment, which itself is set arbitrarily.

One can also differentiate PO measures along their estimation methods. Horn, Logeay and Tober (2007, p.6) distinguish three categories: purely statistical methods, semi-structural methods and economic/structural methods. Only univariate filters are purely statistical methods as no relationship of economic variables is needed. In semi-structural models interaction between different economic variables are estimated but none of the factors are exogenous, i.e. multivariate filters. The structural methods are driven by one or more exogenous variables. Following this classification, only the structural models do measure capacity utilization not necessarily relying on averaging economic variables.

2.2. Austria's Potential Output

Austria's PO is measured by multiple institutions. Two of the politically most important estimates, as well as a Hodrick-Prescott filter (HP-filter) for comparison, are briefly discussed below. The most important measure is the one estimated by the EC as it directly influences Austrian fiscal politics through the EMU fiscal rules. The second measure is estimated by the *Österreichisches Institut für Wirtschaftsforschung* (WIFO), which is one of the most important economic research institutes in Austria. The second estimate is closely related to the first one, still estimates differ.

Havik et al. (2014) describe the production function approach to estimate PO used by the EC. A production function approach is used whereby working age population, the labor force participation rate, the NAWRU, an investment to PO ratio, the total factor productivity and hours worked are exogenous variables and potential labour input, investment, capital stock and PO are endogenous variables. The production function itself is a Cobb-Douglas production function, where the output elasticity is estimated using the wage share and assuming constant returns to scale and a factor price elasticity equal to one. Both the total factor productivity, which is taken as a Solow residual and the NAWRU are estimated using a Kalman filter. The estimation method used by WIFO is based on the model by the EC. However trend output is smoothed stronger and restrictions to the closing up of the output gap are dropped (Baumgartner and Kaniovski, 2021).

Figure 2.2 shows these different estimates for Austria, beginning in the year 2000 up to 2019.[1] The red dashed line is the 2021 estimate of potential output by the EC. The orange line is the 2021 WIFO estimate of potential output, unfortunately only five year averages were available to me, hence the output gap arising is constantly -0.9 from 2011 to 2015 and 0.2 from 2016 to 2019. The blue line is the trend output estimated using a Hodrick-Prescott filter and annual data from 1951 to 2019, where λ is chosen to be 100. All three estimates are within narrow boundaries, even the most extreme gaps during the given period are smaller than +3.5% and greater than -2.7%. Moreover gaps are positive almost as often as they are negative. While the estimate of the EC and the HP-filter are negative in the same years and positive respectively, the HP-filter is smoothing real output a little stronger than the production function procedure by the EC does.

All three estimates indicate that the Austrian economy is close to its potential most of the time, and gaps switch signs within two to four years. Even in the year 2011, only two years after the great depression of 2009, the output gap according to the EC was +0.3%. Moreover the estimates presented above never show shrinking PO, i.e. even major crises like the great depression do not have a negative influence on production capacity, but only on growth rates of PO.

2.3. A Short Critique and Requirements For A Good Estimate

The estimates presented above are clearly not satisfying. And as Heimberger, Huber and Kapeller (2020) show fiscal rules within the EMU, strongly rely on estimation methods of PO provided by the EC. Therefore the need for alternative measures becomes obvious.

[1] Real GDP data are derived from the *WIFO Data System*, WIFO gap is taken from the *WIFO Monatsbericht* (Baumgartner and Kaniovski, 2021), the commissions gap estimate is downloaded from the AMECO data base. PO estimates I calculated by my self using these data. A detailed description of the data can be found in appendix A.1

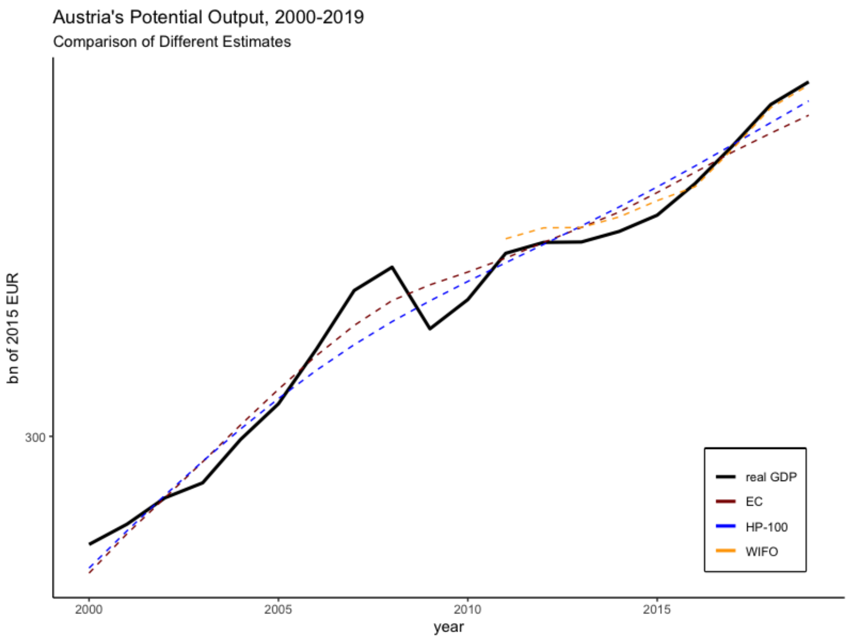

Figure 2.2.: Potential output of Austria, different estimates. Logarithmic scale.

Some of the above discussed methods carry the possibility of unutilized capacity while the economy is operating on potential. And estimates are close to a moving average in the medium run. In what follows I will briefly present my critique and give requirements for a good PO estimate.

First of all smoothing of input variables leads to biased results. Hence two problems arise. Firstly within the framework there is a possibility of unutilized capacity while the economy is predicted to operate at its potential. This is a contradiction to common definitions of PO. The problem may arises if capacity is not fully utilized over a period long enough. Secondly smoothed variables usually suffer from an endpoint bias. Unexpected shocks, e.g. a global pandemic, might appear and hence a few years late estimates for the same year might differ significantly. This is due to the fact that there is no qualitative distinction of shocks and lasting change. Considering real time estimates of PO predictions will be pro cyclical.

Secondly if a univariate filter like the HP-filter is used, it is implicitly assumed that PO is a fictive state of the economy around which the real output oscillates. The idea of real output waving around an equilibrium output is wide spread, but it is not the same as the full utilization of resources. E.g. while according to the HP-filter the Austrian PO oscillated around real output in the period of 2000 to 2019, unemployment increased considerably, hence labor was underutilized. Additionally two sided filters, like the HP-filter, usually suffer from an endpoint bias, hence estimates are reliable only in the center of the series. Both aspects may also apply to multivariate filters, dependent on the precise implementation of the filter.

Third of all production function approaches which strongly rely on the notion of a NAWRU or NAIRU implicitly introduce constraints on labor supply. These are not based on technical or structural arguments but rely on (assumed) market outcomes. On a theoretical level it is clear that there is a supply side constraint on the labor market, other than an unemployment rate of zero, due to frictions on the market, mismatching, etc. Still what exactly this boundary is is not clear. For Austria NAWRU estimates by the EC seem far off. E.g. in 2019 the annual NAWRU estimate was 4.9% and actual unemployment following the ILO definition was 4.5%[2], i.e. a positive employment gap was estimated. Looking at the official Austrian definition which includes all unemployed persons the rate was 7.4%. If moreover all people in training at the Austrian employment agency, *Arbeitsmarktservice* (AMS), are counted as well the unemployment rate was 8.9%[3]. The levels of the different unemployment rates differ due to their definition. Still if one considers an unemployment rate of 8.9%, during an upturn of the cycle, it is hard to believe this is a situation of over utilization of the labor force. It seems more likely that a lack of demand leads to these unemployment rates, and hence PO should be higher than what the EC estimates. Another problem of the notion of the NAWRU becomes clear here, i.e. a certain horizon within which PO can be reached is implicitly assumed. Putting it another way, if higher demand leads to more than proportionally increasing productivity one needs to fix a horizon within which PO is valid. If the NAWRU estimate is somewhat close to a moving average this means that the absence of fiscal or general economic policy is implicitly taken into account in the PO estimate.[4]

Considering these criticisms some requirements for a good estimate arise. First of all following the definition of PO as full utilization of capital and labor, a PO estimate must not show under utilization of capacity. That means PO is a situation of full employment and must not be biased by assumptions about demand, leading to market outcomes determining the structural unemployment. Secondly the possibility of a stable output gap must not be prevented by construction, i.e. full employment of resources must be defined exogenously or has to be based on microeconomic analysis. Thirdly the estimation procedure has to have a meaningful economic interpretation, hence the estimation method needs to follow theoretically founded causality chains. An additional last point is that the PO estimation method has to be in line with an underlying growth model, i.e. if growth is demand driven, estimation of PO has to mirror corresponding theoretical principles.

2.4. Okun's Method Revisited

One already existing procedure full filling many of the above described requirements is Okun's method (Okun, 1962). However the estimation procedure can be improved and crucial points about the structural elements in his calculation need to be revisited.

2.4.1. Okun's Original Approach

Okun's 1962 paper is the starting point of the discussion and estimation of PO as it is performed today. Considering full employment as a policy goal, he presented a procedure to estimate a fictive GNP produced under the assumption that the goal is reached. Full

[2]Data on NAWRU and ILO unemployment measure were downloaded from the AMECO data base, for more information see appendix A.1

[3]Official Austrian unemployment data and data on people in training at the AMS were derived from the AMS database, for more information see appendix A.1

[4]As will be seen later this problem might also apply to my estimate, however only in a very limited way as structural elements in my model are not biased by this.

employment was considered to be reached at a 4% unemployment rate. The target is arbitrarily set, arguing that at this level price stability is given. His estimation approach is based on the idea that changes in the unemployment rate and GNP are negatively correlated, this relatively stable empirical relationship is today known as Okun's law. Hence if one estimates a coefficient which relates unemployment changes to changes of GNP, one could use this coefficient to calculate the GNP if the unemployment rate was 4%. This coefficient is often referred to as Okun's coefficient. Given the estimation procedure Okun presents he answers the question how much would the economy have to grow to reach full employment.

In the original paper three different estimation methods where stated: the *first difference* specification, the *trial gap* method and the *fitted trend and elasticity* approach (Okun, 1962). The *first difference* estimation is implemented as a simple OLS regression, where the first difference of the unemployment rate is the regressand and regressors are an intercept and the growth rate of GNP. The *trial gap* specification of PO is estimated by regressing unemployment rates on a constant and an output gap. The assumed path of PO should thereby fit the GNP trend, residuals must not be trending and PO should be equal to actual GNP if unemployment is equal to 4%. For the third approach a constant elasticity relationship between the output gap and the fraction of the employment rate to a target employment rate is assumed. Additionally the GNP growth rate is assumed to be constant. Subsequently the output elasticity of the employment rate, the potential growth rate and a benchmark PO can be estimated. This third approach does have rather strong assumptions on the functional form of the Okun relationship, hence it has not been used often recently.

The *first difference* approach relies only on changes of output and the unemployment rate. In contrast the *trial gap* method uses levels and one needs to assume a growth trend prior to the estimation of the Okun relationship. Many authors following the latter approach estimate a GDP growth trend using a HP-filter. For my purposes this is not satisfying as a trend of PO is assumed prior to the estimation of the coefficients used to calculate PO. Therefore I am going to focus on the *first difference* approach in what follows.

Beside these three estimation methods Okun (1962) himself pointed out some problems oft his approach. One aspect is the question how average working hours and labor force participation rate changed under a situation of constant full employment. Okun could not answer this question as corresponding data were not collected at this time. Another question raised is how productivity evolved under full employment. Productivity might be influenced by several factors, e.g. the size of the labor force, the average working hours and the utilization rate of capital.

2.4.2. Expansions

It is a common expansion to estimate the Okun's law dynamically and to account for structural breaks in the relationship. One could also think of non linear estimation of Okun's law to catch asymmetries throughout the business cycle. In addition the questions raised by Okun can be answered using a different approach, explained below.

Unemployment Threshold Approach Many authors find evidence that Okun's law is not stable over the business cycle or time (see Jalles, 2019; Lim, Dixon and van Ours, 2019; Ball, Leigh and Loungani, 2017; Meyer and Tasci, 2012; Knotek II, 2007). Most of these studies find that the GDP growth coefficient is larger in absolute terms during recession periods. E.g. performing a rolling regression on quarterly US data Knotek II (2007) finds that the effect of GDP growth on unemployment rates is stronger if there are more recession quarters within the regression window. Ball, Leigh and Loungani (2017) also uses quarterly US data for his analysis, he includes dummies for recession periods to his regression and allows for two lags. He finds that there are fixed effects as well as changes in the Okun coefficient during recession periods. Even though these approaches lead to remarkable results they strongly rely on the identification of recessions. Moreover it is not easy to implement these procedures for annual data, as recessions might last shorter than one year and recession quarters might be distributed over two calendar years.

A different approach is chosen by Fontanari, Palumbo and Salvatori (2020) who link changes in the coefficients of Okun's law to different regimes determined by level of unemployment. Their argumentation is also linked to the business cycle, i.e. that asymmetries in the Okun relationship arise as firms deal differently with layoffs and hiring employees according to the state of the economy. The method they use is promising as one does not have to identify recessions to estimate Okun's law and setting arbitrary thresholds captures the asymmetries of the relationship.[5] Still it is hard to capture effects due to business cycles in annual data. Moreover in the case of Austria there is good evidence that regime changes on the labor market do not come along business cycle up- or downswings, see section 3.2.2.

Beside capturing the position in the business cycle a regime switching model of Okun's law could be a useful tool to investigate different labor market regimes in the medium to long run. As will be discussed in section 3.2.2, I find evidence for at least two regimes of the Austrian economy. A high demand and a low demand regime, the last one is characterized by significantly higher unemployment rates. In a theoretical framework of demand-led growth the high demand regime is characterized by higher productivity, i.e. growth is not solely higher due to more hours worked but also due to an increase in total factor productivity. One argument for that idea is that unemployed people lose skills and knowledge in contrast employed people gain experience[6], therefore the factor productivity of labor varies parallel to employment. Hence if one unemployed person is brought to employment, output is increasing more than the average product of one employee ceteris paribus. On the contrary if demand decreases, unemployment increases and output growth decreases more than proportional. In the medium to long run these effects should be seen if growth is decomposed into hourly labor productivity, employment and other factors.

Output Identity and High Demand Potential Path The idea of a *high demand potential path* (HDPP) as Fontanari, Palumbo and Salvatori (2020) suggest, is to set a benchmark of PO growth. Thereby they also try to answer the questions raised by Okun (1962), i.e. how

[5] Even though I think in their paper the functional form of unemployment rate levels and GDP growth determining unemployment rate changes is captured well, their model selection could be improved. While Fontanari, Palumbo and Salvatori (2020) arbitrarily choose thresholds to be at the first and second empirical tercile, there are more systematic procedures to identify thresholds. Two approaches are provided in section 3.2.2. Still their model is significant and results seem to support their theoretical reasoning.

[6] It is not clear that the average loss of knowledge automatically leads to an average loss of knowledge in the working population. However it seems reasonable to assume that every person in the labor force is employed fewer days each year if unemployment is higher.

productivity, working hours and labor force growth evolve during a high demand period. They use a simple decomposition of output, the *output identity*, proposed by Robert J. Gordon (see Gordon, 2014). It can be seen in equation 2.1. To calculate the HDPP Fontanari, Palumbo and Salvatori (2020) hold unemployment constant and extrapolate the other components of growth during a high demand period over forthcoming periods of lower demand. However Fontanari, Palumbo and Salvatori (2020) omit working age population in their decomposition.

$$Y \equiv \frac{Y}{H} \cdot \frac{H}{E} \cdot \frac{E}{L} \cdot \frac{L}{N} \cdot N \tag{2.1}$$

In equation 2.1 Y corresponds to the real GDP, H to the aggregate hours worked, E to the number of all people employed, L to the labor force and N to the working age population.[7] As one can easily see this identity holds by definition, however the hourly labor productivity could still be interpreted in various ways. Even though it is not a residual like the Solow residual, it is hard to adequately measure hourly labor productivity on a micro level.

[7] Gordon (2014) uses an additional bridge term to combine different survey data of working hours.

3. Adapted Okun's Method

Below I follow the approach of Fontanari, Palumbo and Salvatori (2020) to estimate PO. However I do not try to capture business cycle effects using a regime switching model, but investigate long term regime switches on the Austrian labor market. Hence PO estimation is somewhat closer to Okun's original approach.

3.1. Data I

For the estimation of PO following the adapted Okun method time series data on output and unemployment rates are required. To estimate the HDPP additional data are needed these are described in section 4.1. Okun's law for Austria was significantly estimated applying various procedures using both quarterly (Christl, Köppl-Turyna and Kucsera, 2017; Ball, Leigh and Loungani, 2017; Sögner, 2001) and annual data (Fontanari, Palumbo and Salvatori, 2021; Christl, Köppl-Turyna and Kucsera, 2017; Jalles, 2019; Ball, Leigh and Loungani, 2017).

To capture long run regime changes in the Okun relationship I choose to work with annual data as these are available since 1946. Real GDP data are provided by the *Wifo Daten System* (WDS). Absolute unemployment data, as well as data on people in training at the AMS and employed people are accessed via the AMS database. A detailed description of the sources is found in appendix A.1.

Unemployment rates are calculated by means of the absolute number of unemployed and employed people which together sum up to the labor force. The unemployment rate is calculated as the share of unemployed people in the whole labor force. In what follows I am going to use two different definitions of unemployment rates. The official Austrian definition (from now on *official*) for which people in training at the AMS are counted as employed. And an alternative definition for which people in training at the AMS are counted as unemployed (from now on *training*). I think the alternative definition is more adequate as training programs at the AMS are designed for unemployed persons and participation is often required to get unemployment benefits. These training programs were introduced in 1987, hence both definitions share the same values up to 1986.

Even though data are available from 1946 to 2020 I choose the period of 1951 to 2019. This is necessary as the extreme output growth and the increasing unemployment rates immediately after the war have a huge influence on the overall estimation but do not represent the post war period well. Hence I choose to truncate the data up to the year 1951. This was the first year after the war where unemployment rates where decreasing. It is noteworthy that 1951 was also the first year after the war where GDP growth was below 10%. And it was the first year except for 1946 where changes in output and unemployment pointed in opposite directions. Given the high growth rates above 10% at that time, one intuitively expects decreasing unemployment rates. Hence estimation of Okun's law before 1951 might be biased by indeterminate labor market effects due to recovery of war. 2020 I exclude as I do not want the current Corona crisis to bias my results.

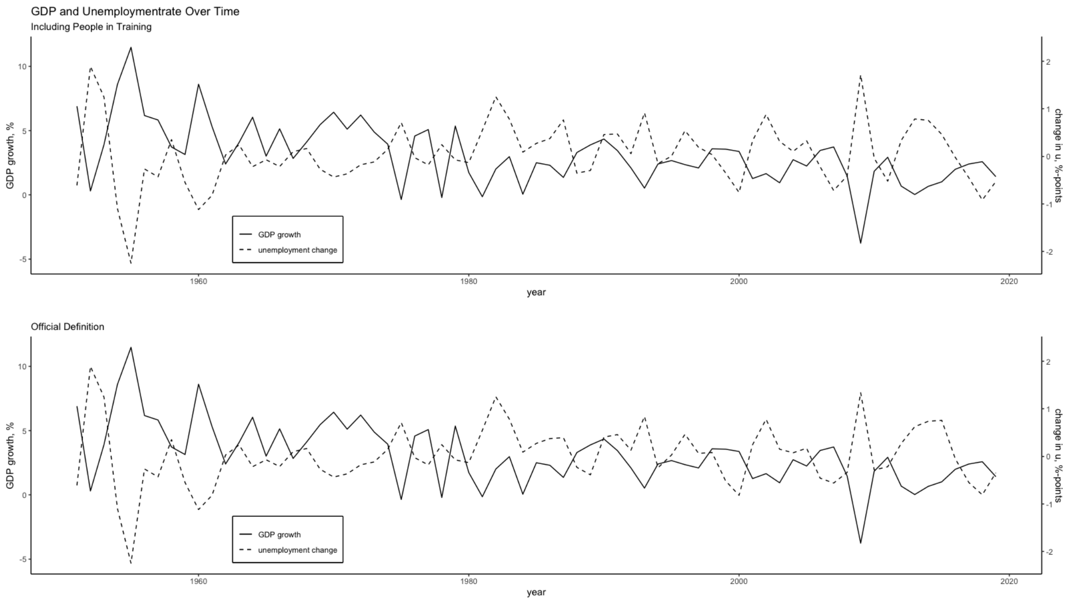

Figure 3.1.: Annual GDP growth rates and annual change of unemployment rates, 1951 to 2019. WDS, AMS (see appendix A.1)

GDP growth rates and unemployment changes can be seen in figure 3.1. Even with the naked eye the correlation of these two variables is visible, however not much more can be said about the Okun relation at this point. Noteworthy as well is that the changes in the unemployment rate do have a mean greater than zero. Hence throughout the given period the unemployment rate increased. However in the 1960s and 1970s unemployment rates where low and reached their minimum at 1.2% in 1973. GDP growth rates are lower on average since the early 1970s. This is not necessarily influencing the estimation process of Okun's law, but is an important aspect if one analyses the post war economy of Austria.

3.2. Model Selection and Estimation of Okun's Law

According to the investigation of the data and the strong theoretical arguments described in the previous chapter, the Okun relationship of Austria might not be as simple as it was estimated originally. Hence I have to select a suitable model. There are statistical procedures to test for auto correlation and structural breaks. However it is up to theoretical argumentation and intuition to decide how to handle potential regime changes of the Okun relationship. In what follows I will present different models to motivate my decision, starting with the simplest one and proceeding to more complicated versions. Thereby I use both *training* and *official* unemployment rates. All calculations and estimations were done using the R Software (R Core Team, 2019).[1]

[1] Thereby I used R-Studio as well as the Packages: AER, diptest, dynlm, forecast, ggplot2, gridExtra, haven, mFilter, psych, stargazer, strucchange, tidyverse, TRAMPR, tseries

3.2.1. Baseline Selection

My starting point is the simplest version of Okun's law, see equation 3.1:

$$\Delta u_t = \alpha + \beta \gamma_t^y + \varepsilon \tag{3.1}$$

Δu_t denotes annual change of unemployment rates measured as percentage points and γ_t^y denotes yearly growth rates of GDP, represented as percentages. To rule out spurious regressions I perform Dickey-Fuller and Phillips-Perron tests on each variable. Both tests reject the null hypothesis of a unit root on each variable, i.e. real GDP growth and absolute change in unemployment rates for *official* and *training* data. Results of a simple OLS regression are shown in table 3.1. The overall models as well as the single coefficients are significant, nonetheless the explanatory power is not very good. Moreover residuals show some structure as indicated by an autocorrelation function and a partial autocorrelation function.

To solve this issue I allow for an autoregressive part of Δu. The number of lags is chosen using the AIC, allowing for a maximum of two lags. I also allowed for a maximum of two lags of γ^y. AIC indicates that two lags of unemployment and no lags of γ^y is the best model. Results of the so selected model can be seen in table 3.1, again OLS estimation was used. Significance of the model again is given and there is no obvious structure in the residuals. Even though models (2) and (4) in Table 3.1 already fit the data well the internationally compared relatively small Okun coefficient (see Ball, Leigh and Loungani, 2017) might indicate further structure in the data, e.g. structural beaks.

To detect breaks I perform a rolling regression, using a simple autoregressive distributed lags model, with two lags of unemployment change and only same period γ^y, such as (2) and (4) in table 3.1. Choosing 30 years per window the first regression period ends in 1981, figure 3.2 presents the Okun coefficient both for *training* and *official* data. Both series of unemployment rates show analog patterns. First of all the coefficient for the periods ending in 2004 and later fall as the regression window shifts towards 2015, with only one exception in 2012. The huge drop as the year 2009 is included most likely is caused by the great depression. Secondly the coefficients rises remarkable as the observation of 1955 drops out of the regression period.[2] Thirdly there is a large drop in the coefficient from the window ending in 1992 to the one ending in 1993. An economic explanation for the one-time changes of Okun's coefficient for the windows ending in 1986 and 1993, is not found right away. The shrinking of the coefficient after 2005 might be due to slowly evolving structural changes, most likely connected to the oil-price shock in 1973.

Additionally I perform a *Quandt likelihood ratio test*. The distribution of the test statistic is nonstandard, but the procedure is easy to implement by running a series of *Chow tests* and choosing the year corresponding to the highest F-statistic as a break point. For more details regarding the procedure see Stock and Watson (2011, Section 14.7). For the required trimming of the sample I allow for breaks to appear earliest in 1957 and latest in 2013 which is a roughly 10% cutoff on both sides. The model I test for structural breaks is the simple difference approach of Okun's law, as shown in equation 3.1. The test is performed using *training* as well as *official* data. Critical values of the test statistic are provided by Andrews (2003). I test both, solely allowing the intercept to change and

[2] In 1955 both the highest GDP growth rate (11.5%) and the greatest reduction in unemployment rate (-2.2 %-points) of the whole sample appear.

Table 3.1.: Baseline static and dynamic estimation of Okun's law

	training		*official*	
	Δu_t	Δu_t	Δu_t	Δu_t
	(1)	(2)	(3)	(4)
γ_t^y	-0.194^{***}	-0.161^{***}	-0.183^{***}	-0.148^{***}
	(0.023)	(0.021)	(0.023)	(0.021)
Δu_{t-1}		0.302^{***}		0.318^{***}
		(0.079)		(0.080)
Δu_{t-2}		-0.276^{***}		-0.256^{***}
		(0.078)		(0.079)
Constant	0.650^{***}	0.525^{***}	0.594^{***}	0.462^{***}
	(0.093)	(0.082)	(0.091)	(0.080)
Observations	69	67	69	67
R^2	0.504	0.623	0.488	0.606
Adjusted R^2	0.497	0.605	0.480	0.587
Residual Std. Error	0.466 (df = 67)	0.390 (df = 63)	0.454 (df = 67)	0.380 (df = 63)
F Statistic	68.102^{***} (df = 1; 67)	34.642^{***} (df = 3; 63)	63.798^{***} (df = 1; 67)	32.251^{***} (df = 3; 63)
Note:				$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

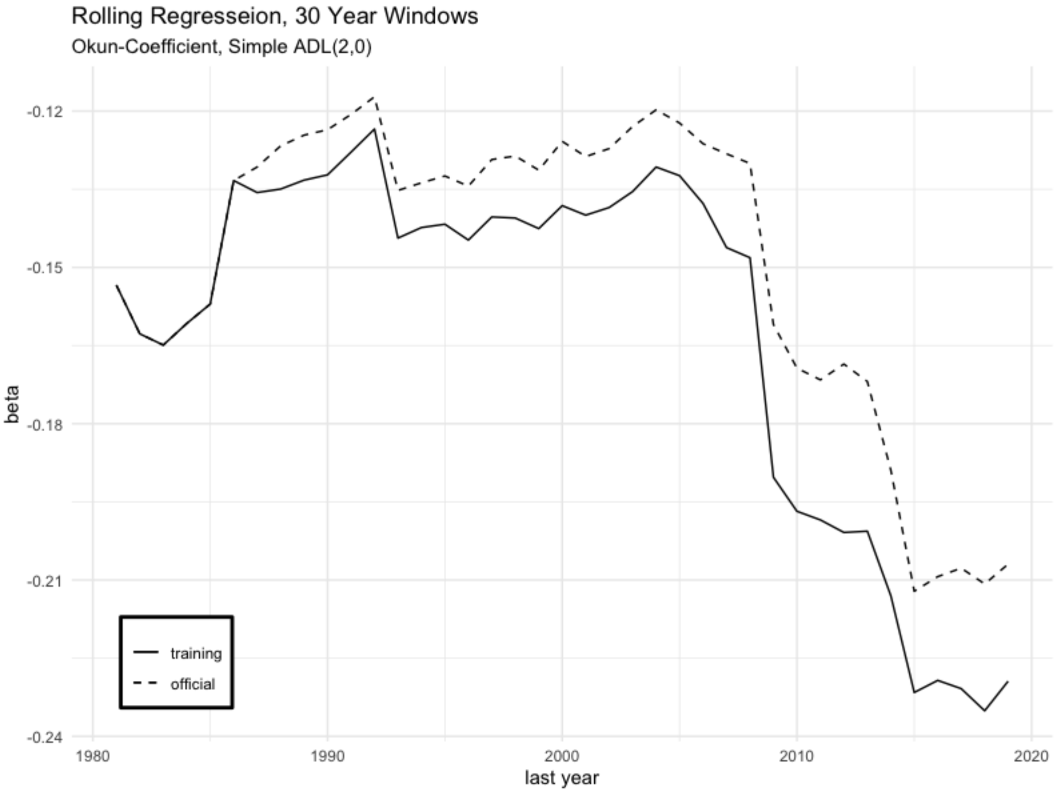

Figure 3.2.: Rolling regression: GDP growth coefficient of a ADL(2,0) model as (2) and (3) of table 3.1 applied to 30-year windows

allowing all coefficients to change simultaneously. While a break regarding the intercept only is found in 1998, if I allow for a break of the other coefficient as well a break is found in 1958. However the second largest value of the series of F-statistics in the latter case, which lies outside a reasonable large region close to 1958, corresponds to 1998.

Aware of the possibility of more than one structural break I test for up to three breaks. Therefore I follow the procedure suggested by Bai and Perron (1998) to detect a good number of breaks and identify breaking years. The model I test again is the simple Okun's law model, as shown in equation 3.1. The cutoff of the data is again set to 10%, however the *strucchange* package in R is rounding slightly different here, hence a break in 1956 is possible. I find two breaks for both time series. The first break corresponds to the year 1956 for both series, however for the *official* data the second break is found in 1998 and for the *training* data a second break appears in 2006.

I suppose each breaking point 1956, 1998 and 2006 is valid, hence in a next step I estimate two different models for *official* and *training* data, including two breaks each. Breaks apply to both output growth and the intercept, in each case. Results of the estimation are shown in table 3.2, column (1) and (3). The model as well as its coefficients are significant and fit the data notably well. Differences between periods are not only significant but also come with a huge difference in coefficient estimates, as well as the GDP growth rate stabilizing the unemployment rate.[3]

[3] In the case of equation 3.1 the stabilizing GDP growth rate is equal to $\frac{-\alpha}{\beta}$.

I additionally estimated a dynamic versions. I use AIC and allow for a maximum of two lags of both change in unemployment and output growth, to select the adequate model. Again including the first lag of unemployment change and no lag of GDP growth is chosen. Estimation results are shown in columns (2) and (4) of table 3.2. All components and the overall models are significant. Compared to the static versions the fit of the model improves, as indicated by an increasing adjusted R^2. All coefficients are smaller in absolute terms in the dynamic versions, with the exception of the coefficient corresponding to GDP growth in the latest segment, for the model using *training* data. However coefficients of the dynamic and static version are somewhat close.

Still the dynamic model with two breaks is not satisfying for my purposes. As discussed in more detail below, if it is used to calculate PO an increase throughout the 1980s and most of the 1990s and a huge drop in 2006 and 1998 is predicted, for *training* and *official* data respectively. The drop in 1998 for the *official* series, might be due to the introduction of the *Euro*, nonetheless the reduction of PO seems too extreme. The drop seen after 2006 described by the other model could be explained as the start of the 2007 financial crisis. The fast growth throughout the 1980s and 1990s appears to be peculiar as it would have happened simultaneously to a lasting slow down of the Austrian economy. Moreover it seems unrealistic that the huge output gap in 1998 or 2006 was partially closed, due to destruction of unused production capacity, coming along with the introduction of the *Euro* or the crash on the financial markets. I discuss this argument again in more detail in section 3.3. Hence I follow a different estimation approach in the next subsection, taking into account that the Okun relationship might change if unemployment rates cross a certain threshold, i.e. demand changes considerably.

3.2.2. Investigating Employment Regimes

Looking at the distribution of unemployment rates gives some insights about the structure of the data. Figure 3.3 shows a histogram and a kernel density function, as well as some distributional parameters of the unemployment rate. First of all the the empirical distribution of the unemployment rate is not unimodal, but the one of real GDP growth is. This is confirmed by a *dip test.* If the unemployment data sets are split into two sub sets separated by the antimode of their kernel density[4], both subsets follow a normal distribution as indicated by a *Shapiro-Wilk test.* Observing a bimodal distribution of unemployment rates indicate that the Austrian economy was facing different labor market regimes. These most likely come with a changed relationship of output and unemployment. Secondly looking at the subset in which unemployment rates are lower than the antimod of the overall distribution, it is noticeable that it includes all observations from 1960 to 1982 and no other observations. This is true for both *training* and *official* data. Hence there are labor market regimes, but they switch in the long run only and not following the business cycle. Hence the findings for the Austrian economy are qualitative different from those Fontanari, Palumbo and Salvatori (2020) find for the USA. Still a regime switching model could be a powerful tool to capture structural change in Okun's law for Austria, in the long run.[5]

[4]Both kernel densities are calculated using a Gaussian kernel. The bandwidth for the training data is 1.094, for the official data it is 0.884. These bandwidths slightly differ from the ones used in figure 3.3.

[5]However for calculative reasons I operate as if the regime switches are break points at a certain date. Hence given the estimation results, discussed below, I can not make any predictive statements about

Table 3.2.: Okun's law including two structural breaks, static and dynamic estimation

	training		*official*	
	Δu_t	Δu_t	Δu_t	Δu_t
	(1)	(2)	(3)	(4)
$du_t^{\leq 1956}$	2.244***	2.242***	2.244***	2.243***
	(0.287)	(0.274)	(0.282)	(0.271)
$du_t^{>1956 \wedge \leq 2006}$	0.594***	0.534***		
	(0.098)	(0.095)		
$du_t^{>2006}$	0.517***	0.512***		
	(0.119)	(0.113)		
Δu_{t-1}		0.190***		0.182***
		(0.062)		(0.064)
$\gamma_t^y \times du_t^{\leq 1956}$	−0.390***	−0.379***	−0.390***	−0.379***
	(0.040)	(0.038)	(0.039)	(0.038)
$\gamma_t^y \times du_t^{>1956 \wedge \leq 2006}$	−0.162***	−0.147***		
	(0.026)	(0.025)		
$\gamma_t^y \times du_t^{>2006}$	−0.371***	−0.376***		
	(0.054)	(0.052)		
$du_t^{>1956 \wedge \leq 1998}$			0.567***	0.510***
			(0.106)	(0.103)
$du_t^{>1998}$			0.505***	0.494***
			(0.109)	(0.104)
$\gamma_t^y \times du_t^{>1956 \wedge \leq 1998}$			−0.151***	−0.136***
			(0.027)	(0.026)
$\gamma_t^y \times du_t^{>1998}$			−0.288***	−0.285***
			(0.046)	(0.044)
Observations	69	68	69	68
R^2	0.743	0.775	0.731	0.760
Adjusted R^2	0.719	0.749	0.706	0.733
Residual Std. Error	0.346 (df = 63)	0.327 (df = 61)	0.339 (df = 63)	0.323 (df = 61)
F Statistic	30.409*** (df = 6; 63)	30.049*** (df = 7; 61)	28.553*** (df = 6; 63)	27.641*** (df = 7; 61)
Note:				*p<0.1; **p<0.05; ***p<0.01

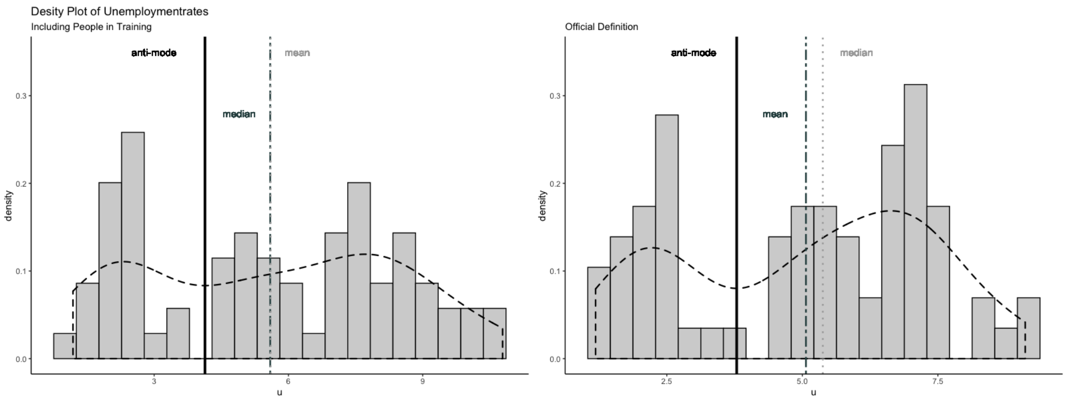

Figure 3.3.: Empirical distribution of unemployment rates and distributional parameters.

In addition I test for breaks in the empirical cumulative unemployment rates distribution. The procedure is not a formal test but helps to interpret the data. Firstly the unemployment rates are ordered increasingly, secondly a linear trend of unemployment rates is assumed, thirdly a test for structural breaks is executed. I again used the *strucchange* package in R and tested for up to two breaking points, changes in the intercept as well as the slope are allowed and the cutoff value is set to 10%. For both *training* and *official* data I find two breaking points, i.e. three segments of unemployment rates. The observations corresponding to the lowest segment are the same as the ones detected using the kernel density approach. The other segments differ slightly across the different definitions of unemployment and do not cover a contiguous period each. Therefore I choose the two regime model described in the previous paragraph. It is however notable that the third segment found within the *training* data corresponds to the years from 2009 to 2018 with the exception of 2011 and 2012.

As a first step I estimate a static version of the regime switching model using OLS. The model is specified as follows:

$$\Delta u_t = \alpha_l L_t + \alpha_h H_t + \beta_l L_t \gamma_t^y + \beta_h H_t \gamma_t^y + \varepsilon_t \tag{3.2}$$

Where L (H) is a dummy taking the value one (zero) for all years from 1960 to 1982 and zero (one) otherwise. This corresponds to the threshold unemployment rates found, i.e. 4.14% for *training* data and 3.79% for *official*, each are the antimode arguments of the kernel densities. Estimation results are overall significant and all coefficients are significant for both data sets. Okun's coefficients of the low demand periods are greater in absolute terms compare to the ones of the high demand periods. Nonetheless this simple model does not explain the data much better than the simple static Okun relation without breaks if one considers adjusted R^2.[6]

In a next step a break for the introduction of the *EURO* is included, as it is a crucial change to the economy and coefficients were highly significant in estimations above.[7] The fit of the model improves and the coefficient for the introduction of the *EURO* is highly

upcoming regime switches. A detailed discussion is given in appendix A.2.1. For a detailed overview on threshold models in time series analysis see Tong (2011)

[6]The estimation table A.9 is found in appendix A.2.2.

[7]Results can be seen in table A.9.

significant. However as the residuals show some structure an autoregessive part is included. The resulting model is shown in equation 3.3.

$$\Delta u_t = \alpha_l L_t + \alpha_h H_t + \theta euro_t + \phi \Delta u_{t-1} + \beta_l L_t \gamma_t^y + \beta_h H_t \gamma_t^y + \varepsilon_t \tag{3.3}$$

euro in the above equation corresponds to a dummy variable taking the value one for every year after 1998 and zero otherwise. Results of the estimation of the above model are shown in table 3.3. For the estimation process in *R* an ARMAX model is chosen, i.e. a maximum likelihood estimation. All coefficients are significant for *training* as well as *official* data[8] and variance of errors is considerably smaller than variance of Δu_t. In addition I perform a real time estimation of the unemployment rate, which shows values close to the experienced unemployment rate of the same period. Moreover regarding the goal of estimating PO of Austria, only the elasticity of changes in the unemployment rate with respect to output growth is needed. Therefore PO estimates might suffer from a small bias due to partially non stationary data but effects do not accumulate as estimates are corrected by new data in every period PO is estimated.

3.3. Intermediate Results

Once the estimation model of Okun's law is chose and estimated, one can calculate PO. Beside the model selection discussed above it is crucial to choose a suitable target unemployment rate. And robustness of the PO estimate has to be checked.

3.3.1. Potential Output and Output Gaps

Before continuing to calculate Po using the elasticity of the unemployment rate with respect to output it is necessary to clarify the interpretation of the result. One can calculate how the unemployment rate changes given the growth of GDP. Hence if a target unemployment rate is defined one can answer the question, "How much needs the economy to grow, such that the unemployment rate target is reached". The corresponding growth rate is then transformed into PO.

The definition of PO given by Okun (1962) can be seen in equation 3.4.[9]

$$Y_t^* = Y_t \cdot [1 - \frac{1}{100\beta_t}(u_t - u_t^*)] \tag{3.4}$$

Here Y_t refers to real output, Y_t^* is the PO and u_t^* is the target unemployment rate. Time indices of β and u^* display that changes over time occur, e.g. across different labor market regimes. PO is positively related to real output and the unemployment rate, as β is negative. The target unemployment rate and PO are negatively related, i.e. the closer the experienced unemployment rate is to the target the closer real GDP is to its potential.

Setting the target unemployment rate is the second most important task, beside the selection of the estimation model of Okun's law. Okun (1962) himself chose the target unemployment rate arbitrarily to be 4%. Fontanari, Palumbo and Salvatori (2020) chose it to be 3.4%, arguing that it corresponds to a historical minimum rate. Following this approach target unemployment for Austria would be roughly 1.2% reached in 1973.

[8] Coefficients are tested performing a z test, using the *coeftest* function in *R*.

[9] The formula is slightly adapted as I performed the estimation in terms of percentages.

Table 3.3.: A dynamic regime switching model of Okun's law

	training	official
	(1)	(2)
Δu_{t-1}	0.355***	0.334***
	(0.130)	(0.126)
du_t^L	0.469**	0.473***
	(0.188)	(0.183)
du_t^H	1.118***	1.025***
	(0.154)	(0.148)
$du_t^{>1998}$	−0.577***	−0.564***
	(0.173)	(0.166)
$\gamma_t^y \times du_t^L$	−0.120***	−0.122***
	(0.037)	(0.036)
$\gamma_t^y \times du_t^H$	−0.291***	−0.269***
	(0.031)	(0.029)
Observations	69	69
Log Likelihood	−31.530	−29.979
σ^2	0.146	0.139
AIC	77.060	73.958
Note:	*p<0.1; **p<0.05; ***p<0.01	

However in the respective year on average 31,327 people were unemployed, whereas 66,060 job vacancies were opened[10], which might indicate that targeting the minimum rate is targeting a situation of an over utilized labor market.

An alternative measure of structural unemployment could be defined by a Beveridge curve framework. Hence one defines the unemployment rate target such that the number of unemployed is equal to the number of job vacancies. Still this measure suffers from two other problems. Firstly it is not independent of the business cycle as firms hire workers over proportionally in an upturn and less than proportional in a downturn, hence it is rather a lower bound of structural unemployment than a direct measure. Secondly it is not necessarily true that everyone who wants to work is needed in the production process, given a certain stock of physical capital and technology. This means only labor market frictions are measured and again structural unemployment as defined within a Beveridge curve framework is a lower bound only. Within the sample for Austria the highest such lower bound is 2.5%, again occurring in 1973.

[10]Data on job vacancies were derived from the AMS, for a detailed description see appendix A.1

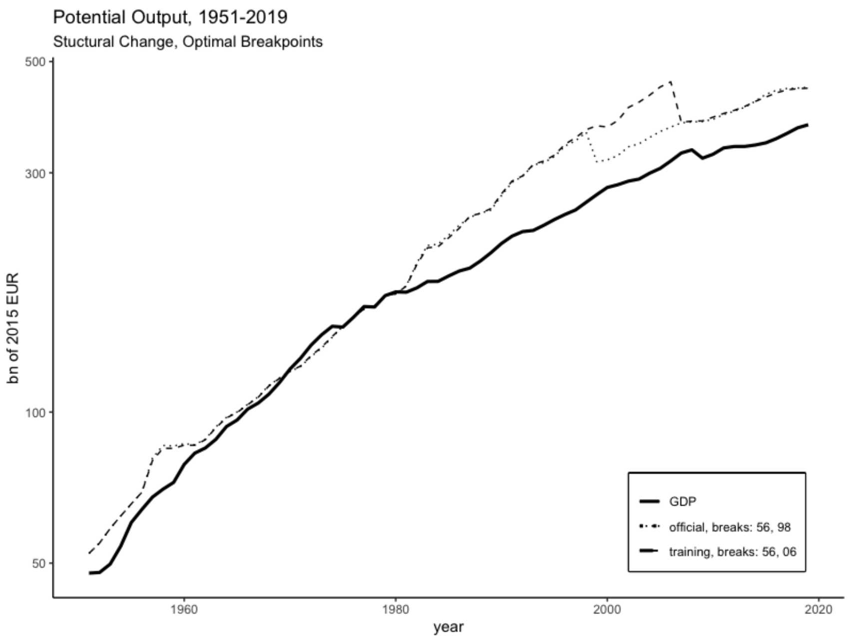

Figure 3.4.: Potential output, estimated with two structural breaks.

There is a wide variety of other measures of structural unemployment, however it was beyond the scope of this thesis to adapt more complex measures to the Austrian economy. If one follows the approach to set a single constant unemployment target, PO is a linear function of the target unemployment rate ceteris paribus.[11] Therefore it is not much of a problem if the rate is set arbitrarily, if one is interested in short to medium term analysis, as the target just shifts PO up or down. In what follows I am going to use a 2% target, which is slightly lower than the mean of the unemployment rates throughout the high demand period from 1960 to 1982.

Figures 3.4 and 3.5 show the PO of Austria from 1951 to 2019, for the model selected in section 3.2.1 and 3.2.2 respectively and *official* and *training* data each. Both models depict a stable under utilization except for a short period from 1970 to 1974, as well as the years 1977 and 1980, for which unemployment was below 2%.

It is clear that the PO estimates according to the baseline selection (section 3.2.1) do not show a realistic pattern of PO. The kinks in the series estimated seem unrealistic sharp. It is due to the estimation method that kinks instead of slow adjustment are predicted, hence estimates close to structural breaks are not meaningful. Still it seems unlikely that a negative shock to PO or a long lasting stagnation of it do not come simultaneously with crisis or shocks to the real economy. Breaks in the regime switching models are easily seen as well, but the kinks seem to be within boundaries reasonable close to estimates of previous years.

Looking at the regime switching model some thing can be said. Since the end of the 1980s output gaps are negative and perennially above 10% in absolute terms (see figure 3.6). Hence the Austrian economy has been constantly operating below its potential since then. Another interesting aspect is that PO does react to crisis such as the 2009 depression

[11]Three other possibilities to set the target unemployment rate are presented in section 5.2.

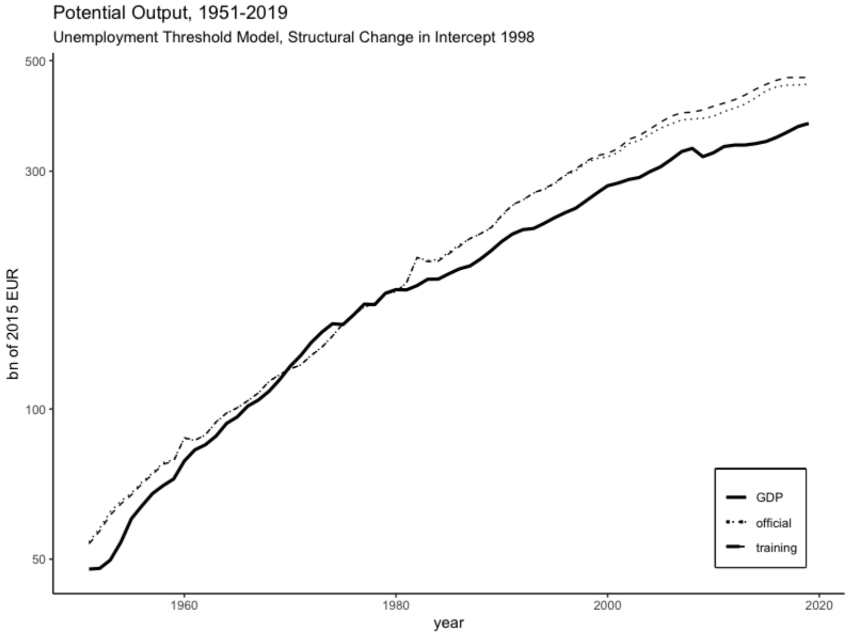

Figure 3.5.: Potential output, different unemployment regimes.

but is more stable. It is up to other work to discuss whether capacity was destroyed during the 2009 depression or not, however it is clear that the shock to the real economy was stronger than the one to PO. PO of Austria behaves anti cyclical aside from deep recessions as well, see e.g. the period of recovery after the 2011 recession. This indicates that during an upturn new capacity is build faster than it is utilized, until at some point utilization of capacity is faster than the build up of new capacity and hence full utilization of production factors is reached eventually.

3.3.2. Robustness

Checking the PO estimates for robustness one needs to look at two aspects. On one hand it is necessary to check for deviations of the estimated coefficients. On the other hand one needs to look at measurement errors of real output, the unemployment rate and the target rate of unemployment.

Figure 3.7 shows the evolution of Okun's coefficient from 2000 to 2019, whereas all previous observations back to 1951 are taken into account for each estimate. The graph shows that the coefficient estimated using training data is getting smaller after 2008 and steadily falls thereafter. The one using *official* data is also falling as 2019 is approached but only after 2012 and with a tiny increase from 2015 to 2016. There are other movements as well but these are comparatively small and do not show a clear tendency. To illustrate the difference in the PO estimate using different coefficient estimates it is easiest to look at output gaps. E.g. consider Okun coefficients estimated in 2000 and 2019, which are -0.263 and -0.291 respectively. Given a target unemployment rate of 2% the output gap in 2019 is -20.7% if the estimate of 2000 is taken and -19.1% if current one is used. Assuming that the 2019 measure is exact, the gap estimate using the 2000 coefficient is off by roughly 7.7%. Considering that the coefficients differ by 19 observations this is reasonable small.

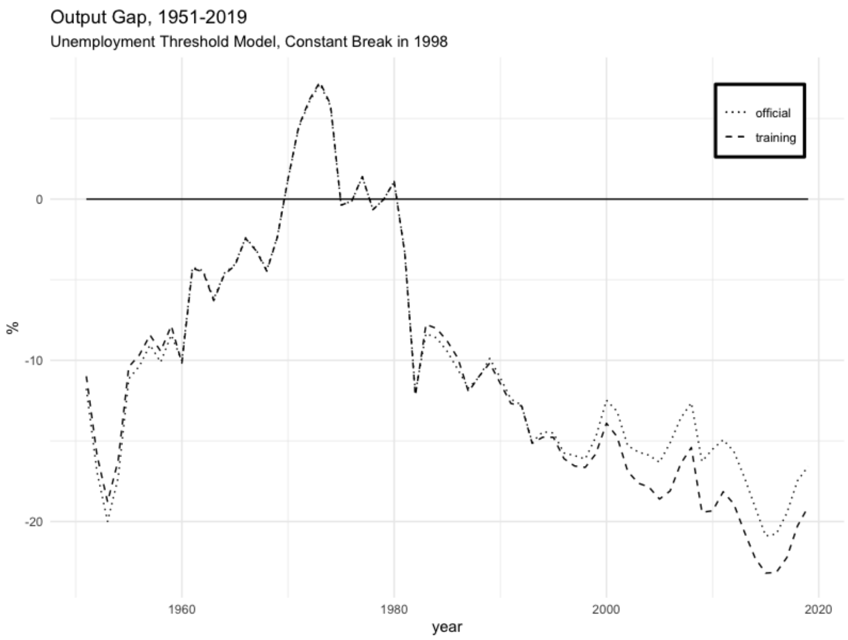

Figure 3.6.: Output gap, unemployment threshold model.

Especially if one works with forecasting data it is also important to consider how sensible PO estimates are with respect to real output and unemployment. From equation 3.4 one can see that PO estimates are a linear homogeneous function of real output ceteris paribus. Hence if the real output measure is biased the percentage error in terms of the true value is the same for real output and PO. Moreover gap estimates are independent of real output and PO. Likewise measurement errors of the unemployment rate, are linearly translated into PO. However as the relationship is not homogeneous percentage estimation errors of unemployment are not the same as corresponding errors of PO estimates. Equations 3.5 and 3.6 show how estimation errors of the unemployment rate translate into errors of PO estimates.[12] Equations for the target unemployment rate look quite similar.

$$\frac{u+\varepsilon}{u} = 1 + \frac{\varepsilon}{u} \tag{3.5}$$

$$\frac{\widehat{Y^*}(u, u^*, \beta; \varepsilon)}{Y^*} = 1 + \frac{\varepsilon}{-100\beta + (u - u^*)} \tag{3.6}$$

The symbol ε denotes an estimation error corresponding to unemployment and $\widehat{Y^*}$ is PO estimated using the incorrect unemployment rate. One can see that as long as the divisor of equation 3.6 is greater than the unemployment rate, estimation errors of the unemployment rate have a proportionally smaller effect on PO estimates. This will be the case usually. E.g. given the model described in table 3.3 column (1) and consider actual u is 8%, the measurement error in u is 1.6% and u^* is 2%, PO is 4.56% off while u is off by 20%.

[12]This equation only holds if $u - u^* \neq 100\beta$, however one does not have to consider this situation, as is would indicate that PO is equal to zero.

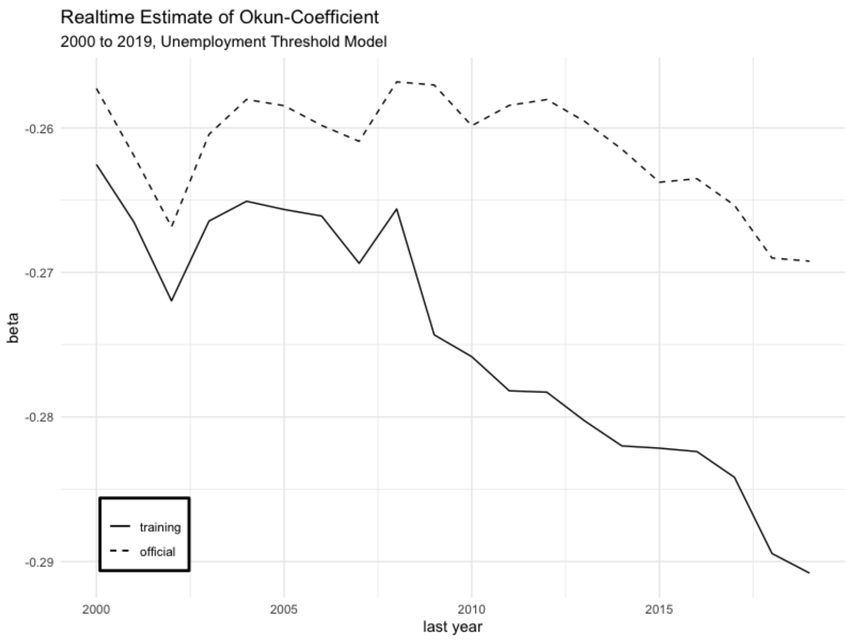

Figure 3.7.: Real time estimates of the GDP growth coefficient, 2000-2019, unemployment threshold model.

3.4. Conditional Forecasting

As discussed above to predict future PO one needs to predict future real output and unemployment. It is beyond the scope of this thesis to elaborate on a forecasting model for real output and unemployment. Hence I give a short intuition using existing forecasting data for 2021 to 2025 provided by WIFO (Baumgartner and Kaniovski, 2021).

If forecasting data for unemployment and real output are available it is easy to conditionally predict future PO. The procedure is exactly the same as described in section 3.3. Using the forecasting data and historical data of 2020, I performed conditional PO forecasting. Figure 3.8 and 3.9 show conditional forecasts of PO and the output gap respectively, the corresponding target unemployment rate is 2%. One can see that PO will stay fairly stable over the first phase of the Corona crisis and in the second year of recovery PO jumps to a higher level. The output gap will constantly get smaller in absolute values from 2020 on but convergence slows down as the economy reaches its pre-crisis level.[13]

To unconditionally estimate a PO forecast one has to predict future real output and use historical unemployment data to calculate unemployment rates out of the Okun's law model. The resulting GDP and unemployment series can then be used to estimate PO.

[13]These plots are for illustrative purposes only as it was not checked how forecast data of unemployment and GDP match my model.

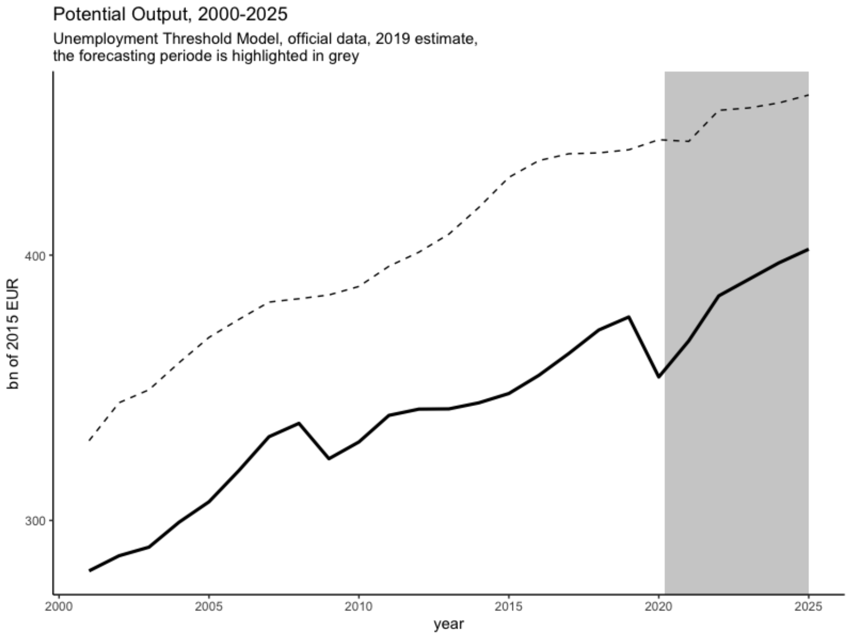

Figure 3.8.: PO pseudo forecast 2021 to 2025, official data, regime switching model.

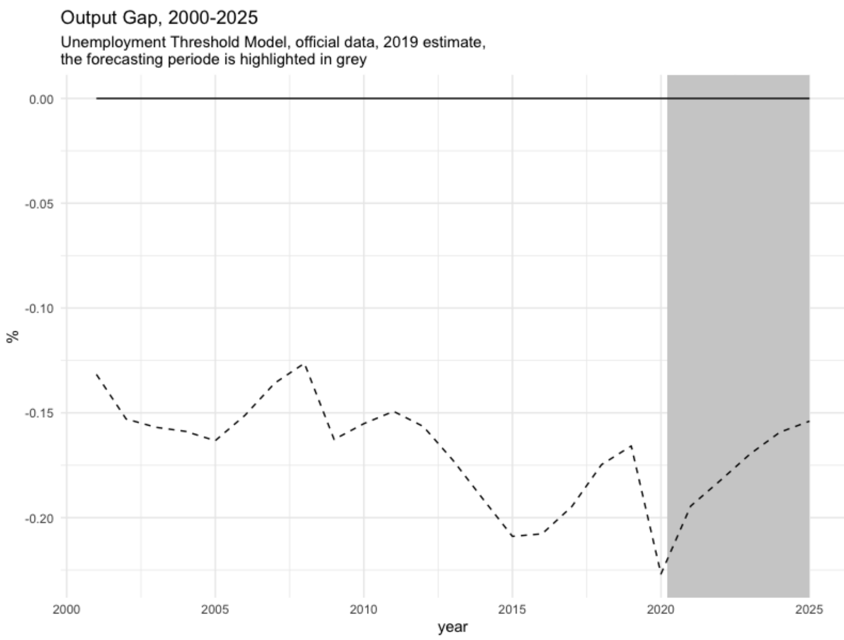

Figure 3.9.: Output gap pseudo forecast 2021 to 2025, official data, regime switching model.

4. High Demand Potential Path

In addition to the PO estimate presented in the previous chapter I calculate a benchmark case, to show how the Austrian economy would have evolved if demand was high during the second low demand period. To do so I follow Fontanari, Palumbo and Salvatori (2020) with their calculation of the HDPP. However I adapt their procedure slightly, by including working age population as an exogenous component of real output. Therefore I use the *output identity* proposed by Gordon (see 2014) described in equation 2.1.

4.1. Data II

Complementing the framework through a HDPP additional time series data on working age population and total hours worked are necessary. Working age population is calculated using the share of working age population and the total population at the beginning of each year. The corresponding data are downloaded from *Statistik Austria*, a detailed description is found in appendix A.1.

While data quality of working age population is good, procedures to collect data on total hours worked changed considerably over time and the quality of raw data is bad. To use the data collected one needs to harmonize the time series. Unfortunately I had no access to raw or harmonized data.[1] Alternatively I used data on hourly labor productivity, defined as real GDP per hour worked. Annual data are provided by the OECD and available since 1976. A detailed description of the data is given in appendix A.1. The calculated volume of labor shows some differences to the more precisely collected date available since 2004 via *Statistik Austria* (see appendix A.1). Hence estimates presented in what follows are not precise, still these data are sufficient to give an intuition on how working time and hourly productivity evolved since the mid 1970s.

4.2. Theoretical Framework and Estimation

The purpose of the HDPP is to show how output could have evolved if demand was high, i.e. the economy operated on its potential all the time. Considering the circumstance that growth is mainly driven by hourly labor productivity, which itself depends on skills and knowledge of the workers, it is likely that demand is driving long term growth. If employment is high, skills and knowledge rather accumulate than diminish. Hence one would expect the HDPP to grow faster than real output. However opposite effects could arise as well, e.g. labor force participation rate could increase in low demand periods due to lower bargaining power of employees and hence a higher retirement age. A connected effect is that lower wages pressure more members of a household to join the labor force.

[1] There are harmonized time series data on total volume of labor from 1974 to 2003, based on the *Mikrozensus*. For a detailed description see Mitterndorfer (2008). However the budget for this thesis was not sufficient to access these data.

Another effect increasing the real output compared to the HDPP is that working hours per employee are reduced slower in low demand periods. How these opposite effects sum up can not be said in general.

To calculate the HDPP I decompose output into hourly labor productivity, average working hours per employed person, the employment rate, the labor force participation rate and the working age population. The average growth of each of these factors during a high demand period is assumed to be feasible in a low demand period as well. Exceptions are the working age population which is independent of demand and the employment rate which is assumed to be permanently high. The average growth rates of the demand dependent components and the experienced population growth are composed to the growth rates of the HDPP. The growth rates accumulate to the HDPP. Equation 4.1 shows the decomposition in terms of growth rates and equations 4.2 and 4.3 show how they are used to calculate the HDPP:

$$y \equiv \frac{y}{h} \cdot \frac{h}{e} \cdot \frac{e}{l} \cdot \frac{l}{n} \cdot n \tag{4.1}$$

$$y_t^{**} = \frac{\hat{y}}{\hat{h}} \cdot \frac{\hat{h}}{\hat{e}} \cdot \frac{\hat{l}}{\hat{n}} \cdot n_t \tag{4.2}$$

$$Y_T^{**} = Y_0 \cdot \prod_{t=1}^{T} y_t^{**} \tag{4.3}$$

Here y_t^{**} denotes the HDPP growth factor of period t, variables with a hat are geometric means of the high demand period growth factors respectively and n_t is the growth factor of working age population in period t. Y_T^{**} denotes the value of the HDPP in period T and Y_0 is the real output in period zero. Setting Y_0 equal to one hundred and choosing 1976 to 1982 as high demand period, the Austrian HDPP from 1976 to 2019 looks as depicted in Figure 4.1.

4.3. Intermediate Results

Figure 4.1 gives insights about two things: how real output was composed since 1976 and how the economy would have evolved if demand was high ever since then. The most important component of output growth during the given period is hourly labor productivity. One can easily see that the major part of real GDP growth was due to an increase of productivity. It is striking that productivity growth slowed down at the beginning of the millennium, while output growth slowed down only a decade later. The second most important component of the output process is working age population growth which follows a rather smooth path from 1976 to 2019. The third component of the Austrian GDP which had a positive influence on growth is the labor force participation rate. After a small downturn in the first half of the eighties labor force participation rate grew fast till the early nineties and remained almost constant until 2005, ever since it grew steadily. On the other side average working time per employed person diminished until the mid nineties and grew since then until it almost reached the level of 1976 in 2010 and slightly fell afterwards. The last component is the employment rate which fell on average throughout the period.

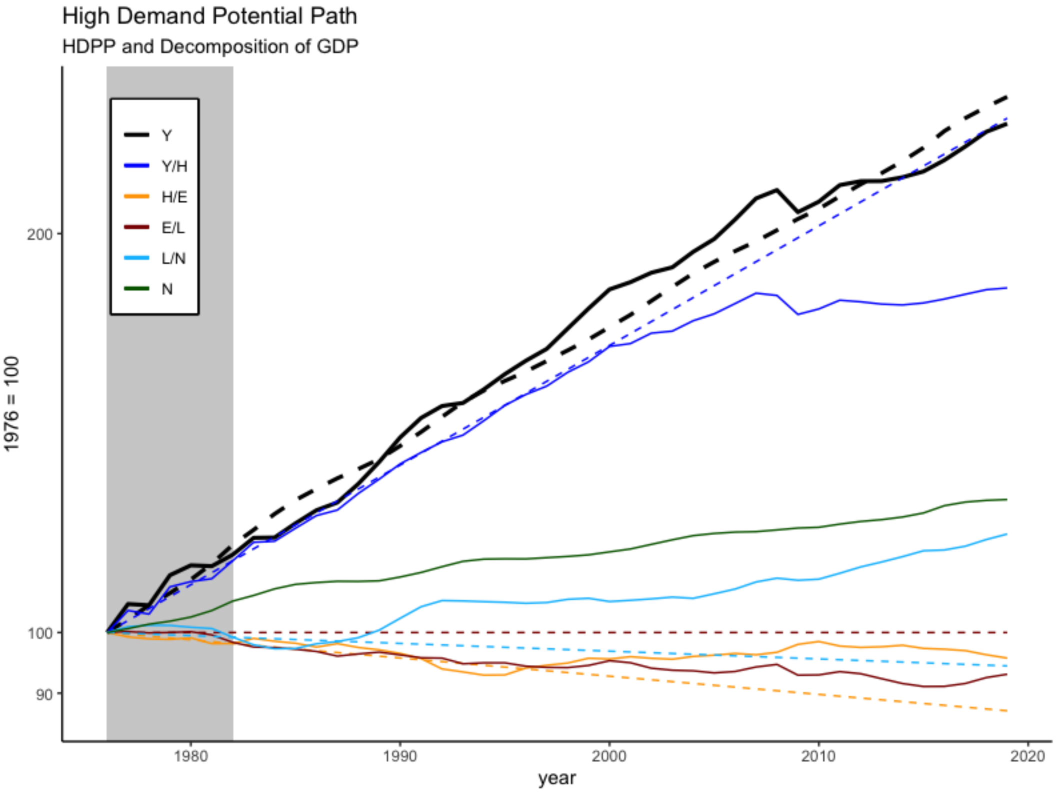

Figure 4.1.: Real output and components (solid lines), HDPP and components (dashed). The historical high demand period is highlighted in gray.

One can see that output is growing parallel to hourly labor productivity until the end of the eighties, when labor force participation rate jumped up. For a few years the participation rate increase dominated the decrease of other demand depending components. However beside this short period output grew almost perfectly in line with productivity till the begin of the millennium when productivity growth slowed down. Nonetheless output growth did not change remarkably until the great depression. This is due to an increase in working time per employed person and a fast growing labor force participation rate.

The second aspect Figure 4.1 shows is the HDPP. Considering the definition of the HDPP given in equation 4.2 and 4.3 it is possible to compare the components of the HDPP and the realized values of each variable. As high demand is defined as a situation of full employment, employment has no influence on the HDPP, while it had a negative influence on the real output growth. Working hours per employed person decrease during the estimation period from 1976 to 1982. The realized movement of hours worked per employed person however shows a similar pattern till the mid 1990s. Only since the second half of the 1990s working hours are increasing again. While in the year 1995 the working hours component of the HDPP is reduced to approximately 94.2% of the 1976 level, the real working hours are reduced to 92.9% compared to the base year. In 2019 the HDPP component is 87.3% and the real working hours are 95.7% compared to 1976. Labor force participation rate decreases during the high demand period, hence the HDPP component has a negative influence on growth. Compared to the realized participation rate in 2019 which is roughly 18.7% greater than in 1976 this is far off the HDPP prediction. Hourly labor productivity is expected to grow faster during a high demand period as skills and knowledge accelerate if people work and decelerate if they are unemployed. However the hourly labor productivity component of the HDPP is almost perfectly in line with realized labor productivity until productivity starts to decelerate in the year 2000. It is important to note that this does not mean that knowledge and skills do not diminish while unemployed on a personal level. If the unemployment rate increases, the labor force grows and the number of employed persons is constant, on average every person in the labor force is unemployed longer. Skills however do only vanish if a single person is unemployed longer, i.e. if people enter the labor force and do not work this does not change the productivity of the employed labor force. Hence the distribution of unemployment among the labor force matters.

Comparing the output process and the HDPP one can see that in terms of GDP the economy would not be better off if the high demand regime was still in charge. In 2019 the HDPP shows a higher value than output, however the HDPP is a very stable estimate and the prediction period is huge, hence medium deviations of the HDPP and real output should not be thought of as qualitative difference. Moreover one can see that, aside from the productivity argument discussed above, it would have had positive effects, if labor had been distributed differently. The historic data show that the labor force participation rate went up simultaneously to the unemployment rate. It is not clear whether a high or a low labor force participation rate is better. But it is a common argument of symmetry that total working hours and unemployment should not increase along each other in the medium to long run. This is the case for the predicted components of the HDPP, in contrast to the realized composition of output, where working hours are distributed less equal among the labor force.

Unfortunately the analysis of the HDPP cannot tell us anything about a fictive adjustment process to a structural change within a high demand regime. Hence it is not possible to answer the question how a high demand regime would have reacted to a structural change in productivity as seen in the historical data. A second limitation concerns the definition of the high demand period. As discussed in section 3.2.2 I define high and low demand periods following the unemployment rate only. It seems reasonable to me that the only high demand period in the post war economy of Austria was from 1960 to 1982, but here two problems arise. Firstly as turning points are set to single years some observations perhaps be specified to be in a high demand period even though they are in the low demand era. This again leads to serious issues. Consider the labor force participation rate which is almost constant throughout the high demand period, but in 1982 it is slightly below the level of 1976, hence the corresponding component of the HDPP is negative. If 1982 was defined as a low demand period the participation rate component of the HDPP would have been positive. Secondly a high demand period is not said to be a static situation, hence it might not be adequate to estimate the HDPP using data only covering the last third of this period. If one looks at the output growth rates the most important break for the period of 1951 to 2019 is found in 1973, prior to the first observation I used to estimate the HDPP. Still demand was high and the unemployment rate did not drastically rise after 1973. Therefore HDPP growth rates calculated in this thesis are much lower than they were if the whole high demand period was taken into account.

5. Overall Results, Limitations and Extensions

5.1. Austria's Potential Output: An Alternative Approach

Considering both the adapted version of Okun's method to estimate PO and the HDPP as a benchmark case for high demand regimes, some things can be said about the Austrian economy. Firstly there has been a situation of stable under utilization of production capacity since the beginning of the 1980s. Hence a structural deficit by the government was absent since then. Secondly the GDP pf Austria is close to the level where it would have been, if the high demand regime ending in the early 1980s had continued. However as the labor force grew more than proportional, PO today is much higher. Thirdly the deceleration of hourly labor productivity growth since millennium was followed by an increase of total working time, mainly due to a growing labor force participation rate, which kept up growth rates. Since the depression of 2009 GDP growth rates did not catch up to the pre-crisis level and the labor force participation rate cannot grow for ever, this might indicate that some structural changes of the Austrian economy are about to come.

Recalling figure 3.6 one can see that ever since the early 1980s Austria faced a negative output gap. My estimate strongly relies on the target unemployment rate of 2%, however even if the rate is set to 5% (for the low demand period) output gaps are negative ever since 1986. The stable under utilization of production capacity shows that there was a stable lack of demand throughout the past forty years. The gaps might were too big to be closed within one year. Still real GDP could have caught up to PO if demand had been higher over a decent amount of time. Consequently the cyclically-adjusted budget balance (CAB), as defined by the EC, should have been positive throughout this period. The CAB is defined as a function of the budget deficit, the output gap and a budgetary semi-elasticity, as described in equation 5.1 (Mourre et al., 2019):

$$CAB_t = B - \varepsilon OG_t \tag{5.1}$$

Here B is the budget balance, ε is the budgetary semi-elasticity and OG_t is the output gap. Budgetary balance data by *Statistik Austria* (see appendix A.1 for more information) available since 1995 never showed a deficit greater than 6.1% of nominal GDP until the year 2020. Mourre et al. (2019) estimate a budgetary semi-elasticity for Austria of 0.571 and output gaps according to the adapted Okun's method in its *training* data specification and a target of 2%, are below -13.9% in all years since 1996. One can easily see that the structural budget balance of Austria never was negative, since 1996.

Seemingly contradicting to the above discussed results, is the fact that the benchmark case of output under high demand in 2019 is just above real GDP (see figure 4.1). From 1994 to 2012 real GDP is even higher than the HDPP. As already discussed in section 4.3, this is probably due to a lack of data, i.e. the estimation period starts in 1976, while the high demand regime was in charge since 1960. However the composition of output can be analyzed still. Output in the high demand regime is only growing because of productivity growth and a growing working age population. Hours worked per employee as well as the labor force participation rate decrease under the high demand regime. Comparing real output and the HDPP which roughly predicts the same output, other dimensions are in need to evaluate the different regimes normative. There is no common rule to asses the labor force participation rate development, without investigating it's driving forces, e.g. retirement age and age of entrance to the labor force. Considering a high demand regime facing a deceleration of hourly labor productivity similar to the one seen at the beginning of the century, the analysis of the HDPP gives no insight about possible dynamics evolving. However unemployment and working time per person can be evaluated regarding their symmetry, i.e. it is fair that unemployment is low, even if the number of total hours worked shrinks.

Beside the normative analysis the deceleration of hourly labor productivity growth since 2000 gives a hint to further changes in the Austrian economy. While output had grown almost parallel to hourly labor productivity until millennium, from then to 2009 output grew faster than productivity. The widening gap between productivity and output was due to a growing labor force and increasing working hours per worker. However since the depression of 2009 GDP growth rates decreased. Form 2000 to 2008 the geometric mean of growth rates was 2.31% and from 2010 to 2019 1.55%. After 2009 output grew particularly due to an increasing labor force participation rate, which again rose because of the opening up of the labor market to eastern Europe in 2011.[1] This effect may only temporarily add to output growth and hence growth after the Corona crisis needs to be driven by other factors. Yet there is no proper evidence, but a slowdown of output growth and some remarkable changes at the labor market may be signs of the beginning of a new labor market regime.

5.2. Limitations and Extensions

Beside the cutbacks due to availability of data, two more limitations of the presented method itself need to be discussed as well. Firstly the choice of the target unemployment rate. Secondly some insights from the HDPP analysis might make it necessary to revisit the selection of the estimation model of Okun's law.

I already mentioned that my PO estimate is crucially sensitive to the target unemployment rate (see section 3.3). Still an in-depht discussion is in line. It is questionable if unemployment rates as observed during the high demand period from 1960 to 1982 could be reached within a couple of years given the current state of the economy. Hence if these unemployment rates are targeted resulting PO estimates might need to be interpreted quiet differently to common estimates. To compare my PO estimate with others and use it as input for already existing models, it is useful to think about other methods to set an unemployment target.

The original approach by Okun (1962) was to set the unemployment rate target such that price stability is given. Hence despite all critique one possibility would be to target a NAIRU estimate. An illustrative PO estimate using the EC's NAWRU and the adapted

[1]For detailed analysis of changes in the Austrian labor market after 2011 see Schiman (2020), who found an increased share of foreign workers as well as a temporary increased unemployment rate.

Okun's method in its *training* specification can be seen in figure 5.1.[2] Output gaps are much smaller compared to the 2% target. One can see that the resulting PO estimate is a rather volatile measure, this is due to the fact that sign of the difference of the unemployment rate and the unemployment rate target is changing on a high frequency. The volatility of the estimate using the NAWRU is contrary to the common notion of PO, which usually is thought of as a slowly changing variable. Moreover the critique on PO estimates strongly relying on the NAWRU also apply to this estimate. Hence for a targeting strategy following the goal of price stability an alternative to the common notion of NAIRU is necessary.

Another approach to the problem of the target unemployment rate could be to calculate a weighted moving minimum (wmm). The idea is that if a certain low unemployment rate was possible once at least close to that moment a only slightly higher unemployment rate is possible as well. Hence it is a loosening of targeting approach by Fontanari, Palumbo and Salvatori (2020), i.e. to set the target to the historic minimum unemployment rate. The calculation algorithm is the following: firstly a period to choose from is fixed, secondly all observed unemployment rates are weighted with a factor geometrically increasing with greater distance to the year the target has to be chosen for, thirdly the minimum of the weighed unemployment rates is chosen as target. More formally spoken:

$$u_t^* = min\{u_1\delta^{t-1}, u_2\delta^{t-2}, ..., u_{t-1}\delta, u_t, u_{t+1}\delta, ..., u_{T-1}\delta^{T-t+1}, u_T\delta^{T-t}\} \tag{5.2}$$

u_t^* is the unemployment rate target in period t, u_1 to u_T are the unemployment rates within the observation interval and δ is a discount factor to weight unemployment rates. For the illustration in figure 5.1, I chose 1983 to 2019 as my observation interval, i.e. the second low demand period, and the discount factor δ to be 1.05, which is slightly lower than the mean of the absolute change rates of unemployment over the period under consideration.[3] The estimate is smoother than the NAWRU estimate and estimated gaps are very small. A problem arising is that gaps are restricted to be at maximum zero and aside from periods of fast changing observed unemployment rates, gaps are restricted to be small. The wmm approach uses realized unemployment rates as structure to evaluate the state of the economy, hence the interpretation is straight forward. However aside from deep recessions the estimate will be close to the realized output and gaps are smaller than or equal to zero by construction. Therefore it does not fully match the the requirements for a good PO estimate discussed in section 2.3. A further expansion would be to use a mirrored algorithm to target the absolute number of employed persons and calculate the target unemployment rate using the current absolute labor force. The benefit of this targeting strategy would be that changes in the labor force, such as the opening up of the labor market to eastern Europe, are taken into account more precise.

A third way to target unemployment rates is to choose a piecewise constant (pwc) target. Hence for a given period in which no structural changes on the labor marked happened a constant target is set. The crucial point however is to find these periods, especially

[2] The data published in the AMECO data base are in terms of the ILO definition of unemployment. I transformed these date into a NAWRU in terms of the *training* data by calculating a percentage deviation of the ILO unemployment rate to the given NAWRU and defined the *training* pseudo NAWRU such that the percentage deviation to the *training* unemployment rate is the same. As the ILO and the *training* unemployment rates are different not only by scale but also differ in change rates, this *training* pseudo NAWRU is a rough approximation only.

[3] $\delta \approx 1 + \frac{1}{T}\Sigma_{t=1}^{T}|\frac{u_t}{u_{t-1}} - 1| = 1.065$ where T is equal to 2019 minus 1983

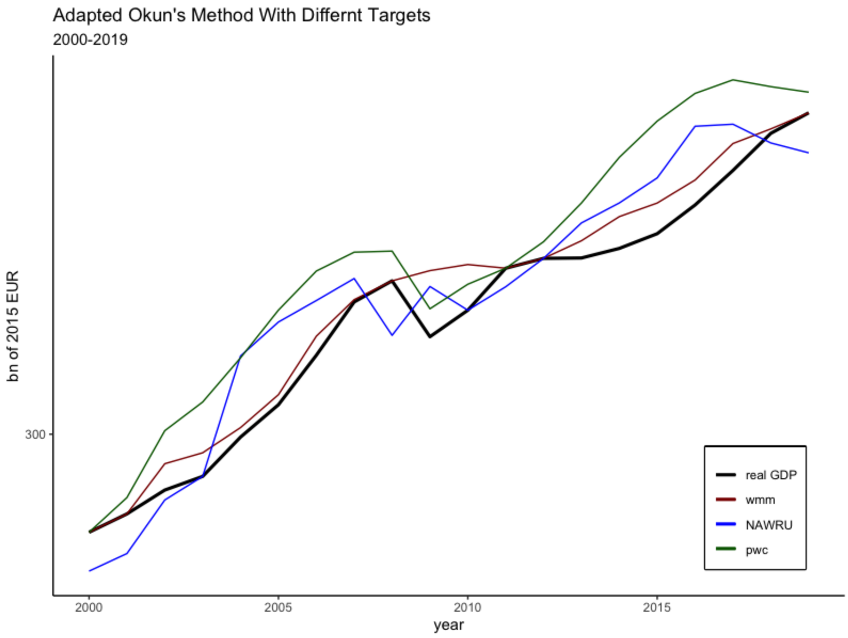

Figure 5.1.: PO estimates, different unemployment rate targeting strategies. Logarithmic scale.

if they just stared and to set the target reasonable. For the illustration in figure 5.1, I chose 1999-2008, i.e. from the introduction of the *EURO* to the last year before the great depression and 2009-2019 as periods with a constant target. The target itself is set to be the minimum unemployment rate within each period. PO estimated using a pwc targeting strategy and the adapted Okun's method matches the requirements for a good PO estimate presented in section 2.3 best of all presented approaches. However it needs further analysis to set the breakpoints of the labor market regimes and the target rates properly.

A look at the time series data of output and unemployment considering the insights from the decomposition of GDP and the analysis of the HDPP gives a hint that there were more than two different labor market regimes in Austria. Hence it might be promising to investigate these regimes further. The presented evidence for a high and a low demand regime is strong, however the presented framework can not explain satisfyingly how these regimes started and ended. Taking into account breaks of the output process one finds several additional possible break points of Okun's law. GDP data of Austria show three (four) segments of different growth rates. The first period of reconstruction ending with a recession in 1953 shows massive growth rates of 6.9% to 27.2%. In the second period growth rates are still high but not as high as during the previous period. This period shows no year with a GDP growth rate below 2%. The second period ends in 1973, the year of the oil price shock. The third period shows even lower growth rates on average and in some years GDP growth is below 1% and negative growth rates occur for the first time. Probably a fourth period started in 2009, ever since growth rates were below 3% and in the eleven years up to 2019 four years had a growth rate below 1%. Interestingly these output growth regimes do not change simultaneously with the regimes characterized by the unemployment rate. Considering both patterns it might be accurate to distinguish between different output growth regimes followed by changes on the labor market. To find the exact break points and characteristics of the different stages further work is in need.[4]

[4] One possible model to estimate Okun's law accounting for these multiple regime switches could be such that breaks in the intercept are allowed in all years the output regime changes and breaks in Okun's coefficient are allowed in all years the unemployment rate regime changes. Hence the elasticity of the unemployment rate with respect to GDP changes only if a certain unemployment threshold is crossed. However as the intercept is allowed to change whenever a new output growth rates regime is reached, the unemployment stabilizing growth rate of GDP is allowed to change more often. Still even if the stabilizing growth rate is allowed to change several times estimated coefficients strongly depend on each other throughout the whole observation period.

6. Conclusion

The adapted Okun's method and the HDPP analysis presented in this thesis are a small contribution to a broader debate about PO and the analysis of the Austrian business cycle. Taking a look at common approaches to estimate PO and concrete measures for Austria, I found that most estimates are close to a moving average of GDP. These estimates are in line with the idea that real output is swaying like a rocking horse passing PO several times along the way. Considering PO to be a supply side measure of capacity utilization, I formulate requirements for a good estimate in section 2.3. The two most important requirements are that a stable situation of under utilization of capital is possible and that PO can only be reached in a situation of full employment. Finding that Okun's 1962 method matches most of my requirements, I follow his approach in a version adapted by Fontanari, Palumbo and Salvatori (2020). I estimate the Austrian PO for the period of 1951 to 2019, therefore I distinguish between a high and a low demand regime. Results show that the Austrian economy is operating with a growing negative output gap ever since the beginning of the 1980s. Additionally I estimate a HDPP to relate my PO estimate to a framework of demand-led growth and find vague evidence that a high demand regime might not have greater GDP growth rates than a low demand regime. However working time is distributed more equal among the population.

Concluding I believe my estimate produces good results, although the model would probably benefit from an updated unemployment rate targeting strategy. However even if the unemployment rate target is set to be constant for a long period, PO estimated can help to evaluate economic policy. This contrasts many other PO estimates, which are mainly driven by averages and hence rather prescribing economic policy than helping to evaluate it. E.g. my results show that crisis like the one of 2020 are not the result of an overheating economy, but existing capacity is suddenly not used anymore.

Especially during the current Corona crisis and the upcoming recovery process PO estimates will be of great importance to economic policy makers. Not only economic advisers will rely on PO estimates when consulting politicians, but also the European fiscal rules will again strongly depend on PO estimates once in charge again. Therefore Heimberger (2020) for example argues that the criticized PO estimates by the EC should be locked in at its 2019 autumn prediction. This might be a short term solution, but sooner or late a PO model different from the one used by the EC (Havik et al., 2014) is needed or fiscal rules have to be cut lose of PO at all.

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A. Appendix

A.1. Description of Data

Table A.1.: All series are on an annual basis and refer to Austria.

variable	period	unit/measure	specification	source	creation/access
Budget balance	1995-2020	percentage of GDP	Öffentliches Defizit (-)/Öffentlicher Überschuss (+)	Statistik Austria	2021-09-30
employed, job vacancies, unemployed	1946-2019	total numbers	Arbeitsmarktlage seit 1946	AMS (https://www.ams.at/arbeitsmarktdaten-und-medien/arbeitsmarkt-daten-und-arbeitsmarkt-forschung/berichte-und-auswertungen)	2020-12-24, 14:14
GDP	1946-2019	chained 2015 EUR		WDS - WIFO Data System	2020-10-07, 16:19
Labour Productivity Forecast	1976-2022	GDP/hour worked, 2015=100[a]		OECD, (https://data.oecd.org/lprdty/labour-productivity-forecast.htm)	2021-03-19, 09:41
NAWRU	1965-2022	percentage of active population	2021 EC estiamte	AMECO (http://ec.europa.eu/economy_finance/ameco)	2021-10-27, 17:20
Output Gap	1965-2022	percentage of PO at constant prices	2021 EC estimate	AMECO (http://ec.europa.eu/economy_finance/ameco)	2021-10-27, 21:10
population	1952-2021	total numbers	Bevölkerung zu Jahresbeginn 1952-2021 nach Bundesland	Statistik Austria	2021-02-11
PO	1965-2022	chained 2015 EUR	2021 EC estimate	AMECO (http://ec.europa.eu/economy_finance/ameco)	2021-10-26, 17:30
Total Hours Worked	2004-2019	hours	Tatsächlich geleistete Arbeisstunden (Arbeitsvolumen) nach beruflicher Stellung	Statistik Austria	2020-03-17
training at AMS	1987-2020	total numbers		AMS (https://iambweb.ams.or.at/ambweb/)	2021-03-10, 11:34
unemployment	1960-2022	percentage of active population		AMECO (http://ec.europa.eu/economy_finance/ameco)	2021-10-26, 18:02
Working Age Population	1962-2021	quotient	Demographische Abhängikeitsquotienten und Durchschnittsalter seit 1869	Statistik Austria	2021-02-11

[a] Labour productivity is defined as real gross domestic product (GDP) per hour worked. This captures the use of labour inputs better than just output per employee, with labour input defined as total hours worked by all persons involved. The data are derived as average hours worked multiplied by the corresponding and consistent measure of employment for each particular country. Forecast is based on an assessment of the economic climate in individual countries and the world economy, using a combination of model-based analyses and expert judgement. This indicator is measured as an index with 2010=1 (sic!).

A.2. Model Estimation Matters

A.2.1. Cutbacks On the Interpretation of the Threshold Model

If the model presented in equation 3.3 and as well the one presented in equation 3.2 is interpreted as a (dynamic) threshold model and thresholds are linked to same period unemployment, serious logical errors arise. Which however can be easily solved in the case of the Austrian data, as thresholds are crossed only two times within the observation period. Hence breaks in the equation are simply related to historical dates.

Equation 3.2 can also be written as:

$$u_t - u_{t-1} = \begin{cases} \alpha_l + \beta_l \gamma_t^y + \varepsilon_t & , \quad u_t \in [0, \Theta] \\ \alpha_h + \beta_h \gamma_t^y + \varepsilon_t & , \quad u_t \in (\Theta, 100] \end{cases} \tag{A.1}$$

Where Θ is the unemployment threshold. If one wants to predict changes in unemployment one has to consider the following.

$$\mathbb{E}u_t = \begin{cases} \alpha_l + \beta_l \gamma_t^y + \mathbb{E}\varepsilon_t + u_{t-1} & , \quad \mathbb{E}u_t \in [0, \Theta] \\ \alpha_h + \beta_h \gamma_t^y + \mathbb{E}\varepsilon_t + u_{t-1} & , \quad \mathbb{E}u_t \in (\Theta, 100] \end{cases} \tag{A.2}$$

If $\alpha_l \neq \alpha_h$, $\beta_l \neq \beta_h$ and u_{t-1} is held constant, it is possible to find a $\gamma_t^y \in$ such that $\mathbb{E}\varepsilon_t \neq 0$ or $\mathbb{E}u_t$ does not exist. Given the size of $\alpha_l, \alpha_h, \beta_l$ and β_h this will often be the case for $\gamma_t^y \in [-100, \infty)$. Breaking this down a simple necessary condition arises:

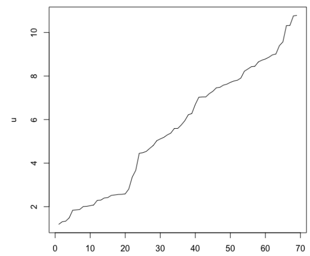
$$\begin{aligned} \exists \mathbb{E}u_t : \mathbb{E}\varepsilon_t = 0 \Rightarrow & \\ \alpha_l + \beta_l \gamma_t^y + u_{t-1} \leq \Theta \vee & \\ \Theta < \alpha_h + \beta_h \gamma_t^y + u_{t-1} & \\ \iff \neg(\alpha_l + \beta_l \gamma_t^y + u_{t-1} > \Theta \wedge & \\ \Theta \geq \alpha_h + \beta_h \gamma_t^y + u_{t-1}) & \end{aligned} \tag{A.3}$$

The negated term of equation A.3 will be true in many cases, even within boundaries of experienced growth and unemployment rates as well as the above estimated coefficients. E.g. take the coefficients for training data of table A.9, the corresponding threshold of 4.135% and set $\gamma^y = 1.50\%$ and $u_{t-1} = 3.78\%$, the resulting estimates are 4.141% for the low regime and 4.129% for the high regime, hence both estimates for u_t are invalid. Therefor estimation as presented in section 3.2.2 is not correct if one thinks of a threshold model. However as observed data are such that there are not many switches between high and low demand regimes a different interpretation is possible, ie. considering the model as one with two breaks at given points in time and setting the model for the first and the third segment equal.

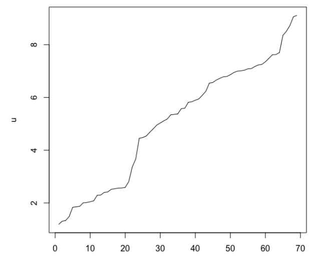
$$u_t - u_{t-1} = (\alpha_l + \beta_l \gamma_t^y) J(t) + (\alpha_h + \beta_h \gamma_t^y)(1 - J(t)) + \varepsilon_t \tag{A.4}$$

$$J(t) = \begin{cases} 1 & , \quad t \in [T_1 + 1, T_2] \\ 0 & , \quad t \in [1, T_1] \vee t > T_2 \end{cases} \tag{A.5}$$

Where T_1 and T_2 are two different discrete time points. Hence the prediction of the model for $t > T_2$ is the same no matter how high the unemployment rate is.



(a) training



(b) official

Figure A.1.: Sorted unemployment rates, 1951 to 2019.

A.2.2. Documentation of the Model Selection Process

Looking at the cumulative empirical distribution of unemployment rates in figure A.1 one can see a jump in the otherwise somewhat uniform distributed picture. I used the *strucchange* package in *R* to informally test for up to two breaks in the uniform distribution i.e. breaks in the regression of the order of unemployment rates and an intercept, on unemployment rates. The cut off value was chosen at 10%. I found a break at an unemployment rate of 3.67%, i.e. the 23rd lowest unemployment rate, found in 1982, for both training and official data. One at 9.40% for training data and 7.23% for official data. Note the lowest segment of both corresponds to the period of 1960 to 1982, hence training and official data share the same values.

Table A.2.: Stationary tests

	$\Delta u^{training}$	$\Delta u^{official}$	γ^y
Augmented Dickey-Fuller Test			
test statistic	-5.994	-5.901	-7.001
Lag order	0	0	0
p-value	0.01	0.01	0.01
Philipps-Perron Test			
test statistic	-42.64	-42.17	-53.81
Truncation lag parameter	3	3	3
p-value	0.01	0.01	0.01

Annual data, 1951 to 2019.

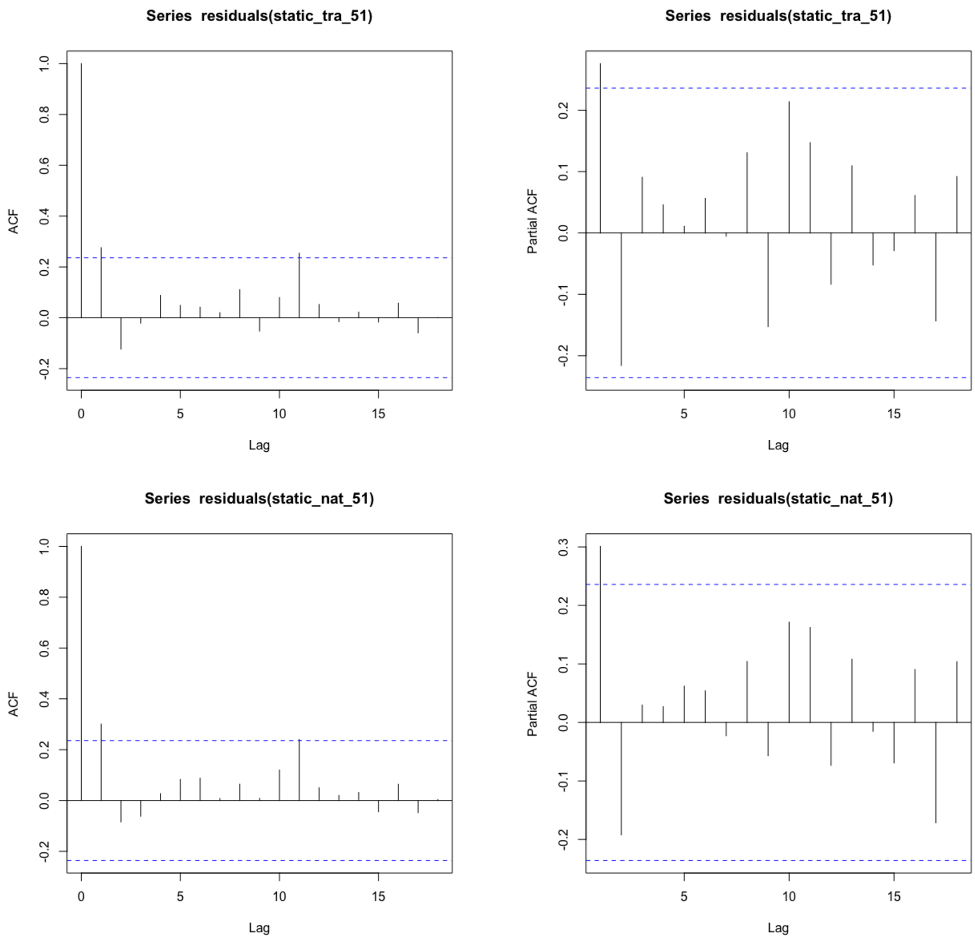


Figure A.2.: Autocorrelation and partial autocorrelation functions of residuals of equation 3.1, 1951 to 2019.

Table A.3.: AIC simple dynamic estimation training data, 1951 to 2019.

			γ^y	
	lags	0	1	2
		94.27	95.72	79.56
Δu_t	1	92.00	91.96	74.41
Δu_t	2	69.87	71.69	73.23

Table A.4.: AIC simple dynamic estimation official data, 1951 to 2019.

		γ^y		
	lags	0	1	2
		90.91	92.43	76.62
Δu_t	1	88.23	87.69	70.40
Δu_t	2	66.24	67.89	69.51

Table A.5.: AIC dynamic estimation including breaks of the intercept as well as the coefficient for GDP growth in 1956 and 2006. Traning data, 1951 to 2019.

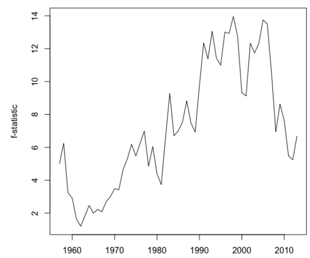
		γ^y		
	lags	0	1	2
		57.07	53.33	57.25
Δu_t	1	49.55	53.74	56.87
Δu_t	2	49.57	52.96	54.81

Table A.6.: AIC dynamic estimation including breaks of the intercept as well as the coefficient for GDP growth in 1956 and 1998. Official data, 1951 to 2019.

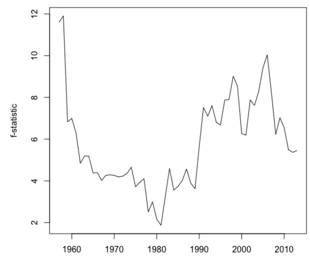
		γ^y		
	lags	0	1	2
		54.38	52.70	57.09
Δu_t	1	48.03	52.38	56.00
Δu_t	2	48.85	52.33	55.28

Table A.7.: Dip test, 1951 to 2019

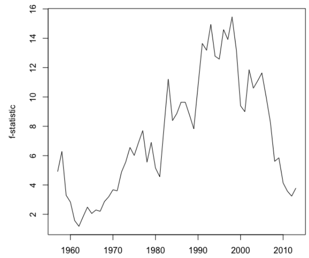
	training	official	γ^y
p-value	0.009	0.003	0.9926
D	0.070	0.076	0.025



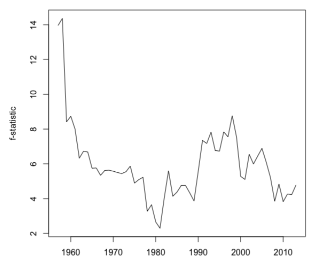
(a) Intercept only, training



(b) Intercept and slope, training



(c) Intercept only, official



(d) Intercept and slope, official

Figure A.3.: QLR test for equation 3.1, the cutoff value is 10%, 1951 to 2019.

Table A.8.: Shapiro-Wilk normality test for subsets of the unemployment rate, 1951 to 2019.

	W	p-value
training data		
low regime	0.959	0.441
high regime	0.962	0.139
official data		
low regime	0.959	0.441
high regime	0.966	0.201

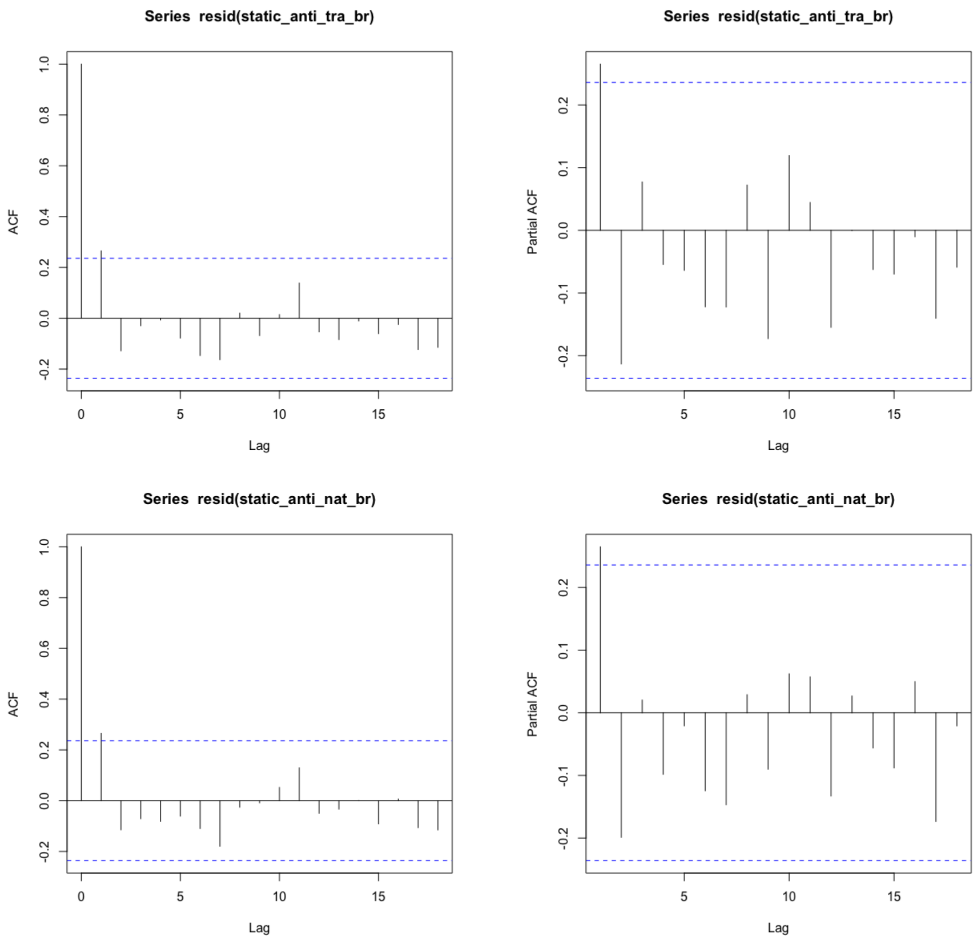
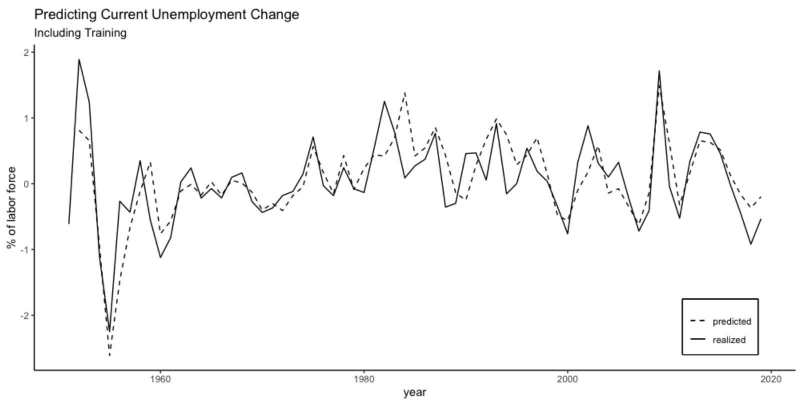


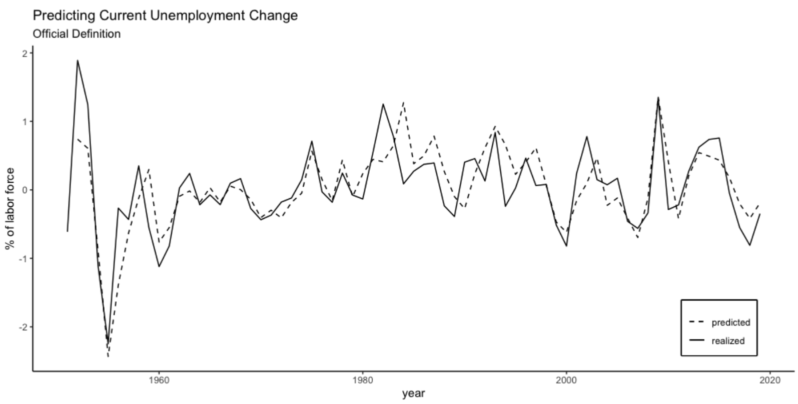
Figure A.4.: Autocorrelation and partial autocorrelation function of residuals of static regime switching model with breaks (see table 3.2 (2) and (3)), 1951 to 2019.

Table A.9.: Different static regime switching models of Okun's law

	training		*official*	
	Δu_t	Δu_t	Δu_t	Δu_t
	(1)	(2)	(3)	(4)
du_t^L	0.599***	0.599***	0.599***	0.599***
	(0.198)	(0.178)	(0.193)	(0.173)
du_t^H	0.677***	1.049***	0.604***	0.969***
	(0.105)	(0.132)	(0.102)	(0.129)
$du_t^{>1998}$		−0.543***		−0.530***
		(0.134)		(0.131)
$\gamma_t^y \times du_t^L$	−0.159***	−0.159***	−0.159***	−0.159***
	(0.043)	(0.039)	(0.042)	(0.038)
$\gamma_t^y \times du_t^H$	−0.219***	−0.265***	−0.205***	−0.250***
	(0.029)	(0.028)	(0.028)	(0.028)
Observations	69	69	69	69
R^2	0.525	0.621	0.508	0.608
Adjusted R^2	0.496	0.592	0.477	5.77
Residual Std. Error	0.463 (df = 65)	0.417 (df = 64)	0.452 (df = 65)	0.406 (df = 64)
F Statistic	17.955*** (df = 4; 65)	20.993*** (df = 5; 64)	16.763*** (df = 4; 65)	19.856*** (df = 5; 64)
Note:				*p<0.1; **p<0.05; ***p<0.01



(a) training



(b) official

Figure A.5.: Same period prediction of Δu_t, coefficient estimates see table 3.3, historical Δu_{t-1} and γ_t^y.