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The natural rate of unemployment in Estonia: empirical determinants and a new semi-structural model

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Abstract

This paper addresses the empirical modelling of the natural rate of unemployment in Estonia. It has two interlinked parts. The first part considers potential empirical determinants of the natural rate of unemployment in a sample of 31 OECD countries, and the second incorporates many of those determinants into a new quarterly semi-structural model of the natural rate of unemployment for Estonia, which we estimate over the period 1998–2019. Our methodological approach to building this new semi-structural model is to explore a space of 4×2^{12} alternative model specifications, each one featuring a distinct combination of extrinsic determinants of the natural rate, and measures of the rate of unemployment and the state of the labour market in Estonia. We find that although some of these potential determinants enter our model in a statistically significant way, the overall time dynamics of the estimated natural rate of unemployment for Estonia are not much affected by these factors, and our estimates of the natural rate are quite similar across all of these determinants over the full sample period. However, we also find that our estimates of the natural rate of unemployment are quite sensitive to the choice of measures of the state of the labour market and the rate of unemployment used in estimating the new model.

JEL classification: E32, E58, C32, C52

Keywords: natural rate of unemployment, unemployment gap, NAIRU, panel data, semi-structural modelling, model averaging

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*E-mails: dmitry.kulikov@eestipank.ee (corresponding author) and nicolas.reigl@eestipank.ee We thank all the seminar participants from the Economics and Research Department of Eesti Pank and the 2021 Baltic Central Banks meeting for their insightful comments and helpful suggestions. We are especially grateful to Kaspar Oja and Orsolya Soosaar for their invaluable help with constructing the dataset used in this paper.

Non-technical summary

This paper addresses the estimation of the natural rate of unemployment in Estonia using an empirical modelling approach. Our interest in this topic is motivated by the great practical importance of the natural rate for the proper conduct of monetary policy by a central bank. The two main goals of the paper are to identify the potential structural determinants of the natural rate of unemployment in Estonia over the period 1998–2019, and to provide estimates of the natural rate for Estonia that take the effect of these structural factors into account.

The paper has two interlinked parts. The first part surveys recent empirical literature and considers potential empirical determinants of the natural rate of unemployment in a sample of 31 OECD countries, and the second part incorporates many of those determinants into a newly developed quarterly semi-structural model of the natural rate of unemployment for Estonia, which we estimate over the period 1998Q1–2019Q4.

The literature survey indicates that four broad groups of potential determinants of the natural rate of unemployment are particularly important. These four groups are active labour market policies, unemployment benefits and labour taxation, large macroeconomic shocks such as those affecting the housing market, and various government policies that are designed to facilitate economic growth and development. Contrary to our prior expectations, the literature does not seem to demonstrate any well-established links between the natural rate of unemployment and immigration policies or the supply of the short-term foreign labour.

We then construct a panel of 31 OECD countries, which we use for an empirical investigation into what the determinants of the natural rate might be. Most of our empirical panel data models suggest that important drivers of the natural rate may be active labour market policies and the share of the construction sector in the total employment in the economy. Measures of labour taxation and capital accumulation are additional determinants of the natural rate, although they are not always statistically important in all our models.

Finally, we develop a new semi-structural quarterly time series model of the natural rate of unemployment in Estonia, which incorporates many determinants of the natural rate that are identified as potentially important in our earlier empirical panel data analysis. We explore a large space of alternative model specifications, each one featuring a distinct combination of the determinants of the natural rate, and measures of the rate of unemployment and the state of the labour market in Estonia. We find that some of these potential drivers of the natural rate enter our semi-structural model in a statistically significant way, but their overall effect on the evolution of the natural rate of unemployment in Estonia appears to be quite subdued over the sample period 1998–2019. We also report that our estimates of the natural rate of unemployment are quite sensitive to the choice of which measures of the state of the labour market and the rate of unemployment are used as inputs in our new model. Another important lesson from our semi-structural analysis is that incorporation of the extrinsic drivers of the natural rate into the model tends to reduce the volatility of the resulting estimates of the natural rate of unemployment over the business cycle.

Contents

1 Introduction

This paper addresses the estimation of the natural rate of unemployment in Estonia using an empirical modelling approach. Our interest in this topic is motivated by the great practical importance of the natural rate for the proper conduct of monetary policy by a central bank. We address this issue in two interlinked steps, where we first consider what the determinants of the natural rate of unemployment are in a sub-sample of OECD countries, and then incorporate many of these determinants into a newly developed semi-structural model of the natural rate of unemployment for Estonia, which we estimate over the period 1998Q1–2019Q4.

The two main goals of this paper are to identify the potential structural determinants of the natural rate of unemployment in Estonia between 1998 and 2019, and to provide estimates of the natural rate for Estonia that take the effect of these structural factors into account. The methodological approach we use for this is to:

(a) Survey the recent theoretical and empirical literature on the natural rate of unemployment in a broad international context;

(b) Analyse empirically the potential determinants of the natural rate in a sample of 31 OECD countries using panel data methods;

(c) Develop a new semi-structural model of the natural rate of unemployment in Estonia that takes a broad range of the potential natural rate drivers into account and provides estimates of the natural rate over the last two decades.

The literature survey indicates that four broad groups of potential determinants of the natural rate of unemployment are particularly important. These four groups are active labour market policies, unemployment benefits and labour taxation, large macroeconomic shocks such as those affecting the housing market, and various government policies that are designed to facilitate economic growth and development. Contrary to our prior expectations, the literature does not seem to demonstrate any well-established links between the natural rate of unemployment and immigration policies or the supply of the short-term foreign labour.

We construct a panel of 31 OECD countries, which we use for an empirical investigation into what the determinants of the natural rate might be. Most of our empirical panel data models suggest that important drivers of the natural rate may be active labour market policies and the share of the construction sector in the total employment in the economy. Measures of labour taxation and capital accumulation are additional determinants of the natural rate, although they are not always statistically important in all our models. An important caveat to all the empirical panel models we estimate in this paper is that we have quite a limited sample, and so our findings should be regarded as tentative and must be used together with the preceding meta-analysis of the literature.

Finally, we develop a new semi-structural quarterly time series model to capture the evolution of the natural rate of unemployment in Estonia over time. One of the explicit goals of the new model is to incorporate the extrinsic determinants of the natural rate that are identified as potentially important in our earlier empirical panel data analysis.[1] To this end we explore a space of 4×2^{12} alternative model specifications, each one featuring a distinct combination of the determinants of the natural rate, and measures of the rate of unemployment and the state of the labour market in Estonia. Some of these potential drivers of the natural rate enter our semi-structural model in a statistically significant way, but their overall effect on the evolution of the natural rate of unemployment in Estonia appears to be quite subdued over the sample period 1998–2019. However, we report that our estimates of the natural rate of unemployment are quite sensitive to the choice of which measures of the state of the labour market and the rate of unemployment are used as inputs in our new model.

The rest of the paper is organised as follows. Section 2 gives a short review of the literature on potential empirical determinants of the natural rate of unemployment in the international context, which is followed by details of our panel data analysis of the empirical drivers of the natural rate in Section 3. In Section 4 we build, estimate and summarise results from our new semi-structural quarterly time series model of the natural rate of unemployment for Estonia. Finally, the conclusion and a summary of our main findings are at the end of the paper.

2 Literature overview

There is an extensive literature on the economic determinants of the natural rate of unemployment; the table in Appendix A of this paper gives a concise summary of the most recent contributions to it.[2] This literature can be divided into two main parts, of which one is on statistical methods of estimating unobserved structural unemployment, and the other on the theoretical and empirical determinants of structural unemployment. We focus only on the second part, though some of the estimation methods are discussed in Section 4 of this paper.

Policy institutions like the OECD and the European Commission largely take a neoclassical view of NAIRU as a proxy for the natural rate of unemployment.[3] The neoclassical view is that the natural rate of unemployment is determined solely by equilibrium market forces and the prevailing labour market conditions in each time period.[4]

Overly protective labour market institutions are found to be a major factor behind unemployment rates being elevated in many OECD countries (Siebert, 1997; Bernal-Verdugo,

[1] We avoid the term "exogenous determinants of the natural rate" in this paper because many of the factors that we use in our semi-structural time series model in Section 4 cannot be considered exogenous from the econometric point of view.

[2] In this paper we use the terms "natural rate", "structural rate" and "NAIRU" synonymously, unless specifically indicated otherwise.

[3] Other schools of thought take a different view about what determines the natural rate of unemployment. The Keynesian view sees capital accumulation as the key factor influencing aggregate demand, which in turn determines the natural rate of unemployment over time.

[4] In this paper, we use the term "labour market conditions" in a broad sense that includes both institutional labour market arrangements, like active labour market policies, and a set of wider macroeconomic indicators that affect the labour market, such as real house prices.

Furceri and Guillaume, 2012; Belot and Van Ours, 2004). Nickell, Nunziata and Ochel (2005) find in an empirical panel regression study that the unemployment benefits replacement ratio and labour union density have significant effects on the long-term unemployment rates. Flaig and Rottmann (2013) find similar results for a panel of nineteen OECD countries from 1960 to 2000, and they report that employment protection regulation, the unemployment benefit replacement rate, and the labour tax wedge have statistically significant effects. Bassanini and Duval (2007) focus on a dynamic panel of 21 OECD countries over the period 1982–2003 and find that the generosity of unemployment benefits and the tax wedge are the only statistically significant explanatory factors for the unemployment rate in their panel. Other studies such as Arestis, Baddeley and Sawyer (2007) and Stockhammer and Klar (2011) argue along Keynesian lines that capital accumulation is an important factor in determining aggregate demand and employment. They provide empirical evidence to support their hypothesis, finding that a rise of one percentage point in the rate of capital accumulation reduces unemployment by around 0.87 percentage points in the medium term.

Another part of the empirical literature finds there to be no meaningful and stable relationships between various labour market conditions (LMCs) and changes in the natural unemployment rate. A number of studies point out that the empirical links between the LMCs and increasing unemployment are not robust w.r.t. the estimation techniques, or to variations in the set of countries and sample periods (Baccaro and Rei, 2007; Howell, Baker, Glyn and Schmitt, 2007; Vergeer and Kleinknecht, 2012). Blanchard and Wolfers (2000) investigate the rise in unemployment since the 1960s through a panel analysis of 20 OECD countries. Their findings indicate that while adverse macroeconomic shocks can account for most of the rise in unemployment during that period, the heterogeneity in these shocks is not enough to explain the disparities in unemployment rates across different nations. Their results simultaneously indicate that although labour market institutions may be responsible for the cross-sectional variations in unemployment rates between countries, those institutions are not able to explain the broader temporal trends in unemployment. Blanchard and Wolfers (2000) underscore the importance of the interplay between macroeconomic shocks and labour market institutions in providing an understanding of the evolution of unemployment. Baccaro and Rei (2007) attempt to replicate the results of the influential IMF (2003) report using updated data. The original report found that employment protection, union density, the labour tax wedge, the interest rate and productivity shocks all had statistically significant effects, but the replication study finds that union density is the only labour market factor that has significant effect in the new dataset.

Ball and Onken (2022) argue that large shocks which affect the economy can also influence NAWRU through hysteresis effects, as the cyclical changes in unemployment can become entrenched in the share of the long-term unemployed. Countries experiencing large housing market boom and bust cycles or financial crises tend to show more variation in NAWRU. Orlandi (2012) picks this idea up and estimates a panel regression model controlling for four labour market indicators and three broader macroeconomic factors, including a measure of the boom and bust cycle in the housing market.[5] His results indicate that broader macroeconomic factors may influence NAWRU in addition to labour market conditions, and a proxy for the boom and bust cycle in the housing market in his models shows a sizeable and stable effect across all specifications.

Finally, there is little evidence on the effects of immigration and the supply of short-term and foreign labour and the natural rate of unemployment. This finding in the literature might be due the postulated property of long-run neutrality of labour supply in standard macroeconomic models of unemployment. However, there is a long literature on how immigration affects the wages of native workers and the employment rates in receiving countries; see Edo (2019) for a review. The work that comes closest to the literature on structural unemployment is Bentolila, Dolado and Jimeno (2008) who analyse the effects of an immigration boom in Spain between 1995 and 2006. Although it is not part of their main analysis, they claim that the decrease in the Spanish NAIRU from 15% to 9% within this period could be partly explained by the strong influx of foreign labour.

In summary, there is little consensus in the recent literature on the relevance and performance of various LMC variables in explaining long–run unemployment rates.

3 Empirical determinants of the natural rate of unemployment

This section considers the empirical determinants of the natural rate of unemployment in a sample of 31 OECD countries. We start by describing our panel data methodology and the panel dataset that we use to study potential empirical factors that might drive the natural rate of unemployment in advanced economies. We then proceed to estimate panel data regression models and summarise our results, highlighting the factors that might be of particular importance for the Estonian labour market.

3.1 Panel data models

We estimate panel data regression models using three different dependent variables in our empirical specifications. The first panel regression specification takes the following form:

$$\text{Structural Unemployment}_{i,t} \;=\; \beta\,\text{LMC}_{i,t} + \delta_1 \text{FE}_i + \delta_2 \text{FE}_t + \epsilon_{i,t}\,, \tag{1}$$

where the dependent variable $\text{Structural Unemployment}_{i,t}$ is a measure of the natural rate of unemployment in country i at time t. We use two proxies for structural unemployment in our analysis, one based on the OECD NAIRU methodology, and a second based on the AMECO NAWRU methodology. The regressors in the group of $\text{LMC}_{i,t}$ variables include a broad set of labour market conditions that contain various institutional labour market arrangementsand a

[5]Other studies which control for boom and bust cycles in the housing market include DGECFIN (2013) and Stockhammer, Guschanski and Köhler (2014).

set of macroeconomic factors, all of which are detailed in Subsection 3.2. The fixed-effects terms FE_i and FE_t take time–invariant country–fixed effects and year–fixed effects into account, while $\epsilon_{i,t}$ denotes the residual error term of this model.

Our second panel data model specification focuses on the cross-sectional and time dynamics of the growth in real wage:

$$\Delta\text{Real Wage}_{i,t} \;=\; \eta\,\text{Unemployment Gap}_{i,t} + \beta\,\text{LMC}_{i,t} + \delta_1\text{FE}_i + \delta_2\text{FE}_t + \epsilon_{i,t}\,, \tag{2}$$

where the variable $\Delta\text{Real Wage}_{i,t}$ denotes the year–on–year growth in real wages in country i at time t. On the right hand side we control for pressures from the business cycle using a measure of the contemporaneous unemployment gap, which is the difference between the unemployment rate and the corresponding NAIRU rate in country i at time t. The remaining terms are the same as in (1). This empirical panel data model is similar in spirit to the new semi-structural model of the natural unemployment rate for Estonia in Section 4.

3.2 Panel dataset

This section describes the panel dataset that we construct for our empirical models. Our analysis uses data from 31 OECD countries,[6] and our annual dataset spans the years from 2001 to 2019. The size and composition of our sample are dictated by the availability of data at the beginning of the period and the onset at the end of it of the COVID-19 pandemic, which had profound macroeconomic effects, particularly on employment. Detailed definitions of the data are shown in Table 8 in Appendix B.

The data on the NAIRU are taken from the OECD, which defines the NAIRU as the equilibrium unemployment rate as a percentage of the labour force. The modelling framework used by the OECD embeds the concept of anchored inflation expectations into a backward-looking Phillips Curve. This additional term can be interpreted as the deviation of lagged inflation from expected long-term inflation. Within this Phillips Curve construct, is the underlying assumption that inflation expectations are firmly tethered to the central bank's inflation target. The NAIRU based on the Phillips Curve is then calculated using Kalman filter; see Rusticelli, Turner and Cavalleri (2015) for a detailed description of the model.[7]

The data on the NAWRU are taken from the European Commission's (EC) AMECO database. The EC methodology for estimating the NAWRU combines the structural components of a New Keynesian model that incorporates the idea that the labour market is in long-term equilibrium, with estimates from a statistical approach that decomposes the unemployment rate into a cycle and a trend. This approach combines a structural model with a

[6]The list of countries in our panel dataset is: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, South Korea, Switzerland, the United Kingdom and the United States.

[7]The OECD stopped publishing NAIRU estimates in 2021. The NAIRU has been replaced by a new variable that is closer to the concept of trend employment; see page 14 of OECD (2021) for details.

reduced–form model, and is built on the unobserved components framework proposed by Kuttner (1994) and Gordon (1997).

We also analyse the determinants of real wage growth in our panel data study. Real wage growth is calculated from the OECD data on average annual real wages.

We consider a wide set of potential LMC variables that may determine structural unemployment. The first category of LMC variables covers labour taxes, and we use the OECD data to calculate the country-specific average labour tax wedge[8]. The labour tax wedge is defined as the ratio between the amount paid in labour taxes by an average worker and the total labour cost of that worker for the employer. The second variable in this category is the marginal personal income tax, which includes social contributions. We also use the variable for the top tax rate to account for the possible disincentive effects that high income taxes can have on the labour supply. The second broad group of LMC variables contains various measures of social security and labour protection. The average replacement rate captures the unemployment benefits replacement ratio and follows the approach of Orlandi (2012), who constructs a replacement rate measure that accounts for the probability of finding a job and for unemployment benefits varying for unemployment spells of different duration.

The index for active labour market policies (ALMP) is built from thirteen individual indicators of labour market policies that are aimed at helping people to find jobs, to retrain and to create new jobs.[9]. The variable is first transformed into the ratio of ALMP expenditures to GDP. We then divide this ratio by the share of the population that is unemployed to control for the size of the country and the potential for an increase in expenditures when the unemployment rate goes up.

To gauge the effect of minimum wage policies we use the ratio of minimum wages to the mean earnings of full-time employees. Another variable called the union density measures the proportion of union membership, and is constructed using administrative data.

We also use the OECD indicators for employment protection. These synthetic indicators measure how strict regulations on dismissals and the use of temporary contracts are. To give a comprehensive representation across the sample, we calculate the mean of all component indicator series for use in our panel data models.

An additional focus of our research is to analyse how changing employment patterns and labour migration affect the natural rate of unemployment; this constitutes the third broad group of LMC variables in our models. To do this we construct two indicators. First, we use the European Union labour force survey (EU-LFS) from Eurostat and filter the data for those who are not born in the country and those who are employed on a temporary labour contract. We use migration statistics to calculate labour migration and assume that migration in the age group 15-64 is for the purpose of working in another country. This variable captures the

[8]We construct the labour tax wedge by averaging the data on the labour tax wedge by family types. The family type labour tax wedge is a function of marital status, number of children, and earnings bracket within the income distribution.

[9]See the detailed list of component variables in our ALMP index variable in Table 8.

share of temporary foreign labour. Second, we proxy migrants as a share of the labour force by subtracting the number of people who emigrated from a given country from the number of people who immigrated into that country. Net migration is then divided by the size of the active population in the country.

As discussed in Section 2, the literature has found that narrow institutional labour market arrangements are insufficient for explaining the dynamics of structural unemployment. We control for a broader set of macroeconomic factors by including variables that capture the boom and bust cycles in employment in the construction sector, the growth rate of total factor productivity (TFP), the real interest rate, capital accumulation, housing price cycles, and terms of trade. This comprises the fourth broad group of LMC variables in our models.

We capture the boom and bust patterns in employment in the construction sector by using the proportion of labour employed in the construction sector after subtracting its average over time. We use Eurostat data on sectoral employment shares to calculate the share of employees working in construction. In addition to this, we account for broader housing price cycles by using the cyclical component of the seasonally adjusted real house price index in our panel data models.

Like for the construction sector variable, we use the proportions of employees working in the information and communication technology (ICT) sector and trade sector from the combined Eurostat and OECD data on sectoral employment shares. Deviations from the means of these proportions allow us to capture country-level fluctuations in employment levels in these sectors relative to their averages over the sample period.

Including real interest rates can be justified from the Keynesian perspective, as high real interest rates exert a dampening effect on investment and employment. Prolonged periods with low real interest rates can also trigger macro–financial instabilities and asset price bubbles, thereby affecting medium–run unemployment rates. Fluctuations in TFP growth rates can impact medium–term unemployment through changes in productivity. We measure year-on-year TFP growth using the OECD data. The rate of capital accumulation captures both the demand-side and supply-side effects of the business cycle, which may affect the unemployment rates over different time horizons. Investment is the most volatile component among the macroeconomic aggregates, and so changes in the capital accumulation may have an effect on medium–run unemployment through the hysteresis effect. In this paper, we measure capital accumulation as the ratio of real gross fixed capital formation to the net capital stock.

Finally we control for shocks to terms of the trade by including data from the national accounts on the relative price of imports. The year-on-year growth in the terms of trade is based on data from the AMECO database.

3.3 Empirical panel data results

This section presents the results of our empirical panel data estimations, which we carry out in three stages. First we perform a regression analysis of NAIRU against a set of factors across the full sample of 31 countries in our dataset. This baseline regression analysis gives a broad picture from which we can identify and understand the factors that are associated with the NAIRU across a diverse set of countries.

Then we narrow our sample down to a subset of 23 countries for which we have NAWRU data, and we compare the results from the NAWRU–based and NAIRU–based panel regression models. This comparison lets us determine which factors are more closely related to the NAWRU measures of the natural rate of unemployment and which ones have a stronger association with the NAIRU measures.

In the third and final stage of our analysis, we use real wage growth as the dependent variable in our panel regression model. This allows us to look at the factors using a specification that more closely mimics the semi-structural time series described in Section 4 of this paper.

Our empirical panel data models in Tables 1 to 4 are organised around the following eight empirical specifications:

Specification (i) studies the effects of labour taxes on the dependent variable;

Specification (ii) analyses the effects of active labour market policies and average unemployment replacement rates. Active labour market policies represent the costs of training workers borne by the government. The second regressor in this specification captures the degree of generosity of unemployment benefit schemes;

Specification (iii) has controls for minimum to mean wages, the degree of union density, and the degree of employment protection, as all these variables are of particular importance in the modelling framework for wage bargaining;

Specification (iv) combines the variables from the previous three specifications to construct a block of regressors that aims to capture the effects of all the structural labour market indicators;

Specification (v) examines the factors that are considered structural, but fall outside the domain of narrow labour market indicators in the literature. These factors include broader macroeconomic dynamics, the effects of monetary policy, and asset prices;

Specification (vi) explores the effects of labour migration and foreign labour factors on the dependent variable. Note that data coverage is limited for this specification;

Specification (vii) combines the labour market indicators from (iv) with the broader structural macroeconomic factors from (v);

Specification (viii) is a comprehensive model that includes all the available explanatory variables;

Note that in Table 4 we additionally introduce the unemployment gap into each of the eight empirical panel data model specifications.

3.3.1 Empirical NAIRU determinants in the full dataset

Table 1 presents the results of the panel data model shown in (1). For specification (ii), active labour market policies have a negative effect on the NAIRU. This association between increased spending on active labour market policies and a reduction in the NAIRU aligns consistently with established economic theory.

In the full LMC specification (iv), four factors stand out as significant. The top rate of income tax has positive effect on the NAIRU, and while the outcomes for the top rate of income tax align with neoclassical theory, the findings for average replacement rates and employment protection legislation deviate from the expectations set by the theoretical literature and empirical evidence. The coefficients for active labour market policies align with theoretical predictions, and their magnitude is comparable to that in the results reported in Orlandi (2012). Other labour market indicators in specification (i) to (iii) have no statistically significant effect on the NAIRU. Specification (v) turns to the broader factors in the LMC regressors, and we find that the variable proxying boom and bust cycles in the employment in the construction sector has strong and significant effects.

While we find only a weak negative link with the long-term real interest rate in specification (viii), the results for specifications (v), (vii) and (viii) indicate that there is a statistically significant negative relationship between capital accumulation and the NAIRU. The literature usually assumes that a rise in the real interest rate triggers a decline in capital accumulation, after which employment has to decrease to restore the equilibrium ratio between capital and labour. However, other channels can also explain the negative relationship between capital accumulation and the NAIRU, as capital accumulation usually leads to increased labour productivity for example. If workers anticipate that higher productivity will translate into higher wages, this could affect wage bargaining and could then reduce unemployment rates, gradually lowering the NAIRU over time.

Specification (vi) explores the relationship between the NAIRU and temporary labour and the net migration shares. In our analysis, we do not identify a statistically significant relationship between these variables and the NAIRU, which may be because there is a limited number of observations in our sample. In the next subsections we see that these variables exhibit a stronger relationship with the NAWRU than with the NAIRU, and we delve into possible explanations for this observation.

Specification (vii) resembles the model specifications widely used in the literature, as it combines narrow labour market arrangements and a broader set of macroeconomic factors. The average replacement rate appears to influence the NAIRU, but the sign of the coefficient does not align with the theoretical predictions. Similarly, a negative statistically significant coefficient emerges for the variable for the minimum-to-average wage. This outcome is exclusive to this specification and is challenging to reconcile with established economic theory. Within the block of non-labour market factors, only the capital accumulation exhibits a negative relationship with the NAIRU.

Table 1: Panel model of OECD NAIRU for the full dataset

	(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*	*(vii)*	*(viii)*
Tax wedge	0.0703			0.0215			-0.0080	0.0732
	(0.0829)			(0.0735)			(0.0493)	(0.0480)
Marginal income tax rate	-0.0143			-0.0305			-0.0146	-0.0079
	(0.0277)			(0.0278)			(0.0163)	(0.0147)
Top income tax rate	0.0568			0.0804**			0.0790**	0.0222
	(0.0530)			(0.0353)			(0.0343)	(0.0160)
Average replacement rate		-0.0094		-0.0631**			-0.0410**	-0.0183
		(0.0194)		(0.0249)			(0.0155)	(0.0494)
Active labour market policies		-0.0833*		-0.0573*			0.0122	0.0068
		(0.0422)		(0.0316)			(0.0171)	(0.0301)
Minimum to mean wage			-0.0518	-0.0374			-0.1089*	-0.1046
			(0.0487)	(0.0460)			(0.0593)	(0.0733)
Union density			0.1024	0.0619			-0.0007	-0.1141**
			(0.0745)	(0.0554)			(0.0330)	(0.0526)
Employment protection			-0.0204	-0.0138*			-0.0037	0.0070
			(0.0120)	(0.0077)			(0.0084)	(0.0043)
TFP growth					-0.0129		0.0070	0.0153
					(0.0284)		(0.0467)	(0.0358)
Capital accumulation					-0.0552**		-0.1518*	-0.2616***
					(0.0257)		(0.0782)	(0.0278)
Long-term real interest rate					0.0461		0.0160	-0.1418*
					(0.0361)		(0.0425)	(0.0713)
Terms of trade growth					0.0231		0.0131	-0.0125
					(0.0151)		(0.0229)	(0.0434)
Construction share					-0.2888**		-0.1678	-0.2422*
					(0.1351)		(0.1032)	(0.1213)
ICT share					-0.1423		-0.3554	-0.3165
					(0.1582)		(0.2284)	(0.2595)
Trade share					0.0229		-0.0142	0.0220
					(0.2007)		(0.1316)	(0.1637)
Cyclical house prices					-0.0031		-0.0075	0.0329**
					(0.0167)		(0.0175)	(0.0118)
Temporary foreign labour share						-0.0129		0.0050
						(0.0443)		(0.0254)
Net migration share						-0.2024		0.0668
						(0.1966)		(0.1890)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	588	485	296	270	416	219	206	105
R^2	0.9142	0.9106	0.9418	0.9440	0.9356	0.9045	0.9736	0.9890
Within R^2	0.0761	0.0706	0.0964	0.2290	0.2208	0.0176	0.4460	0.6051

Notes: The variables Construction share, ICT share and Trade share refer to the proportions of employment in the construction, information and communication technology and trade sectors respectively, with each measure de-meaned. Cyclical house prices are derived by applying the Hodrick–Prescott filter to the logarithm of the real seasonally adjusted house price index. TFP and terms of trade enter as year-on-year growth rates. Country-level clustered standard-errors are shown in parentheses. Statistical significance: *** 0.01, ** 0.05, * 0.10.

Specification (viii), the final model in this subsection, includes additional controls for the dynamics of labour migration. Union density, capital accumulation, long-term real interest rates, the construction share and cyclical house prices all demonstrate statistically significant impacts.

While the results for the long-term real interest rate and cyclical house prices are statistically significant, we advise prudence in interpreting these results, as this finding does not occur in the previous specifications in Table 1, and the number of observations is limited relative to the number of estimated parameters. In general, the findings from specification (viii) warrant careful interpretation given the large number of regressors relative to the number of observations.

3.3.2 Empirical determinants of the NAIRU and the NAWRU

The NAIRU and the NAWRU are distinct concepts, but they share certain similarities. In the long term they both capture the notion that a certain level of unemployment is attributable to supply-side factors, such as structural and frictional unemployment when the economy is nearing full employment. How they are composed and how variable they are in the short term can, however, differ.

In the empirical part of this paper we treat the NAIRU and the NAWRU interchangeably, even though there are nuanced differences between them. In our baseline analysis, we have chosen to focus solely on the NAIRU because more comprehensive data are available and so we can streamline our analysis. Concentrating on the NAIRU and not delving into the short-run disparities between the NAIRU and the NAWRU, lets us maintain a clearer and more focused examination of the factors that influence the long-term relationship between unemployment and inflation.

However, we acknowledge that it is important to understand the specific divergences and dynamics between the NAIRU and the NAWRU. This short subsection sheds some light on the similarities and differences in the drivers of the two measure of the natural unemployment rate, provided that they share the same sample in our dataset. To ensure comparability, we restrict our analysis to countries where data for both the NAIRU and the NAWRU are available. By examining the nuances within this restricted sample, we can gain a deeper understanding of how various factors influence the way both the NAIRU and the NAWRU are determined.

We employ the specification shown in (1) and focus our analysis on a subset of 23 countries for which NAWRU data from the AMECO is available.[10]

For the sake of comparability, we further narrow our analysis down by restricting the NAIRU data obtained from the OECD to the same subset of countries. This restriction ensures consistency across estimations and makes the sample more comparable across both the NAWRU and NAIRU measurements.

[10]From the initial dataset of 31 countries we have NAWRU data from AMECO for 23 countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, the United Kingdom and the United States.

Table 2: Panel model of AMECO NAWRU for a subset of 23 OECD countries

	(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*	*(vii)*	*(viii)*
Tax wedge	0.1233			0.1388			-0.0986	0.1204**
	(0.1062)			(0.1080)			(0.1074)	(0.0525)
Marginal income tax rate	-0.0197			-0.0791*			-0.0337	-0.0234
	(0.0337)			(0.0408)			(0.0289)	(0.0160)
Top income tax rate	0.1497**			0.1641***			0.1247**	0.0672*
	(0.0540)			(0.0509)			(0.0449)	(0.0367)
Average replacement rate		0.0225		-0.0396			0.0044	-0.1082*
		(0.0302)		(0.0382)			(0.0383)	(0.0595)
Active labour market policies		-0.1940**		-0.1552**			-0.0323	-0.0962***
		(0.0874)		(0.0669)			(0.0317)	(0.0250)
Minimum to mean wage			0.0277	0.0890			-0.0911	-0.2446***
			(0.1293)	(0.1226)			(0.0794)	(0.0642)
Union density			0.3531***	0.2049***			0.0040	-0.0185
			(0.0932)	(0.0649)			(0.0566)	(0.0419)
Employment protection			-0.0159	-0.0019			0.0196	0.0149**
			(0.0226)	(0.0111)			(0.0126)	(0.0052)
TFP growth					-0.0141		0.0165	-0.0502
					(0.0495)		(0.0731)	(0.0452)
Capital accumulation					0.0525		-0.0834	-0.2586***
					(0.0732)		(0.0613)	(0.0590)
Long-term real interest rate					0.0399		0.0036	-0.1043
					(0.0717)		(0.0880)	(0.0965)
Terms of trade growth					0.0683		0.1028*	0.0747
					(0.0602)		(0.0547)	(0.0530)
Construction share					-0.7045***		-0.7280***	-0.3768***
					(0.1362)		(0.1384)	(0.1009)
ICT share					0.0001		-0.0100	-0.0249
					(0.2278)		(0.4039)	(0.1533)
Trade share					0.0194		0.0218	-0.1130
					(0.2664)		(0.2639)	(0.1901)
Cyclical house prices					-0.0129		-0.0153	0.0055
					(0.0202)		(0.0141)	(0.0151)
Temporary foreign labour share						-0.0289		0.0705***
						(0.0495)		(0.0217)
Net migration share						-0.8367**		-0.5328**
						(0.3381)		(0.2084)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	437	387	225	216	362	220	190	105
R^2	0.8485	0.8394	0.8686	0.9116	0.8917	0.9044	0.9579	0.9892
Within R^2	0.2521	0.2037	0.2186	0.4839	0.3785	0.1600	0.6536	0.8017

Notes: The variables Construction share, ICT share and Trade share refer to the proportions of employment in the construction, information and communication technology and trade sectors respectively, with each measure de-meaned. Cyclical house prices are derived by applying the Hodrick–Prescott filter to the logarithm of the real seasonally adjusted house price index. TFP and terms of trade enter as year-on-year growth rates. Country-level clustered standard-errors are shown in parentheses. Statistical significance: *** 0.01, ** 0.05, * 0.10.

Table 3: Panel model of OECD NAIRU for a subset of 23 OECD countries

	(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*	*(vii)*	*(viii)*
Tax wedge	0.0724			0.0387			-0.0124	0.0699
	(0.1069)			(0.1066)			(0.0449)	(0.0430)
Marginal income tax rate	-0.0149			-0.0300			-0.0105	-0.0081
	(0.0367)			(0.0284)			(0.0159)	(0.0151)
Top income tax rate	0.0635			0.0867**			0.0667*	0.0270
	(0.0603)			(0.0353)			(0.0364)	(0.0206)
Average replacement rate		-0.0095		-0.0691**			-0.0394**	-0.0211
		(0.0195)		(0.0277)			(0.0146)	(0.0495)
Active labour market policies		-0.0806*		-0.0478			0.0175	0.0126
		(0.0468)		(0.0360)			(0.0180)	(0.0317)
Minimum to mean wage			-0.0541	-0.0537			-0.1454**	-0.1058
			(0.0746)	(0.0615)			(0.0638)	(0.0671)
Union density			0.1096	0.0625			-0.0583	-0.1065*
			(0.0718)	(0.0563)			(0.0342)	(0.0524)
Employment protection			-0.0220	-0.0135			-0.0011	0.0075*
			(0.0135)	(0.0081)			(0.0087)	(0.0042)
TFP growth					-0.0230		0.0027	0.0168
					(0.0349)		(0.0432)	(0.0378)
Capital accumulation					-0.0602**		-0.1720*	-0.2538***
					(0.0243)		(0.0895)	(0.0331)
Long-term real interest rate					0.0303		0.0150	-0.1367**
					(0.0463)		(0.0460)	(0.0585)
Terms of trade growth					0.0007*		0.0008	-0.0005
					(0.0004)		(0.0005)	(0.0006)
Construction share					-0.2908*		-0.2059*	-0.2187
					(0.1444)		(0.1115)	(0.1361)
ICT share					-0.1350		-0.3472	-0.2913
					(0.2008)		(0.2130)	(0.2897)
Trade share					0.0360		-0.0179	0.0351
					(0.2373)		(0.1349)	(0.1541)
Cyclical house prices					-0.0082		-0.0153	0.0348***
					(0.0176)		(0.0175)	(0.0113)
Temporary foreign labour share						-0.0129		0.0068
						(0.0443)		(0.0267)
Net migration share						-0.2024		0.0800
						(0.1966)		(0.1774)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	436	387	225	216	362	219	190	105
R^2	0.8809	0.8844	0.9193	0.9295	0.9196	0.9045	0.9712	0.9892
Within R^2	0.0848	0.0598	0.1072	0.2383	0.2524	0.0176	0.4847	0.6119

Notes: The variables Construction share, ICT share and Trade share refer to the proportions of employment in the construction, information and communication technology and trade sectors respectively, with each measure de-meaned. Cyclical house prices are derived by applying the Hodrick–Prescott filter to the logarithm of the real seasonally adjusted house price index. TFP and terms of trade enter as year-on-year growth rates. Country-level clustered standard-errors are shown in parentheses. Statistical significance: *** 0.01, ** 0.05, * 0.10.

Table 2 presents the results when the NAWRU from AMECO is used as the endogenous variable in the panel regression model. The top rate of income tax has a robust and statistically significant positive effect on the NAWRU in specifications (i), (iv), (vii), and (viii). The variable for active labour market policies has a statistically significant negative impact on the NAWRU, particularly in specifications (ii) and (iv).

Higher degrees of union density are associated with a larger NAWRU in specifications (iii) and (iv). When the other labour market factors are controlled for, capital accumulation in specification (viii) and the construction share in all the specifications appear as statistically significant and have the expected sign and size. The variables that are designed to capture the dynamics of labour migration tend to be significant in the NAWRU results, as a higher share of net migration is associated with a significant decrease in the NAWRU. One possible explanation for this is that an increase in net migration, particularly if migrants are individuals of the working age group, can expand the available labour pool. This increased labour supply may exert downward pressure on wages, which could lower the NAWRU over time.

The results of estimating the NAIRU from the OECD dataset for the sample of 23 countries are remarkably similar to those presented in Table 1. This consistency should not come as a surprise, given that the number of observations is similar for both the specifications with combined labour market factors and broader macro factors in the two tables. In both cases the most important labour market factors are the top rate of income and the average replacement rate.

While the sign of the coefficients for the top rate of income tax aligns with our expectations, the negative coefficients for the average replacement rate leave room for interpretation. Similarly, the negative sign of the coefficient for active labour market policies in specification (ii) and the negative coefficient for the minimum-to-average wage in specification (vii) are challenging to reconcile with standard theoretical arguments.

Among the non-labour market factors, capital accumulation, long-term interest rates, and the construction share exhibit statistically significant effects on the NAIRU. The variables for capital accumulation and the construction share both notably demonstrate a strong negative relationship with the NAIRU across most specifications in Table 3.

As we compare our findings for the NAIRU in Table 3 with those for the NAWRU in Table 2, both of which are estimated on the same sample of 23 countries, we find that the results for the two measures of the natural rate of unemployment are similar. The coefficients of the labour market indicators appear slightly larger in the NAWRU model, but overall, the factors that matter are similar for both the NAWRU and the NAIRU. Capital accumulation, which is a significant predictor of the NAIRU, exhibits a less strong relationship with the NAWRU, while variables related to taxation play a slightly more prominent role in the NAWRU model than those in the NAIRU model. The results for capital accumulation can be explained by the fact that it impacts the productive capacity and potential output of an economy over the long run, thereby affecting the NAIRU through these long term effects.

One final notable difference between the results for the NAWRU and those for the NAIRU lies in the variables for labour migration. The variables for the foreign labour share and net migration demonstrate a stronger association with the NAWRU. Labour migration can impact the NAWRU directly by affecting the supply of labour in specific regions or industries, which can put downward pressure on wages if labour migrants enter areas where there are more job opportunities or higher wages.

In summary, we find some amount of variation in the estimated coefficients of the various LMC variables across the NAIRU and the NAWRU measures of the natural rate of unemployment. However, it is evident from our findings that core labour market factors and broad macroeconomic conditions influence both the NAIRU and the NAWRU similarly. It therefore appears reasonable to treat these two concepts equivalently throughout the remaining analysis.

3.3.3 Real wage growth determinants

Finally, we delve into the factors that influence growth in real wages. Real wage growth is typically viewed within the framework of the Phillips curve as a function of the discrepancy between actual unemployment and the NAIRU, a measure often referred to as the unemployment gap. In this subsection the unemployment gap serves as a pivotal determinant of wage inflation in our panel data models, which bear similarity to the semi-structural time series model that we develop in Section 4.

Table 4 presents empirical results for our real wage growth model in (2). The first row of Table 4 shows that a positive unemployment gap has a negative effect on real wage growth in every specification, indicating that a larger unemployment gap is associated with slower growth in real wages as expected from economic theory.

Among the labour market variables, the tax wedge consistently exhibits negative coefficients in the specifications where it is included. This implies that an increase in the tax wedge is associated with a deceleration in real wage growth, which is in line with the theoretical expectations. The average tax wedge is often considered a deterrent to both employers and employees, but an increase in the tax wedge caused by a rise in income tax or social security contributions rises labour costs for employers. This could potentially reduce demand for labour, resulting in slower wage growth and a possible uptick in unemployment. Employees meanwhile perceive a larger tax wedge as a decrease in the net return from their labour, which may influence their labour supply decisions. Having diminished take-home pay could deter them from expanding their working hours or pursuing higher-paying positions, thereby contributing to slower real wage growth.

Among the wider macroeconomic variables, total factor productivity (TFP) growth emerges as particularly notable. The coefficient for TFP growth is consistently positive, sizeable, and statistically significant across all the specifications in which it is included. This is in line with theoretical arguments. An increase in productivity can lead to higher profits for firms, and in a competitive labour market, firms may share these increased profits with their employees in

Table 4: Panel model of year-on-year real wage growth for the full dataset

	(i)	*(ii)*	*(iii)*	*(iv)*	*(v)*	*(vi)*	*(vii)*	*(viii)*
Unemployment gap	-0.5078***	-0.4028**	-0.2815**	-0.2468*	-0.2923	-0.5809**	-0.2526*	-0.3528
	(0.1681)	(0.1699)	(0.1270)	(0.1395)	(0.2869)	(0.2241)	(0.1384)	(0.2143)
Tax wedge	-0.0926			-0.2061**			-0.3254**	-0.5338***
	(0.1037)			(0.0953)			(0.1374)	(0.1479)
Marginal income tax rate	-0.0294			0.0195			0.0403	0.0767**
	(0.0464)			(0.0220)			(0.0303)	(0.0334)
Top income tax rate	0.1628**			0.0418			-0.0059	0.0696
	(0.0686)			(0.0589)			(0.0409)	(0.0829)
Average replacement rate		0.0180		0.0609			0.0517	0.1578
		(0.0264)		(0.0608)			(0.0740)	(0.1566)
Active labour market policies		-0.0124		0.0456			0.0805	0.2619
		(0.0344)		(0.0375)			(0.0553)	(0.1522)
Minimum to mean wage			0.0123	0.0119			-0.0352	-0.1069
			(0.0498)	(0.0568)			(0.0700)	(0.1456)
Union density			0.1579*	0.1003			0.1366	0.1354
			(0.0867)	(0.0748)			(0.0817)	(0.1140)
Employment protection			-0.0271*	-0.0299			-0.0140	-0.0424
			(0.0152)	(0.0176)			(0.0169)	(0.0301)
TFP growth					0.2923*		0.4123***	0.3898**
					(0.1609)		(0.1328)	(0.1551)
Capital accumulation					0.3380		0.0592	0.0865
					(0.2138)		(0.1199)	(0.2403)
Long-term real interest rate					-0.0431		0.2155	0.3980
					(0.2506)		(0.1422)	(0.3611)
Terms of trade growth					0.1325		-0.0951	0.0403
					(0.2079)		(0.0675)	(0.2246)
Construction share					-0.2065		-0.0030	0.1548
					(0.1988)		(0.1764)	(0.4912)
ICT share					-0.0518		1.458**	0.0192
					(0.2401)		(0.6596)	(0.8943)
Trade share					0.0120		-0.2574	-0.4231
					(0.2827)		(0.2896)	(0.5761)
Cyclical house prices					0.0639*		0.0408	0.0424
					(0.0313)		(0.0269)	(0.0340)
Temporary foreign labour share						-0.0466		-0.1411**
						(0.0796)		(0.0518)
Net migration share						-1.047***		-0.0643
						(0.3522)		(0.6022)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	575	485	294	270	405	219	206	105
R^2	0.3942	0.3694	0.4931	0.5201	0.4530	0.5022	0.6648	0.7604
Within R^2	0.1161	0.0887	0.0779	0.1243	0.2446	0.1490	0.2300	0.4658

Notes: The unemployment gap is calculated as the difference between the actual unemployment rate and the OECD NAIRU. The variables Construction share, ICT share and Trade share refer to the proportions of employment in the construction, information and communication technology and trade sectors respectively, with each measure de-meaned. Cyclical house prices are derived by applying the Hodrick–Prescott filter to the logarithm of the real seasonally adjusted house price index. TFP and terms of trade enter as year-on-year growth rates. Country-level clustered standard-errors are shown in parentheses. Statistical significance: *** 0.01, ** 0.05, * 0.10.

the form of higher wages in order to attract and retain the best talent. Growth in TFP can consequently lead to growth in real wages. Rising productivity also leads to economic growth, which increases demand for labour and puts upward pressure on wages.

Finally, the net migration share in specification (vi) and the temporary foreign labour share in specification (viii) both have a statistically significant negative impact on real wage growth. Although the number of observations is limited in both specifications, these results provide an indication of how these variables might relate to real wage growth. A rise in net migration or influx of temporary foreign labour can increase the supply of labour in an economy. The increased supply can exert downward pressure on wages, leading to the negative relationship observed with real wage growth.

4 Semi-structural model of the natural rate of unemployment

In this section we discuss a new semi-structural model of the natural rate of unemployment for Estonia. We start by describing models and estimates of the natural rate of unemployment for Estonia that were previously available, and take a look at existing methodologies used by the European Commission and the OECD for estimating the natural rate. We then build and estimate a new semi-structural quarterly time series model of the natural rate for Estonia that explicitly takes account of additional factors stemming from the institutional and macroeconomic environment and the labour market conditions that could affect the dynamics of the estimates of the natural rate over time. We also describe the data and the estimation results of the new model, and we finally conclude by assessing the impact of various factors and the potential determinants of the natural rate of unemployment in Estonia over the sample period.

4.1 Econometric methodology and conceptual building blocks

There are several existing sources of estimates of the natural rate of unemployment for Estonia. Eesti Pank earlier estimated and used the natural rate in its quarterly macroeconomic model; see Kattai (2005). These estimates were later revised in several unpublished internal research papers at the bank in 2012 to 2015. The main motivation behind these later revisions was to pin down the dynamics of the natural rate of unemployment after the global financial crisis in the environment of low inflation rates that predomined at the time. However, none of these revised models were designed to account for any extrinsic labour market factors or the macroeconomic or institutional environment, though these could be relevant for pinning down the dynamics of the natural rate.

In addition to these internal Eesti Pank assessments, there is at least one academic publication that provides a completely independent set of estimates of the natural rate of unemployment for Estonia in Posta (2015). The empirical results of this paper suggest a relatively high degree of flexibility in the time dynamics of the natural rate of unemployment, which is obtained from a model built on the foundations of the New Keynesian Phillips Curve (NKPC) and is estimated

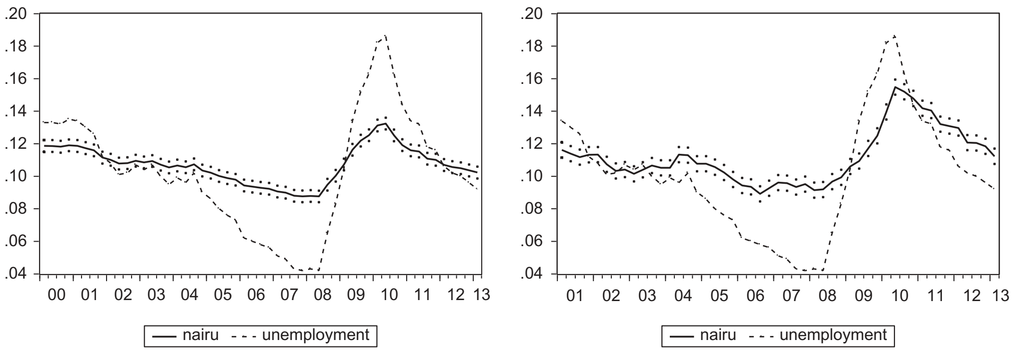

Figure 1: Two alternative NAIRU estimates for Estonia in Posta (2015)

using quarterly data from 1998 to 2013; two of these estimates are shown in Figure 1.[11] Finally, the European Commission and the OECD provide annual estimates of the natural rate of unemployment for Estonia in the course of their regular economic monitoring; see Subsection 3.2 of this paper.

Our approach to building a new semi-structural model of the natural rate of unemployment in this paper is based on the following main conceptual building blocks:

(a) The classical formulation of the natural rate hypothesis in Friedman (1968), Phelps (1967) and Phelps (1968), which argues that the dynamics of the natural rate are constant or vary very slowly over time. Its main determinants are recognised to be market forces and pre-existing institutional arrangements in a given country in a given time period;

(b) The canonical form of the time-varying NAIRU, specified as a random walk, found in the "triangle model" of Gordon (1997) and the early stock-taking paper by Blanchard and Katz (1997). These papers also use real wage growth and labour productivity in their auxiliary wage equations;

(c) The theoretical foundations of the time–varying natural rate models provided by Blanchard and Katz (1999), where an explicit link is made between the dynamics of real wages and the unemployment rate;

(d) An applied paper by Laubach (2001) on measuring the time-varying NAIRU, which is widely used by many economic institutions around the world as the benchmark semi-structural time series model of the natural rate of unemployment;

(e) A modern approach to the natural rate formalised in the papers by Ball and Mankiw (2002) on the theory and practice of the NAIRU, and by Hall (2005) on the natural rate of unemployment through the lens of the search and matching theory;

[11]The left panel shows the estimates for the natural rate obtained from the baseline NKPC specification in Posta (2015). The right panel displays the estimates for the natural rate from an extended NKPC specification that additionally includes the long–term unemployment rate and real labour costs, which makes it closer to the New Keynesian Wage Phillips Curve framework of Galí (2011).

(f) The New Keynesian framework of modelling and measuring the natural rate of unemployment in Galí (2011), known as the New Keynesian Wage Phillips Curve. The forward–looking nature of this model makes the time–dynamics of the natural rate even more volatile than in previous approaches, which can be seen in Figure 1.

As mentioned in the introduction, one of the explicit goals of designing and building a new semi-structural model of the natural rate of unemployment for Estonia is to incorporate the effects of the macroeconomic and institutional environment and labour market conditions into the dynamic estimates of the natural rate. Most of our empirical panel data models in Section 3 of the paper tentatively suggest that such factors as active labour market policies and the share of employment in the construction are important. Other possible drivers of the natural rate, though they are not always statistically or economically important in our limited sample of 31 OECD countries, include various measures of labour taxation and productivity. In the new semi-structural time series model of the natural rate of unemployment for Estonia we want to account for these and other potential extrinsic drivers of the natural rate, and to incorporate the findings of the most recent theoretical and empirical literature into the design of our new model.

Below we summarise the main innovations in our new semi-structural model of the natural rate of unemployment for Estonia from its previous version in Kattai (2005) and its subsequent internal revisions over the years 2012 to 2015. All these innovations and features of the new model will be expounded upon later in this section in more detail:

(a) The new model accounts for a set of extrinsic drivers of the natural rate of unemployment that includes labour market and institutional factors in Estonia;

(b) It incorporates elements of the most recent state–of–the–art approaches to estimating the natural rate of unemployment from the European Commission in Orlandi (2012) and Hristov, Planas, Roeger and Rossi (2017);

(c) Other measures of the unemployment rate and the state of the labour market can be used if alternative assessments of the evolution of the natural rate of unemployment over time are required;

(d) The model uses an up–to–date structure with a new dynamic term for the cyclical unemployment gap as in Laubach (2001).

Our conceptual approach to building the new semi-structural model of the natural rate of unemployment is broadly similar to the one that was used by Eesti Pank in the previous generations of such models. The core foundation of the model is theoretically grounded and derived from a semi-structural wage bargaining framework by Blanchard and Katz (1999); more recently the same theoretical foundations were used by Havik, McMorrow, Orlandi, Planas, Raciborski, Roeger, Rossi, Thum-Thysen and Vandermeulen (2014) in the methodology developed by the European Commission for measuring the output gap. The dependent variable, which is linked to the cyclical unemployment gap in both of these studies, is the *growth rate* of the real unit labour cost. The intuitive justification for using the growth rate of the real unit labour cost in these models instead of its level comes from wage bargaining, as employers and employees observe the *changes* in labour productivity in each time period, which is taken to be one quarter, and bargain over the corresponding shares of the real wage *changes* that accrue to each party. The outcome of this process depends on the tightness of the labour market in every time period. An alternative framework for the *levels* of the real unit labour cost would require the two parties to bargain over the *levels* of productivity and real wages, but those levels are largely determined by the history of technological progress which neither party has any control over in the short–term bargaining time horizon. It should of course be remembered that these are only semi-structural considerations, while reality is usually more complicated. However, the growth rate of the real unit labour cost was found to work well in many previous empirical studies that Blanchard and Katz (1999) and Havik et al. (2014) refer to.

The fundamental equation of the model therefore links the current state of the labour market, the cyclical unemployment gap, and various extrinsic drivers of the natural rate of unemployment in the following way:

$$S_t \;=\; \theta(U_t - U_t^\star) + \boldsymbol{\alpha}^T \boldsymbol{x}_{t-1} + e_t \;=\; \theta\gamma_t + \boldsymbol{\alpha}^T \boldsymbol{x}_{t-1} + e_t\,, \tag{3}$$

where the list of the underlying variables in this relation is as follows:

Labour market state:	S_t	Growth of the real unit labour cost
Unemployment rate:	U_t	Observed variable
Natural rate of unemployment:	$U_t^\star$	Unobserved variable of interest
Cyclical unemployment gap:	γ_t	Tightness of the labour market
Extrinsic drivers:	$\boldsymbol{x}_{t-1}$	Vector of factors affecting the natural rate
Error term:	e_t	Unexplained part of the model

The error term e_t in (3) is cast into a simple autoregressive dynamic framework $e_t = \phi\, e_{t-1} + \epsilon_{1t}$ for added flexibility and to give a better fit to the data. The same provision is also made in the new model for the cyclical unemployment gap $\gamma_t := U_t - U_t^\star$ following Laubach (2001).

The way the extrinsic drivers of the natural rate $\boldsymbol{x}_{t-1}$ enter the fundamental model equation (3) can also be justified from the same wage bargaining perspective, as the vector $\boldsymbol{x}_{t-1}$ contains any additional indicators for the institutional and macroeconomic environment and labour market conditions that may be relevant for the process of bargaining about the changes in any surpluses or any shortfalls between the real wage and labour productivity in each time period described by the model. We use the lagged values of these drivers to avoid possible endogeneity issues in the model.

In a broad sense, the dependent variable S_t in the fundamental model equation (3) can be interpreted as any indicator that responds to the current state of the labour market. In our baseline specification this indicator reflects the surplus or shortfall between the real wage and labour productivity as measured by the real unit labour cost and entering the model in growth terms. In our alternative specification in Subsection 4.3 we use another proxy of the state of the labour market in order to gauge its effect on the estimates of $U_t^\star$ produced by our new model.

To cast the new model of the natural rate of unemployment (3) into a format suitable for statistical inference, we use the Kalman filtering approach to inference on unobserved components models.[12] We use the conventional maximum likelihood estimator to obtain statistical inference on all the unobservables in the following set of state and measurement equations:[13]

$$\begin{aligned} e_{t+1} &= \phi\, e_t + \epsilon_{1t} \\ \gamma_{t+1} &= \rho\, \gamma_t + \epsilon_{2t} \\ U^\star_{t+1} &= U^\star_t + \epsilon_{3t} \\ S_t &= \theta\gamma_t + \boldsymbol{\alpha}^T \boldsymbol{x}_{t-1} + e_t \\ U_t &= \gamma_t + U^\star_t \end{aligned} \tag{4}$$

where the observed inputs include S_t, U_t and $\boldsymbol{x}_{t-1}$, the latent state variables are given by e_t, γ_t and $U_t^\star$, and we use the standard normality assumptions on the three stochastic innovations in our model:

$$\begin{pmatrix} \epsilon_{1t} & \epsilon_{2t} & \epsilon_{3t} \end{pmatrix}^T \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Sigma})\,, \quad \text{where:} \quad \mathbf{0} := \begin{pmatrix} 0 & 0 & 0 \end{pmatrix}^T \text{ and } \boldsymbol{\Sigma} := \begin{pmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{pmatrix}.$$

This dynamic statistical framework allows us to obtain inference on the structural parameters of interest θ and $\boldsymbol{\alpha}$, and on the two auxiliary dynamics parameters ρ and ϕ. The unemployment gap parameter θ determines the slope in the fundamental model equation (3). The loading coefficients on the vector of the drivers of the natural rate in $\boldsymbol{x}_{t-1}$ correspond to different elements of $\boldsymbol{\alpha}$. The two auxiliary dynamics parameters ρ and ϕ provide additional flexibility to the entire framework and improve the fit of our model to the available data sample. Finally, statistical estimates of the unobserved time evolution of the natural rate of unemployment $U_t^\star$ are obtained by the standard Kalman filter smoothing procedure; see Hamilton (1994).

The next question is how we select the set of potential drivers of the natural rate in $\boldsymbol{x}_{t-1}$ in our new model. Since our semi-structural modelling framework offers very little guidance on the exact combination of these drivers in the model, we use the available computational capacity to explore the full model space spanned by all the possible combinations of the extrinsic drivers of the natural rate in $\boldsymbol{x}_{t-1}$. This is needed to assess how sensitive our estimates of $U_t^\star$ are to all possible ways that these drivers can enter our model. We iterate on the following estimation steps: (i) we choose a labour market state indicator S_t and an unemployment rate measure U_t, and (ii) we evaluate the in–sample ability of our model to explain the dynamics of the dependent variable using the estimated cyclical unemployment gap $\hat{\gamma}_t$ and the particular combination of

[12] For the technical details on the particular form of the Kalman filter used to estimate the model see de Jong (1991). The new model is built and estimated entirely in MATLAB®, which should make it suitable for policy simulation and forecasting processes in a central bank.

[13] Additional extensions of this model, not entertained in this paper, may include: (i) a more general form of the variance–covariance matrix $\boldsymbol{\Sigma}$, and (ii) additive measurement errors in the last two equations of (4).

the extrinsic drivers of the natural rate in $\boldsymbol{x}_{t-1}$. These steps are repeated for all the possible combinations of the twelve available extrinsic drivers of the natural rate and four different combinations of the measures of the state of the labour market and the rate of unemployment, giving us the full model space dimension of $4 \times 2^{12} = 16384$ alternative specifications for assessing the performance of our model.[14] The evaluation of the in–sample ability of each model to explain the left hand side variable in (3) is based on a very simple correlation metric between the particular choice of the dependent variable and $\hat{\theta}\hat{\gamma}_t + \hat{\boldsymbol{\alpha}}^T \boldsymbol{x}_{t-1}$, where the hats signify the parameter estimates. More precisely, $\hat{\gamma}_t$ contains the estimated natural rate of unemployment $U_t^\star$ that is obtained for the given combination of factors in $\boldsymbol{x}_{t-1}$. Another metric for evaluating the model that we use in this paper is based on the likelihood ratio test of the elements of $\boldsymbol{\alpha}$ being jointly statistically different from zero, that is against the alternative of the zero–factor model that contains no added extrinsic drivers of the natural rate in $\boldsymbol{x}_{t-1}$.

The estimation methodology used in this paper is reminiscent of the subset regression methods in the literature on machine–learning; see Hastie, Tibshirani and Friedman (2009). The goal of our statistical approach here is not to identify a single preferred model that delivers the "best" estimates of the natural rate $U_t^\star$ for Estonia. We rather view all 4×2^{12} estimated specifications in combination and look at the average estimates of $U_t^\star$ across all these models. In this way our statistical approach is close to that in the literature on model averaging in economics; see Moral-Benito (2015).

4.2 Time series dataset

Our quarterly dataset covers the period from the 1998Q1 to 2019Q4 and is sourced mainly from the Eesti Pank quarterly macroeconomic model EMMA, in conjunction with some internally produced and publicly available data series. We describe these data below.

Figure 2 shows two alternative measures of the state of the labour market S_t, which represents the left hand side variable in our model equation (3). In this figure, $\Delta\mathsf{RULC}_t$ is the growth in the real unit labour cost from the Eesti Pank quarterly macroeconomic model EMMA, together with the output gap from the same source.[15] We use the output gap as an alternative indicator of the state of the labour market state because its time dynamics in the later part of the sample period are quite different from those of the the growth in the real unit labour cost, and we need to understand the implications of these differences for our estimates of $U_t^\star$ for Estonia.

Figure 3 displays two alternative measures of the unemployment rate for Estonia. One is based on the ILO methodology and is used by the Eesti Pank quarterly macroeconomic model EMMA, and the other is based on data from the Estonian unemployment register with

[14]This is a simplified version of the full possible model–space exploration approach. We do not consider levels and differences and alternative lag structures of the drivers of the natural rate in $\boldsymbol{x}_{t-1}$, as that would make the full dimension of the model space too big to handle given the available computational capacity and time budget for the estimation.

[15]We use the March 2020 vintage of the Eesti Pank quarterly macroeconomic model EMMA.

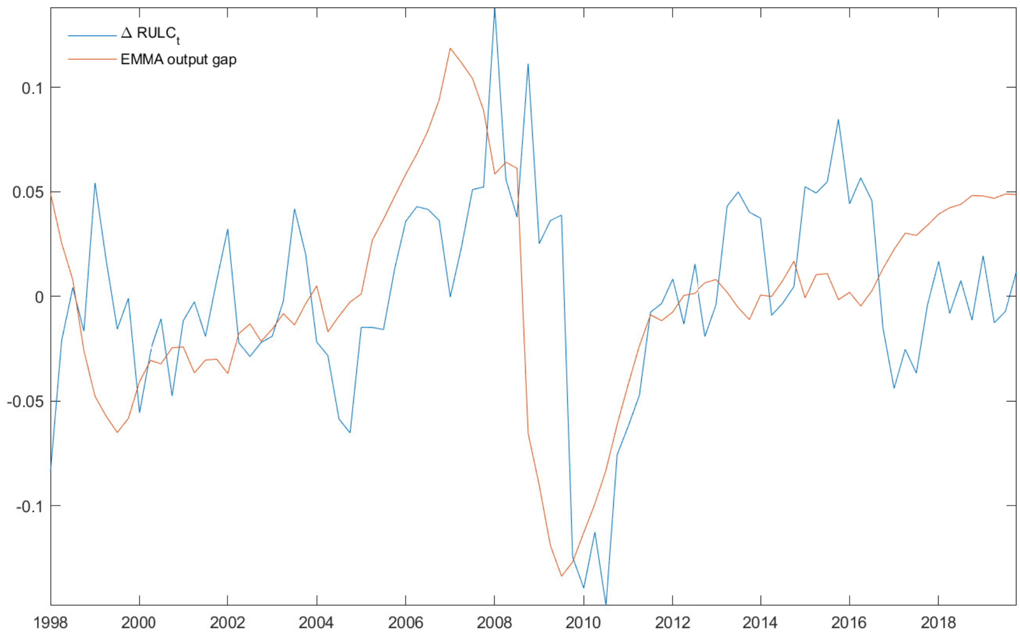

Figure 2: Two alternative data choices for the state of the labour market variable S_t

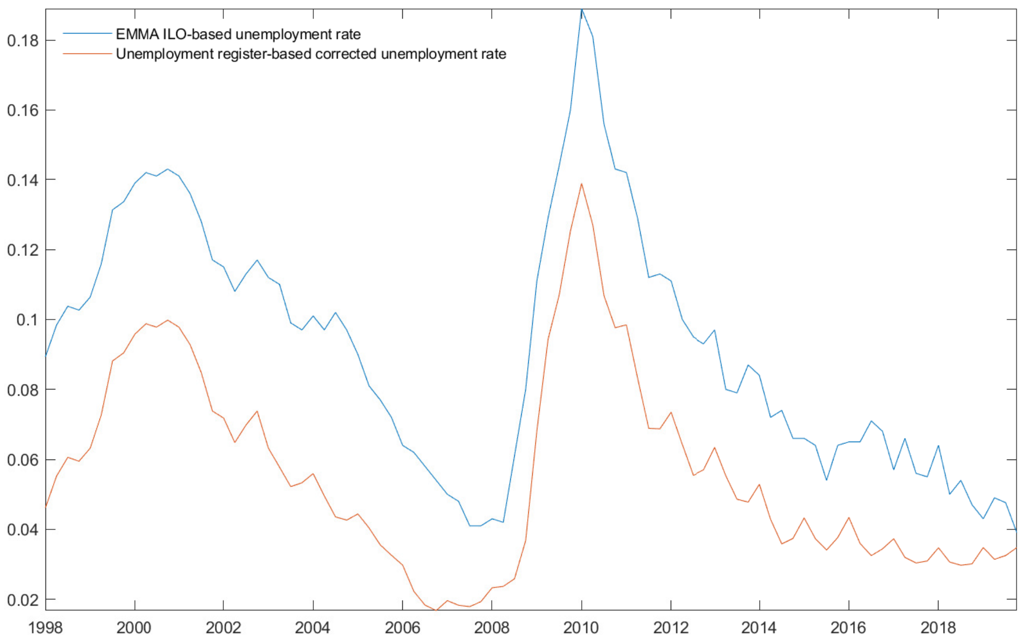

Figure 3: Two alternative data choices for the unemployment rate variable U_t

corrections for disabled people and those of limited–employability, which are compiled internally by Eesti Pank.[16] Although the levels of these two data series differ markedly, our semi-structural model of the natural rate in Subsection 4.1 uses de-meaned versions of them, and so any possible dynamic differences in the estimates of $U_t^\star$ can be explained mainly by the very different evolutions of the unemployment rate in the later part of the sample; see Figure 3.

Our literature survey and empirical panel data models suggest a tentative list of potential drivers of the natural rate of unemployment that consist of the following broad measures of labour market conditions:[17] (i) real house prices; (ii) terms of trade index; (iii) marginal income tax rate; (iv) trade union density; (v) share of ICT sector employment; (vi) active labour market policies index; (vii) employment protection legislation index; (viii) minimum wage to mean wage; (ix) share of construction sector employment; (x) share of trade sector employment; (xi) tax wedge; and (xii) unemployment benefits replacement rate. All of them enter our new model as growth rates in the corresponding elements of $\boldsymbol{x}_{t-1}$; see equation (3). The data sources and detailed definitions of these variables are outlined in Subsection 3.2 of this paper.

Finally, for comparison with our new estimates of the natural rate of unemployment for Estonia we use the European Commission annual NAWRU data series from the AMECO dataset; see Hristov et al. (2017).

4.3 Empirical results from the semi-structural model

In this section, we first discuss the parameter estimates in our new model (3). Then we discuss the estimation results of the zero–factor model, which does not include any of the extrinsic drivers of the natural rate. This baseline model provides estimates of the natural rate of unemployment similar to those used previously by Eesti Pank in Kattai (2005) and later revisions. Next we summarise the effects of the extrinsic drivers on our estimates of the natural rate of unemployment for Estonia, and highlight some of the statistically important ones. Finally, we display our results for the full model space of 4×2^{12} alternative specifications, and draw conclusions about the overall impact of the extrinsic drivers of the natural rate in our new semi-structural model.

Figure 4 shows the distributions of the parameter estimates across all models with $\Delta\mathsf{RULC}_t$ and the ILO measure of unemployment. The unemployment gap parameter θ, which determines the slope in our model of the natural rate of unemployment (3), is estimated to be around -1.6 across all 2^{12} models in this figure.[18] Its negative sign indicates that whenever a positive gap is open between U_t and U_t^* in the economy, meaning there is a cyclical labour market slack, employees tend to have less leverage over the gap between real wages and labour productivity in

[16]The corrections for disability and limited employability are applied from the 2016 onward; see Eesti Pank (2017) for detailed background on the work ability reform.

[17]We select these broad measures of LMC for their statistical significance in our panel data models in Subsection 3.3 and subject to data availability for Estonia over the sample period from 1998Q1 to 2019Q4. Note that the order of enumeration in this list corresponds to the ordering of the elements in $\boldsymbol{\alpha}$.

[18]In the previous generation of models of the natural rate of unemployment used by Eesti Pank the estimates of this slope parameter tended to be below -2.0 on average.

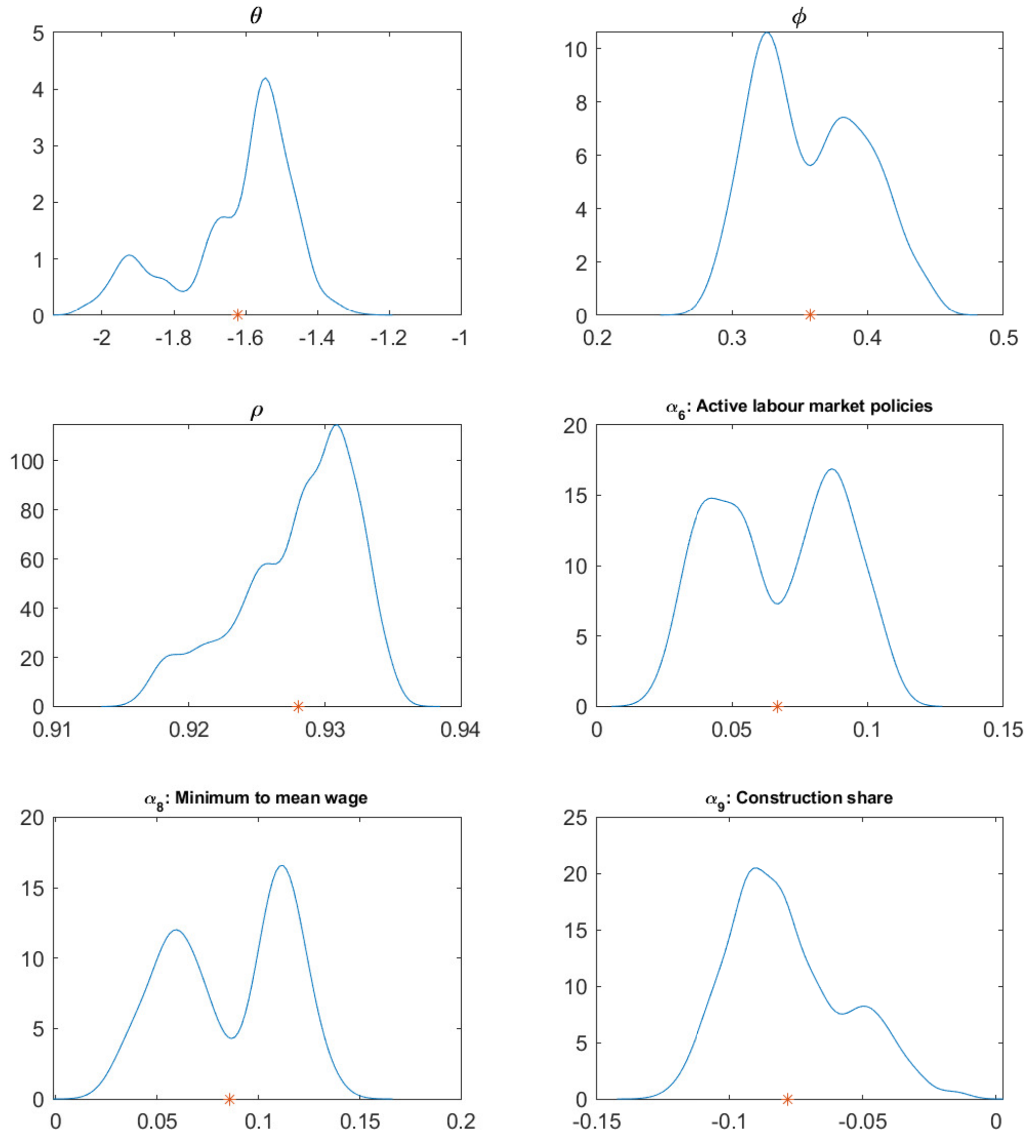

Figure 4: Parameter estimates across 2^{12} specifications with $\Delta\mathsf{RULC}_t$ and ILO unemployment

the wage bargaining process. This corresponds to the economic intuition presented in Subsection 4.1, and is in line with the panel data model results in Table 4. The two dynamic parameters ρ and ϕ indicate the presence of mean–reverting dynamics in the cyclical unemployment gap and the error term in our model.

The three estimates of the loading coefficients on the extrinsic drivers of the natural rate, which are also shown in Figure 4, are of considerably more interest for this paper. The ones chosen in this figure correspond to the three drivers identified to be the most relevant by our semi-structural model using the likelihood ratio test approach described in Subsection 4.1. They are active labour market policies, the ratio of the minimum wage to the mean wage, and the share of employment in the construction sector. As will be seen later in this subsection, even though none of these parameters are individually statistically significant in any of our estimated models following the usual frequentist statistical criteria, they are found to be jointly statistically significant in one of our models. The point estimates of all three loading coefficients tend to lie well away from zero across the model space, as can be seen in the figure, and the estimated signs of these factor loading parameters make economic sense. Both active labour market policies and the ratio of the minimum wage to the mean wage tend to increase the wage bargaining power of employees in the economy, while the share of employment in the construction sector works the in opposite direction, probably because of the prevalence of low–paid and low–skill employment in this sector in Estonia. The negative sign of the coefficient for construction sector employment is also in line with our panel data results in Tables 1 to 3.

We next describe the baseline model specification that contains no drivers of the natural rate in the $\boldsymbol{x}_{t-1}$ vector. This zero–factor model is estimated using the growth in the real unit labour cost $\Delta\mathsf{RULC}_t$ and the unemployment rate based on the ILO methodology, and its results are summarised in Table 5 together with the corresponding Figure 5. Overall, the empirical estimation results indicate that the model has a great deal of explanatory power when we use the correlation criterion described in Subsection 4.1. The estimated time dynamics of U_t^* tend to be rather volatile, and closely follow the ups and downs of the actual unemployment rate series, as can be seen in Figure 5. This behaviour of the estimated natural rate corresponds closely to that reported in Posta (2015), especially for their second model specification. And our zero–factor model delivers more volatile dynamics of U_t^* than the EC NAWRU estimates do. As will be seen shortly, this volatility is excessive and decreases markedly after the extrinsic drivers of the natural rate are added into the model.

Table 5: Parameter estimates of the zero–factor model (M0)

	Point est.	*Std. error*	*z-statistic*
θ	-1.9245	0.6093	-3.1585
ϕ	0.4209	0.0982	4.2862
ρ	0.9178	0.0435	21.099
σ_1^2	0.0295	0.0028	10.536
σ_2^2	0.0071	0.0013	5.4615
σ_3^2	0.0060	0.0014	4.2857

Notes: Sample period: 1998Q1–2019Q4; Total number of observations: 2×88; Log–likelihood: 620.48; LHS vs. RHS correlation: 0.79; RHS: $\Delta\mathsf{RULC}_t$; Unemployment rate: ILO; No factors in $\boldsymbol{x}_{t-1}$ are present in this model.

We may now discuss the role of the extrinsic drivers in estimating the natural rate of unemployment in Estonia. To answer this question, we explore a high–dimensional model space consisting of all the possible combinations of extrinsic drivers of the natural rate, as described previously in Subsection 4.1. Figure 6 shows U_t^* estimates across the space of 2^{12} models with $\Delta\mathsf{RULC}_t$ and the ILO unemployment rate as the main variables. We see that the average U_t^*

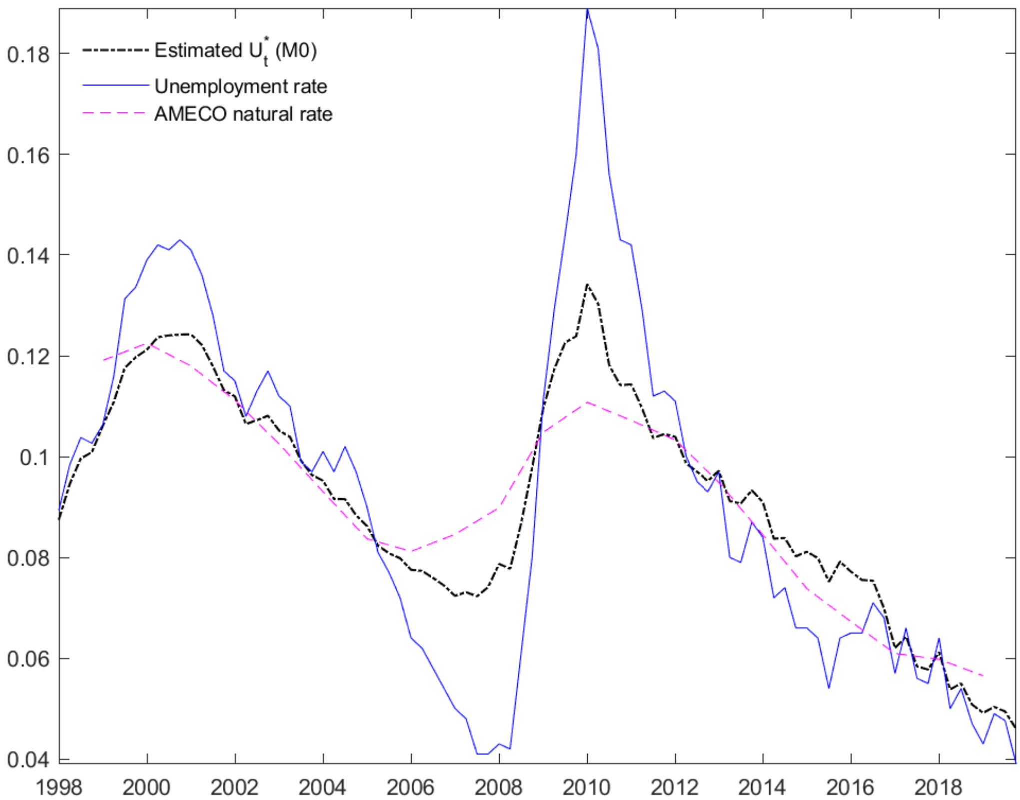

Figure 5: Zero–factor model estimates of $U_t^\star$ using $\Delta\mathsf{RULC}_t$ and ILO unemployment

estimates across all 2^{12} models, shown in black in this figure, are markedly less volatile than the ones displayed in Figure 5 for our zero–factor model. We conclude that including the extrinsic drivers of the natural rate in our model (3) leads to smoother estimates of U_t^* by filtering out the effects of labour market institutions and other macroeconomic factors.

As indicated earlier in this subsection, one of our models in the large model space contains three additional extrinsic factors that happen to be statistically important. We have already identified these factors as active labour market policies, the ratio of the minimum wage to the mean wage, and the share of employment in the construction sector in the economy. This three–factor model is estimated using the growth in the real unit labour cost $\Delta\mathsf{RULC}_t$ and the unemployment rate based on the ILO methodology, and its results are summarised in Table 6 together with the corresponding Figure 7. The model has a high level of explanatory power when we use our correlation criterion from Subsection 4.1, and we also observe from Figure 7 that the estimates of U_t^* in this model are not as volatile as the ones in our zero–factor model in Figure 5. And even though none of the estimated loading coefficients on the drivers of the natural rate in Table 6 are individually statistically significant by the usual criteria, the likelihood ratio test points to their joint significance in this model.[19] We also note that the time dynamics of U_t^* in our three–factor model are very close to those in the EC NAWRU estimates, and are perhaps only slightly out of phase in the period before the global financial crisis.

[19]However, the usual critical values that are used for the various test statistics in Tables 5 and 6 are likely to be too optimistic because they do not take the model uncertainty into account across our large model space.

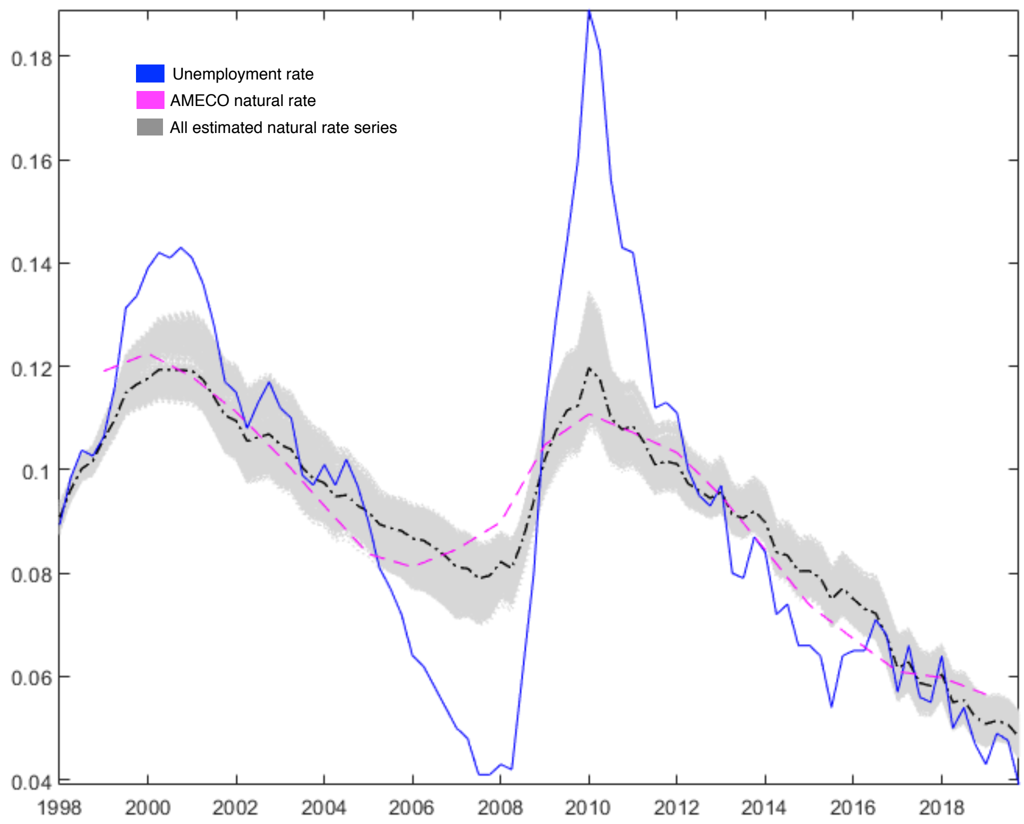

Figure 6: 2^{12} estimates of $U_t^\star$ from models using $\Delta\mathsf{RULC}_t$ and ILO unemployment

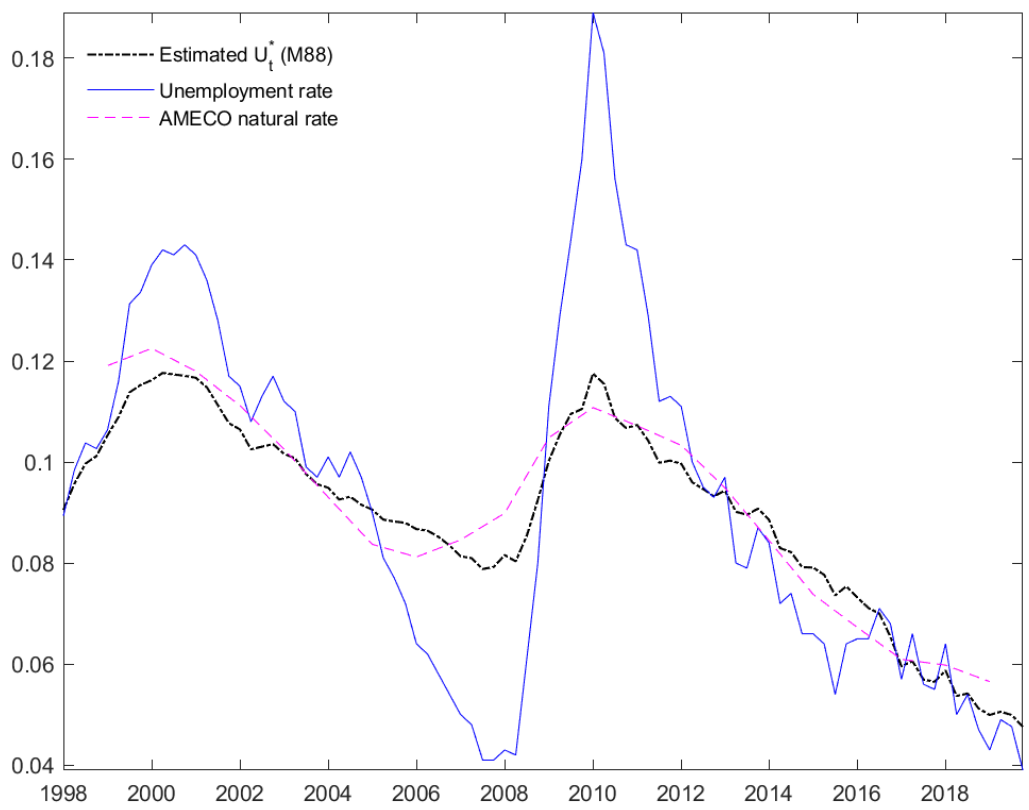

Figure 7: Three–factor model estimates of $U_t^\star$ using $\Delta\mathsf{RULC}_t$ and ILO unemployment

Table 6: Parameter estimates of the three–factor model (M88)

	Point est.	*Std. error*	*z-statistic*
θ	-1.5868	0.5546	-2.8612
ϕ	0.3382	0.0660	5.1242
ρ	0.9285	0.0385	24.117
σ_1^2	0.0283	0.0025	11.320
σ_2^2	0.0080	0.0014	5.7143
σ_3^2	0.0049	0.0018	2.7222
α_6	0.0519	0.0627	0.8278
α_8	0.0670	0.0603	1.1111
α_9	-0.0476	0.0414	-1.1415

Notes: Sample period: 1998Q1–2019Q4; Total number of observations: 5×88; Log–likelihood: 625.13; LHS vs. RHS correlation: 0.80; RHS: $\Delta\mathsf{RULC}_t$; Unemployment rate: ILO; Factors in $\boldsymbol{x}_{t-1}$: (vi) active labour market policies; (viii) minimum wage to mean wage; (ix) share of construction sector employment. Likelihood ratio test against M0: 9.37.

Finally, we show the full space of the estimated models and the corresponding band of U_t^* series across all possible combinations of both the extrinsic drivers of the natural rate and the choices of measures for the state of the labour market and the rate of unemployment available in our dataset. As described in Subsection 4.1, this space contains the grand total of 4×2^{12} models. All these models are shown in Figure 8, with the corresponding labels attached to the different subsets. From this large modelling exercise we learn first that the particular choice of the main variables in our model of the natural rate of unemployment induces notable variability in the estimated U_t^* series, which is especially pronounced at the end of our sample. It may be recalled from the discussion in Subsection 4.2 that different measures of the labour market state and the unemployment rate display quite different dynamics at the end of the sample period. This variation in the input data clearly spills over into the estimates of the natural rate delivered by our new model. A second lesson is that despite all this variability, our mean estimates of U_t^* for most of the sample period correspond quite closely to those from the EC NAWRU series, as indicated by the shaded area in Figure 8.

In summary, we have shown that the new model of the natural rate of unemployment for Estonia delivers U_t^* estimates that are quite insensitive to the particular choice of the extrinsic drivers of the natural rate. However, the overall effect of including these drivers is that it reduces the volatility of U_t^* over the business cycle. This is an important lesson in view of the previous generation of models of the natural rate used by Eesti Pank. We also find that although none of

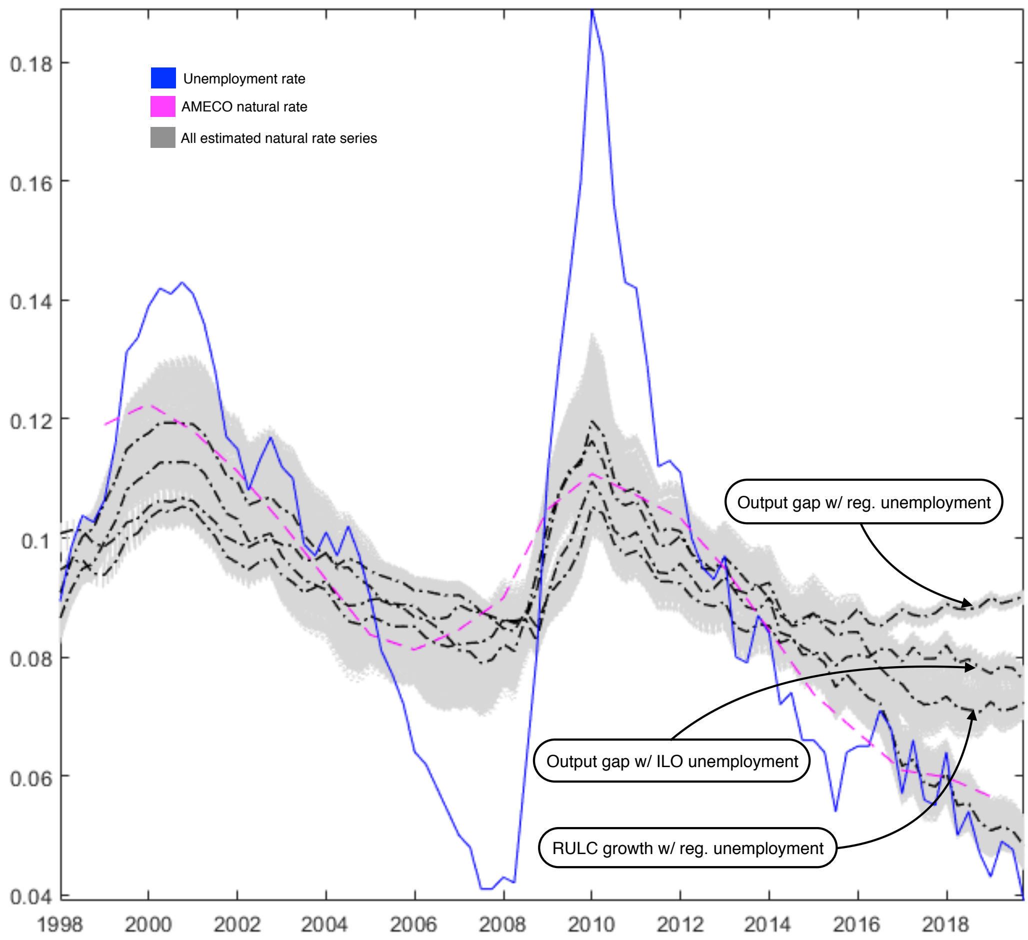

Figure 8: Full 4×2^{12} model space estimates of $U_t^\star$

the extrinsic drivers of the natural rate appear to be individually statistically significant in any of our estimated models, three of these drivers — active labour market policies, the ratio of the minimum wage to the mean wage, and the share of employment in the construction sector — appear most often in the list of our top models. But their economic effect on the U_t^* estimates remains quite small, and the resulting estimates of the natural rate of unemployment for Estonia are very similar across all combinations of these extrinsic factors. On the other hand, our U_t^* estimates appear to be quite sensitive to the choice of the particular measures of the state of the labour market and the rate of unemployment that are used during the estimation.

5 Conclusion

In this paper we revisit the estimation of the natural rate of unemployment for Estonia. The paper has two interlinked parts, where we first address the determinants of the natural rate of unemployment in a sample of 31 OECD countries using panel data techniques, and then incorporate most of these determinants into a new semi-structural quarterly time series model of the natural rate of unemployment for Estonia, which we estimate over the period 1998Q1 to 2019Q4.

Our literature review points to active labour market policies, labour taxation and the generosity of unemployment benefits, macroeconomic factors such as those that affect the housing market, and policies designed to facilitate economic growth and development as possibly being important determinants of the natural rate of unemployment. The effects of immigration and the short-term foreign labour supply on the natural rate of unemployment are, however, not well established in the literature. Our empirical panel data models find some supporting evidence for the roles played by active labour market policies, capital accumulation, and the share of employment in the construction sector in the economy. The results from our panel data models should be regarded as tentative because of the limited size of the available sample.

We develop a new semi-structural model of the natural rate of unemployment for Estonia with the explicit goal of incorporating the effects of these and other potential determinants of the natural rate into the dynamic estimates of the natural rate. To this end we use the exhaustive model space exploration methodology, as the exact combination of the potential drivers of the natural rate and their effect on the outcomes of the model cannot be known in advance. Our methodology is to explore a 4×2^{12}–dimensional model space that contains all the possible combinations of the extrinsic drivers of the natural rate together with alternative measures of the state of the labour market and the rate of unemployment. For each of these models we calculate the likelihood ratio test of the loading coefficients of the extrinsic drivers being different from zero, which is a test of whether a particular model is statistically different from the baseline model that contains no added divers of the natural rate.

Using this methodology, we identified the statistically important extrinsic drivers of the natural rate in Estonia as active labour market policies, the ratio of the minimum wage to the mean wage, and the share of employment in the construction sector in the economy. Although they appear as jointly statistically significant in one of our model specifications, their overall effect on the estimates of the natural rate is quite subdued. However, our estimates of the natural rate appear to be very sensitive to the choice of the particular measures of the state of the labour market and the rate of unemployment that are used in estimating the model. Since the natural rate of unemployment is an intrinsically unobserved quantity for which no indisputably true measure exists, the best possible way to guard against such statistical uncertainties is to combine estimates from many alternative models into one.

Another important lesson from our semi-structural analysis is that incorporation of the extrinsic drivers of the natural rate into the dynamics of the model tends to reduce the volatility of the resulting estimates of the natural rate of unemployment over the business cycle.

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A Literature Review

Table 7: Literature on economic determinants of structural unemployment

Study	*Data*	*LHS*	*RHS*
Nickell (1997)	20 OECD countries (1983-1994), Panel with two 6-year averages	UNEMP	UBR, BD, UnD, EPL, CBC, TW, ALMP
Elmeskov, Martin and Scarpetta (1998)	19 OECD countries (1983-1995), Panel (annual)	UNEMP	UBR, UnD, EPL, CBC, TW, ALMP, MW
Blanchard and Wolfers (2000)	20 OECD countries (1960-1996), Panel with 5-year averages	UNEMP	UBR, BD, UnD, COORD, TW, ALMP, MW, LTI, TFPS, TOTS, LDS
Debrun (2003)	20 OECD countries (1960-1998), Dynamic panel (annual)	UNEMP	UBR, EPL, UnD, COORD, TW, LTI, TFPS, TOTS, CBI
Belot and Van Ours (2004)	17 OECD countries (1960-1999), Panel with 5-year averages	UNEMP	UBR, EPL, UnD, CWB
Glyn, Baker, for Economic, Research, Washington, Howell, University, York and Schmitt (2003)	OECD countries (1960-1999), Panel with 5-year averages	UNEMP	UBR, BD, UnD, EPL, COORD, ALMP
Nickell et al. (2005)	20 OECD countries (1961-1995), Dynamic panel (annual)	UNEMP	UBR, BD, UnD, EPL, COORD, TW
Bassanini and Duval (2007)	21 OECD countries (1982-2003), Dynamic panel (annual)	UNEMP	UBR, BD, EPL, UnD, COORD, ALMP
Palacio-Vera, Martinez-Canete, de la Cruz and Aguilar (2006)	USA (1964:2-2003:1), Time series (TS)	NAIRU (OECD)	—
Arestis et al. (2007)	9 OECD countries, (quarterly data, max. 1979-2002) TS	UNEMP	UBR, strike activity
Baccaro and Rei (2007)	18 OECD countries (1960-1998), Dynamic panel	UNEMP	UBR, BD, UnD, EPL, COORD
Bertola, Blau and Kahn (2007)	20 OECD countries (1960-1996), Panel with 5-year averages	Employment rate	UBR, BD, UnD, EPL, COORD, ALMP
Bentolila et al. (2008)	Spain (1995-2006), TS/ Kalman filter (KF) (quarterly)	INF, FNPCI, HNPCI	IMM, UNEMP
Gianella, Koske, Rusticelli and Chatal (2008)	19 OECD countries (1978-2002), Panel (annual)	NAIRU (OECD)	TW, PMR, UBR, UnD
Stockhammer and Klar (2011)	20 OECD countries (1983-2003 1999)		
Orlandi (2012)	13 EU countries (1985-2009), Panel (annual)	NAWRU (EC)	UBR, TW, UnD, ALMP, HBOOM
Vergeer and Kleinknecht (2012)	20 OECD countries (1961-1995), Dynamic panel (annual)	UNEMP	UBR, BD, UD, EPL, COORD, TW
Avdagic and Salardi (2013)	32 EU and OECD countries (1980-2009), Panel (annual)	UNEMP	UBR, EPL, TW, COORD, UnD

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Study	*Data*	*LHS*	*RHS*
DGECFIN (2013)	15 EU Countries (1985-2008), Panel (annual)	NAWRU (EC)	TW, PLM, ALMP, SMI, MEI
Flaig and Rottmann (2013)	19 OECD countries (1960-2000), Panel (annual)	UNEMP	EPL, UnD, UBR, CWB, TW
Stockhammer et al. (2014)	12 OECD countries (2007-2011), Panel (annual)	UNEMP	EPL, ALMP, MW, UnD, GRR
Posta (2015)	7 CEECs (1997-2013), TS-KF (quarterly)	NAWRU (EC)	UNEMP, RLC, TOT, (NKPC)
Gechert, Rietzler and Tober (2016)	Spain (2009 - 2016), TS-KF (quarterly)	NAWRU (EC)	UNEMP, RULC, NKPC
Fay and Ketcheson (2016)	US (1998 - 2016), conditional correlations	NAIRU (US)	UNEMP, AGE, DISAB, FINDISAB
Bell and Blanchflower (2018)	UK and OECD (1998 - 2016), Panel and TS	NAIRU (OECD, UK)	UNEMP, WAGE, UNDEREMP, DISAB
Duca (2018)	US (1962/1993 - 2018), TS (quarterly)	INF	UNEMP ORS, SE, INF, RER
Mojon and Ragot (2019)	19 OECD(1999 - 2016), Panel (annual)	NKPC	UNEMP, PARTR, INF, LPRO

Notes: This table offers a comprehensive overview of the literature based on Stockhammer and Klar (2011). The coverage includes studies up until 2020. The following abbreviations are used in the table: ACCU, capital accumulation; ALMP, active labour market policy; BD, benefit duration; CBC, collective bargaining coverage; CBI, central bank independence index; COORD, wage bargaining coordination; CWB, centralisation of wage bargaining; EPL, employment protection legislation; HBOOM, proxy for boom-bust patterns in housing; LMI, labour market institution; LDS, labour demand shock; LTI, long-term real interest rate; MEI, matching efficiency indicator; MW, minimum wage; PLM, passive labour market policies; PMR, product; MS, money supply; market regulation; SMI, skill mismatch indicator; TFPS, deviation of total factor productivity from its trend; TOT, terms of trade (ratio import export deflators); TOTS, terms of trade shock; TW, tax wedge; UnD, trade union density; UBR, unemployment benefit replacement rate; INF, inflation; FNPCI, forward–looking and, HNPCI, hybrid New Keynesian Phillips Curve; IMM, immigration; IMPPR, imported input prices; RLC, real labour costs; RLC, real labour costs; RULC, real unit labour costs; AGE, fixed-age participate rate; DISAB, share of people with disabilities; FINDISAB, financial incentives to apply for disability insurance; WAGE, wage growth; UNDEREMP, underemployment; STUD, students; APPR, apprenticeship (related to underemployment); DISAB, disabilities; RER, real exchange rate; ORS, online retail sales; SE, self-employed; LPRO, labour productivity; PARTR, participation rate per age cohort; UNEMP, unemployment.

B Data Appendix

Table 8: Data definitions

Variable	*Description*	*Source*
NAIRU	OECD Non-Accelerating Inflation Rate of Unemployment estimate. Unit: Percentage	OECD
NAWRU	European Commission's Non-Accelerating Wage Rate of Unemployment estimate. Unit: Percentage	AMECO
Unemployment gap	Unemployment rate minus NAIRU. Unit: Percentage	OECD
Real wage growth	Average annual wages at constant prices per full-time and full-year equivalent employee in the total economy. Unit: Year on year growth rate	OECD
Average tax wedge	The ratio between the amount of taxes paid by and the corresponding total labour cost for the employer. Unit: Percentage	OECD
Marginal personal income tax rate including social contributions	The marginal personal income tax rate is derived on the basis of a unit increase in gross wage earnings at the threshold. It includes the personal income tax rate and employee social contributions. Unit: Percentage	OECD
Top tax rate	Top statutory tax rates for the combined central and sub-central governments. Unit: Percentage	OECD
Average replacement rate	A measure of the unemployment benefit replacement ratio adjusted for the duration of the unemployment spell. Unit: Percentage	OECD
Active labour market policies	Sum of seven individual labour market policies expenditures over GDP. Then adjusted for the unemployment rate. Unit: Percentage	OECD
Minimum to mean wage	Ratio of minimum wages to mean earnings of full-time employees. Unit: Percentage	OECD
Union density	Proportion of union membership based on administrative data. Unit: Percentage	OECD
Employment protection	Synthetic indicators measure the strictness of regulation on dismissals and the use of temporary contracts. Mean of all four indexes. Unit: Index	OECD
Temporary foreign labour share	Share of age group 15-64 years, not born in the country and employed on a temporary contract. Unit: Percentage	Eurostat
Migration share	Net migration: Difference between the number of people who emigrated from the country from the number of people who immigrated into the country. Net migration is then divided by the number of active population in the country. Unit: Percentage	Eurostat
Construction share	Variable captures housing construction employment boom bust cycles. Deviation from the mean of the proportion of persons working in the construction sector. Unit: Percentage	Eurostat & OECD
ICT share	Variable captures employment boom bust cycles in the information and communication technology (ICT) sector. Deviation from the mean of the proportion of persons working in the ICT sector. Unit: Percentage	Eurostat & OECD
Trade share	Variable captures trade sector employment boom bust cycles. Deviation from the mean of the proportion of persons working in the trade sector. Unit: Percentage	Eurostat & OECD
TFP	Total factor productivity. Unit: Year on year growth rate	OECD
Cyclical house prices	Real seasonally adjusted house price index Unit: Log-deviation from the HP–filtered trend ($\lambda = 6.25$)	OECD
Real interest rate	Real long-term interest rates, deflator GDP. Unit: Percentage	OECD

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Variable	*Description*	*Source*
Capital accumulation	The ratio between gross fixed capital formation and the net capital stock. Unit: Percentage	OECD
Terms of trade	Terms of trade goods and services (National accounts). Unit: Year on year growth rate	AMECO

Notes: The average replacement rate is computed as a weighted average of replacement rates at different unemployment spell horizons, with the weights varying across countries based on the level of the unemployment exit rate, also known as job finding rates. For a detailed description of how to calculate the average replacement rate, refer to Orlandi (2012). The active labour market policies (ALMP) index measures the expenditures on the following seven sub-items, where the numbers refer to the OECD classification scheme:

- 10: Public employment services (PES) and administration
  - 11: Placement and related services
  - 12: Benefit administration
- 20: Training
  - 21: Institutional training
  - 22: Workplace training
  - 23: Integrated training
  - 24: Special support for apprenticeship
- 30: Job rotation and job sharing
- 40: Employment incentives
  - 41: Recruitment incentives
  - 42: Employment maintenance incentives
- 50: Supported employment and rehabilitation
  - 51: Supported employment
  - 52: Rehabilitation
- 60: Direct job creation
- 70: Start-up incentives

The ALMP index is normalised as follows: Share of ALMP expenditures in GDP / Share of unemployed in the population.

Table 9: Data summary

	Mean	*Std. dev.*	*Min*	*Max*	*Obs.*	*Incomplete observations*
NAIRU	0.072	0.030	0.028	0.157	588	LT
NAWRU	0.082	0.032	0.024	0.176	437	AU, CA, CH, IS, JP, KO, NO, NZ
Real wage growth	0.015	0.030	-0.154	0.233	589	
Unemployment gap	-0.005	0.021	-0.070	0.104	575	CH, FR, IS, LT
Average tax wedge	0.330	0.088	0.094	0.511	589	
Marginal personal income tax rate	0.444	0.132	0.000	0.816	589	
Top tax rate	0.419	0.110	0.150	0.623	589	
Average replacement rate	0.467	0.141	0.114	0.774	554	EE, KO, LT, LV, SI
Active labour market policies	0.074	0.069	0.000	0.515	508	AU, AT, BE, CA, CH, CZ, DE, DK, ES, EE, FI, FR, GB, GR, HU, IR, IS, JP, KO, LT, LU, LV, NL, NO, NZ, PO, PR, SK, SI, US
Minimum to mean wage	0.382	0.068	0.223	0.562	437	AT, CH, DE, DK, FI, IR, IS, IT, NO, SV
Union density	0.280	0.190	0.043	0.925	463	AU, AT, BE, CA, CH, CZ, DE, DK, ES, EE, FI, FR, GB, GR, HU, IR, IS, IT, JP, KO, LT, LU, LV, NL, NO, NZ, PO, PR, SK, SI, US
Employment protection	2.253	0.596	0.758	3.641	537	EE, IS, LT, LU, LV, SI
Total factor productivity	0.007	0.024	-0.121	0.221	568	AU, KO, NZ
Capital accumulation	0.097	0.047	0.026	0.419	568	AU, KO, NZ
Real interest rate	0.016	0.031	-0.123	0.245	493	AU, CA, CH, EE, IS, KO, NO, NZ, SI
Terms of trade	0.002	0.032	-0.168	0.204	589	
Construction share	0.001	0.013	-0.034	0.056	536	AU, CA, JP, KO, NZ, US
ICT share	-0.001	0.008	-0.034	0.048	535	AU, CA, JP, KR, LV, NZ, US
Trade share	0.000	0.007	-0.028	0.046	536	AU, CA, JP, KO, NZ, US
Cyclical house prices	-0.006	0.054	-0.449	0.235	542	CZ, EE, HU, LT, LU, LV, PO, SK, SI
Temporary foreign labour share	0.162	0.105	0.021	0.564	417	US, AU, CA, CH, CZ, EE, IR, IS, IT, JP, KO, LT, LV NZ, PO, SK, SI, US
Migration share	0.011	0.016	-0.044	0.066	247	AU, AT, BE, CA, CH, CZ, DE, DK, ES, EE, FI, FR, GB, GR, HU, IR, IS, IT, JP, KO, LT, LU, LVNL, NO, NZ, PO, PT, SK, SI, US

Notes: This table presents summary statistics for the variables included in the panel regression models. The statistics pertain to the baseline sample spanning annual data from 2001 to 2019 and encompass all 31 countries. The last column shows the countries (using ISO 3166 codes) for which there is at least one missing observation for the corresponding variable.

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