An evaluation of the structural unemployment rate in Finland*

Background report for the Economic Policy Council

Niklas Gäddnäs

23 January, 2019

Keywords: structural unemployment, NAWRU, NAIRU

Abstract

This background report provides a literature review of research papers and an analysis of structural determinants contributing to the Finnish structural unemployment rate. The literature review examines current microeconomic research and policy reports on distinctive factors contributing to the structural unemployment rate in Finland. The analysis section utilizes a macroeconometric model to derive structural determinants of unemployment for Finland. The structural determinants are estimated with a model built by the European Commission's Directorate-General for Financial and Economic Affairs, utilizing an EU13 panel setup for the time frame 1987–2016. The estimation of structural determinants yields a decomposition of the non-accelerating wage rate of unemployment (NAWRU), thus allowing for a closer assessment of how various structural determinants relate to the Kalman-filtered unemployment trend and to one another in scope and significance. The main findings of the analysis suggest that structural labor market indicators, such as the tax wedge, union density and the unemployment benefit replacement rate, heavily influence NAWRU. The results also indicate that the NAWRU component is affected by demand-side boom-and-bust cycles, proxied by the proportional size of the construction labor force.

* Niklas Gäddnäs, Master's student at Aalto University School of Business, E-mail: niklas.gaddnas@aalto.fi. I am grateful for the guidance and supervision by Seppo Orjasniemi, Economic Policy Council, and for the helpful comments by Tomi Kyyrä, VATT, concerning microeconomics questions. I am also grateful for the helpful comments and assistance of Petteri Juvonen and Meri Obstbaum, both at the Bank of Finland, concerning labor market models and data questions.

Table of contents

1 Introduction

In the aftermath of the dual economic crises of the last decade, the Finnish labor market has been struck by an unrelenting rigidity in the unemployment rate. The late arrival of the current upswing in the business cycle has had a positive, albeit modest, effect on the unemployment rate. The business-cycle upswing, in conjunction with certain government policy reforms, has managed to increase the employment participation rate to such a degree that the current government's target of 72% is possible. This positive improvement has already prompted discussions of increasing the employment participation rate target further, to ranges between 75 and 80 percent. When changing the scenery from the realms of political discussions to more analytical realms, one quickly stumbles upon the problems of such ideas; the Finnish unemployment gap is nearing zero, implying that further increases in the employment participation rate are constrained by structural issues. Going beyond this level will be increasingly difficult for a multitude of reasons, e.g. increasing pressure on wage build-ups, as well as employment mismatches in the labor market. As a negative unemployment gap is not a stable long-term alternative, the structural unemployment rate needs to be decreased to achieve further increases in the employment participation rate.

The goal of this background report is to assess the primary contributors to the structural unemployment rate in Finland. The first section relies on a literature review of relevant theory and research and policy papers to ascertain the special characteristics rooted in the Finnish labor market. The review of recent policy papers also provides a robust backbone for the analysis section. The second part utilizes a macroeconometric model to estimate structural and non-structural labor market determinants which affect the non-accelerating wage rate of unemployment.

The objective of the second part is to derive a decomposition of the structural unemployment rate in Finland by using the NAWRU model developed by the European Commission's Directorate-General for Financial and Economic Affairs. This model makes use of several structural and non-structural labor market indicators, with EU27 & EU13 panel set-ups. The estimation of structural determinants allows for a closer inspection of the composition of the Finnish structural unemployment rate, especially as regards their scope and significance.

2 Structural unemployment theory

The literature review of this paper is divided into two sections. The first section is a survey of the Finnish labor market conditions in conjunction with structural unemployment theories, while the second section (chapter 3) provides a review of research papers with relevance to structural unemployment.

2.1 The Finnish labor market setting

This section lists the basic traits of the Finnish labor market. The Finnish setting has unique characteristics not necessarily present elsewhere, implying that certain domestic characteristics need to be accounted for before any cross-country studies are considered. The established traits in this section will serve as the main stepping stones throughout this paper. The rest of this section is organized as follows: (i) labor supply- and demand-related issues, (ii) labor market institutions and (iii) active labor market policies.

The (i) question, dealing with market clearings and the reservation wage, is approachable from supply and demand perspectives. The first part pertains to labor demand, where factors influencing the *unit cost of labor* are listed. Increases in labor taxes and costs, both direct and indirect, are deemed as a main hinder for market clearings, as these increase the cost of labor. Value-added taxes also impact the cost of labor, as workers may shift a part of the VAT to the employer (by negotiating a higher wage), depending on the internalization weight.[1] This implies that the reservation wage is going to reflect, partially or completely, depending on the internalization weight, any increases in value-added taxes.

The second part—matters regarding labor supply—includes factors that affect the workers' *reservation wage*. The main contributors in this group relate to (1) unemployment insurance (henceforth UI) benefits and wage formation, and (2) efficiency

[1] The internalization wage refers to the size of the VAT tax, which may be levied onto employers in the form of higher wages.

of benefits. The (1) group includes all benefits unemployed people are entitled to, as increases in these correlate positively with the reservation wage equation.[2] These benefits, regardless of their composition, i.e. different combinations of amount, duration and associated conditions, all affect the reservation wage of the workers. Here it is also fair to point out that the effects of the UI benefits are not solely an "obstacle," as there are positive externalities, such as the option of being able to focus on job hunting more effectively.[3] The (2) group lists two sides affecting the efficiency of benefits issue, i.e. how flexible the trade-off between labor income and benefits income is. This group includes costs levied on workers, e.g. the tax wedge and compulsory fees pertaining to retirement savings and UI. The other side of the problem is how benefits adjust to work-related incomes: if the opportunity cost for accepting work is steep, the reservation wage of the workers will increase, thus making the labor market more rigid. Combined, these factors yield the final reservation wage equation, and by extension, the final labor supply curve. In a worst case scenario, where unemployment has become entrenched due to welfare traps, the risk of hysteresis becomes a reality.[4] As individuals maximize the expected income taking into account the value of leisure, the social insurance system should be geared toward ensuring that work is more profitable than benefits. (Räisänen 2002, p. 31–33)

The (ii) question takes into account all institutions influencing the labor markets, e.g. the traditional tripartite negotiations of unions, the government and groups representing employers. Therefore, questions related to unions and employers groups are of importance here.[5] For example, the wage negotiations usually yield an outcome where the labor markets do not clear, as the agreed-upon market wage, or other conditions related to it, might result in rigidities. However, given the presence of imperfect markets and asymmetric information, collective bargaining may also have opposite effects, if market

[2] This phenomenon is also referred to as a moral hazard, as unemployed people indirectly receive an artificial income which may be used to increase leisure (Chetty 2008; Kyyrä et al 2017, p. 35).

[3] These are also referred to as the liquidity effect and moral hazard. "Liquidity effect" implies that an UI benefit allows unemployed people to commit time to finding a more suitable job, while "moral hazard" refers to cases where the said benefit only creates welfare traps. (Chetty 2008; Kyyrä et al 2017, p. 35–36).

[4] The most usual welfare traps are (1) poverty and (2) unemployment traps. Poverty traps entails a steep wedge in the trade-off between supplying more labor and benefits income, resulting in an inefficient outcome due to the decreased labor supply. Unemployment traps pertain to conditions where benefits have removed all incentives to work. (1) is also referred to as an intensive margin, while (2) is referred to as an extensive margin of labor supply.

[5] Density in this context refers to bargaining strength, which in turn is a function of membership figures (in relation to all workers), tools at one's disposal, willingness to use them, and so forth.

deficiencies are targeted (and corrected). The worst outcome, according to Räisänen (2002), is when wage negotiations are conducted independently on a union level (i.e. decentralized), because such negotiations do not account for the total impact on the economy. In other words, when unions are negotiating en masse, they reduce the risk of *overshooting,* and by extension, manage to limit the damage to market-clearing conditions. With the loss of the sovereign monetary policy, in conjunction with high collective bargaining coverage, it might be more conducive to coordinate, for example, an internal devaluation around a broad table.[6] (Räisänen 2002, p. 35)

A summarizing list is presented below (Räisänen 2002, p. 34–36):

- The entire tax burden: an increase in taxes is going to increase the reservation wage and/or increase the unit cost of labor.
- Centralized (versus decentralized) wage negotiations correlate with wage rigidities. This builds on the fact, among others, that the economy is not symmetric: e.g. certain rigidities localized to a regional level are not necessarily present on a national level.
- Labor mobility is also affected by the living situation, e.g. owner-occupied housing has an anchoring effect.
- Depending on the level of cooperation, the flexibility and timing of labor market institutions in recessions also have an effect on the final outcome.

The final question makes a distinction between active and passive (iii) labor market policies, with an emphasis on the former. Even though certain LM policy effects have been discussed indirectly above, a few issues related to active LM policies, or specifically government intervention in the labor market, are worth mentioning. In the past, the most efficient tool at the government's disposal has been the adjustment of nominal factors through devaluation.[7] In conjunction with the entry into the EMU, the weight was shifted toward more broad and targeted fiscal measures, such as direct subsidization of wages and (re)education, as well as more indirect measures, such as industry-specific subsidies.

[6] This theorem is usually referred to as the Calmfors-Driffill hypothesis, which states that unemployment is a nonlinear function of union activity. The relationship between unemployment and union activity is argued to be hump-shaped, i.e. unemployment is minimized at low and high levels of union activity, whereas states in between these two yield a higher unemployment rate. (Driffill 2006)

[7] The operational authority of the central bank is technically independent, but no such distinction is required here.

One of the main concerns with such methods is budgetary, i.e. subsidizing wages on a broad, or even targeted level, is fiscally unsound in the long term. The second problem of wage subsidies is the issue of productivity. These subsidies seek to ease market-clearing conditions, by decreasing the unit cost of labor, to match the marginal product of labor.[8] However, for this subsidy to have any impact beyond the expiration of the subsidy (long term), there must be an increase in the marginal product of labor, or otherwise the whole point of the subsidy unravels. On the other hand, if this temporal employment has decreased the risk of hysteresis, such costs might be motivated.

Regardless of the extensive collection of previous research, there is no definitive guideline as to how structural unemployment should be tackled. The fundamental problem traces back to the definition of the term; is it an obvious level of unemployment that does not solely depend on above factors? Should the baseline indicators be everything not related to cyclical factors, e.g. long-term unemployment and continuous unemployment, or a policy-based limit, e.g. the number of insured unemployment days?[9]

By approaching the question from a microeconomics perspective, a more comprehensive answer may be ascertained as to why certain people remain unemployed, despite cyclical factors. By decomposing the units of labor supply into personal attributes, such as education, work experience, language skills, personal attributes, etc., the level of uncertainty (regarding potential productivity), or transaction costs, might be decreased. Thus, the threshold for filling vacant positions is also decreased. If there is, on the other hand, a steady stream of unfilled vacant positions, it might be more relevant to study the characteristics pertaining to these specific jobs instead. By decomposing vacancies, i.e. units of labor demand, into different attributes—such as uncertain job contracts, commuting time to work, nature of working days (day/night), part-time nature, etc.—the analysis might yield a better understanding of why certain vacancies suffer from matching problems. By combining these two questions, the issue of market rigidities, and more importantly, whether any fundamental changes have occurred over time may be investigated.

[8] Alternatively affect the supply of labor, by increasing the income for a specific assignment.

[9] This group is further divided into two groups, those who repeatedly move between employment and unemployment and those who, despite having participated in a labor market program, still keep getting unemployed.

2.2 Structured unemployment theories

The decomposition of structural unemployment, provided by Räisänen et al (2002), gives a thorough theoretical perspective to the factors relevant for the Finnish labor market. However, the report consists of different idiosyncratic factors, which by themselves are of limited use in an analysis. Therefore, this section extends the theoretical discussion with well-established theories pertaining to structural unemployment. The general foundation of the theories listed in this paper is the existence of trend and cyclical unemployment components.[10] An introductory remark will be provided by Friedman and Phelps, followed by a discussion of three general theories inherent to modern labor market theory: efficiency wages, contracting models, and search and matching models.

The first insight into the general consensus dates back to the work of Friedman and Phelps in late-60's (Romer 2012, p. 257), who first argued for a natural rate hypothesis. This hypothesis laid the foundation for the most widely used estimate, the non-accelerating inflation rate of unemployment (henceforth NAIRU) method. The primary concern of the NAIRU estimate is to assess the level of unemployment which is compatible with a stable *("non-accelerating")* rate of inflation. The essence of the NAIRU approach is the so-called unemployment gap, or the difference between the natural and the actual rate of unemployment.[11] In Friedman's original formulation:

"The natural rate of unemployment … is the level that would be ground out by the Walrasian system of general equilibrium equations, provided there is embedded in them the actual structural characteristics of the labor and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and labor availabilities, the costs of mobility, and so on."

– Milton Friedman (1968, p. 8; Romer, 2012, p. 257)

[10] In theory, this is referred to as a non-Walrasian labor market. In a Walrasian labor market, wages adjust according to the marginal product of labor (in every period), while in an opposite scenario there are certain rigidities which hinder market clearings. (Romer 2012, p. 457)

[11] The general objective of policy makers is to keep the value of the gap as close to zero as possible, which is also the steady-state solution of the labor market. The gap correlates (to varying degrees) with fluctuations in the business cycle, implying that a negative (positive) gap value usually coincides with overheating (a downturn) in the economy.

In other words, the natural rate also accounts for idiosyncratic factors. These factors are embedded as assumptions, rather than having been proven through empirical means. From a policy analysis perspective, this is a key deficiency of the method. Modern estimates have attempted to rectify this issue, but attempting to extrapolate bits and pieces from an unobservable component based on multiple fluctuating variables is easier said than done. Nevertheless, this method retains its usefulness for its intended purpose, the determining of steady-state unemployment rate estimates.

The first theory deviating from a Walrasian labor market is the efficiency-wages-theory. The gist of the model is that firms are willing to deviate from market-clearing conditions by offering workers higher wages. This might be motivated by different reasons, e.g. boosting productivity, loyalty, motivation, etc. (Romer 2012, p. 461) This scenario implies that the offered wage rate is above the market-clearing conditions, resulting in an (increased) structural unemployment level.

In the Shapiro–Stiglitz extension of the efficiency-wages model (1984; Romer 2012, p. 467–473), worker traits are separated into two groups: those who exert effort and those who succumb to shirking.[12] This model assumes imperfect monitoring, implying that firms have a limited capacity to identify shirkers. This lack of oversight yields a new second-best labor market equilibrium, where the offered wage rate should be sufficiently high to motivate shirkers to contribute.[13] Regardless of the stylized assumptions in the original model, the extensions made to it have been more beneficial; e.g. how caught shirkers might redeem themselves with a short-term decrease in the wage rate (Alexopoulous 2004; Romer 2012, p. 477).

The following unemployment theory deals with labor market rigidities as a function of wage contracts, i.e. firms are incapable of adjusting the real wage of workers. A general assumption in models based on contract theory is that the wage contracts build on a discrete state of the economy: they are set with respect to a randomly drawn, exogenously given factor, determining this period's output in firms. If this exogenous factor were to fluctuate over time, then the output function of firms would also fluctuate, while the wage

[12] Shirking is not defined in a deeper sense, but refers to people who, for some reason or another, have a low marginal product of labor due to laziness.

[13] The general conclusion also entails that those exerting an effort are not taken into account, i.e. the market wage is solely based on bringing shirkers into the fold.

contracts would not.[14] These (explicit) wage contracts thus result in wage rigidities, and by extension, structural unemployment. (Romer 2012, p. 480–482)

A proposed way of overcoming this issue are the so-called implicit contracts, which implicitly account for the discrete distribution of different states.[15] This results in an equilibrium situation, as the marginal product of labor equals the marginal disutility of labor. This equilibrium is achieved when the worker's utility function remains constant across time, regardless of which discrete state of the economy is drawn at the onset of employment. The firm, in other words, collects rents when times are good, and in return (fully) insures workers in bad states of the economy. However, this non-Walrasian wage setting is, by extension, going to impact the employment level in the economy. As wages are constant across time, as specified in (long-term) wage contracts, they also account for any boom-time effects. This in turn implies that the firm has less capacity to hire new workers, as the wages in such a setting are countercyclical.[16] (Romer 2012, p. 480–482) To quote Barro (1977; Hall, 1980; Romer 2012, p. 482): *"The problem is that with long-term contracts, the wage is no longer playing an allocative role. That is, firms do not choose employment taking the wage as given. Rather, the level of employment as a function of the state is specified in the contract."*

This contracting model has been extended to account for two worker groups, insiders and outsiders. The insider–outsider model implies that the first group, at the beginning, is able to bargain (implicit) wage contracts to their benefit. The positive effect of these wage contracts is, at first, limited to insiders only. As the labor market clearing conditions are altered through this insider-firm bargaining, an outsider group emerges. This outsider group, regardless of its reservation wage being below the market wage, is constrained by the insider-firm-established wage contracts. The unemployment issue is stressed by the fact that, as insiders are capable of negotiating insurance conditions to their benefit, the wage level may be set at a subpar level. This has been extended further to a European setting, where labor market institutions may have altered the wage-setting to such an

---

[14] Consider the (expected) profit function $E[\pi] = \sum_{i=1}^{k} \rho_i [A_i F(L_i) - w_i L_i]$, where labor is the only input factor. The subscript *i* denotes a discrete distribution of different settings the economy jumps through, while A determines the (fixed) wage contract. (Romer 2012, p. 479).

[15] In this stylized setting, any uncertainty regarding the discrete distribution of different states is assumed away.

[16] See the fourth point in section 2.1, where risks related to decentralized wage negotiations are mentioned.

extent that the size of the outsider group has become larger and even partially decayed into hysteresis. (Romer 2012, p. 482–485)

The next model series attempts to incorporate transaction costs, such as information asymmetries, into the market clearing conditions. These search and matching (henceforth SaM) models depart from the Walrasian assumptions of perfect information and identical workers, by arguing that the labor market consists to a high degree of heterogeneity. In this model, the matching function is a product of the amount of resources the (i) worker and (ii) firm devote to this problem. This yields a very elegant model, as the matching function serves as a unique tool for modeling the flow of workers between the two pools of unemployed and employed workers. Combined with a vacancy destruction rate, the SaM model is capable of producing an estimate of the prevailing unemployment rate, based on the actual variance within the labor market. (Romer 2012, p. 486–487)

The key in this model lies in the specifics: depending on the scope and input specifics in the search function, the model can be extended to incorporate different sorts of (i) workers and (ii) firms. Regarding the (i) worker's search function, the fundamental equation here relies on the reservation wage equation. The most basic reservation wage equation assumes workers who maximize utility through consumption and leisure. An employed worker earns an income, while an unemployed individual earns an UI benefit of some sort. The worker also has a discount rate above zero. These basic assumptions imply that an unemployed worker optimizes between applying for work or remaining unemployed, where the value associated with leisure and, more importantly, the UI benefit directly determines whether to enter the fold or not. (Romer 2012, p. 488–492)

Intuitively, this model may also be approached from a cost minimization perspective, i.e. in the presence of substantial transaction costs, firms might opt away from attempts at replacing the current pool of employees.[17] This is especially acute if the firm's search model is extended to include a *cost per search*. This cost is then affected by an increase in transaction costs (or uncertainty), as every search becomes more costly, which directly affects the matching function.

[17] E.g. in the presence of imperfect information regarding the skills of the pool of unemployed workers, transaction costs might affect the outcome.

3 Research and policy papers

This section will focus primarily on factors contributing directly to the efficiency of labor markets, e.g. taxes, UI and their impact on incentives, but also factors which have more of an indirect effect on the labor market. This section—especially factors relating to the tax wedge and UI—should be viewed as a complement to the analysis section (chapter 4).

Much of the literature pertaining to the efficiency of UI benefits and labor costs revolves around components related to behavioral questions. These questions tend to focus on the building blocks of intensive and extensive margins of labor supply. Labor and, more recently, public economics have advanced the methodological instruments needed for measuring causal effects. This section will therefore mainly focus on components related to the reservation wage equation, as these components are the ones usually discussed.[18]

The recent OECD Economic Surveys for Finland (February 2018) provides a thorough analysis of the Finnish labor market. One of the main emphases of the report are *work incentives*, depicted by two methods: (i) decomposition of net income, i.e. how the household net income is affected at different wage levels in relation to different UI benefits, taxes and social security contributions, and (ii) effective tax rates (henceforth ETR).[19] The OECD report paints a dire picture. Factoring in all the benefits and costs, the Finnish social benefits system has created abnormalities in the ETR, as seen in figure 1 and 2 below.

[18] The flexibility and usage of these tools depends on whether they are included in the tripartite labor market institution negotiations or decided by the parliament (e.g. taxes and social security benefits).

[19] To clarify, in this report the term work incentives (or effective tax rate) refers to both extensive and intensive margins of labor supply, unless stated otherwise.

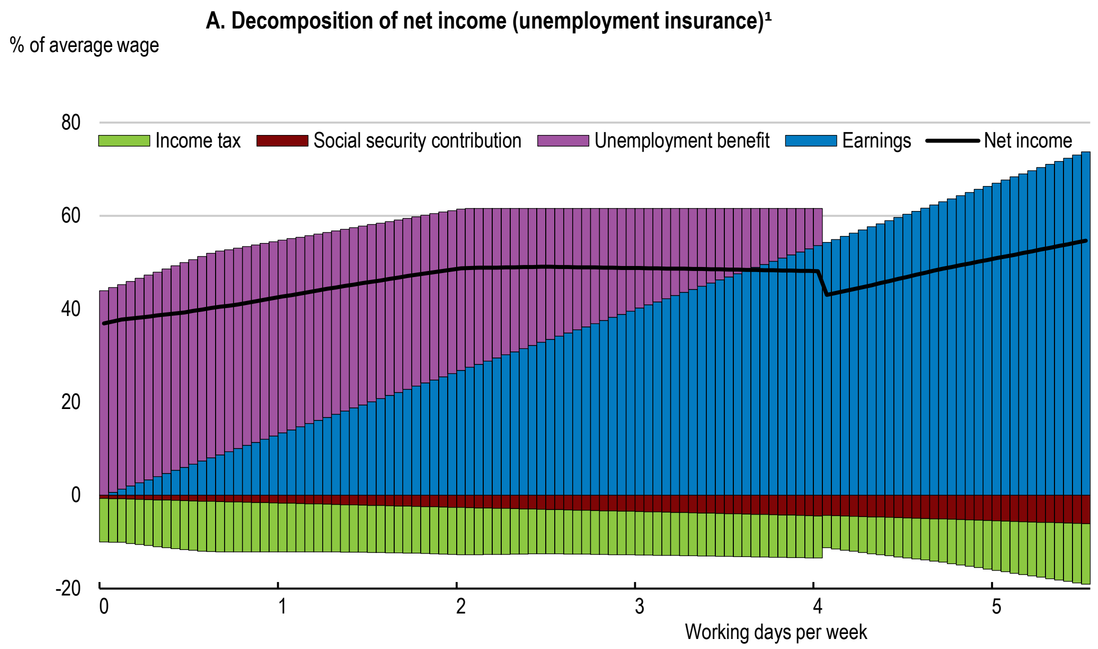


Figure 1. Decomposition of net income (unemployment insurance). Source: OECD (2018).

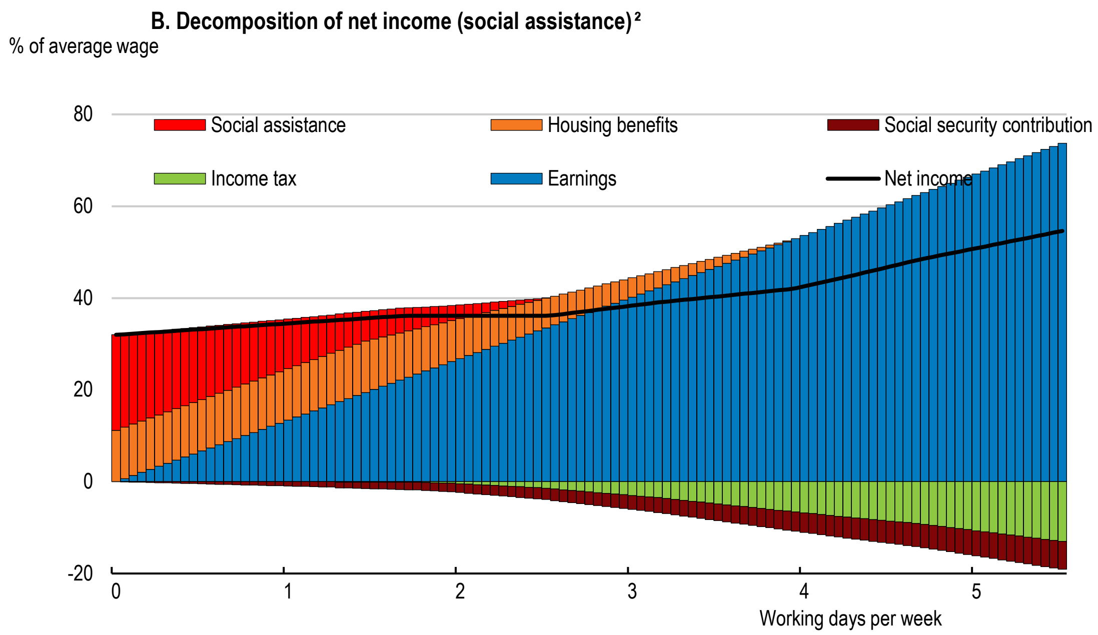


Figure 2. Decomposition of net income (social assistance). Source: OECD (2018).

The first figure illustrates the decomposition of income for households entitled to UI benefits. The net income is affected positively by labor earnings and UI benefits, and negatively by income tax and social security contributions. The net income for households in the UI benefit scheme is seen to behave in a nonlinear fashion, as the net income increases with wage increases between days 0–2, before reaching a plateau between days 2–4 and going through a drop *("cliff-edge")* at day 4.[20] From the specifications in figure 1, two things are apparent: the plateau and gap are both disincentivizing in nature. The plateau between days 2–4 implies that the increase in net income remains zero, despite more effort being exercised. The gap, on the other hand, has a negative effect on the intensive margin, as the incentives to accept part-time work are negative. (OECD 2018, p. 46–47, 98) The second illustration (figure 2) covers households which are not entitled to UI benefits, but receive social assistance instead. The household net income variable in the social assistance case is behaving in a more conducive way, as there is no plateau or gap in the variable.[21]

Another study, by Kärkkäinen and Tervola (2018b, p. 15–16), decomposes the social benefits system further in order to analyze the effects by empirical means. The authors utilize the SISU microsimulation model to compute the effective tax rates for a large sample of households (Kärkkäinen et al 2018b, p. 12–13). The authors separate the allowance recipients into three groups—recipients of earnings-related UI benefit, social assistance and homecare allowance—to better account for the different allowances they might be receiving. When studying changes in benefits over time, it is not straightforward to distinct the changes due to active policy decisions from annual inflation adjustments. For this reason, the authors conduct their analysis using two approaches: (A) tracks the effects of the changes made to benefits and taxes when taking into account inflation adjustments, while (B) focuses solely on active policy decisions made on behest of the government.[22] The second group also studies the effects of these changes in an alternative scenario without any inflation adjustments to e.g. benefits, such as index freezes. (Kärkkäinen et al 2018b, p. 9–10)

[20] The drop in net income might be partially explained with the loss of partial benefits, as: *"UI recipients who take up a full-time job for less than two weeks or a part time job (up to 80% of full time work hours) may qualify for partial benefits."* (Kyyrä et al 2017, p. 11)
[21] The social assistance benefits also have a kink at day four, or 80% of full-time work hours. However, instead of a complete reduction in benefits, social assistance is tapered at a euro for euro rate (OECD 2018, p. 97)
[22] The (B) group scenario implies further, that changes in for example municipality taxation and the effects of the competitiveness pact are not taken into account in this analysis (Kärkkäinen et al 2018b, p. 10).

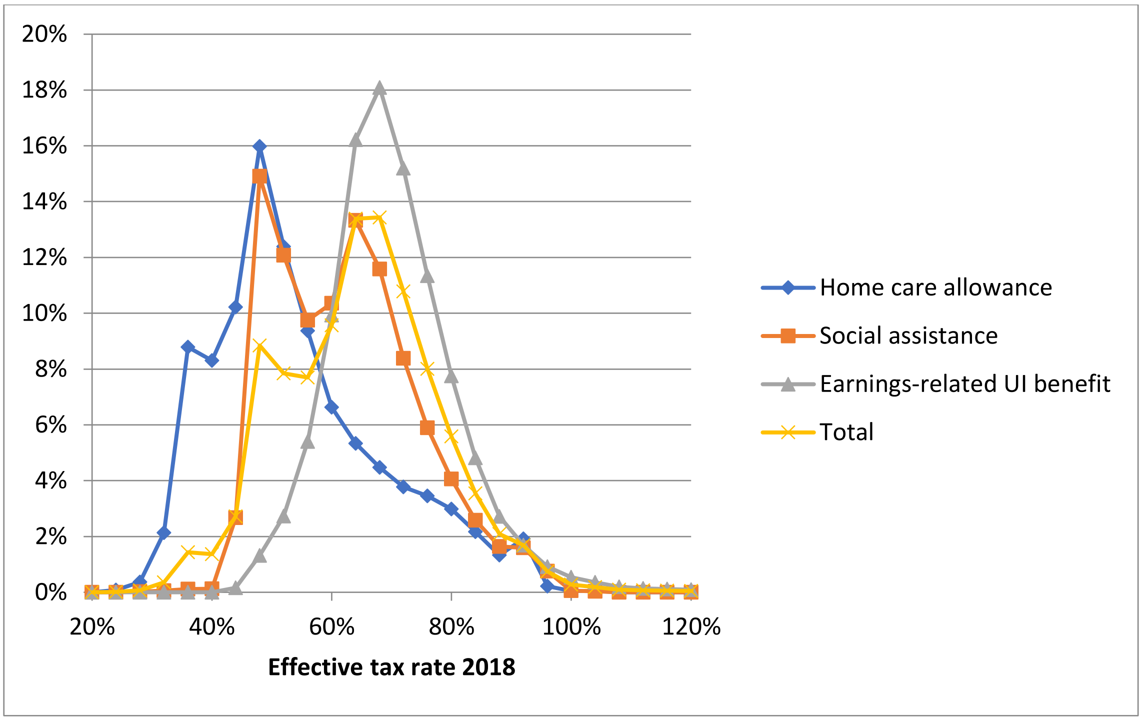


Figure 3. Illustration of the effective tax rate of three different benefits recipients. Source: Kärkkäinen and Tervola (2018b, p. 29).

Figure 3 illustrates the effective tax rate (2018) of three groups of benefits recipients. Among earnings-related UI benefit recipients there is a spike at 68%, which implies that the effective tax rate for participation increases at rates 44%–68%, thus leading to a state of decreased participation incentives. The same holds true among the recipients of social assistance; here too spikes emerge at rates 48% and 64%.

According to the estimation results, the incentives to accept work have improved during 2015–2018. The study finds that that the average effective tax rate has improved for (A) and (B) by -2.4 pp and -3.1 pp, respectively. As a result, the average effective tax rate is, as of 2018, 64% (see table 1 for details). According to a previous study (Kotamäki et al 2014; Kärkkäinen 2018a, p. 22), the opposite was true for 2011–2015, when the average tax rate increased by 3.5 percentage points, resulting in a state of decreased incentives.

Individuals entitled to:	**A: 2015**	**B: 2018**	**A&B: 2018**	**ΔA**	**ΔB**
Unemployment insurance	71.9	72.5	69.3	-2.6	-3.2
Social assistance	63.6	64.4	61.9	-1.8	-2.5
Home care allowance	57.5	58.3	54.2	-3.3	-4.1
Average	66.4	67.1	64.0	-2.4	-3.1

Table 1. The average effective tax rate of three different benefits recipients. Source: Kärkkäinen and Tervola (2018a).

As the studies above have illustrated, the effective tax rate, for different endowment recipient groups, is characterized by heterogeneity and nonlinearity. By extension, the household net income is heavily contingent on the level of wage income in conjunction with the different ETRs' associated with previous work history (i.e. whether the household is entitled to unemployment insurance or not), social assistance and home care allowance. However, these studies do not by themselves discuss behavioral changes, i.e. the theorized outcome on labor supply is not observable from these. This is why the elasticity of labor supply (henceforth ELS[23]) to underlying changes is a crucial point. Different estimates have been found in literature: e.g. Jäntti (2015) finds an average rate of 0.17, while Kotamäki (2016) finds 0.25 and VATT (2012) 0.1 (according to Kärkkäinen et al 2018b, p. 13). By combining the ETR with ELS estimates, changes in the labor supply may be analyzed, due to changes in benefits and taxation. According to the analysis by Kärkkäinen et al (2018b, p. 26–30), the measurement settings consisting of ELS parameters 0.1 and 0.25, in conjunction with an average ETR decrease of 2.4 and 3.1 pp respectively, yield an increase in person years within the range of 13 000–33 000 and 17 000–42000.

Further inquiries into the relationship between the ELS and taxation have been made in the field of public economics. The question of elasticity of taxable income (henceforth ETI[24]) has been persistently difficult to ascertain, as any estimates of ETI are easily prone

[23] This is in reference to the link between the participation tax rate and the extensive margin of labor supply.

[24] The estimated ETI parameter indicates how prone to changes the intensive (and extensive) margin of labor supply is to a change in tax rates. A higher parameter value implies that the labor supply is more elastic, i.e. decreasing it could increase the participation rate of labor.

to errors.[25] The classical paper of Feldstein (1995, p. 37) finds ETI parameters of 1.04–3.05 for the United States, while more recent (and improved papers) have found significantly lower estimates of the parameter; Gruber et al (2002, according to Selin 2018) finds 0.3–0.4 and Kleven et al (2014, according to Selin 2018) find 0.05–0.1. For Finland, Pirttilä et al (2005; Matikka 2018, p. 4) find ETI estimates of 0.3. The most recent ETI estimate for Finland, by Matikka (2018, p. 19), utilizing variation in the municipal income tax rate, is an average of 0.21.

As discussed in section 2.1, the incentives affecting the supply of labor are made up of conditions associated with the different UI benefit allowances and their duration alongside the rest of the social security system. The effects are also different, depending on whether the UI benefits are full- or part-time. Different estimates for full-time benefits have been performed in order to isolate the effects of UI benefit levels. The primary approach to assessing the effects of UI benefits is with elasticity measures, just as in the previous paragraphs with ELS and ETI. In a Finnish setting, Uusitalo et al (2010; Kyyrä 2017, p. 44–45) study the effects of the 2003 UI reform and find an elasticity value of 0.8. Another study by Kyyrä et al (2016; Kyyrä 2017, p. 45–46) finds an elasticity value of 1.5–2, though the effects are very imprecisely estimated. The sharp difference in elasticity estimates between these two studies may be because the former investigated a reform that was limited to workers with a long work history. Furthermore, higher benefits are linked to lower wage earnings (1) immediately after starting the new job and (2) over the next two years.[26] The authors offer two possible explanations to this: either employer discrimination (of the long-term unemployed) or human capital depreciation.

Next up is the question regarding the duration of UI benefits.[27] As the duration of the UI benefit is a semi-popular component to adjust, for a multitude of reasons, this has spawned opportunities for empirical research into behavioral effects. The duration of the UI benefit, like the monetary amount of the allowance, is tightly related to the unemployment spell, as different durations might have varying behavioral effects.

---

[25] These problems usually relate to mean reversion and sample problems, as e.g. different groups might bunch at different tax rates for different reasons, etc.

[26] This also implies that there remains some difficulty with establishing whether there is a link between longer search periods and a higher quality job. According to these estimates, such a link does not exist.

[27] The maximum duration of the basic unemployment allowance is 400 days in Finland (for people under the age of 58).

According to Kyyrä (2017, p. 52–53), several studies have investigated the linkage between unemployment spells and the (maximum) duration of the UI benefit; e.g. Krueger and Mueller (2010; Kyyrä 2017, p. 52) find an increase in the amount of time spent on job searching toward the expiration of the UI benefit, while Tatsiramos and van Ours (2014; Kyyrä 2017, p. 52) find that the average unemployment duration changes by approximately 20% of the adjustment amount. In a Finnish setting, Kyyrä et al (2017, p. 53–59) investigate the effect of *exit rate spikes* found usually at the expiration of UI benefits. According to their results, the unemployment exit rate, at the final week of the allowance, spikes to 16%, as seen in figure 4. This is further decomposed to analyze where the unemployed person moves onto; approximately 5% find jobs, while almost as many (4%) exit the labor force entirely. This implies, by extension, that the workers capable of finding work may be postponing the transition from unemployment to employment purposefully. However, it is useful to bear in mind that the unemployment pool in question, toward the final UI benefits week, is very small.

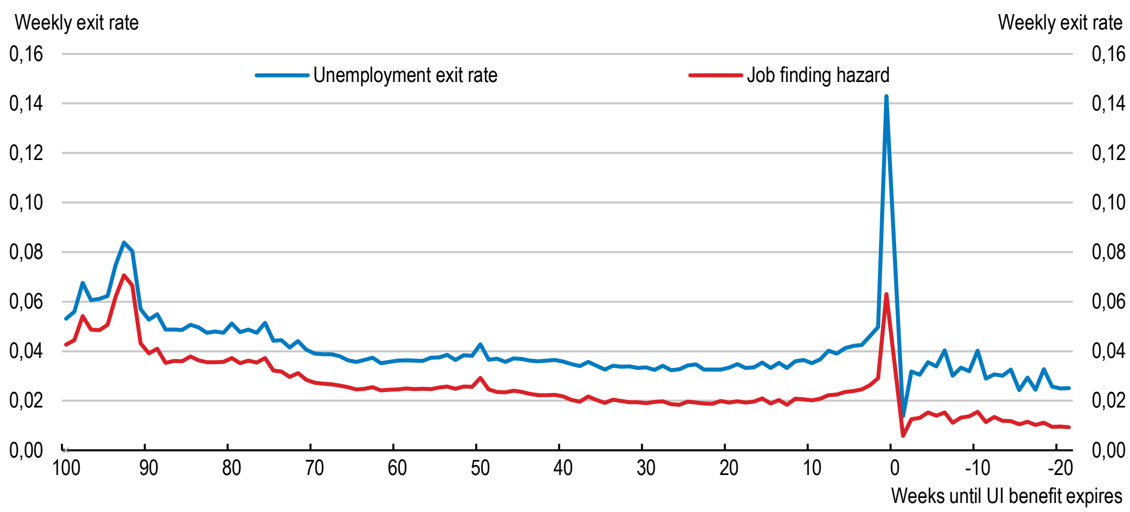


Figure 4. Unemployment exit rate. Source: Kyyrä et al 2017, according to OECD 2018

Beyond these reports dealing directly with issues pertaining to the reservation wage equation and welfare traps, other studies have also shown results which might have a behavioral impact on the supply of labor. One such issue is related to home care allowances and childcare fees. While these policy tools are of a different kind, they nevertheless have the same outcome. Childcare fees might incentivize *second earners* to stay at home. Considering that these fees increase with family income, this is not only isolated to low income earners. The second piece of the puzzle, i.e. the home care allowance, has the same effect on the duration of the unemployment spell. The OECD (2018, p. 47–48) summarizes: *"The homecare allowance is equivalent to a direct subsidy to stay out of the workforce for parents, notably second earners."* Adjusting these parameters in conjunction with one another could decrease the incentives to stay at home, and thus increase the participation rate. Another study, by Huttunen and Kosonen (2018), investigating the effects of home care allowance on children and mothers, finds that the labor supply of mothers decreases in conjunction with an increase in home care allowance: an increase of 100 euros decreases (on average) the working months of mothers of 9–20-month-old and 16–27-month-old babies by 2.7% and 3.4%, respectively.[28] (Huttunen et al 2018, p. 18–22)

Another subject of interest is the Oswald hypothesis, i.e. the correlation between homeownership and unemployment. The basic premise states that mobility frictions are caused by both supply and demand inefficiencies in the housing market. A lack of demand causes mobility rigidities, as relocating to another job market might be contingent on selling the current resident first. On the other hand, a lack of supply on the housing market may also lead to rigidities, as the budget constraint may hinder those relocating from acquiring a new resident. Chan (2001; Haavio 2018) and Ferreira (2010; Haavio 2018) argue that asymmetric accelerations in housing prices might increase rigidities; as decreasing net worth of the current residence (starting destination) and increasing residential prices in job centers (target destinations) together lead to a negative spiral where budget constraints might cause prolonged pockets of unemployment. According to Haavio (2018), any increases in transaction costs might distort the housing market, thus leading to an increase in frictional unemployment. One such study is provided by Eerola et al (2018), who find that housing transfer taxes have a distorting effect on the mobility rate of homeowners.[29]

[28] The authors also control for other attributes, such as income groups and educations, and find statistically significant effects in all of them.

[29] The housing transfer tax is an additional temporary tax, in effect 2 years after purchase, which implies that anyone selling the house within that time frame has to face an additional tax cost. The methodological approach by Eerola et al takes into account both cross- and intramobility in municipalities and counties, utilizing a difference-in-difference method between co-ops and single family housing. The results indicate that the housing

To conclude, the issue of structural unemployment, from a microeconomics perspective, is partly explained by a set of bottlenecks caused by complex interactions between taxation and various income transfer programs. The main emphasis today in policy discussions has shifted toward the coming reform of the social security system. A multi-party unit has been tasked with overhauling the basic social security system and activeness in a so-called TOIMI project, which seeks to provide long-term reform alternatives to the government by approaching the question from a bottom-top perspective. This decomposition of the social security system allows the unit to identify the redundant parts of the system and assemble suggestions for a more efficient social security system. Nevertheless, the microeconomics perspective is not limited to the question of welfare traps, but extends to any and all market failures causing (negative) ripple effects in the labor market.

transfer tax causes more friction in the labor market, as homeowners become more reluctant to move due to the extra tax cost. (Eerola et al 2018)

4 NAWRU in theory and practice

This section discusses the policy relevance and theoretical specifications underpinning the NAWRU model. The NAWRU model used in this study has been constructed by the EU Directorate-General for Economic and Financial Affairs (ECFIN) for policy analysis purposes. Their simulation of the natural unemployment rate is arguably one of the most developed ones to date, as the underlying theory has been updated and improved over the course of the past decade. The ongoing research to improve the model is motivated by the fact that the ECFIN NAWRU estimates have actual policy implications. The role of the model in the European Commission's structural budget balance analysis will therefore be discussed in subsection 4.1. The model's theoretical underpinnings, revisions and updates will be discussed in subsection 4.2. A brief illustration of alternative structural unemployment estimates will be given in section 4.3.

4.1 NAWRU and the Stability and Growth Pact

Before proceeding, it is crucial to understand the importance of the NAWRU model. While NAIRU models are frequently used in policy analysis, they are not delegated any official capacity. This is usually motivated by the uncertainty associated with these models. ECFIN breaks from this trend, as its NAWRU estimates are incorporated into the European Commission's evaluation of budgetary structural deficits within the European Union.

The *Stability and Growth Pact* (henceforth SGP) is the primary treaty governing the fiscal viability of EU member states.[30] The SGP relies on a so-called preventive program, known as the *Medium-Term Budgetary Objective* (henceforth MTO), which entails that if a treaty member violates the SGP, the preventive MTO program dictates budgetary reforms to cope with the deficit. This translates into compulsory general government budgetary cuts, where the benchmark fiscal downsizing is usually -0.5% of GDP (on an annual level). The MTO sets its required budgetary adjustments in relation to the potential GDP (i.e. structural level), known as the *cyclically adjusted budget balance* (henceforth CAB). This component determines the adjusted budgetary imbalances, also known as a structural

[30] The two primary criteria of concern in the SGP are: (1) the maximum budgetary deficit may not exceed 60% of GDP, while (2) the annual growth rate of debt may not transgress 3%.

budget balance. (Huovari, et al 2017, p. 6–7) The adjustment component is seen in equation (i) as an adjusted output gap component.

$$CAB_t = \frac{(R_t - G_t)}{Y_t} - \varepsilon * OG_t \qquad \text{(i)}$$

The first component CAB_t is the difference between the nominal budget balance, i.e. the sum of government revenues (R_t) and expenditures (G_t), divided by the GDP (Y_t), from which the second component, i.e. the product of the budgetary semi-elasticity parameter (ε) multiplied with the output gap (OG_t) is then subtracted.[31] (Huovari et al 2017, p. 8, 45)

$$OG_t = (Y_t - Y_t^p)/Y_t^p \qquad \text{(ii)}$$

The output gap determines the difference between the actual (Y_t) and potential GDP (Y_t^p), where a negative (positive) value implies a state of recession (boom). The potential GDP is an unobservable component, implying that it has to be estimated. This term is estimated with the so-called *production function* (henceforth PF). (Huovari et al 2017, p. 8)

$$Y_t^p = TFP_t(K_t^{\propto} L_t^{1-\propto}) \qquad \text{(iii)}$$

The production function follows a rudimentary Cobb–Douglas model, where all three components are estimated and calculated separately.[32] The component of interest, i.e. the labor component, is illustrated below. (Havik et al 2014, p. 10, 14)

$$L_t^p = \left(POPW_t * PARTS_t * (1 - NAWRU_t)\right) * HOURST_t \qquad \text{(iv)}$$

The potential labor component is a product of the working age population $(POPW)$, smoothened participation rate $(PARTS)$, one minus NAWRU and trend or average hours worked $(HOURST)$ (Havik et al 2014, p. 14).

The series of equations listed above illustrate that the estimated NAWRU component affects the potential labor component (iv). This in turn is a subcomponent of the production function (iii), which finally affects the output gap (ii) in the cyclically adjusted budget balance (i). The CAB equation, according to the SGP treaty, is the primary tool for

[31] The nominal budget balance is the sum of current government revenues and expenditures. The semi-budgetary elasticity parameter *"captures the absolute variation of the budget balance as a percentage of GDP to the relative variation of output gap."* (Huovari et al 2017, p. 10).

[32] The components do not have a superscript *p* inserted to indicate the potential level, but are nevertheless components for potential capital and labor.

policy analysis, which, by extension, also comes with actual fiscal policy implications to the treaty signatories. Therefore, any potential biases in the NAWRU estimate will echo throughout the chain of equations, with the potential to cause policy failures.

This may be studied further by investigating the revisions to the NAWRU estimate. Figure 6 below illustrates how the Kalman filter-based estimates for structural employment have been revised. The six biannual NAWRU estimates for Finland were made for 2015–2018 by ECFIN.[33] To illustrate the impact of revisions on the structural budget balance, the impact of revisions made to the NAWRU estimate has been calculated, as illustrated in table 2.

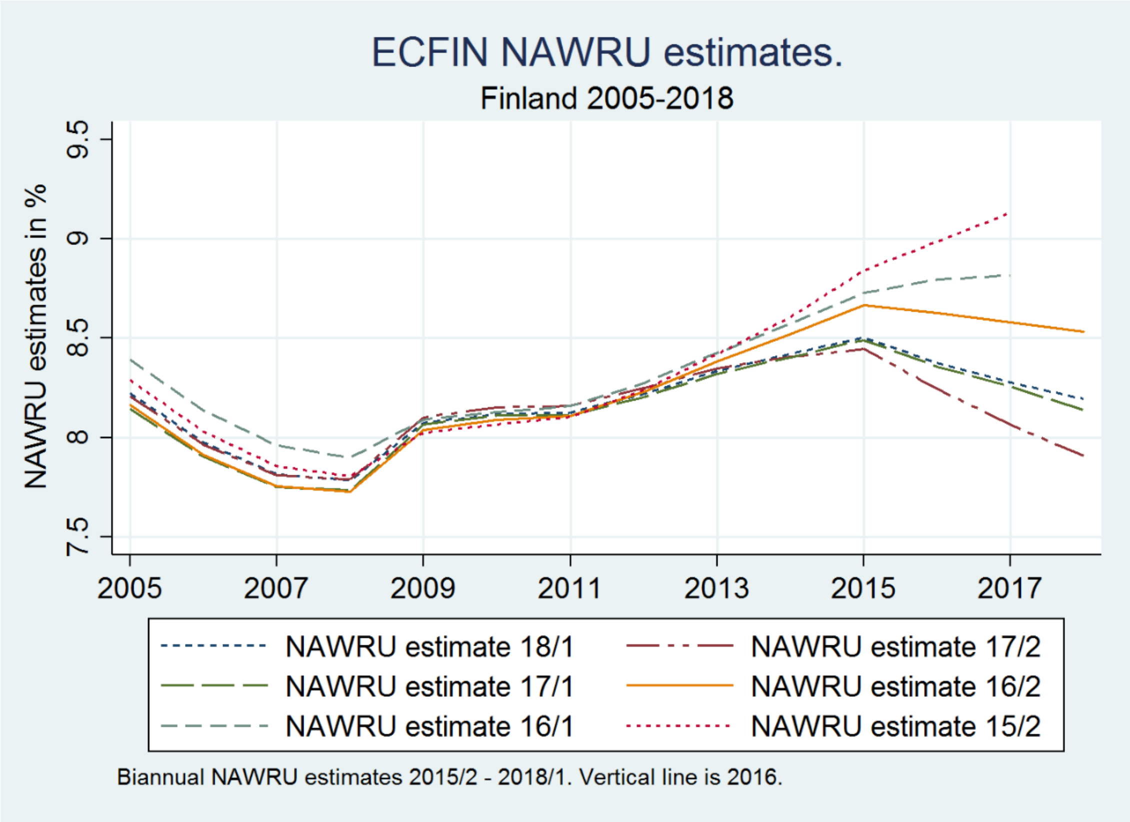


Figure 5. Source: European Commission Financial and Economic Affairs NAWRU estimates for Finland (2018)

[33] ECFIN regularly performs two NAWRU estimations per year, during Autumn and Spring. These estimates are made for T+2, implying that the one made in 2015 extends to 2017, 2016 to 2018, etc.

	(1) NAWRU (ECFIN) estimate 16/2	(2) NAWRU (ECFIN) estimate 18/1	(3) NAWRU (ECFIN) estimate 17/2	(4) NAWRU (ECFIN) estimate 17/1	(5) NAWRU (ECFIN) estimate 16/1	(6) NAWRU (ECFIN) estimate 15/2
UNEMP	8.8%	8.8%	8.8%	8.8%	8.8%	8.8%
NAWRU	8.63%	8.375%	8.25%	8.36%	8.8%	0.89%
YREAL	190.79	190.79	190.79	190.79	190.79	190.79
YPOT	194.93	195.29	195.47	195.31	194.7	194.44
OG	-2.12%	-2.3%	-2.39%	-2.31%	-2.01%	-1.87%
SB (CAB)	-0.6%	-0.5%	-0.4%	-0.5%	-0.7%	-0.7%

Table 2. Comparative statistics regarding the effects of NAWRU revisions on the EU structural budget balance. The table depicts the impact of NAWRU revisions on the cyclically adjusted budget balance (ceteris paribus), as described with equations (i)–(iv). Source: Ministry of Finance (2018) and Mourre et al (2014) and author's own calculations.

The results in table 2 are calculated for Finland, using the equations listed in (i)–(iv). The calculation contains six different NAWRU estimates for 2016. This year was chosen as the benchmark year, as it contains both forecast and revision estimates. The columns present different figures, as they represent both forecasts (5)–(6) and revisions (2)–(4), while column (1) is the benchmark year. Figure 5 illustrates how all estimates had a kink at 2015. The estimates prior to the benchmark year (16/2) have a positive slope after the kink, while the ones following have a negative slope. The most optimistic estimate (17/2) is revised upward in the most recent estimate (18/1).

The concept of a structural budget balance has been criticized for its heavy reliance on the above equations, as some of the underlying components in equation (iv) might be estimated with different methodological techniques.[34] Huovari et al (2017, p. 43–49) perform sensitivity diagnostics on the output gap with different assumptions regarding the TFP, NAWRU, participation rate and average hours worked components—and find that potential revisions in the NAWRU component impacts the output gap equation (ii) the most.

[34] For the purposes of this study, only uncertainty in equation (iv) is considered. As stated, the potential GDP is also subject to estimation techniques, implying that it also is subject to potential biases.

4.2 Theoretical background of the model

The theoretical model considered in this analysis builds on that created by Orlandi (2012), Havik et al (2014) and Hristov et al (2017). The core model was outlined in the first paper, which was a complete overhaul of the previous ECFIN model. The extensions in the following methodological papers modify the model to better distinguish between the characteristics of the EU member states and deal with the issue of the pro-cyclicality of the NAWRU estimate. Most of the model extensions have been prompted by the issue of pro-cyclicality.

The first paper by Orlandi (2012) describes the theoretical and empirical approach to deriving the NAWRU estimate. In practice, the ECFIN's approach decomposes the unemployment rate into cyclical and structural components by using an unobserved components model, or more specifically, a multivariate Kalman filter. However, the actual estimation of the structural component does not rely on any economic information. Instead, the method builds on a wage Phillips curve to identify the cyclical component in the unemployment variable, from which the (trend) structural component is then derived. In other words, the NAWRU estimate is the residual of the multivariate wage-Phillips Kalman-Filter exercise. As Orlandi underscores, this method merely provides a proxy for structural unemployment—and might still be influenced by temporary shocks. (Orlandi 2012, p. 1–2)

The residual component (NAWRU) obtained with the filtering technique is evaluated with a theoretical model consisting of a set of structural and non-structural determinants. By including a theoretical model with economic information, the wage-Phillips model is linked to a theoretical structural unemployment model, thus becoming coherent and closed. These structural and non-structural determinants are also used in the actual analysis.[35] (Orlandi 2012, p. 2–3)

The wage-Phillips curve is described by Havik et al (2014, p. 15–16) as a static and adaptive expectation cases-based model, or as a *Traditional Keynesian Phillips* curve (henceforth TKP), i.e. a backward-looking model. As the structural component had a

[35] Therefore a more detailed description of their theoretical and practical attributes may be studied in sections 5.1.1–5.1.3.

significant pro-cyclical tendency due to this specification, it prompted the first revision of the multivariate filtering component. The new wage-Phillips curve specification considered a model based on rational expectations, or a *New-Keynesian Phillips* curve (henceforth NKP), i.e. a forward-looking model. However, the purely forward-looking NKP was found to be empirically unsound, given its *"failure to match the persistence of inflation variables"* (Havik et al 2014, p. 58). Therefore, a hybrid *alternative Keynesian Phillips curve* (henceforth AKP) model was designed, combining the rational expectations assumptions of the NKP, in conjunction with the adaptive based ones of the TKP. The models are identical, differing only in terms of timing and expectations (Havik et al 2014, p. 15).[36]

The new AKP wage-Phillips curve is formulated as follows:

$$\Delta rulc_t = \beta(s\Delta rulc_{t+1}^{e} + (1-s)rulc_{t-1}) - \lambda(u_t - u_t^*) \qquad \text{(i)}$$

Here the rate of *real unit labor cost* ($rulc_t$) is determined by the discounted (β) parenthesis, which is a weighted combination of the forward-looking ($\Delta rulc_{t+1}^{e}$) and backward-looking ($rulc_{t-1}$) models, corrected by the unemployment gap ($u_t - u_t^*$). The weight parameter (s) illustrates the different combinations of worker (union) behavior. (Havik et al 2014, p. 15–17, 57–89). The original wage-Phillips curve cyclical component was modeled as a stationary, zero-mean, AR(2) process. (Orlandi 2012, p. 2). This AR(2) process is also incorporated into the unemployment gap of the extended AKP model, yielding the following backward model (Havik et al 2014, p. 58)

$$\Delta rulc_t = \gamma_0 \Delta rulc_{t-1} + \gamma_1(u_t - u_t^*) + \gamma_2(u_{t-1} - u_t^*) \qquad \text{(ii)}$$

where the first parameter (γ_0) determines the weight of the forward-looking component, implying that a zero value would render the backward-looking model redundant. Consequently, a value approaching one would also reduce the importance of the forward-looking component to null. (Havik, et al 2014, p. 58)

[36] For a further (technical) read with regard to the formulations of the wage-Phillips curve model, please consult Havik et al (2014, p. 53–58). The technical derivations, and their theoretical assumptions, are illustrated step-by-step in their paper.

In practice, ECFIN estimates both the TKP and NKP models for each and every nation separately. Depending on the results, either the TKP or the NKP is assigned to that country, which then remains as the country-specific model for three years.[37] In the case of Finland, the NKP model is deemed significant with a p-value of 0.05, compared to the insignificant TKP model.[38] (Havik et al 2014, p. 21-22)

The final implication of the AKP model is the zero-mean assumption of the NKP model. This constraint is not imposed on the TKP model, thus resulting in diverging NAWRU averages between the TKP and NKP models. To correct for the different averages, the mean difference of the unadjusted TKP and NKP NAWRUs is calculated and is then used to correct the NKP estimate toward the TKP measure. If the mean difference is positive, the NKP is adjusted downward. (Havik et al 2014, p. 23).[39] The NKP adjustment factor for Finland is -0.72, implying that the Finnish NAWRU figure is revised downward. The zero-mean sample implications are described as *"specifying the unemployment gap as a process that reverts to zero mean [...] seems to capture Friedman's (1968) view that the unemployment rate cannot be kept away indefinitely from the natural rate [of unemployment]"* (Laubach 2001, p. 221; Heimberger et al 2017, p. 886–887). Alternative models to the one specified above are also considered, where e.g. terms of trade shocks, different AR processes, etc. are also modeled (Orlandi 2014, p. 9).

The report by Havik et al (2014) also incorporates the new NAWRU methodology into the so-called T+10 projections methodology. This serves as an estimation tool for different policy analysis purposes in order to produce stable projections for the long-term haul. As long-term potential labor input is a function of the NAWRU component, as may be seen from equations (iii) and (iv) in section 4.1, it is crucial to construct a trustworthy T+10 estimate of the NAWRU component. The output gap working group (henceforth OGWG) deemed it difficult to find a baseline potential NAWRU prior to the Great Financial Crisis—due to the distortions in pre-crisis unemployment statistics—the NAWRU anchor relying

[37] The country-specific methodological revision does not affect the structural budget balance, as any effects on the output gap and structural budget balance are accounted and corrected for. (Havik et al 2014, p. 20)
[38] In cases where the results are similar, NKP is given priority due to its modeling advantages. However, in certain cases Member States are consulted separately to determine which model should be chosen. (Havik et al 2014, p. 22)
[39] In the 2014 methodological paper, an upward adjustment of the NKP is not utilized. The authors also conclude that an imposition of the zero-mean restriction on the TKP model is under consideration. (Havik et al 2014, p. 23)

on estimated structural determinants was regarded as a best viable option in determining a stable long-term structural unemployment rate.[40] (Havik et al 2014, p. 39–44)

The latest methodological paper by Hristov et al (2017) includes an anchoring module to the NAWRU estimate. The purpose of the anchoring module is to reduce the pro-cyclical tendencies of the NAWRU estimate. According to Hristov et al (2017, p. 2), this pro-cyclical bias has been noticeable at the most recent unemployment observation. The authors draw on theoretical justifications to motivate the presence of some pro-cyclicality. However, the technique in the Orlandi (2012) methodological paper—which utilizes no economic information for the structural component—is deemed *"arbitrary [as] it does not affect the in-sample estimates, it does not address the problem of pro-cyclicality"* (Hristov et al 2017, p. 2). The anchor is further extended by utilizing the same panel regression setup as in Orlandi (2012) and Havik et al (2014), implying that a set of structural and non-structural determinants function at the core of the country-specific anchors.

The improvements performed by Hristov et al (2017) include model-based anchoring. The original anchoring technique used in the T+10 projections methodology relied on a set of different measures to reduce pro-cyclical tendencies, while the new improvements in Hristov's paper include econometric improvements in the anchoring technique.[41]

[40] For further details concerning medium- and long-term projections, see Havik et al (2014).
[41] For further details concerning the econometric specifications introduced in their paper, see Hristov et al (2017).

4.3 Alternative models for structural unemployment

The following section will introduce selected studies dealing with structural unemployment estimate, comparable to the NAWRU estimate. This section will merely introduce certain estimates of the natural rate of unemployment.

Figure 6 illustrates four different structural unemployment estimates for Finland, compiled by both national and international institutions. These estimates rely on different estimation techniques to derive the trend component.

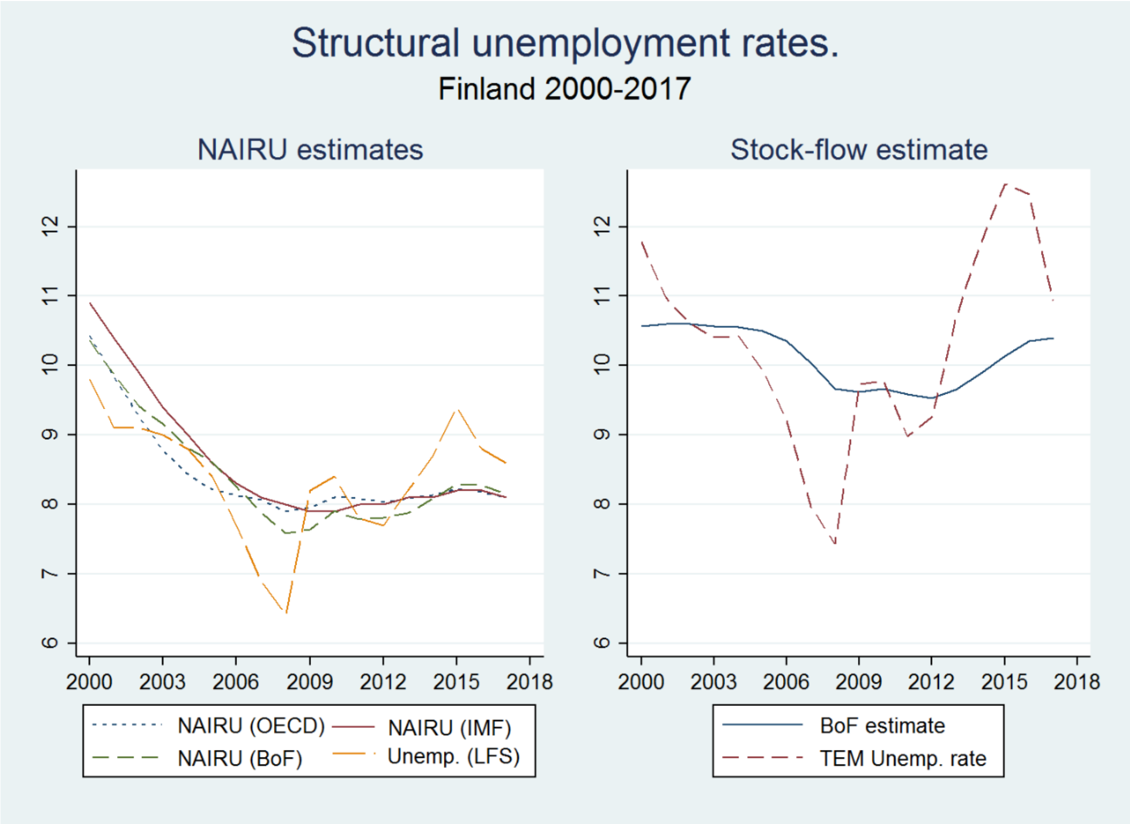


Figure 6. Natural unemployment rates. Source: OECD, BoF, IMF, Statistics Finland (Tilastokeskus). The depicted annual stock-flow estimate above has been converted from quarterly to annual rates by the author, the quarterly estimates are provided by Juvonen et al (2018). The depicted annual rate is the average of quarterly rates.

The first selection of estimates deals with estimation models for the level of unemployment which keeps inflation and wage pressures stable. These NAIRU models utilize unobserved components models to decompose unemployment figures into trend and cyclical parts. The presented NAIRU estimates are produced by the OECD, Bank of

Finland and the IMF. The OECD has recently introduced a new methodology for deriving the trend component, as their previous method was based on a purely backward-looking Phillips curve specification. This has since been updated to combine forward-looking elements to better anchor the estimate (Rusticelli et al 2015, p. 302–305). The IMF model is based on a Hodrick–Prescott (HP) filter technique.

The second figure depicts the stock-flow of structural unemployment developed and estimated by Juvonen and Obstbaum (2018). This method utilizes trend transition rates, i.e. movements between unemployment–employment (UE) and vice versa (EU), to determine a structural unemployment rate. To distinguish between cyclical and structural transition rates, the authors utilize a Kalman filtering technique. The structural transition rate is defined as the rate of unemployment which would remain constant in a state of equilibrium. The authors add that the equilibrium rates of job finding and destruction *"are determined by matching efficiency, search intensity, firing costs"* (Juvonen et al 2018, p. 3).

The structural unemployment rates are divided into separate graphs, as they use different data sources. The NAIRU estimates utilize data from labor force surveys, while the stock-flow estimate utilizes register data obtained from the Ministry of Economic Affairs and Employment. Aside from differences in data and methodology, certain similarities may be found between the models. The common denominator for these models is the Kalman filtering technique, albeit with differences in calibrations. As the stock-flow model for Finland is relatively new, no in-depth evaluations or comparisons between the two frameworks are yet to be found. However, the results of Juvonen et al (2018, p. 5) *"do not support the view that labour market slack could be considerably higher than indicated by nairu estimates."*

5 Analysis

The objective of the analysis section is to derive a decomposition of the Finnish structural unemployment rate, which will rely on the NAWRU model developed by the European Commission's Directorate-General for Economic and Financial Affairs (henceforth ECFIN). The estimated model in this analysis differs from the results obtained by Orlandi (2012) and ECFIN (2017), as the dataset and estimation procedure have been altered (see section 5.1 and 5.2 for details).

Section 5.1 depicts the dataset and associated data adjustment methodologies. Section 5.2 presents the econometric specifications and pre-regression tests. Section 5.3 showcases the initial results, while section 5.4 introduces several postestimation tools and diagnostics to improve the results. Section 5.5 is devoted to drawbacks of the data and the model.

5.1 Data

The data section presents the dataset utilized in this analysis. As the foundation of the analysis relies on the ECFIN NAWRU model, the dataset is built according to the specifics in Havik et al (2014, p. 83–84). However, this study diverges from the analysis of Orlandi (2012) and Havik et al (2014) for several reasons. The primary differences are related to time series splicings, interpolations and seasonal adjustments. The instructions in the Havik et al (2014) appendix laid out a very detailed schematic for how to construct the dataset, but did not specify the time series adjustment methodologies. Therefore, the methodologies used in this analysis diverge, as will be discussed in 5.1.1. Subsections 5.1.2–5.1.3 discuss the dependent and independent variable groups utilized in this analysis.

The estimation is for 27 EU nations for the 1985–2016 time frame.[42] The panel dataset is more balanced for the recent years, as many new Eastern European EU member states are lacking data due to the regime shifts in the late 1980s and early 1990s. The dataset in

[42] The EU27 includes Belgium, Bulgaria, the Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, the Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden and the United Kingdom.

this study consists of 556 observations, while ECFIN's latest published dataset contains 620 observations. Beyond the differences in the number of observations, other differences between these two datasets originate from time series splicings, interpolations for missing values as well as seasonal adjustments. Certain variables are also constructed with different parameters, as will be shown in section 5.1.2. While there is a case to be made for exploring other independent variables as well, this analysis does not explore that option. Heimberger, Kapeller and Schütz (2017) include additional explanatory variables in their study, such as employment protection legislation, terms of trade shock, capital accumulation, minimum wage, etc. According to their literature review, these are the variables most often used in this exercise.

5.1.1 Data methodology

As previously stated, this dataset has undergone a different adjustment and splicing process than ECFIN's model. This is due to the missing specifications in the Havik et al (2014) methodology paper.

The utilized splicing technique in this paper relies on *retropolation*, as Fuente (2009) calls it. Retropolation features two techniques used in splicing, i.e. matching both the level and the growth rates to the benchmark series. This is especially useful with the utilized dataset, as five variables in this series had to be extended backward in time. The benchmark time series in this study is defined as the most recent dataset.[43] The first process links the time series together, by raising or lowering the secondary time series level with a constant. This linking process alone does not ensure that the combined time series is stationary; therefore the retropolation process is further extended to use the growth rate of the benchmark series. This secondary measure kicks in at the endpoint of the benchmark series, implying that the growth rates of the benchmark series are used as a smoothening factor in the secondary time series. These two measures ensure that the extension to the benchmark series remains as uniform as possible.

The second adjustment in this analysis involves interpolations to fill gaps in different time series. Interpolation techniques are performed to fill short gaps in time series data. Small

[43] The most recent time series had complete time series (i.e. no missing value gaps) and were available from large institutions, e.g. AMECO and OECD.

gaps consisting of one missing value have been filled with an average of the two closest values. Larger gaps, of two or above, have been filled with a weighted average, where the constant weight has been the first available observation backward in time and the moving value has been the most recent observation, where the moving value keeps changing whenever new values become available. This weighted average smoothens the interpolated values disproportionately, as the interpolated values converge toward the constant value. This approach, as any interpolation without confirmation (e.g. with qualitative data), excludes any sudden and deep changes in the data, such as significant policy effects.

The last technique utilized in this paper involves seasonal adjustment. Most of the data in this study is available with seasonal adjustments, except for the parameter value (see 5.1.2) used in the unemployment benefit replacement rate (UBRR). The utilized SA tool is the US Census Bureau's *X-13ARIMA-SEATS Seasonal Adjustment Program* (2017).

Appendix D.1 demonstrates the time series graphs of all variables for all countries, including the first difference of every time series. The outliers visible in the appendix have not been accounted for, implying that they impact the actual regression analysis.

5.1.2 Structural variables

The first set of variables is a mixture of four labor market structural indicators: trade union density, tax wedge, unemployment benefit replacement rate and active labor market policy. Each determinant will be briefly described from a theoretical perspective, as will any data adjustments (according to the methods described in 5.1.1). See Appendix D.1 for the time series graphs of the variables. The dataset below has been built in accordance with the appendix of Havik et al (2014, p. 83–84).

Trade union density (UD) is a degree of unionization, measured as the ratio of employees with a union membership. This variable is used as a proxy to measure the tightness of the labor market, as the assumption is that a higher density level results in a higher reservation wage (Orlandi 2012, p. 3–4). Therefore this determinant is expected to have a positive sign in the regression analysis. UD has been decreasing in most of Europe throughout the estimation time horizon. The primary source for the UD determinant is the OECD, which has an unbalanced registry for 1960–2016. This variable has been spliced with amendments from the Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) and the International Labour Organization (ILO) database. Interpolation has been used to fill gaps.

The tax wedge (TW) determinant, as described by Orlandi (2012, p. 8), is a measure of the proportional difference between total cost and net earnings. The total cost consists of wage and social security contributions, while net earnings consist of family benefits and the net wage (i.e. adjusted for personal income tax and social security contributions). The TW predictor may be considered a proxy for the intensive and extensive margins of labor supply discussed in section 3. Therefore this determinant is expected to have a positive sign in the regression analysis. The primary source (Eurostat) measures the TW of a single-person household without children, with an average wage. The spliced series considers a household consisting of a single-earner couple with two children, earning average wage. The primary source for the TW determinant is Eurostat, which has an unbalanced registry for 1996–2016. This variable has been spliced with the Bassanini-Duval database.

The active labor market policy (ALMP) determinant is an aggregate of seven sub-items, measuring the allocation of resources toward active labor market policies.[44] The ALMP determinant is given in ratio to the GDP, which is then divided with the unemployment rate. This allows for cross-country comparisons, as it effectively measures how committed each country is to labor market policies, when taking into account the proportional differences in country unemployment sizes. This determinant is expected to have a negative sign in the regression analysis. (Orlandi 2012, p. 9) The primary time series is from Eurostat, while the splicing data comes from the OECD. This variable has been interpolated.

The last determinant is the unemployment benefit replacement rate (UBRR), which serves as a proxy for expected average replacement rates (Orlandi 2012, p. 7). The purpose of UBRR is to measure the effect of unemployment benefits on the reservation wage. In accordance with the reservation wage equation, a higher UBRR increases the

[44] In the case of Italy, the sub-item "public employment services" has been excluded to increase the time series length.

wage requirements, thus leading to increased structural unemployment. Therefore, this determinant is expected to sign positively. (Orlandi 2012, p. 7–8) Formally, the determinant is constructed as follows:

$$b_t^0 = \theta b_t^{0,<13} + \left(\frac{(1-\theta)b_t^{0,>60} - b_t^{0,<13}0.2}{0.8}\right) \qquad \text{(i)}$$

$$\theta = \sum_{i=0}^{11} \alpha(1-\alpha)^i \qquad \text{(ii)}$$

The UBRR equation (i) is a weighted combination of two average replacement rates. The first one is for unemployment spells up to 13 months, while the second is the average replacement rate received after five years. The short-term unemployed are removed from the second component to avoid duplicity. The weight parameter (ii) is calculated with the monthly unemployment exit probability rate (α), which is reconfigured to an annual level. (Havik et al 2014, p. 83–84) This analysis does not use the same unemployment exit probabilities as described in Orlandi (2012) and Havik et al (2014), as these rates are from 2005–2007, just prior to the *Great Financial Crisis*. By calculating new rates using Eurostat stock-flow figures, this study is able to calculate country-specific rates for almost all countries.[45] The new rates have been calculated according to the following specification (Shimer 2005, p. 31),

$$f_t = 1 - \left(\frac{u_{t+1} - u_{t+1}^s}{u_t}\right) \qquad \text{(iii)}$$

where the probability of exiting unemployment (f_t) is one minus the transition rate from unemployment rate to employment (parenthesis). These unemployment rates are then used in equation (ii) to complete the weight parameter for equation (i). The unemployment rates are not time-varying, as they are found to cause multicollinearity with NAWRU (Orlandi 2012, p. 7).[46] Therefore an average unemployment exit probability rate is calculated from the time series.

[45] Havik et al (2014, p. 84) have probability rates for 13 countries, using a cross-country average for the rest. This study has probability rates for 24 countries, using a cross-country average for Belgium, Germany and Malta. The data retrieved from Eurostat has been seasonally adjusted with the X13 method described in section 5.1. The stock-flow data ranges from 2010 Q2 – 2017 Q4, which (after the SA method) is converted to annual averages.

[46] Also confirmed in this study.

The terms $b_t^{0,<13}$ and $b_t^{0,>60}$ are joint averages for the following households: one-earner couple, two-earner couple (second earner 67%) and single. The primary earner is further divided into two scenarios, receiving 67% and 100% of the average wage. This implies that $b_t^{0,<13}$ alone consists in total of six different types of households (three types of households with two types of income). This is the unemployment benefit replacement rate for those with an unemployment spell for up to 13 months. The same household types are used for those with an unemployment spell over 5 years. (Havik et al 2014, p. 83–84) The replacement rate includes the unemployment benefit, housing benefit and salary adjustment.

The net replacement rate time series for 2001–2016 comes from ECFIN's annual macroeconomic AMECO database. This data has been spliced with gross replacement rate time series from the Bassanini-Duval and University of Leiden databases.[47] The Bassanini-Duval time series provides 13-month and 60-month replacement rates, which are spliced with their respective time series before the calculations of equation (i).[48] Some countries have the same replacement rate for short- and long-term unemployed, implying that there is no distinguishable difference between 13-month and 60-month replacement rates in these cases. All negative UBRR values are corrected to zero, (Havik et al 2014, p. 83–84), and to correct for the differences in net and gross replacement rates, Orlandi (2012, p. 19–20) proposes a dummy to distinguish between the two series, which is also included in this study. The UBRR determinant has been spliced.

5.1.3 Non-structural variables

The second set of variables is a control group, used to check for non-structural effects on the labor market. The original paper by Orlandi (2012) lists total factor productivity, the real interest rate and a proxy for boom–bust patterns. The boom–bust variable measures the ratio of construction workers in relation to total employment. Each determinant will be briefly described from a theoretical perspective, as will any data adjustments (according to the methods described in 5.1.1). See Appendix D.1 for the time series graphs

[47] The time series from the University of Leiden does not distinguish between 13-month and 60-month periods. This time series is used for Bulgaria, Cyprus, the Czech Republic, Estonia, Greece, Latvia, Lithuania, Hungary, Malta, Poland, Romania, Slovenia and Slovakia.
[48] Not only is the replacement rate different, but the type of households in the fold also differs.

of the variables. The dataset below has been built in accordance with the appendix of Havik et al (2014, p. 83–84).

The annual growth of the total-factor productivity (TFP) measures the productivity residual in the economy. An increase in the TFP component leads to a higher real productivity, or in an opposite case, a decrease in TFP might result in a need to adjust to the new output, and by extension, decrease the real wage. Depending on the level of rigidity in wages, this might cause temporarily higher structural unemployment. Therefore the TFP component is assumed to sign negatively in the regression analysis. Orlandi (2012, p. 5, 9) states that an increase in TFP could also result in worker reallocations as technology changes, thus opening up the possibility of having a positive effect on the structural unemployment rate.[49] The TFP data has been retrieved from the AMECO database.

The real interest rate (R) is the difference between the long-term nominal interest rate and a five-year moving average GDP deflator. As Orlandi (2012, p. 5) maintains, the effects of the real interest rate are seen through the investment variable, as an increase in the interest rate decreases capital accumulation. A decrease in capital accumulation translates into a decrease in aggregate output, thus mandating a decrease in employment to maintain the equilibrium capital–labor ratio. Therefore the real interest rate component is expected to sign positively. The real interest rate components are from the AMECO database.[50]

The construction (CONS) component is the share of construction workers in the labor force. According to Orlandi (2012, p. 6), additional boom–bust indicators may be useful in explaining prolonged mismatch problems in the labor market. This is prompted by the fact that an above average increase in the proportion of construction workers is caused by a period of overheating, which might lead to a prolonged structural unemployment spell after a bust. Therefore this variable is expected to sign negatively. The CONS subcomponents are from the AMECO database.

[49] This further complicates the matter, as the negative and positive effects might cancel each other out.
[50] According to Havik et al (2014, p. 83), the R value for Luxembourg should be replaced with zeros due to the strong link between its rate and the large banking sector present there.

5.2 Econometric specification

This section introduces the general econometric specification and pre-regression tests. The data in this analysis covers 27 EU countries for the years 1985–2016. Due to annual observations and the relatively short time span (T=31), a broad regression including multiple countries (N=27) is deemed necessary. To account for the heterogeneity among the EU nations, a panel setup is envisioned. The panel set is heavily unbalanced, especially for new members in the EU, amounting to a total of 556 observations.

	NAWRU	UD	TW	ALMP	UBRR	UBRR2	TFP	R	CONS
NAWRU	1.0000								
UD	-0.3399	1.0000							
TW	-0.0191	0.0575	1.0000						
ALMP	-0.5081	0.4715	0.2073	1.0000					
UBRR	-0.2247	0.3243	0.0752	0.1208	1.0000				
UBRR2	-0.1184	-0.0238	-0.0685	-0.0268	0.4347	1.0000			
TFP	0.0612	0.0454	-0.0433	-0.0441	0.0511	-0.0911	1.0000		
R	0.1841	0.2304	0.0747	0.1492	0.0852	-0.3094	-0.0100	1.0000	
CONS	-0.1598	-0.1306	-0.4136	-0.1162	-0.2040	-0.0845	-0.1358	-0.2233	1.0000

Table 3. Correlation matrix for NAWRU, SLMI and NSI predictors.

The correlation matrix indicates that the strongest correlation is caused by the ALMP predictor, as its correlation with NAWRU and UD is -0.51 and 0.47 respectively. This is not deemed as a significant problem, especially considering the heterogeneous panel setup. Therefore, no remedies to the dataset are proposed.

The next test uses the Hausman and Mundlak tests to determine whether the panel regression should be geared toward a fixed effects or a random effects setup. The Hausman test checks whether the country-specific error terms (FE dummies) are correlated with the predictors, therefore the (test) null hypothesis is that they are not. The test score (0.0000) indicates that the FE model is the correct one. The alternative Mundlak test also arrives at the same conclusion (0.0000). The underlying econometric model in this analysis relies on the least squares dummy variable (LSDV) model. The LSDV model is the same as the fixed effects model, only that it includes country- and period-specific dummies in the regression table.

The Orlandi (2012, p. 19) paper finds period effects to be insignificant in their panel setup, which is also tested for in this analysis. The period effects checkup is a joint test to determine whether the dummies for all years are equal to 0, i.e. if the test finds them to be equal to 0, then period effects are deemed necessary for the regression. The test returns a significant value (0.0000), so they are included in this analysis.

Beyond the pre-estimation tests listed above, two additional tests are performed to assess the best initial fit for the model. The first test checks for heteroskedasticity, which is found to be a factor. This was an issue in the original Orlandi (2012, p. 19–20) methodological paper, but also in more recent papers such as Heimberger et al (2017). Therefore a suitable method utilizing panel-corrected standard error (PCSE) estimates is deemed necessary. Orlandi (2012, p. 19–20) deems serial autocorrelation to be present, and therefore extends the PCSE method to account for this as well. This PCSE extension is also tested in postestimation diagnostics.

In light of the pre-estimation tests, the primary econometric model is defined as follows:

$$NAWRU_{i,t} = \beta_1 SLMI_{i,t} + \beta_2 NSI_{i,t} + \gamma_1 FE_{i,t} + \gamma_2 FE_{i,t} + \varepsilon_{i,t}$$

The country-specific NAWRU is estimated by two sets of vector coefficients—$SLMI_{i,t}$ and $NSI_{i,t}$—and two sets of fixed effects, γ_1 for country-specific dummies and γ_2 for period effects. The first set of vector coefficients consists of structural labor market indicators described in section 5.1.2, while the second set consists of non-structural labor market indicators described in 5.1.3.

The first set of vector coefficients is defined as follows:

$$SLMI_{i,t} = \beta_{1,1} * UD_{i,t} + \beta_{1,2} * TW_{i,t} + \beta_{1,3} * ALMP_{i,t} + \beta_{1,4} * UBRR_{i,t} + \beta_{1,5} * UBRR2_{i,t}$$

The second set of vector coefficients is defined as follows:

$$NSI_{i,t} = \beta_{2,1} * TFP_{i,t} + \beta_{2,2} * R_{i,t} + \beta_{2,3} * CONS_{i,t}$$

Section 5.4 performs alternative postestimation diagnostics, i.e. testing for changes by examining different time and panel compositions.

5.3 Regression analysis

The regression tables in this section are based on the econometric specifications in section 5.2 and data descriptions in 5.1. The primary regression analysis results are presented in table 4. The complete regression table, with country effects and period effects, is available in appendix A.1

VARIABLES	(1) OLS	(2) LSDV	(3) LSDV2	(4) LSDV-PCSE	**(5) LSDV2-PCSE**
UD	0.0186*	0.0429***	0.0829***	0.0475***	0.0829***
	(0.0112)	*(0.0126)*	*(0.0166)*	*(0.0134)*	*(0.00802)*
TW	0.178***	0.201***	0.231***	0.200***	0.231***
	(0.0205)	*(0.0214)*	*(0.0208)*	*(0.0115)*	*(0.0157)*
ALMP	-0.0634***	-0.0623***	-0.0601***	-0.0627***	-0.061***
	(0.00563)	*(0.00548)*	*(0.00543)*	*(0.00420)*	*(0.00451)*
UBRR	0.0398***	0.0679***	0.0924***	0.0664***	0.0924***
	(0.0125)	*(0.0133)*	*(0.0131)*	*(0.00754)*	*(0.00794)*
UBRR2			-0.0258***	0.00285	-0.0258***
			(0.00719)	*(0.00319)*	*(0.00459)*
TFP	-0.0869***	-0.104***	-0.0634**	-0.102***	-0.0634**
	(0.0232)	*(0.0224)*	*(0.0287)*	*(0.0264)*	*(0.0268)*
R	0.101***	0.0724***	0.0661***	0.0759***	0.0661**
	(0.0214)	*(0.0211)*	*(0.0249)*	*(0.0218)*	*(0.0276)*
CONS	-0.460***	-0.526***	-0.543***	-0.521***	-0.543***
	(0.0547)	*(0.0552)*	*(0.0596)*	*(0.0634)*	*(0.0587)*
Constant	4.751***	-4.835***	-9.953***	-5.069***	-9.953***
	(1.089)	*(1.514)*	*(1.742)*	*(0.866)*	*(0.730)*
Observations	556	556	556	556	556
R-squared	0.417	0.880	0.899	0.880	0.899
Number of countries	27	27	27	27	27
Country FE	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	YES
PCSE cross section	NO	NO	NO	YES	YES

Table 4. The primary regression table. Standard errors in parentheses. The bolded LSDV-PCSE model in column (5) depicts the preferred model. For a complete regression table with country and year fixed effects, see appendix A.1. *** p<0.01, ** p<0.05, * p<0.1

Column (1) is a regular least squares regression, omitting fixed effects and the UBRR2 component. Columns (2)–(3) are the first least squares dummy variable models, where (2) includes country-specific effects and (3) extends the model with period-specific effects. The LSDV2 model also includes the UBRR2 term. Column (4) is the LSDV model from column (2), extended with the panel-corrected standard errors accounting for heteroskedasticity. Column (5) is the full model, i.e. the one suggested by the pre-estimation diagnostics.

The LSDV2-PCSE model is deemed to be the best fit, as all structural labor market indicators are significant on a 1% level. Among the non-structural labor market indicators, the traditional production function components mirroring capital and productivity (R and TFP) are significant on a 5% level, while the boom–bust component is significant on a 1% level. The plotted fit is visible in figure 7.

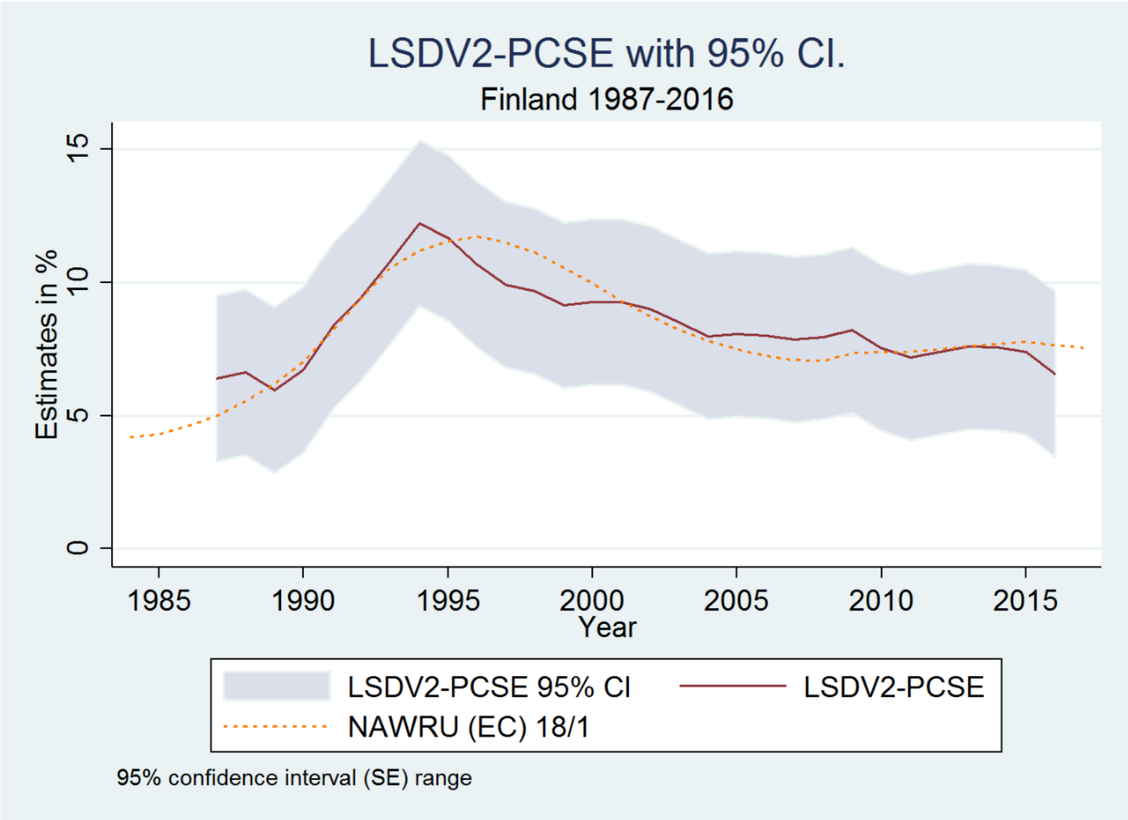


Figure 7. The LSDV2-PCSE regression model fit, confidence interval and NAWRU (EC) 18/1.

All main variables are signed as expected (see sections 5.1.2–5.1.3), with the interactive UBRR term being negative in this model. The interactive UBRR term is found to be positive by Orlandi (2012, p. 20-21) and Heimberger et al (2017), but signs negatively in this analysis. According to model 5, the gross replacement rate coefficient (UBRR) is 0.0924, while the net replacement rate coefficient is 0.0666 (UBRR+UBRR2). Whether this deviation from other studies is caused by the pre-regression adjustments (e.g. splicing), different unemployment exit probability rates or regression analysis tools remains unanswered.

The fixed effects for countries are all significant on a 1% level. Interestingly, the period effects become significant at the turn of the millennium, with 2001 being the first to turn significant (5% level). This suggests that a structural break has happened in the time series, as the annual dummy coefficients for the new millennium are all positive. The annual coefficients also fluctuate quite rapidly, both before and after the crisis of 2008 (see appendix for details). The size of the annual coefficients has been decreasing during 2013–2016 (1.760–1.179), suggesting that the unknown period-specific effects have decreased.

5.4 Postestimation and diagnostics

To further ascertain the fit of the model, a series of alternative regressions are performed. The postestimation diagnostics are categorized into two primary groups: LSDV2-PCSE with (1) serial autocorrelation and (2) different panel composition effects.

The first postestimation group includes five different regression alternatives on the LSDV2-PCSE model. The first phase is to add AR(1) extensions to the predictor variables by first considering lags to the structural sets (column 1) and non-structural sets (column 2) of vector coefficients separately, and then estimating a joint model (column 3). The joint model with one-period lags added to the regression is then evaluated in the second phase by considering extended PCSE models where serial autocorrelation within panels is (ii) common to all panels (column 4) and (ii) the AR(1) process is specific to each and every panel (column 5). The results are summarized in table 5.

The first diagnostics test indicates that there are several statistically significant lags in the dataset. As Heimberger et al (2017, p. 900) argue, institutional changes in structural labor market indicators might have a lagged effect, thus yielding a theoretical basis for lags in this model. By extension, this implies that the SLMI coefficients should be considered in a dynamic model rather than a static one. The benchmark model in column (3), with an AR(1) process for every term, suggests that policy changes (TW, ALMP and UBRR) all have a significant lag on a 1% level. While the traditional production function elements of capital (significant on a 10% level) and TFP are still signed as expected, their effects in this model are rendered insignificant.

VARIABLES	(1) LSDV2-PCSE, LMI AR(1)	(2) LSDV2-PCSE, NSI AR(1)	(3) LSDV2-PCSE, AR(1)	(4) LSDV2-PCSE2, AR(1)	(5) LSDV2-PCSE3, AR(1)
UD	0.0526	0.0804***	0.0546	0.0376**	0.0384*
	(0.0417)	*(0.0101)*	*(0.0384)*	*(0.0188)*	*(0.0196)*
l.UD	0.0387		0.0326	0.0499***	0.0426**
	(0.0389)		*(0.0357)*	*(0.0187)*	*(0.0193)*
TW	0.109***	0.219***	0.0859**	0.0547***	0.0595***
	(0.0372)	*(0.0171)*	*(0.0361)*	*(0.0166)*	*(0.0164)*
l.TW	0.126***		0.138***	0.0597***	0.0570***
	(0.0345)		*(0.0334)*	*(0.0165)*	*(0.0164)*
ALMP	-0.0446***	-0.0587***	-0.0373***	-0.0266***	-0.0246***
	(0.00876)	*(0.00368)*	*(0.00939)*	*(0.00334)*	*(0.00354)*
l.ALMP	-0.0177**		-0.0233***	-0.0145***	-0.014***
	(0.00864)		*(0.00886)*	*(0.00332)*	*(0.00347)*
UBRR	0.0564**	0.0981***	0.0177	0.0187	0.0159
	(0.0233)	*(0.00854)*	*(0.0290)*	*(0.0150)*	*(0.0156)*
l.UBRR	0.0442**		0.0861***	0.0336**	0.0301**
	(0.0209)		*(0.0303)*	*(0.0140)*	*(0.0143)*
UBRR2	-0.00856	-0.0270***	-0.000149	-0.00643*	-0.00828*
	(0.00691)	*(0.00426)*	*(0.00445)*	*(0.00379)*	*(0.00482)*
l. UBRR2	-0.0143**		-0.0230***	-0.0136***	-0.0150***
	(0.00710)		*(0.00442)*	*(0.00327)*	*(0.00367)*
TFP	-0.0651**	-0.0516	-0.0543*	-0.0211	-0.0218
	(0.0328)	*(0.0318)*	*(0.0312)*	*(0.0154)*	*(0.0165)*
R	0.0626**	0.0533	0.0532	-0.000239	0.00242
	(0.0287)	*(0.0388)*	*(0.0386)*	*(0.0158)*	*(0.0171)*
CONS	-0.544***	-0.517***	-0.538***	-0.252**	-0.249**
	(0.0747)	*(0.177)*	*(0.188)*	*(0.104)*	*(0.100)*
l.TFP		*-0.0441*	*-0.0557*	*-0.0310***	*-0.0345***
		(0.0357)	(0.0349)	(0.0153)	(0.0156)
l.R		*0.0231*	*0.0179*	*0.00286*	*0.00211*
		(0.0383)	(0.0384)	(0.0156)	(0.0164)
l.CONS		-0.0273	0.00231	-0.0950	-0.0809
		(0.171)	*(0.184)*	*(0.0938)*	*(0.0945)*
Constant	-11.20***	-9.267***	-10.40***	-3.030*	-2.555
	(0.734)	*(0.836)*	*(0.852)*	*(1.569)*	*(1.930)*
Observations	544	540	529	529	529
R-squared	0.906	0.899	0.906	0.845	0.937
Number of countries	27	27	27	27	27
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
PCSE cross section	YES	YES	YES	YES	YES
PCSE AR(1)	NO	NO	NO	YES	NO
PCSE PSAR(1)	NO	NO	NO	NO	YES

Table 5. The first postestimation regressions. Standard errors in parentheses. For a complete regression table with country and year fixed effects, see appendix B.1.
***** p<0.01, ** p<0.05, * p<0.1**

As a possible remedy, the model in column (4) assumes a first-order serial autocorrelation common to all panels. The additional specification in the postestimation regression analysis manages to reduce the standard errors drastically, when compared to the model in column (3). The LSDV2-PCSE2 model also finds the remaining LMI coefficient UD, and its lag, to be significant. This also applies to the lagged TFP term. As a further check, the LSDV2-PCSE3 model in column (5) assumes instead panel-specific serial autocorrelation.

This model brings no significant changes to the predictors or their serial errors, but certain coefficients are downgraded in their level of significance.

The second phase involves testing the LSDV2-PCSE model with different panel compositions, i.e. changing the time frame (T) and size of the panel (N). Column (1) decreases the time frame to 2001–2016 (15 years) for EU27. Columns (2)–(4) test different panel sizes, that is, EU27, EU13 and EU4.[51] The results of the regression are depicted in table 6.

VARIABLES	(1) EU27 LSDV2-PCSE (2001-2016)	(2) EU27 LSDV2-PCSE	(3) EU13 **LSDV2-PCSE**	(4) EU4 LSDV2-PCSE
UD	0.0389***	0.0829***	0.0997***	0.0500
	(0.0112)	*(0.00802)*	*(0.0154)*	*(0.0447)*
TW	0.0885***	0.231***	0.220***	0.172***
	(0.0282)	*(0.0157)*	*(0.0139)*	*(0.0624)*
ALMP	-0.0571***	-0.061***	-0.0585***	-0.0545***
	(0.00595)	*(0.00451)*	*(0.00338)*	*(0.00610)*
UBRR	0.124***	0.0924***	0.0942***	0.0880***
	(0.0178)	*(0.00794)*	*(0.0140)*	*(0.0277)*
UBRR2		-0.0258***	-0.00969*	-0.00812
		(0.00459)	*(0.00497)*	*(0.0184)*
TFP	-0.0297	-0.0634**	-0.113**	-0.0922
	(0.0247)	*(0.0268)*	*(0.0498)*	*(0.0936)*
R	0.0569***	0.0661**	0.0750**	0.114
	(0.0194)	*(0.0276)*	*(0.0312)*	*(0.0806)*
CONS	-0.595***	-0.543***	-0.623***	-0.116
	(0.0907)	*(0.0587)*	*(0.0752)*	*(0.198)*
Constant	-2.217	-9.953***	-10.29***	-5.888
	(1.578)	*(0.730)*	*(1.089)*	*(4.024)*
Observations	370	556	368	116
R-squared	0.916	0.899	0.913	0.842
Number of countries	27	27	13	4
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
PCSE cross section	YES	YES	YES	YES

Table 6. Second postestimation regressions. Standard errors in parentheses. The bolded LSDV2-PCSE (EU13) model in column (3) depicts the preferred model. For a complete regression table with country and period fixed effects, see appendix B.2.
***** p<0.01, ** p<0.05, * p<0.1**

The time frame 2001–2016 was chosen because of the structural break indication from the regression analysis section. This specification omits the UBRR2 effect, as it was a dummy for the same time frame. All structural coefficients sign as expected and have a p-

[51] The composition of the EU13 set is: **Denmark**, **Germany**, Ireland, Spain, France, Italy, the Netherlands, Austria, Portugal, **Finland**, **Sweden** and the United Kingdom. The EU4 set consists of the bolded countries above.

value significance of 1%. Among the non-structural coefficients, all sign as expected and have a p-value significance of 1%, with the exception of TFP. The coefficients with little to no change are ALMP, R, CONS and UBRR, while UD and TW have remarkable changes to their coefficients.

The LSDV2-PCSE model in column (2) is the benchmark model, with no changes to composition. The EU13 model coefficients, which remain relatively unchanged, are TW, ALMP, UBRR and R, while UD, UBRR2, TFP and CONS are affected by the change in composition. The EU4 model suffers from a loss of observations, thus influencing the reliability of the predictors—where most of the coefficients are rendered insignificant due to this. Interestingly, TW, ALMP and UBRR retain their high levels of significance (p-value significance of 1%).

To assess the best fit among the regressed models, figure 8 shows the plotted fit of LSDV2-PCSE, LSDV2-PCSE (EU13), LSDV2-PCSE (2001–2016), LSDV2-PCSE2 and LSDV2-PCSE3, while figure 9 plots the residuals of these models.

Finally, the root mean square error (RMSE) is calculated for these lines to assess the best fit in the case of Finland. Table 7 below illustrates the results:

Models	RSME
LSDV2-PCSE	0.758834
LSDV2-PCSE (EU13)	0.640501
LSDV2-PCSE (2001-2016)	0.454656
LSDV2-PCSE2	0.962585
LSDV2-PCSE3	1.009537

Table 7. The RSME results. The bolded LSDV2-PCSE (EU13) depicts the preferred model. The results have been calculated according to the following equation: $RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(regression_{i,t} - NAWRU_{i,t}\right)^2}{T}}$

According to the table, the LSDV2-PCSE (2001–2016) model has the best fit. However, the RMSE in this model is biased, as its time frame omits the recession of the 1990s. Therefore, after these diagnostics, the LSDV2-PCSE (EU13) model may be considered the best fit.[52] One theoretical reason for this might be Finland's closer structural resemblance to that of Western Europe than that of the entire EU. The sample of Eastern Europe may, to some extent, corrupt the EU estimate, as these nations had significant restructurings of their economies during the 1990s. The general fit of the LSDV2-PCSE (EU13) model has also been plotted for all EU13 nations and may be seen in appendix C.1.

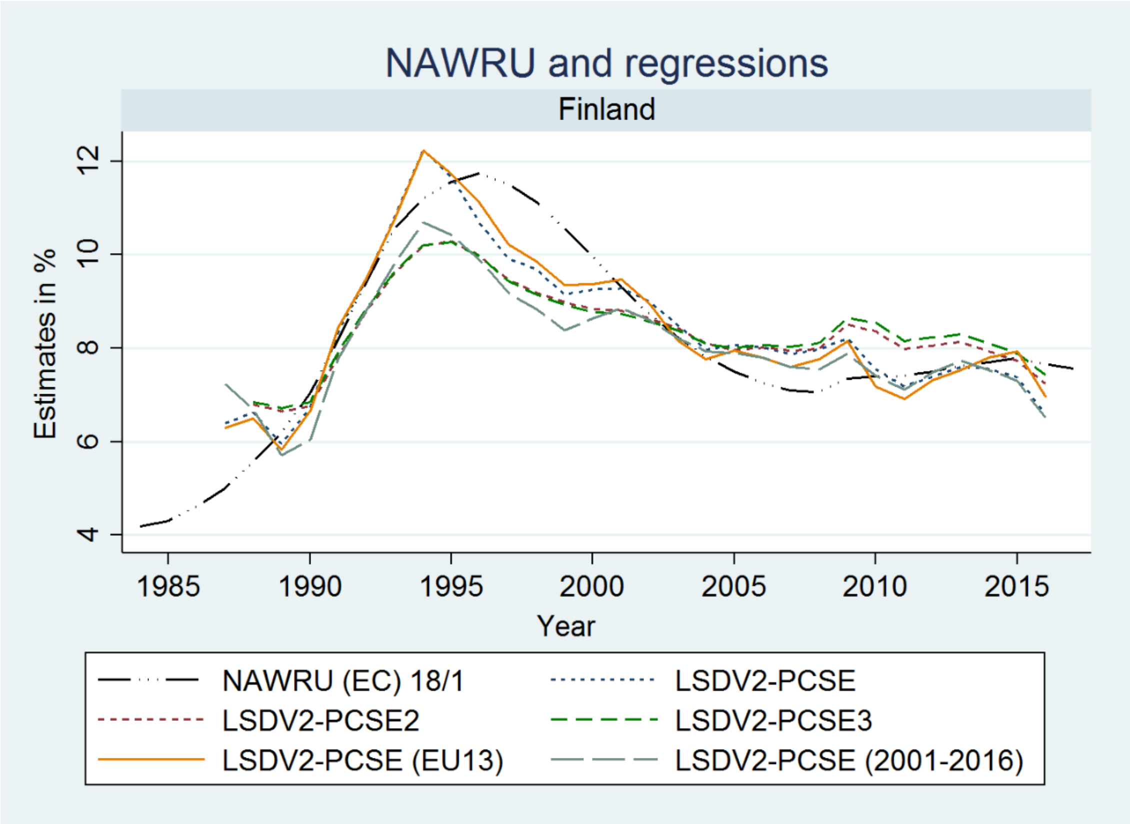


Figure 8. Regression models and NAWRU (EC) 18/1.

[52] The LSDV2-PCSE (EU13) was also regressed for the time frame 2001–2016, but due to the smaller panel composition, some of the coefficients lost their significance, therefore resulting in a trade-off between a smaller N or T composition. The importance of group composition might be considered more important than the time frame, as the coefficients for Western Europe might be more in line with the Finnish economy.

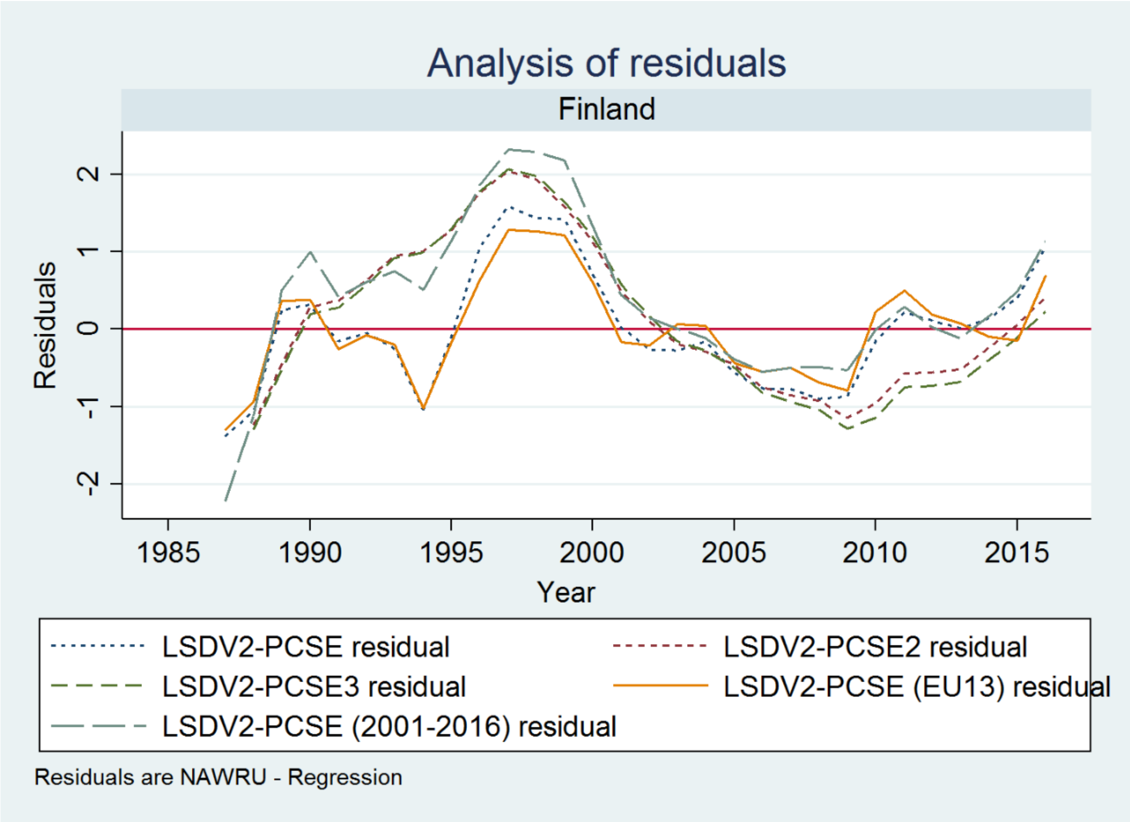


Figure 9. Regression models and their residuals (NAWRU - regression).

5.5 Drawbacks of the model

This subsection lists the primary deficiencies with the LSDV2-PCSE (EU13) model. The main drawbacks of the analysis are related to the dataset and theoretical framework. From an econometrics perspective, certain components in the dataset contain significant outliers (appendix D.1), which might have an impact on the actual regression analysis.

The estimated results are produced with an EU panel composition, implying that the coefficients contain a lot of variance and noise not present within the Finnish labor market. This implies that the LSDV2-PCSE (EU13) estimate assumes homogeneous structural and non-structural labor market indicators in the EU13 composition. Although country-specific fixed effects have been introduced to capture heterogeneity, this setting may nevertheless be challenged, as the assumptions in this model rely on minimal heterogeneity within the structural labor market indicators. The unadjusted R^2 value for this model is also 0.913, but should nevertheless be taken with a grain of salt, as the unadjusted R^2 includes the effects of the country- and period-specific dummies. The purpose of the analysis was to derive a comprehensive estimate of the explanatory variables, which the unadjusted R^2 is unable to give in its entirety.

As previously stated, the main drawbacks in the analysis are related to the theoretical framework. The variables created and used by Orlandi (2012) have managed to include new predictors related to the unemployment benefit replacement rate, which might be considered a proxy for intensive and extensive margins of labor supply. The tax wedge also takes into account the reservation wage equation components, as its subcomponents are related to the supply and demand of labor conditions. The value of the estimated tax wedge predictor suggests, in this case, a linear relationship between itself and NAWRU. However, as discussed in section 3, the reductions in components affecting the intensive and extensive margins of labor supply are not necessarily linear. On the contrary, reforms to the tax wedge should be assessed in conjunction with complementary assessments from the field of microeconomics.

Another issue related to one of the most important components—union density—is also questionable. The union density predictor is highly questionable for two reasons: (i) higher union density does not necessarily imply tighter labor market conditions in itself, nor (ii) measure the impact of unions on labor markets properly. From a theoretical perspective, the membership ratio in unions does not in itself measure the actions taken by unions. Rather, it is the influence of unions on the negotiated outcome which has an impact on the labor market, not membership rates. An example of negotiated outcomes is collective bargaining coverage, which has actual implications for the labor market conditions. The divergence between union density and collective bargaining coverage is exemplified by France, where the influence of unions is the most prominent in Europe. In 2014, France had a collective bargaining coverage of 98.5%, while its union density rate was 8% (ILO). The same is also true for Italy, which in 2014 had a collective bargaining coverage of 80% and a (decreasing) union density rate at 34.4%. Collective bargaining coverage is also in a sense biased, as its composition with regard to employment protection legislation, minimum wage, social security costs, employer dismissal rights, etc. might also differ. It is these (and other) negotiated outcomes which have an impact on the labor market supply and demand conditions. If UD is not deemed as a trustworthy proxy for the labor market institutions, then the estimated effects of that predictor in the LSDV2-PCSE (EU13) model may be questioned.[53]

As previously stated, the R and TFP components are the only control group predictors with a relation to the aggregate production function. The analysis does not incorporate any additional information about R&D or other country-specific advantages with regard to productivity. The TFP component may measure the impact of productivity in the economy to some extent, but may also be argued to be too broad to measure properly the country-specific competitive advantages related to human capital and regulatory differences. The R component may also be an inefficient proxy for capital accumulation, as the relationship between investments in the economy and the interest rate is not necessarily captured by this component. Capital accumulation in a given society might be affected by other components as well, e.g. the general confidence in the economy. Therefore there is a real risk that these control group components do not measure the real economic activity entirely, thus affecting the final outcome.

[53] Nevertheless, the UD component is the most widely used proxy in similar studies. The main reason is the lack of data for collective bargaining coverage, minimum wage, employment protection legislation, employer dismissal rights, etc. for longer time frames in a panel composition.

The boom–bust component (CONS), measuring the proportional number of workers in the construction sector to the rest of the labor force pool, might also be discussed further. The intended purpose of this component is to capture prolonged demand-side boom–bust effects in the economy, by using a proxy variable CONS. However, boom–bust effects extending beyond business cycles might also be present elsewhere in the economy. Beyond that, any additional signals in the economy with prolonged boom–bust effects might not even be correlated with the construction sector and would thus fall outside this component.

The active labor market policy (ALMP) could also be further improved, as its composition includes multiple subcomponents, all of which measure the allocated resources toward different sections of the government's involvement in active labor market policy. The key is that the efficiency of these different ALMP programs might have different effects on structural unemployment; therefore they could be assessed on a case-by-case basis. The current aggregate term does not account for heterogeneity within the composition between countries, which might omit strengths and weakness of specific labor market programs.

6 Results from the analysis

The results from regression analyses performed in sections 5.3–5.4 were able to find significant predictors for their NAWRU estimate. The postestimation diagnostics found a suitable model, LSDV2-PCSE (EU13), which was able to produce a suitable fit. The initial LSDV2-PCSE (EU27) and the preferred LSDV2-PCSE (EU13) model are plotted in figure 10 below, where the 95% CI is plotted for the latter model.

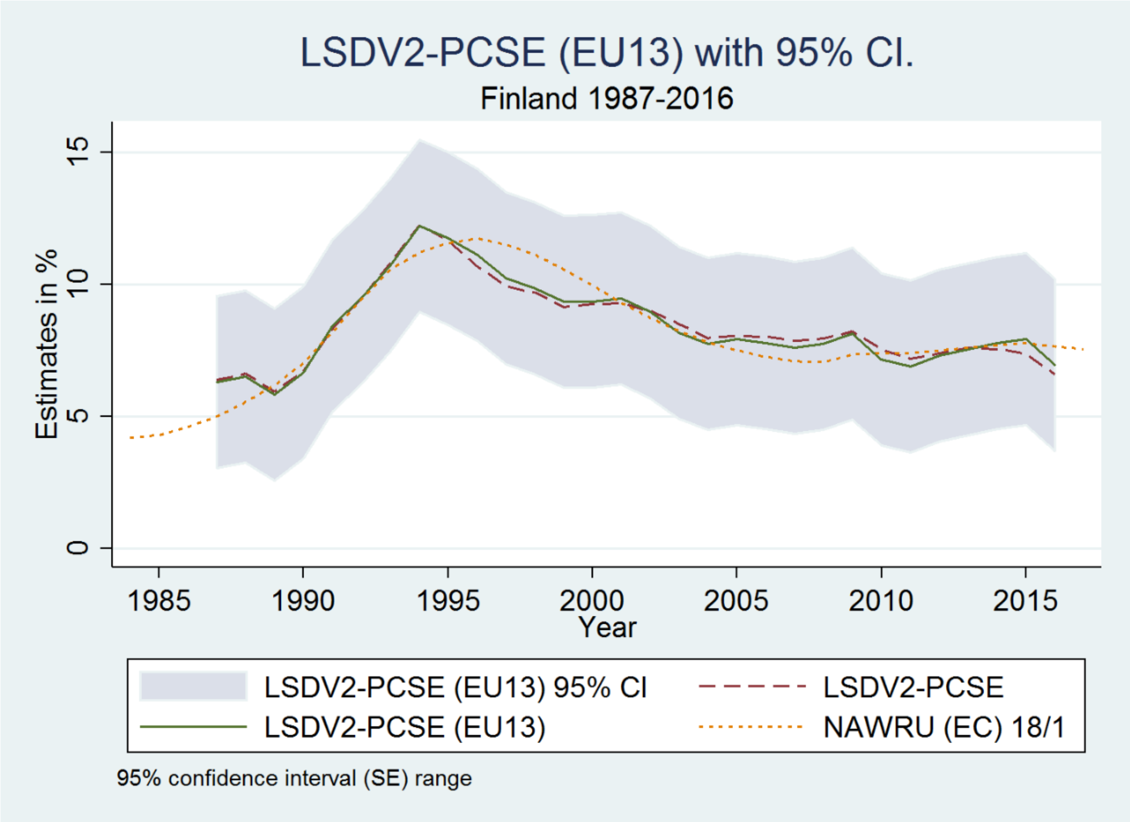


Figure 10. LSDV2-PCSE (EU13) with 95% CI.

The LSDV2-PCSE (EU13) model has a generally good fit, but is thrown off by the large recession during the 1990s and the Great Financial Crisis. Deviations caused by large crises tend to be difficult to model, as is also the case here.

The structural determinants, obtained from the LSDV2-PCSE (EU13) model, indicate that the composition of the NAWRU rate may be categorized according to equation (i).

$$NAWRU_{i,t} = \left(a + \gamma_1 FE_{i,t}\right) + \beta_1 SLMI_{i,t} + \beta_2 NSI_{i,t} + \gamma_2 FE_{i,t} \qquad \text{(i)}$$

The country-specific NAWRU composition, at a given year, is the sum of the readjusted constant (regression constant and country-specific constant) and the two sets of vector coefficients multiplied with their respective structural labor market indicators (ii) and non-structural indicators (iii) as well as the period effect.[54]

$$SLMI_{i,t} = 0.0997 * UD_{i,t} + 0.220 * TW_{i,t} + (-0.0585) * ALMP_{i,t} + \\ 0.0942 * UBRR_{i,t} + (-0.00969) * UBRR2_{i,t} \qquad \text{(ii)}$$

The sum of the structural labor market indicators set is given by the sum of the five coefficients multiplied with their respective indicators.

$$NSI_{i,t} = (-0.113) * TFP_{i,t} + 0.0750 * R_{i,t} + (-0.623) * CONS_{i,t} \qquad \text{(iii)}$$

The sum of the non-structural indicators set is given by the sum of the three coefficients multiplied with their respective indicators.

By summing equation (i) over its components, the country-specific NAWRU composition, at a given year, may be depicted. This composition is depicted in figure 11 below, which stacks the structural determinants multiplied with their respective values in a bar chart for Finland (1987–2016). The sum of components is drawn in reference to the NAWRU (18/1) estimate.

[54] The period effects term is included in the model to illustrate which years the model deviates due to unknown period effects. The year-specific values are depicted in appendix B.2. Contrary to the LSDV2-PCSE model in section 5.3, the period effects have been slightly higher in the LSDV2-PCSE (EU13) model (see appendix A.1 and B.2).

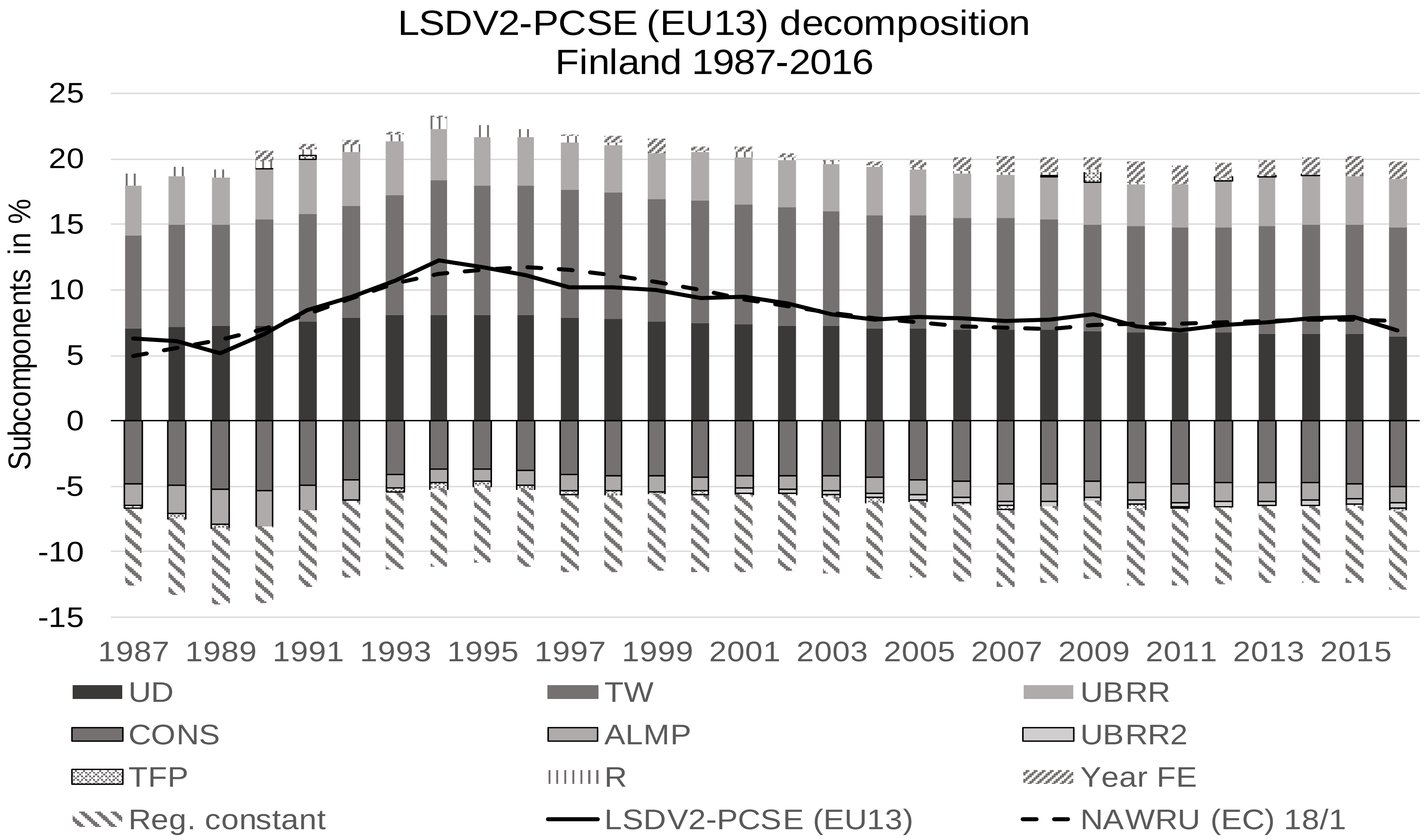


Figure 11. Bar chart with LSDV2-PCSE (EU13) structural determinants stacked for 1987–2016.

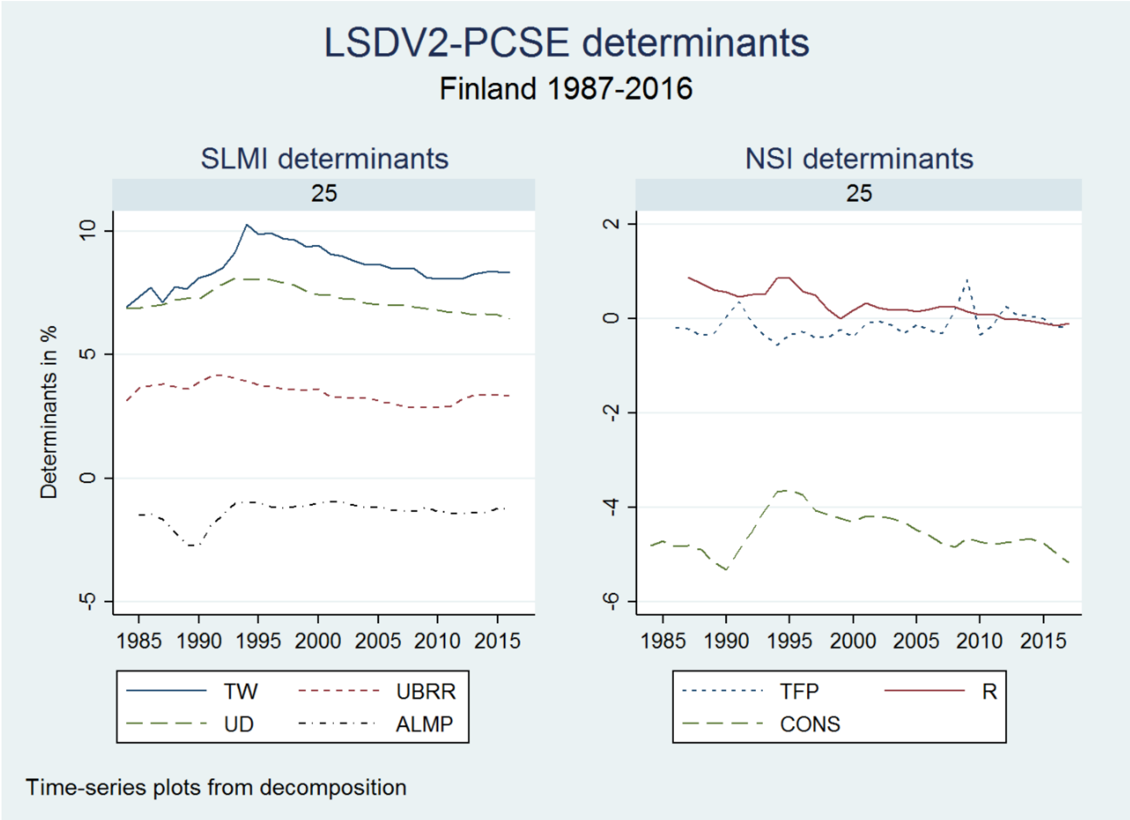


Figure 12. Time series line plots from the decomposition of LSDV2-PCSE (EU13).

The decomposed LSDV2-PCSE (EU13) in figure 12 allows for an alternative inspection of the size of the structural and non-structural determinants in the model.

Finally, the LSDV2-PCSE (EU13) coefficients are compared to those estimated by Orlandi (2012, p. 20) and ECFIN (2017), which are seen in table 8, columns (1) and (2) respectively. The first column illustrates the original results from 2012, while the second results in the second column are those used in the NAWRU anchor calculations. As these three models utilize the same variables, it is reassuring that their variables are significant and correctly signed in all three versions. While the results in the second column extend the timeline of the first model, comparing it with the LSDV2-PCSE (EU13) model is not as straightforward. The primary difference between the three models is their econometric structure, i.e. they all utilize different techniques to correct for serial errors. For example, the first model makes use of a PCSE (AR1) correction, which was not deemed necessary for the LSDV2-PCSE (EU13) model, while the second model does not include a PCSE model. The secondary difference is caused by the underlying data, as illustrated in section 5.1.

Regardless of these econometric differences, only a few major differences arise. The primary difference is the UBRR component, which is found to be lower in models (1) and (2). As discussed in section 5.1.2, the UBRR component utilized in the LSDV2-PCSE (EU13) model relies on updated monthly unemployment exit probabilities. Those utilized in Orlandi (2012) and Havik (2014) rely on pre-crisis averages (2005–2007) of these probabilities, while the LSDV2-PCSE (EU13) model uses average unemployment exit probabilities from 2010–2017. As the probability rates utilized in this study are from a different business-cycle setting, the UBRR component is impacted by the theta parameter in equation (i), section 5.1.2.[55] The second term not found to be in line across the models is the real interest rate contributor, which, as a determinant, is decreasing in impact from model (1) to (3).[56] The post-crisis period characterized by low interest rates has most likely had an impact on this determinant. The third noteworthy deviation is the UD determinant, which is fairly similar in models (1) and (3), but deviating in model (2).

The results depicted in column (2) utilize the same econometric setup as the regular LSDV model in table 4, column 2 (section 5.3). Comparison of these two results enables the study of the differences between datasets (and data methodology). The primary difference between these models is the UBRR component, as the ECFIN (2017) version differs with regard to the data methodology and the use of different transition rates from unemployment to employment. The ECFIN (2017) UBRR component is found to be 0.04, while the results in the LSDV model in section 5.3 estimate a much higher value of 0.07. Other notable differences also arise in e.g. the set of control variables, where the ECFIN (2017) model estimates values of -0.18 and 0.13 for TFP and R respectively, while the LSDV model estimates values of -0.1 and 0.07, respectively.

The similarities between the models (between all three or simply Orlandi (2012) or Havik (2017) to LSDV2-PCSE (EU13)) include TW, ALMP, TFP, and CONS. The statistical significance and similarity in size of the TW component, in all three models, is reassuring,

[55] The effects of the interactive term “UBRR2” have been included in the UBRR component in models (1) and (2), but are presented separately for model (3).
[56] This is most likely caused by different values in the five-year moving average GDP deflator; see section 5.1.3 for further details.

as its impact (as depicted in figure 11 and 12) is of the highest magnitude to the Finnish structural unemployment rate. The statistical significance and similarity of size in the ALMP component is nearly 1:1 between the ECFIN (2017) and LSDV2-PCSE (EU13) models. Finally, the component with the largest negative impact on the NAWRU rate is found to be of similar size and statistically significant across all three models.

VARIABLES	(1) Orlandi (2012) EU13 (1985–2009)	(2) ECFIN (2017) EU13 (1985–2016)	(3) LSDV2-PCSE EU13 (1987–2016)
UD	0.08*	0.0454***	0.0997***
		(0.0127)	*(0.0154)*
TW	0.29**	0.246***	0.220***
		(0.0215)	*(0.0139)*
ALMP	-0.04***	-0.0586***	-0.0585***
		(0.00419)	*(0.00338)*
UBRR	0.07**	0.0429***	0.0942***
		(0.0134)	*(0.0140)*
UBRR2			-0.00969*
			(0.00497)
TFP	-0.16**	-0.181**	-0.113**
		(0.0380)	*(0.0498)*
R	0.19**	0.134**	0.0750**
		(0.0303)	*(0.0312)*
CONS	-0.66**	-0.614***	-0.623***
		(0.0578)	*(0.0752)*
Constant		-0.348	-10.29***
		(1.236)	*(1.089)*
Observations	324	395	368
R-squared	0.88	0.642	0.913
Number of countries	13	13	13
Country FE	YES	YES	YES
Year FE	NO	NO	YES
PCSE cross section	NO	NO	YES
PCSE AR(1)	YES	NO	NO

Table 8. Comparative table with different regression models. Standard errors in parentheses (for those available). The Orlandi (2012) model coefficients have been acquired from the Orlandi (2012) paper, while the ECFIN (2017) model has been regressed by the author, based on the regression anchor setup available on CIRCABC, ECFIN's library. The third model depicts the LSDV2-PCSE (EU13) model utilized in this study.
***** p<0.01, ** p<0.05, * p<0.1**

7 Discussion

The general issue of structural unemployment is difficult to solve, as its composition is extremely difficult to establish. From a theoretical equilibrium perspective, the primary contributors to structural unemployment are inefficiencies in the labor market. These inefficiencies are caused by mismatches in the labor market supply and demand conditions, due to market imperfections such as transaction costs and wage rigidities. Throughout the years, labor market theory has been extended to cover different settings that exempt from the assumptions embedded in the Walrasian equilibrium setting, as discussed in section 2.2. Traditional estimation techniques for the structural (or natural) rate of unemployment rely on the disentanglement of trend and cyclical components with the help of filtering techniques, as discussed in section 4. Univariate filtering techniques have their own drawbacks, e.g. end-point issues, which yield different estimates for the aggregate trend component. More recently, multivariate filtering techniques, such as the Kalman filter, have been introduced into the mix. These multivariate filtering techniques are able to incorporate factors relevant from an economics perspective, thus improving the filtering technique. However, alternative techniques, with roots in matching theory, e.g. the stock-flow model used by the Bank of Finland, have also produced credible estimates, which rely on actual stock-flows in the labor market to derive estimates for the aggregate trend component.

From a policy analysis perspective, these aggregate trend estimates are only partially beneficial. As the trend component is the result of an unobserved components model, where structural determinants are assumed to have a linear relationship to the regressed variable, any serious policy analysis of structural reforms must be performed in conjunction with a microeconomic perspective. This is why the microeconomics perspective has been more beneficial in this respect, as research on specific policy changes might infer causality with a higher validity, as illustrated in section 3. The advances in research methodologies adopted within microeconomics have thus contributed heavily to this subject within the past few years. Matters pertaining to the intensive and extensive margins of labor supply, with regard to tax wedges and different benefits, have been able to ascertain with growing confidence the impact of policy changes on more deeply-rooted unemployment issues. Beyond that, different empirical research results regarding matching problems and policy failures, e.g. the impact of housing transfer taxes, have also contributed to explaining persistent rigidities in the labor market.

However, despite the valuable contributions of policy analysis from the field of microeconomics, constructing an aggregate structural unemployment estimate from these individual studies has not been attempted. Therefore, from a macroeconomics perspective, it is difficult to produce a systematic general equilibrium analysis based on these analyses alone. The NAWRU model construct of the European Commission Directorate-General for Financial and Economic Affairs should be regarded as an interesting advance within this field, especially as it attempts to bridge the relationship between the fields of microeconomics and macroeconomics by making use of more detailed constructs of structural determinants. The LSDV2-PCSE (EU13) model in this study manages to produce a decomposition of structural unemployment, with the help of the NAWRU model foundation.

The utilized tax wedge in this model depicts the reservation wage equation in conjunction with labor costs, creating an indicator for how these two components contribute to structural unemployment. According to the utilized dataset, the tax wedge component has been decreasing since the early 1990s. The 2016 value for TW is 37.9%, which multiplied with its coefficient of 0.22 yields a contribution of 8.4 percentage points in LSDV2-PCSE (EU13). The tax wedge determinant implies that a 10 percentage point increase in TW will increase NAWRU by 2.2 percentage points.

The UBRR in general has decreased since the early 1990s. The 2016 value for this component is 39.6%, which multiplied with the coefficient of 0.09 (UBRR+UBRR2) yields an estimated contribution of 3.6 percentage points in LSDV2-PCSE (EU13). The UBRR component has a cyclical component, as there is a clear dip in its contribution around the Great Financial Crisis. This *dip* starts prior to the actual crisis and has a slow ascent upward to the current level. Whether the UBRR component is impacted by any boom–bust factors or policy changes remains unanswered here. When combined with UBRR2, there is a small correction downward in this rate, but this is explained with the change in regime from gross to net replacement rate. The unemployment benefit replacement rate determinant implies that a 10 percentage point increase in UBRR will increase NAWRU by 0.9 percentage points.

Union density in Finland has been decreasing since the early 1990s, when the density at its height was 81.2%. This figure has since decreased to 64.6% (2016). Multiplying the density of 2016 with the coefficients yields an estimated contribution of 6.5 percentage points in LSDV2-PCSE (EU13). The union density determinant implies that a 10 percentage point increase in UD will increase NAWRU by 1 percentage points.

The active labor market policy component has, since the early 1990s, converged to a mean of roughly 0.2%. This component has been calculated in relation to GDP per capita, implying that boom–bust effects are also present in this determinant; e.g. the increase during 2007–2008. The 2016 value for this component was 21.9%, which multiplied with its coefficient of -0.06 yields an estimated contribution of -1.3 percentage points in LSDV2-PCSE (EU13). The active labor market policy determinant implies that a 10 percentage point increase in ALMP will decrease NAWRU by 0.6 percentage points.

The non-structural (labor market) indicators account for a smaller portion in the LSDV2-PCSE (EU13) model, but are nevertheless present. The impact of traditional production function components measuring the real interest rate and productivity register very low effects, while the proxy for boom–bust cycles has a markedly higher impact. TFP has registered three periods of positive values: the early 1990s, the Great Financial Crisis and the Euro Crisis. This implies that productivity has rapidly decreased during bust periods, but quickly recovered afterward. What's noteworthy about the TFP component is the long recovery time in comparison to the previous recessions. The crises during the 1990s and 2008 registered two consecutive years above zero, while the most recent crisis had three years of positive values (2012–2015). The first negative value thereafter was 0.259, which then emerged to 1.59 and 1.37. The 2016 value of 1.37 multiplied with the TFP coefficient of -0.1 yields an estimated contribution of -0.14 percentage points in LSDV2-PCSE (EU13). The total factor productivity determinant implies that a 10 percentage point increase in TFP will decrease NAWRU by 1 percentage points. The real interest rate component has also moved into a negative domain since 2012, in accordance with the ECB's monetary policy. According to the estimates in LSDV2-PCSE (EU13), the real interest rate component has a very low impact on structural unemployment. The 2016 value of -1.96%

multiplied with its coefficient of 0.08 yields an estimated contribution of 0.16 percentage points in LSDV2-PCSE (EU13). The real interest rate determinant implies that a 10 percentage point increase in R will increase NAWRU by 0.8 percentage points.

The final construction (CONS) component accounting for boom–bust cycles has a more profound impact on the LSDV2-PCSE (EU13) model. The impact of this component has been increasing ever since the crisis of the early 1990s, accounting in 2016 for 7.98% of the labor force. The increase halted as of 2008 and remained stagnant until 2014, when its trajectory changed its course upward. The share of construction workers in relation to the rest of the labor force has increased from a mean of 7.61% (2008–2013) to 7.86% (2014–2016). This rapid increase is also a major contributor to the decrease in the LSDV2-PCSE (EU13) model, as the determinant's estimated impact on NAWRU, in 2016, is -5 percentage points. The construction sector determinant implies that a 10 percentage point increase in CONS will decrease NAWRU by 6.2 percentage points.

By adding together the estimated contributions of the determinants, the LSDV2-PCSE (EU13) model yields an estimated structural unemployment rate of 7% for 2016. By comparison, the ECFIN NAWRU estimate for 2016 is 7.7%, i.e. 0.7 percentage points higher. This is to be expected, as the ECFIN NAWRU estimate for 2016 is the result of the filtering exercise, while the LSDV2-PCSE (EU13) model is the result of a cross-country panel regression on NAWRU. Nevertheless, the general goal of estimating the size and significance of structural determinants has yielded an interesting insight into the composition of the NAWRU rate. These structural determinants, despite their EU13-based coefficients, combine factors studied within the field of microeconomics with methodologies used within the field of macroeconomics.

8 Conclusion

The objective of this analysis has been the evaluation of the structural unemployment rate in Finland. This evaluation has made use of current research and policy studies with regard to different policies, benefits and costs affecting the reservation wage, etc. The analysis section has utilized the NAWRU model developed by the European Commission Directorate-General for Financial and Economic Affairs to further ascertain the composition of the Finnish structural unemployment rate. According to the estimates, the structural labor market indicators of tax wedge, union density and UB replacement rate had the most significant impact on the structural unemployment rate. The effects of the tax wedge and UB replacement rate components are also found by the field of microeconomics to have a distortionary effect on long-term unemployment.

References

Bassanini, Duval (2006). Employment patterns in OECD countries. URL: https://sites.google.com/site/bassaxsite/home

Census Bureau, U. S., & Staff, T. S. R. (2013). X-13ARIMA-SEATS Reference Manual.

de la Fuente, Angel, A Mixed Splicing Procedure for Economic Time Series (December 2009). CESifo Working Paper Series No. 2876. Available at SSRN: https://ssrn.com/abstract=1532638

Driffill, J. (2006). The centralization of wage bargaining revisited: What have we learnt? *JCMS: Journal of Common Market Studies, 44*(4), 731–756.

Eerola, E., Harjunen, O., Lyytikäinen, T., & Saarimaa, T. (2018). *Effects of real estate transfer taxes: Evidence from a natural experiment*. URL: https://vatt.fi/effects-of-real-estate-transfer-taxes-evidence-from-a-natural-experiment

European Commission's Directorate General for Economic and Financial Affairs, AMECO database (2018). URL: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-database-ameco/ameco-database_en

European Commission's Directorate-General for Economic and Financial Affairs, CIRCABC database (2017). URL: https://circabc.europa.eu

Eurostat. (2018). Labour market transitions – quarterly data. URL: https://ec.europa.eu/eurostat/web/products-datasets/product?code=lfsi_long_q

Feldstein, M. (1995). The effect of marginal tax rates on taxable income: A panel study of the 1986 Tax Reform Act. *Journal of Political Economy, 103*(3), 551–572.

Finland: 2017 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Finland. Country Report No. 17/370. International Monetary Fund. European Dept.

Haavio, M. (2018). Asuntomarkkinat, työvoiman liikkuvuus ja työttömyys. *Euro & talous. Suomen Pankin ajankohtaisia artikkeleita taloudesta*. URL: https://helda.helsinki.fi/bof/bitstream/handle/123456789/15580/eurotalousanalyysi11.pdf?sequence=1

Havik, K., Mc Morrow, K., Orlandi, F., Planas, C., Raciborski, R., Röger, W., ... Vandermeulen, V. (2014). The production function methodology for calculating potential growth rates & output gaps (No. 535). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Heimberger, P., Kapeller, J., & Schütz, B. (2017). The NAIRU determinants: What's structural about unemployment in Europe? *Journal of Policy Modeling, 39*(5), 883–908.

Hristov, A., Planas, C., Roeger, W., & Rossi, A. (2017). NAWRU Estimation Using Structural Labour Market Indicators (No. 069). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Huovari, J., Jauhiainen, S., & Kekäläinen, A. (2017). Assessment of the EC cyclical adjustment methodology for Finland – impact on budget balances. PTT Workers Papers 191.

Huttunen, K., & Kosonen, T. (2018). *Kotihoidon tuen vaikutus lapsiin*. Tutkimuksia 115. Helsinki: Palkansaajien tutkimuslaitos.

International Labour Organization database (2018).

J. Visser, ICTWSS Data base. version 5.1. Amsterdam: Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam. September 2016. URL: http://uva-aias.net/en/ictwss

Juvonen, P., & Obstbaum, M. (2018). *Structural unemployment and labour market flows in the euro area*.

Kyyrä, T., Pesola, H., & Rissanen, A. (2017). *Unemployment insurance in Finland: A review of recent changes and empirical evidence on behavioral responses*. VATT Research Reports 184. Helsinki: VATT Institute for Economic Research.

Kärkkäinen, O., & Tervola, J. (26.9.2018b). *Talouspolitiikan vaikutukset tuloeroihin ja työllisyyteen 2015–2018*. Valtioneuvoston selvitys- ja tutkimustoiminnan julkaisusarja 59/2018. Helsinki: Valtioneuvoston kanslia. URL: http://urn.fi/URN:ISBN:978-952-287-610-2

Kärkkäinen, O., & Tervola, J. (29.3.2018a). *Talouspolitiikan vaikutukset työllisyyteen ja tuloeroihin 2015–2018*. Valtioneuvoston selvitys- ja tutkimustoiminta. URL: https://vnk.fi/documents/10616/7477009/Talouspolitiikan+vaikutukset+ty%C3%B6llisyyteen+ja+tuloeroihin+2015-2018.pdf/11657bf5-9242-41a3-8afa-52e64b60ec3e/Talouspolitiikan+vaikutukset+ty%C3%B6llisyyteen+ja+tuloeroihin+2015-2018.pdf.pdf

Matikka, T. (2018). Elasticity of taxable income: Evidence from changes in municipal income tax rates in Finland. *The Scandinavian Journal of Economics, 120*(3), 943–973.

Mourre, G., Astarita, C., & Princen, S. (2014). Adjusting the budget balance for the business cycle: The EU methodology (No. 536). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

OECD. (2018). "OECD Economic Outlook No. 103 (Edition 2018/1)", OECD Economic Outlook: Statistics and Projections (database), https://doi.org/10.1787/494f29a4-en

OECD. (2018). *OECD Economic Surveys: Finland 2018*. Paris: OECD Publishing. https://doi.org/10.1787/eco_surveys-fin-2018-en.

Official Statistics of Finland (OSF): Labour force survey [e-publication]. ISSN=1798-7857. Helsinki: Statistics Finland [referred: 11.11.2018]. Access method: http://www.stat.fi/til/tyti/index_en.html

Olaf Van Vliet & Koen Caminada (2012), Unemployment replacement rates dataset among 34 welfare states 1971–2009: An update, extension and modification of the Scruggs' Welfare State Entitlements Data Set, NEUJOBS Special Report No. 2, Leiden University.

Orlandi, F. (2012). Structural unemployment and its determinants in the EU countries. Economic Papers 455. http://dx.doi.org/10.2765/26367

Romer, D. (2012). *Advanced macroeconomics*. New York, NY: McGraw-Hill/Irwin.

Rusticelli, E., Turner, D., & Cavalleri, M. C. (2015). Incorporating anchored inflation expectations in the Phillips curve and in the derivation of OECD measures of the unemployment gap. *OECD Journal: Economic Studies, 2015*(1), 299–331.

Räisänen, H. (Ed.). (2002). *Rakenteellinen työttömyys. Tutkimusinventaari ja politiikkajohtopäätökset*. VATT-tutkimuksia 92. Helsinki: Valtion taloudellinen tutkimuskeskus.

Sariola, M. (2018). NAIRU data. Bank of Finland.

Selin, H. (2018). Course material from Public Economics course.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review, 95*(1), 25–49.

Suomen virallinen tilasto (SVT): Työnvälitystilasto [verkkojulkaisu]. Helsinki: Työ- ja elinkeinoministeriö [referred: 11.11.2018]. Access method: http://www.stat.fi/til/tyonv/index.htm

Taloudellinen katsaus, kesä 2018. (2018). Valtiovarainministeriön julkaisuja 20a/2018. URL: https://vm.fi/julkaisu?pubid=26701

Appendix

Appendix A.1: Complete regression table for section 5.3.

VARIABLES	(1) OLS	(2) LSDV	(3) LSDV2	(4) LSDV-PCSE	**(5) LSDV2-PCSE**
UD	0.0186*	0.0429***	0.0829***	0.0475***	0.0829***
	(0.0112)	(0.0126)	(0.0166)	(0.0134)	(0.00802)
TW	0.178***	0.201***	0.231***	0.200***	0.231***
	(0.0205)	(0.0214)	(0.0208)	(0.0115)	(0.0157)
ALMP	-0.0640***	-0.0623***	-0.0610***	-0.0627***	-0.0610***
	(0.00563)	(0.00548)	(0.00543)	(0.00420)	(0.00451)
UBRR	0.0398***	0.0679***	0.0924***	0.0664***	0.0924***
	(0.0125)	(0.0133)	(0.0131)	(0.00754)	(0.00794)
UBRR2			-0.0258***	0.00285	-0.0258***
			(0.00719)	(0.00319)	(0.00459)
TFP	-0.0869***	-0.104***	-0.0634**	-0.102***	-0.0634**
	(0.0232)	(0.0224)	(0.0287)	(0.0264)	(0.0268)
R	0.101***	0.0724***	0.0661***	0.0759***	0.0661**
	(0.0214)	(0.0211)	(0.0249)	(0.0218)	(0.0276)
CONS	-0.460***	-0.526***	-0.543***	-0.521***	-0.543***
	(0.0547)	(0.0552)	(0.0596)	(0.0634)	(0.0587)
Bulgaria		9.438***	11.34***	9.576***	11.34***
		(0.898)	(0.957)	(0.791)	(0.631)
Czech Rep		6.811***	8.692***	6.946***	8.692***
		(0.911)	(0.954)	(0.579)	(0.487)
Denmark		4.181***	4.188***	4.102***	4.188***
		(0.715)	(0.713)	(0.433)	(0.426)
Germany		3.981***	5.444***	4.120***	5.444***
		(0.563)	(0.643)	(0.425)	(0.277)
Estonia		9.795***	12.11***	9.965***	12.11***
		(1.020)	(1.101)	(0.714)	(0.538)
Ireland		11.18***	12.92***	11.19***	12.92***
		(0.746)	(0.750)	(0.394)	(0.554)
Greece		11.58***	13.66***	11.67***	13.66***
		(0.912)	(0.950)	(0.631)	(0.448)
Spain		16.79***	19.40***	16.92***	19.40***
		(0.985)	(1.043)	(0.615)	(0.547)
France		6.906***	9.279***	7.105***	9.279***
		(0.810)	(0.945)	(0.634)	(0.404)
Italy		6.695***	8.270***	6.755***	8.270***
		(0.803)	(0.809)	(0.441)	(0.424)
Cyprus		11.33***	12.36***	11.24***	12.36***
		(1.340)	(1.311)	(0.634)	(0.718)
Latvia		10.85***	12.58***	10.98***	12.58***
		(0.920)	(0.966)	(0.614)	(0.523)
Lithuania		10.87***	12.93***	11.04***	12.93***
		(0.993)	(1.056)	(0.672)	(0.547)
Luxembourg		10.33***	12.14***	10.33***	12.14***
		(1.046)	(1.054)	(0.851)	(0.869)
Hungary		5.891***	7.803***	6.044***	7.803***
		(0.924)	(0.982)	(0.626)	(0.466)
Malta		6.040***	6.879***	5.950***	6.879***
		(0.818)	(0.803)	(0.340)	(0.476)
Netherlands		6.267***	8.387***	6.413***	8.387***
		(0.881)	(0.944)	(0.531)	(0.425)
Austria		1.334***	2.512***	1.404***	2.512***
		(0.470)	(0.493)	(0.249)	(0.241)
Poland		11.75***	13.93***	11.89***	13.93***
		(0.936)	(1.001)	(0.584)	(0.408)
Portugal		10.44***	12.89***	10.55***	12.89***
		(0.955)	(0.997)	(0.560)	(0.504)
Romania		4.981***	6.010***	5.076***	6.010***
		(0.869)	(0.870)	(0.470)	(0.416)
Slovenia		5.689***	7.100***	5.777***	7.100***
		(0.867)	(0.878)	(0.502)	(0.451)
Slovakia		13.71***	15.56***	13.83***	15.56***

		(0.883)	(0.932)	(0.680)	(0.545)
Finland		4.695***	4.530***	4.592***	4.530***
		(0.547)	(0.580)	(0.399)	(0.403)
Sweden		3.274***	2.933***	3.178***	2.933***
		(0.718)	(0.731)	(0.483)	(0.504)
UK		7.275***	9.263***	7.346***	9.263***
		(0.769)	(0.800)	(0.459)	(0.571)
1988			0.349		0.349
			(0.498)		(0.496)
1989			0.664		0.664
			(0.498)		(0.494)
1990			0.811*		0.811
			(0.488)		(0.500)
1991			0.434		0.434
			(0.472)		(0.412)
1992			0.390		0.390
			(0.472)		(0.402)
1993			0.260		0.260
			(0.483)		(0.390)
1994			0.0971		0.0971
			(0.476)		(0.404)
1995			-0.0515		-0.0515
			(0.472)		(0.407)
1996			-0.556		-0.556*
			(0.464)		(0.331)
1997			-0.409		-0.409
			(0.469)		(0.333)
1998			-0.207		-0.207
			(0.475)		(0.327)
1999			-0.0239		-0.0239
			(0.469)		(0.320)
2000			-0.137		-0.137
			(0.461)		(0.326)
2001			0.825		0.825**
			(0.516)		(0.372)
2002			0.819		0.819**
			(0.519)		(0.367)
2003			0.878*		0.878**
			(0.518)		(0.365)
2004			0.878*		0.878**
			(0.510)		(0.357)
2005			1.121**		1.121***
			(0.516)		(0.356)
2006			1.566***		1.566***
			(0.504)		(0.375)
2007			1.759***		1.759***
			(0.503)		(0.382)
2008			1.783***		1.783***
			(0.516)		(0.377)
2009			1.796***		1.796***
			(0.547)		(0.384)
2010			2.211***		2.211***
			(0.510)		(0.366)
2011			1.912***		1.912***
			(0.511)		(0.364)
2012			1.737***		1.737***
			(0.521)		(0.362)
2013			1.760***		1.760***
			(0.522)		(0.355)
2014			1.573***		1.573***
			(0.528)		(0.358)
2015			1.394***		1.394***
			(0.537)		(0.359)
2016			1.180**		1.180***
			(0.599)		(0.356)
Constant	4.751***	-4.835***	-9.953***	-5.069***	-9.953***
	(1.089)	(1.514)	(1.742)	(0.866)	(0.730)
Observations	556	556	556	556	556
R-squared				0.880	0.899
Number of countries	27	27	27	27	27
Country FE	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	YES
PCSE cross section	NO	NO	NO	YES	YES

Appendix B.1: First postestimation regression table for section 5.4.

VARIABLES	(1) LSDV2-PCSE, LMI AR(1)	(2) LSDV2-PCSE, NSI AR(1)	(3) LSDV2-PCSE, AR(1)	(4) LSDV2-PCSE2, AR(1)	(5) LSDV2-PCSE3, AR(1)
UD	0.0526	0.0804***	0.0546	0.0376**	0.0384*
	(0.0417)	(0.0101)	(0.0384)	(0.0188)	(0.0196)
l.UD	0.0387		0.0326	0.0499***	0.0426**
	(0.0389)		(0.0357)	(0.0187)	(0.0193)
TW	0.109***	0.219***	0.0859**	0.0547***	0.0595***
	(0.0372)	(0.0171)	(0.0361)	(0.0166)	(0.0164)
l.TW	0.126***		0.138***	0.0597***	0.0570***
	(0.0345)		(0.0334)	(0.0165)	(0.0164)
ALMP	-0.0446***	-0.0587***	-0.0373***	-0.0266***	-0.0246***
	(0.00876)	(0.00368)	(0.00939)	(0.00334)	(0.00354)
l.ALMP	-0.0177**		-0.0233***	-0.0145***	-0.0140***
	(0.00864)		(0.00886)	(0.00332)	(0.00347)
UBRR	0.0564**	0.0981***	0.0177	0.0187	0.0159
	(0.0233)	(0.00854)	(0.0290)	(0.0150)	(0.0156)
l.UBRR	0.0442**		0.0861***	0.0336**	0.0301**
	(0.0209)		(0.0303)	(0.0140)	(0.0143)
UBRR2	-0.00856	-0.0270***	-0.000149	-0.00643*	-0.00828*
	(0.00691)	(0.00426)	(0.00445)	(0.00379)	(0.00482)
l. UBRR2	-0.0143**		-0.0230***	-0.0136***	-0.0150***
	(0.00710)		(0.00442)	(0.00327)	(0.00367)
TFP	-0.0651**	-0.0516	-0.0543*	-0.0211	-0.0218
	(0.0328)	(0.0318)	(0.0312)	(0.0154)	(0.0165)
R	0.0626**	0.0533	0.0532	-0.000239	0.00242
	(0.0287)	(0.0388)	(0.0386)	(0.0158)	(0.0171)
CONS	-0.544***	-0.517***	-0.538***	-0.252**	-0.249**
	(0.0747)	(0.177)	(0.188)	(0.104)	(0.100)
Bulgaria	12.05***	11.32***	11.90***	7.849***	7.273***
	(0.707)	(0.753)	(0.770)	(1.219)	(1.226)
Czech Rep	9.554***	8.711***	9.392***	5.242***	4.597***
	(0.600)	(0.517)	(0.576)	(1.210)	(1.051)
Denmark	4.505***	4.199***	4.511***	0.649	0.783
	(0.453)	(0.474)	(0.456)	(0.999)	(1.117)
Germany	5.935***	5.408***	5.751***	3.582***	2.672**
	(0.274)	(0.291)	(0.318)	(0.612)	(1.294)
Estonia	13.02***	12.09***	12.83***	8.900***	8.167***
	(0.640)	(0.501)	(0.550)	(1.840)	(1.322)
Ireland	13.35***	12.58***	13.01***	8.793***	8.649***
	(0.716)	(0.701)	(0.766)	(1.520)	(1.692)
Greece	14.70***	13.65***	14.57***	10.52***	10.02***
	(0.501)	(0.451)	(0.432)	(1.243)	(1.325)
Spain	20.33***	19.33***	20.08***	15.73***	15.27***
	(0.637)	(0.589)	(0.629)	(1.029)	(1.129)
France	10.03***	9.242***	9.903***	7.288***	6.696***
	(0.407)	(0.430)	(0.465)	(0.764)	(0.906)
Italy	8.987***	8.349***	8.977***	5.695***	5.169***
	(0.502)	(0.419)	(0.441)	(0.927)	(0.933)
Cyprus	13.28***	12.12***	12.96***	5.771***	5.440***
	(0.837)	(0.787)	(0.846)	(1.300)	(1.327)
Latvia	13.43***	12.72***	13.43***	9.658***	9.136***
	(0.648)	(0.529)	(0.547)	(1.374)	(1.291)
Lithuania	13.77***	13.02***	13.73***	9.817***	9.049***
	(0.657)	(0.532)	(0.567)	(1.000)	(1.195)
Luxembourg	13.02***	12.08***	12.79***	5.708***	5.061***
	(1.122)	(1.054)	(1.088)	(1.677)	(1.730)
Hungary	8.650***	7.949***	8.684***	5.182***	4.618***
	(0.532)	(0.416)	(0.465)	(0.992)	(1.127)
Malta	7.159***	6.628***	6.886***	2.313**	2.250**
	(0.590)	(0.549)	(0.616)	(0.924)	(0.924)
Netherlands	9.170***	8.303***	8.990***	4.889***	4.224***
	(0.450)	(0.416)	(0.478)	(1.058)	(1.158)
Austria	2.881***	2.368***	2.727***	0.539	0.324
	(0.302)	(0.291)	(0.329)	(0.458)	(0.494)
Poland	14.80***	13.88***	14.62***	10.21***	
	(0.460)	(0.404)	(0.440)	(0.902)	

Portugal	13.88***	12.81***	13.67***	8.510***	7.875***
	(0.601)	(0.573)	(0.602)	(1.193)	(1.474)
Romania	6.688***	6.137***	6.696***	3.256***	2.608***
	(0.513)	(0.408)	(0.443)	(0.796)	(0.938)
Slovenia	7.942***	7.148***	7.891***	4.073***	3.498***
	(0.522)	(0.414)	(0.481)	(1.110)	(1.064)
Slovakia	16.34***	15.65***	16.38***	11.80***	
	(0.606)	(0.521)	(0.539)	(0.813)	
Finland	4.718***	4.574***	4.792***	1.830***	1.807**
	(0.436)	(0.443)	(0.457)	(0.707)	(0.703)
Sweden	3.268***	3.087***	3.443***	0.0914	-0.267
	(0.527)	(0.519)	(0.503)	(1.139)	(1.227)
UK	9.854***	9.054***	9.577***	5.359***	
	(0.644)	(0.643)	(0.653)	(0.843)	
1988	0.285				
	(0.415)				
1989	0.579	0.338	0.316	0.166***	0.175***
	(0.430)	(0.486)	(0.465)	(0.0211)	(0.0285)
1990	0.799*	0.505	0.587	0.328***	0.344***
	(0.410)	(0.508)	(0.457)	(0.0361)	(0.0433)
1991	0.861**	0.218	0.613	0.340***	0.385***
	(0.414)	(0.466)	(0.474)	(0.0513)	(0.0615)
1992	0.449	0.0164	0.167	0.202***	0.276***
	(0.321)	(0.405)	(0.362)	(0.0562)	(0.0792)
1993	0.331	-0.0608	0.109	0.165*	0.256**
	(0.318)	(0.423)	(0.378)	(0.0872)	(0.116)
1994	0.110	-0.209	-0.121	0.0139	0.100
	(0.332)	(0.389)	(0.358)	(0.101)	(0.131)
1995	-0.146	-0.282	-0.286	-0.0757	0.00550
	(0.341)	(0.396)	(0.362)	(0.0828)	(0.118)
1996	-0.174	-0.856***	-0.365	-0.189**	-0.120
	(0.327)	(0.329)	(0.378)	(0.0909)	(0.126)
1997	-0.506*	-0.732**	-0.745**	-0.337***	-0.287**
	(0.265)	(0.320)	(0.298)	(0.101)	(0.132)
1998	-0.398	-0.485	-0.594*	-0.296**	-0.267*
	(0.272)	(0.332)	(0.316)	(0.120)	(0.148)
1999	-0.199	-0.294	-0.402	-0.237*	-0.232
	(0.267)	(0.324)	(0.308)	(0.131)	(0.155)
2000	-0.184	-0.416	-0.344	-0.181	-0.211
	(0.272)	(0.312)	(0.297)	(0.137)	(0.162)
2001	0.208	0.515	-0.317	0.0391	0.0739
	(0.335)	(0.375)	(0.334)	(0.191)	(0.230)
2002	0.680**	0.509	0.433	0.455**	0.553**
	(0.330)	(0.363)	(0.345)	(0.213)	(0.241)
2003	0.743**	0.593	0.499	0.480**	0.595**
	(0.326)	(0.367)	(0.341)	(0.225)	(0.246)
2004	0.796**	0.627*	0.590*	0.524**	0.657**
	(0.324)	(0.354)	(0.343)	(0.240)	(0.258)
2005	0.901***	0.887**	0.703**	0.625**	0.793***
	(0.315)	(0.362)	(0.336)	(0.246)	(0.273)
2006	1.343***	1.298***	1.108***	0.868***	1.034***
	(0.339)	(0.362)	(0.339)	(0.263)	(0.289)
2007	1.605***	1.513***	1.404***	1.108***	1.275***
	(0.347)	(0.382)	(0.358)	(0.274)	(0.305)
2008	1.618***	1.544***	1.402***	1.225***	1.414***
	(0.349)	(0.412)	(0.388)	(0.285)	(0.324)
2009	1.693***	1.472***	1.362***	1.489***	1.685***
	(0.380)	(0.460)	(0.442)	(0.301)	(0.335)
2010	2.118***	1.668***	1.512***	1.590***	1.807***
	(0.332)	(0.449)	(0.436)	(0.303)	(0.327)
2011	1.912***	1.681***	1.723***	1.689***	1.928***
	(0.314)	(0.379)	(0.363)	(0.271)	(0.298)
2012	1.697***	1.468***	1.469***	1.653***	1.891***
	(0.315)	(0.376)	(0.361)	(0.270)	(0.295)
2013	1.655***	1.399***	1.299***	1.523***	1.768***
	(0.310)	(0.362)	(0.349)	(0.281)	(0.306)
2014	1.439***	1.241***	1.128***	1.279***	1.531***
	(0.310)	(0.362)	(0.349)	(0.291)	(0.321)
2015	1.275***	1.087***	0.999***	0.990***	1.258***
	(0.310)	(0.364)	(0.348)	(0.303)	(0.340)
2016	1.022***	0.976**	0.865**	0.738**	1.020***
	(0.321)	(0.383)	(0.366)	(0.307)	(0.351)
l.TFP		-0.0441	-0.0557	-0.0310**	-0.0345**
		(0.0357)	(0.0349)	(0.0153)	(0.0156)

l.R		0.0231	0.0179	0.00286	0.00211
		(0.0383)	(0.0384)	(0.0156)	(0.0164)
l.CONS		-0.0273	0.00231	-0.0950	-0.0809
		(0.171)	(0.184)	(0.0938)	(0.0945)
Poland					-
Slovakia					-
UK					-
Constant	-11.20***	-9.267***	-10.40***	-3.030*	-2.555
	(0.734)	(0.836)	(0.852)	(1.569)	(1.930)
Observations	544	540	529	529	529
R-squared	0.906	0.899	0.906	0.845	0.937
Number of countries	27	27	27	27	27
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
PCSE cross section	YES	YES	YES	YES	YES
PCSE AR(1)	NO	NO	NO	YES	NO
PCSE PSAR(1)	NO	NO	NO	NO	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix B.2: Second postestimation regression table for section 5.4.

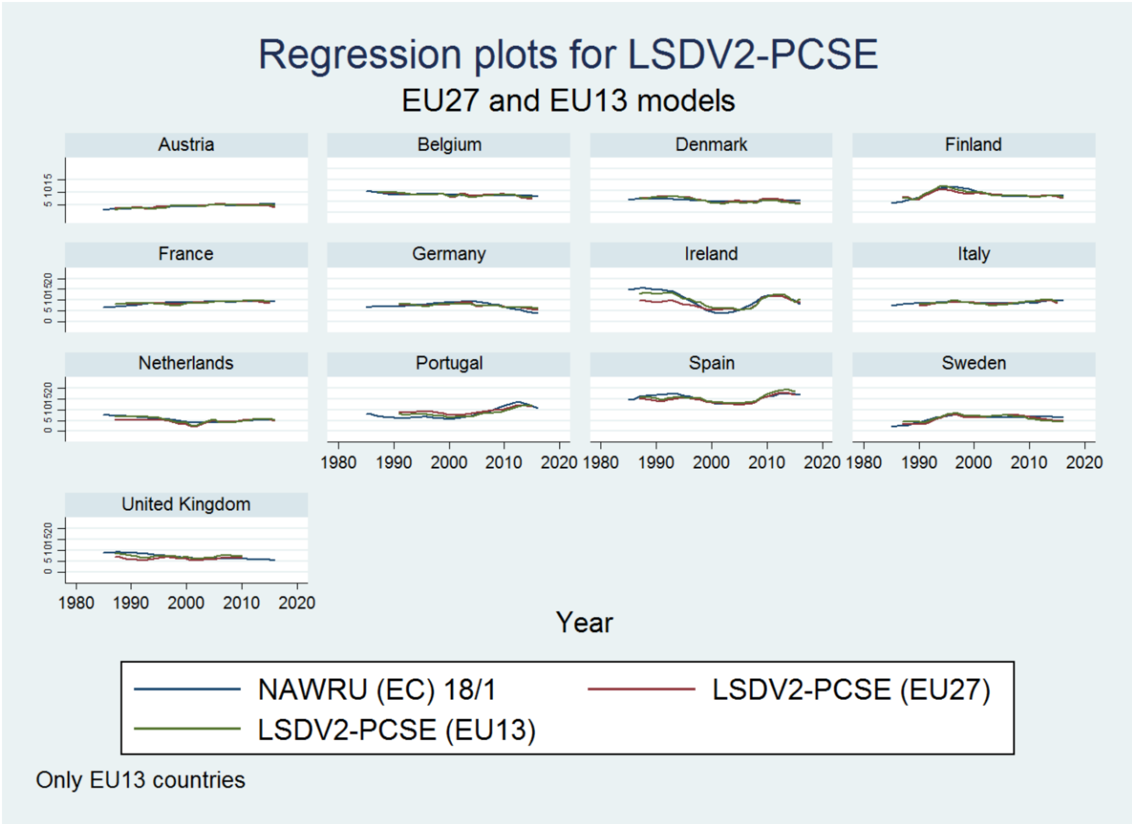
VARIABLES	(1) EU27 LSDV2-PCSE (2001-2016)	(2) EU27 LSDV2-PCSE	(3) EU13 LSDV2-PCSE	(4) EU4 LSDV2-PCSE
UD	0.0389***	0.0829***	0.0997***	0.0500
	(0.0112)	(0.00802)	(0.0154)	(0.0447)
TW	0.0885***	0.231***	0.220***	0.172***
	(0.0282)	(0.0157)	(0.0139)	(0.0624)
ALMP	-0.0571***	-0.0610***	-0.0585***	-0.0545***
	(0.00595)	(0.00451)	(0.00338)	(0.00610)
UBRR	0.124***	0.0924***	0.0942***	0.0880***
	(0.0178)	(0.00794)	(0.0140)	(0.0277)
UBRR2		-0.0258***	-0.00969*	-0.00812
		(0.00459)	(0.00497)	(0.0184)
TFP	-0.0297	-0.0634**	-0.113**	-0.0922
	(0.0247)	(0.0268)	(0.0498)	(0.0936)
R	0.0569***	0.0661**	0.0750**	0.114
	(0.0194)	(0.0276)	(0.0312)	(0.0806)
CONS	-0.595***	-0.543***	-0.623***	-0.116
	(0.0907)	(0.0587)	(0.0752)	(0.198)
Bulgaria	9.438***	11.34***		
	(1.098)	(0.631)		
Czech Republic	7.976***	8.692***		
	(0.954)	(0.487)		
Denmark	5.138***	4.188***	4.062***	
	(0.772)	(0.426)	(0.726)	
Germany	4.008***	5.444***	6.089***	-0.124
	(0.639)	(0.277)	(0.511)	(2.489)
Estonia	10.74***	12.11***		
	(1.019)	(0.538)		
Ireland	7.135***	12.92***	13.20***	
	(0.864)	(0.554)	(0.633)	
Greece	13.47***	13.66***		
	(0.961)	(0.448)		
Spain	17.21***	19.40***	20.63***	
	(1.052)	(0.547)	(0.910)	
France	7.675***	9.279***	10.27***	

	(0.699)	(0.404)	(0.718)	
Italy	8.518***	8.270***	9.039***	
	(0.859)	(0.424)	(0.693)	
Cyprus	9.559***	12.36***		
	(1.336)	(0.718)		
Latvia	12.00***	12.58***		
	(0.972)	(0.523)		
Lithuania	11.93***	12.93***		
	(1.031)	(0.547)		
Luxembourg	11.79***	12.14***		
	(1.474)	(0.869)		
Hungary	8.041***	7.803***		
	(0.965)	(0.466)		
Malta	2.974***	6.879***		
	(0.842)	(0.476)		
Netherlands	6.619***	8.387***	9.230***	
	(0.897)	(0.425)	(0.724)	
Austria	0.920***	2.512***	2.860***	
	(0.306)	(0.241)	(0.349)	
Poland	12.24***	13.93***		
	(0.941)	(0.408)		
Portugal	12.04***	12.89***	13.96***	
	(0.990)	(0.504)	(0.866)	
Romania	6.141***	6.010***		
	(0.859)	(0.416)		
Slovenia	6.766***	7.100***		
	(0.905)	(0.451)		
Slovakia	14.37***	15.56***		
	(0.933)	(0.545)		
Finland	4.414***	4.530***	4.411***	0.104
	(0.593)	(0.403)	(0.548)	(0.560)
Sweden	4.778***	2.933***	2.843***	-0.537
	(0.786)	(0.504)	(0.820)	(0.495)
United Kingdom	5.524***	9.263***	9.862***	
	(0.744)	(0.571)	(0.625)	
1988		0.349	0.387	0.937*
		(0.496)	(0.245)	(0.497)
1989		0.664	0.691***	1.489***
		(0.494)	(0.242)	(0.536)
1990		0.811	0.791***	1.724***
		(0.500)	(0.227)	(0.519)
1991		0.434	0.382**	1.609***
		(0.412)	(0.171)	(0.578)
1992		0.390	0.387**	1.753***
		(0.402)	(0.168)	(0.615)
1993		0.260	0.241	1.759***
		(0.390)	(0.185)	(0.682)
1994		0.0971	0.183	1.588**
		(0.404)	(0.188)	(0.659)
1995		-0.0515	-0.00348	1.696***
		(0.407)	(0.172)	(0.549)
1996		-0.556*	-0.121	2.016***
		(0.331)	(0.168)	(0.625)
1997		-0.409	0.0113	2.330***
		(0.333)	(0.185)	(0.674)
1998		-0.207	0.148	2.721***
		(0.327)	(0.192)	(0.741)
1999		-0.0239	0.359*	2.910***
		(0.320)	(0.203)	(0.791)
2000		-0.137	0.226	2.741***
		(0.326)	(0.205)	(0.728)
2001		0.825**	0.467*	2.730***
		(0.372)	(0.257)	(0.919)
2002	-0.101**	0.819**	0.231	2.516***
	(0.0404)	(0.367)	(0.256)	(0.902)
2003	-0.0745	0.878**	0.0653	2.181**
	(0.0965)	(0.365)	(0.269)	(0.959)
2004	-0.0415	0.878**	0.295	2.315**
	(0.0708)	(0.357)	(0.278)	(1.002)
2005	0.182***	1.121***	0.593**	2.589***
	(0.0699)	(0.356)	(0.274)	(0.939)
2006	0.514***	1.566***	1.021***	2.805***
	(0.0927)	(0.375)	(0.267)	(0.940)
2007	0.686***	1.759***	1.222***	2.688***

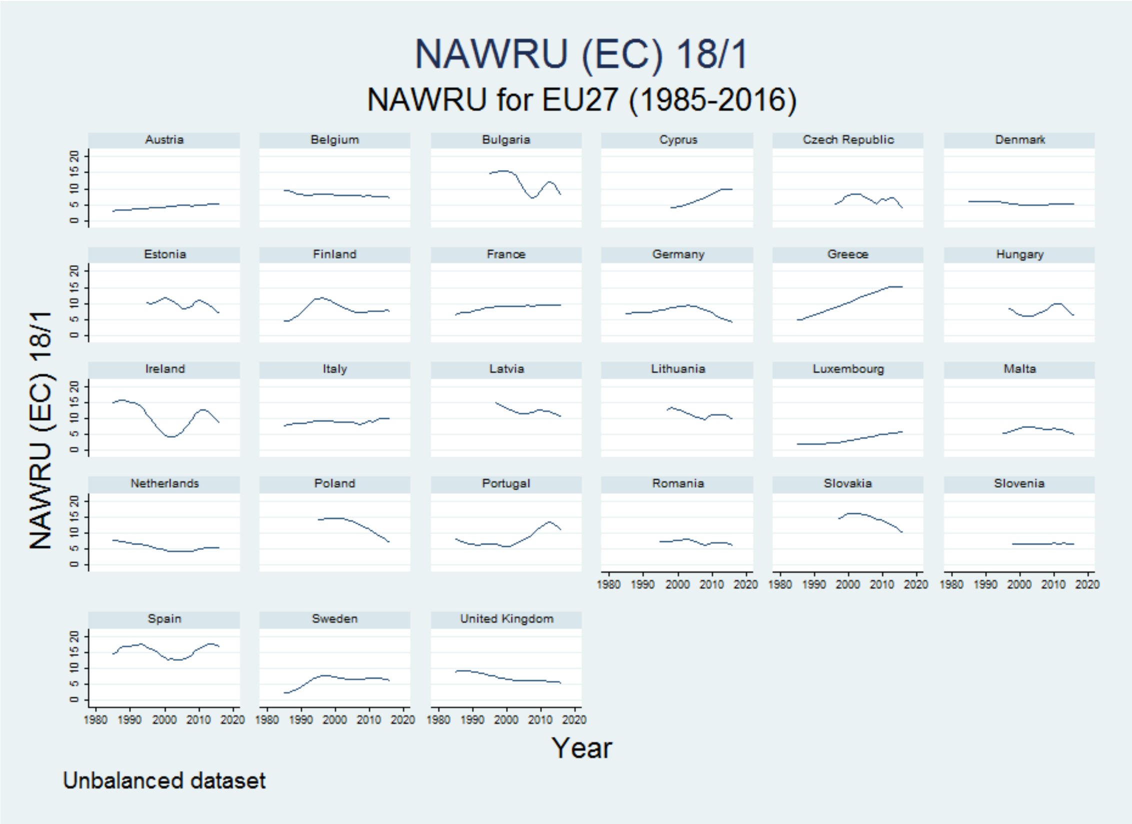
	(0.110)	(0.382)	(0.258)	(0.890)
2008	0.743***	1.783***	1.134***	2.662***
	(0.106)	(0.377)	(0.262)	(0.897)
2009	0.781***	1.796***	0.988***	2.311**
	(0.149)	(0.384)	(0.317)	(1.007)
2010	0.963***	2.211***	1.632***	3.325***
	(0.0546)	(0.366)	(0.281)	(1.055)
2011	0.713***	1.912***	1.346***	3.062***
	(0.0701)	(0.364)	(0.277)	(1.039)
2012	0.601***	1.737***	1.142***	2.864***
	(0.0818)	(0.362)	(0.295)	(1.103)
2013	0.565***	1.760***	1.251***	2.962***
	(0.0901)	(0.355)	(0.300)	(1.118)
2014	0.285***	1.573***	1.361***	3.054***
	(0.0908)	(0.358)	(0.317)	(1.158)
2015	0.0388	1.394***	1.553***	3.111**
	(0.101)	(0.359)	(0.360)	(1.227)
2016	-0.294***	1.180***	1.311***	2.984**
	(0.112)	(0.356)	(0.367)	(1.207)
Constant	-2.217	-9.953***	-10.29***	-5.888
	(1.578)	(0.730)	(1.089)	(4.024)
Observations	370	556	368	116
R-squared	0.916	0.899	0.913	0.842
Number of countries	27	27	13	4
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
PCSE cross section	YES	YES	YES	YES

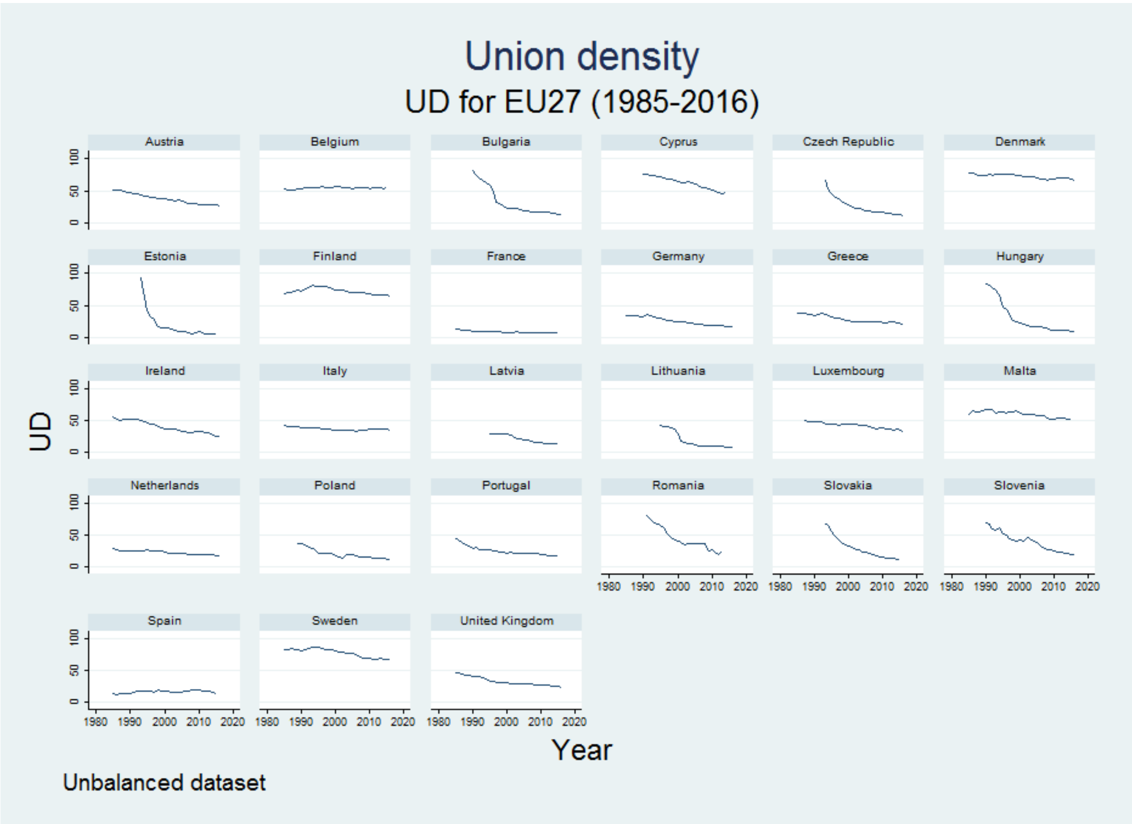
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

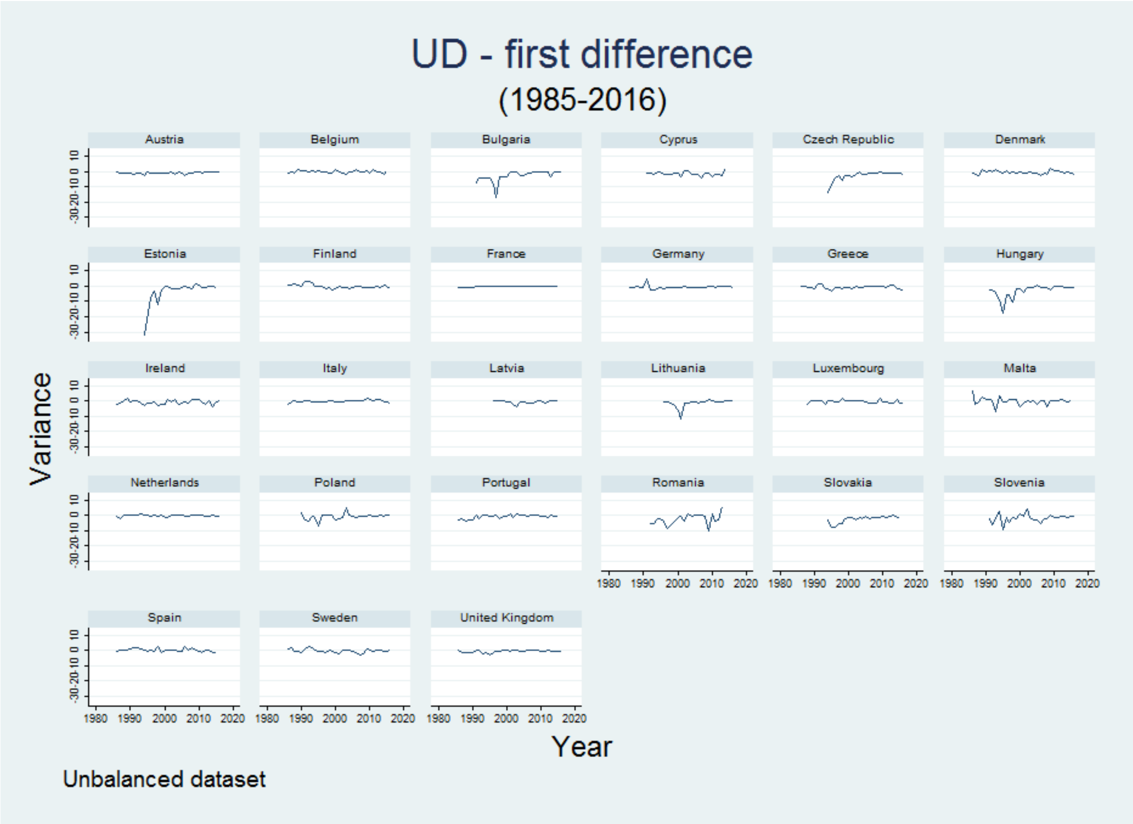
Appendix C.1: Regression plots for LSDV2-PCSE – EU27 and EU13 models.

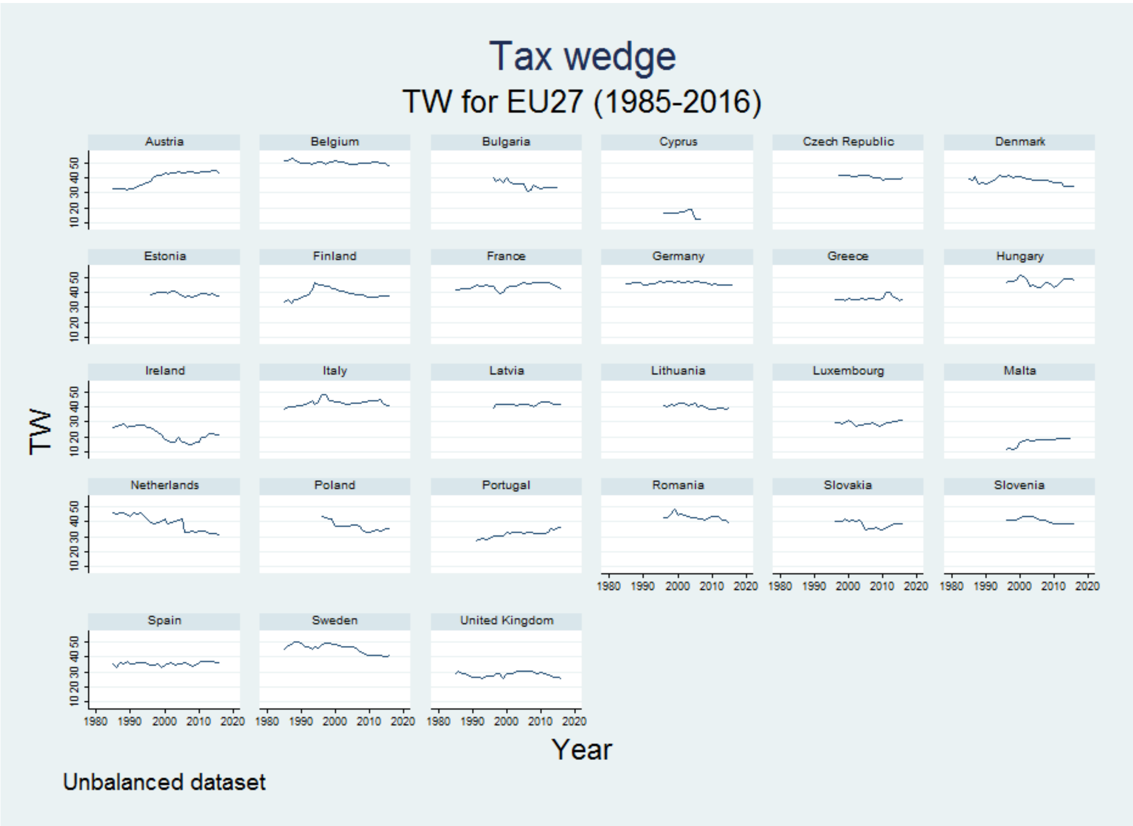


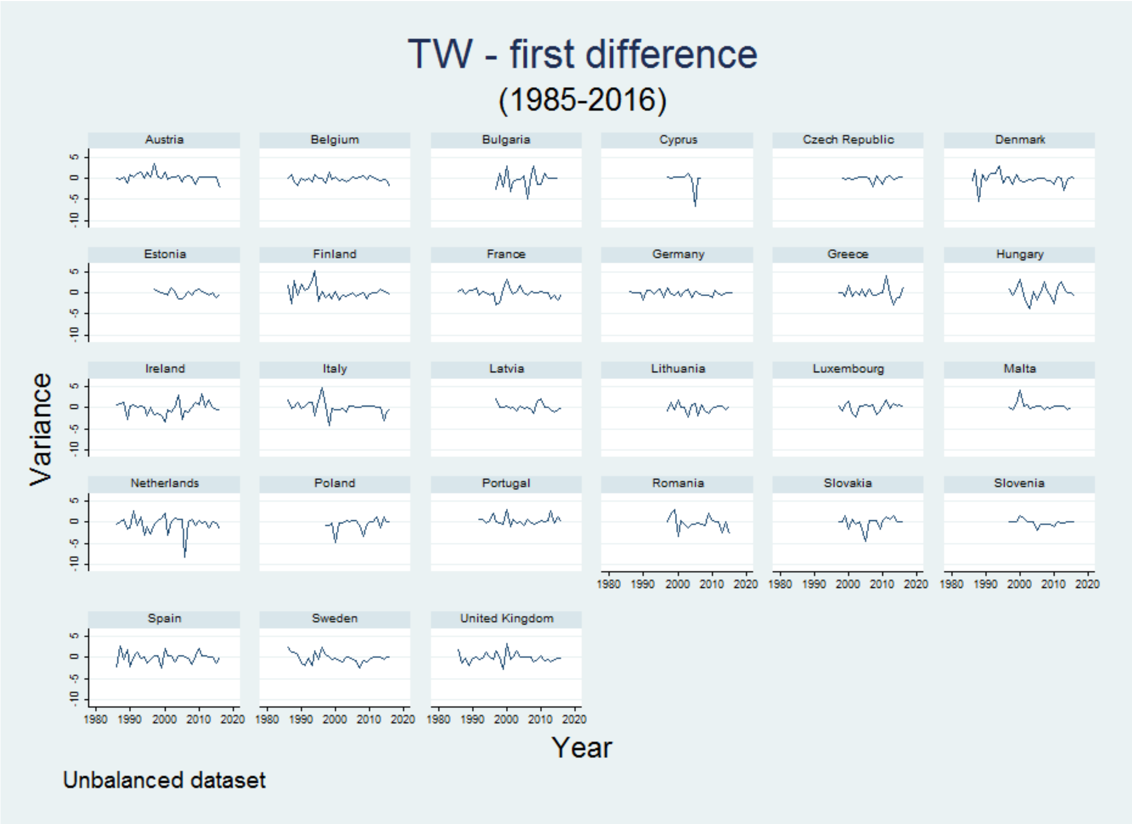
Appendix D.1: Variable line plots for dependent and independent variables. Plots are for actual data and the first difference.

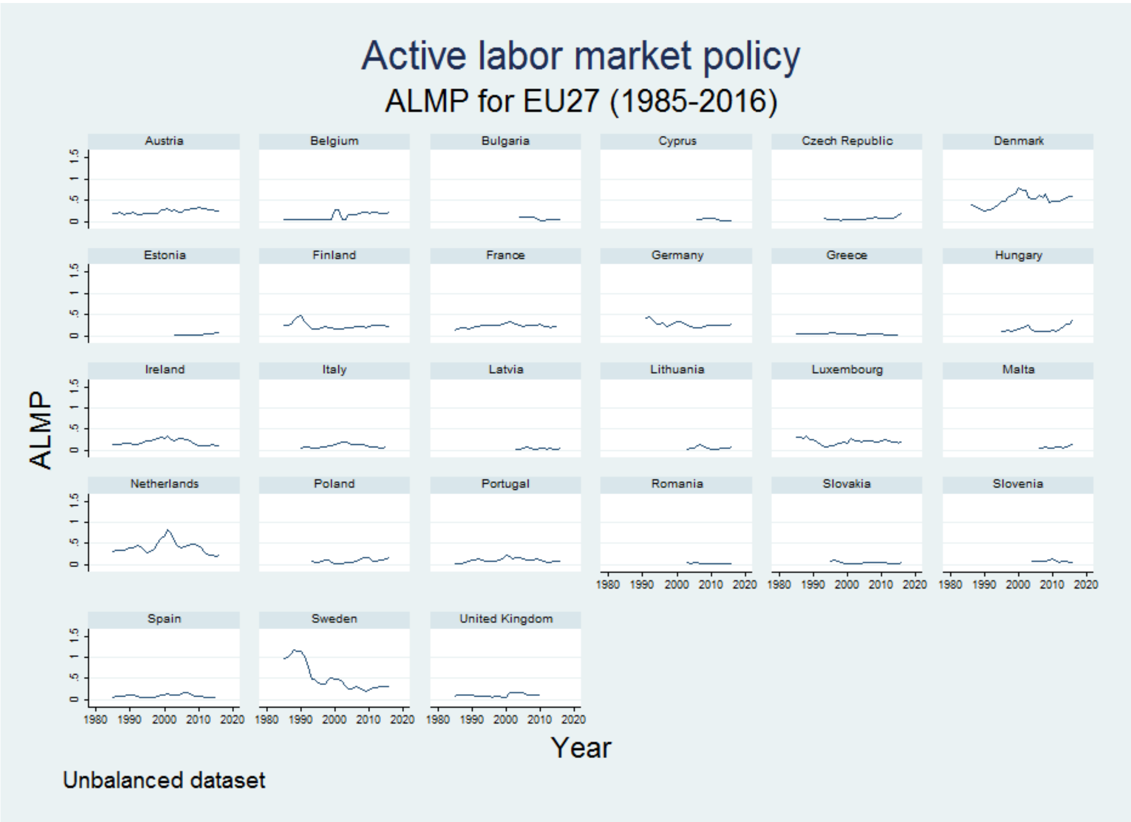


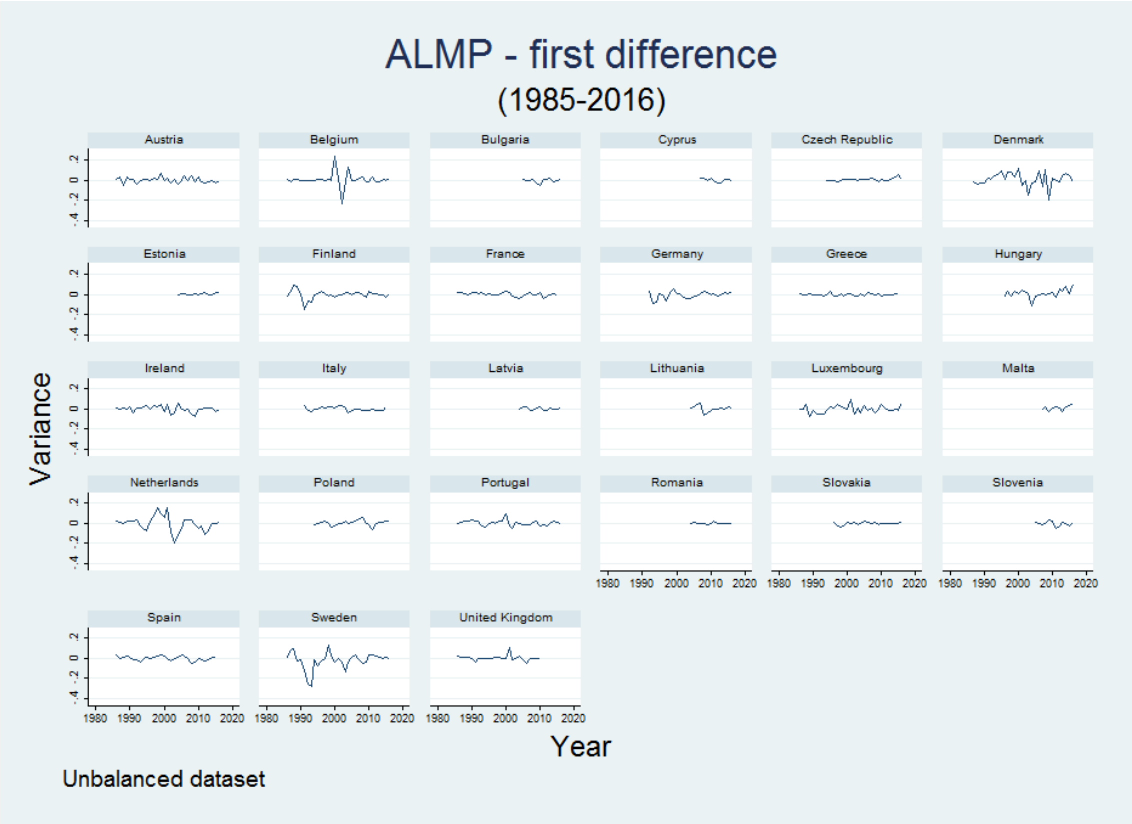


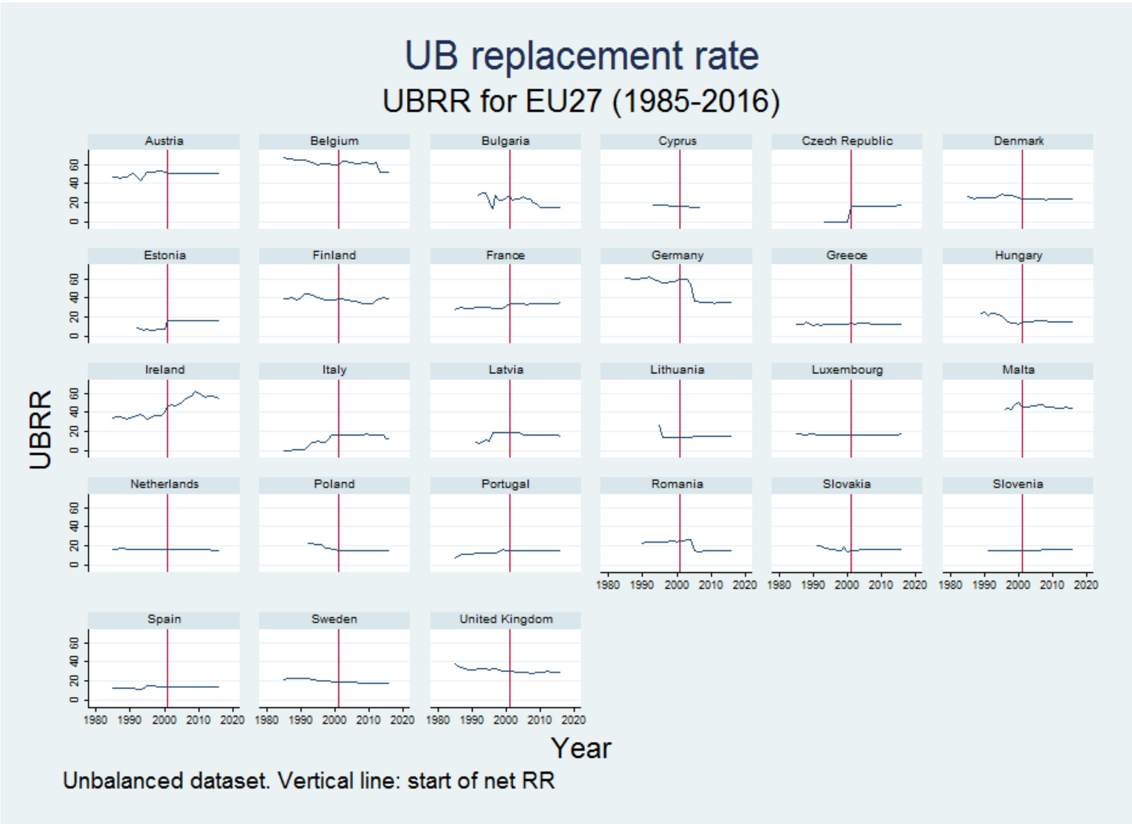

UD - first difference
(1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Variance
Year
Unbalanced dataset

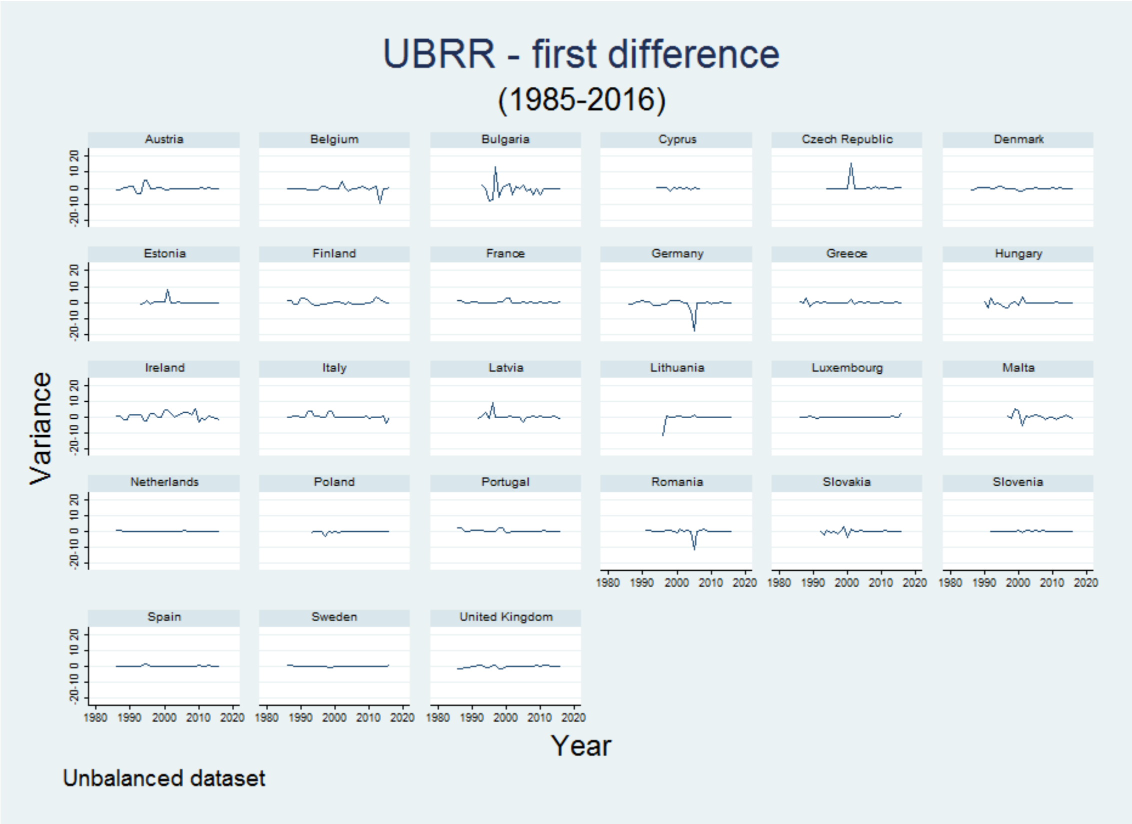

Tax wedge
TW for EU27 (1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
TW
Year
Unbalanced dataset

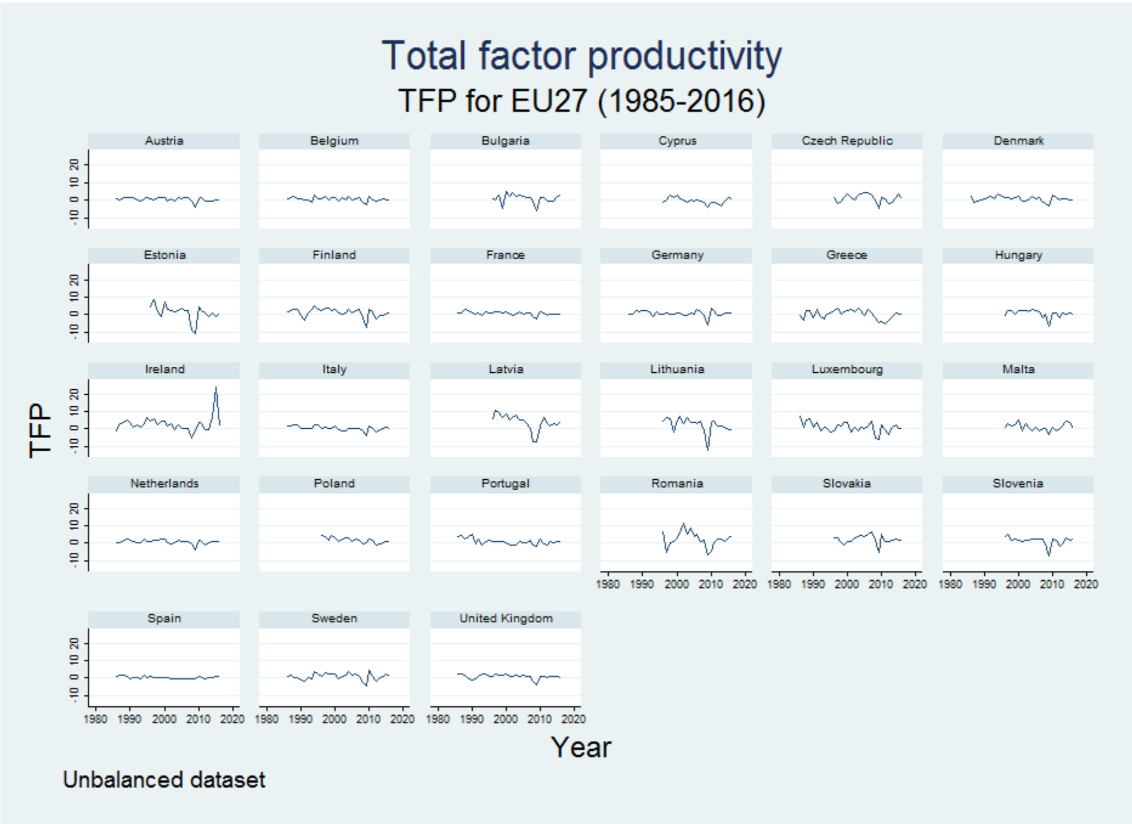

TW - first difference
(1985-2016)
Variance
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Year
Unbalanced dataset

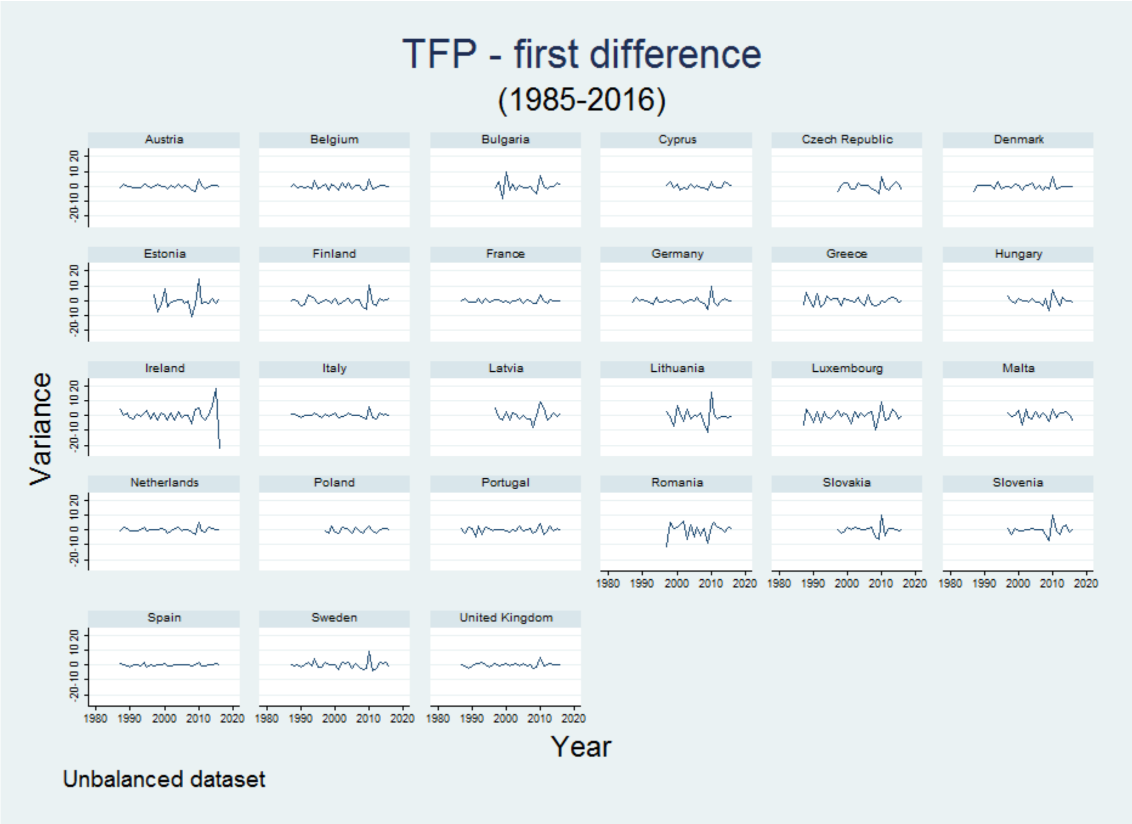

Active labor market policy
ALMP for EU27 (1985-2016)
ALMP
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Year
Unbalanced dataset

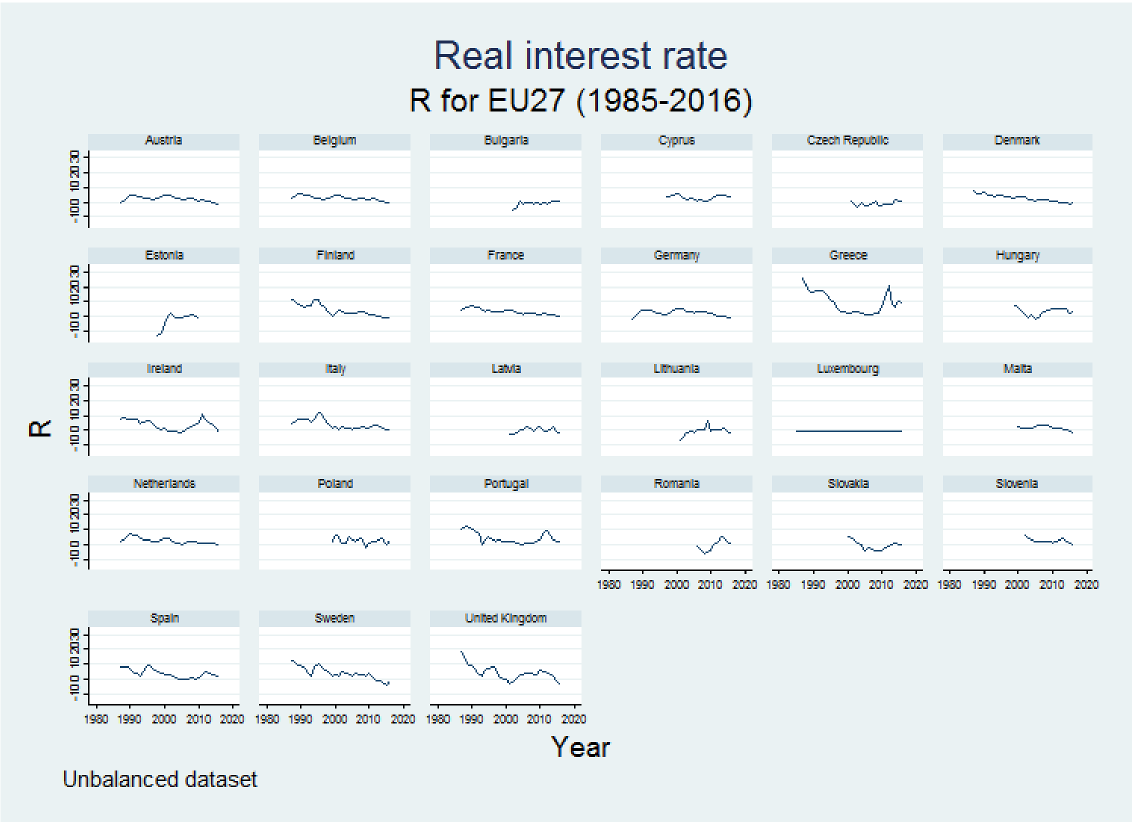

ALMP - first difference
(1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Variance
Year
Unbalanced dataset

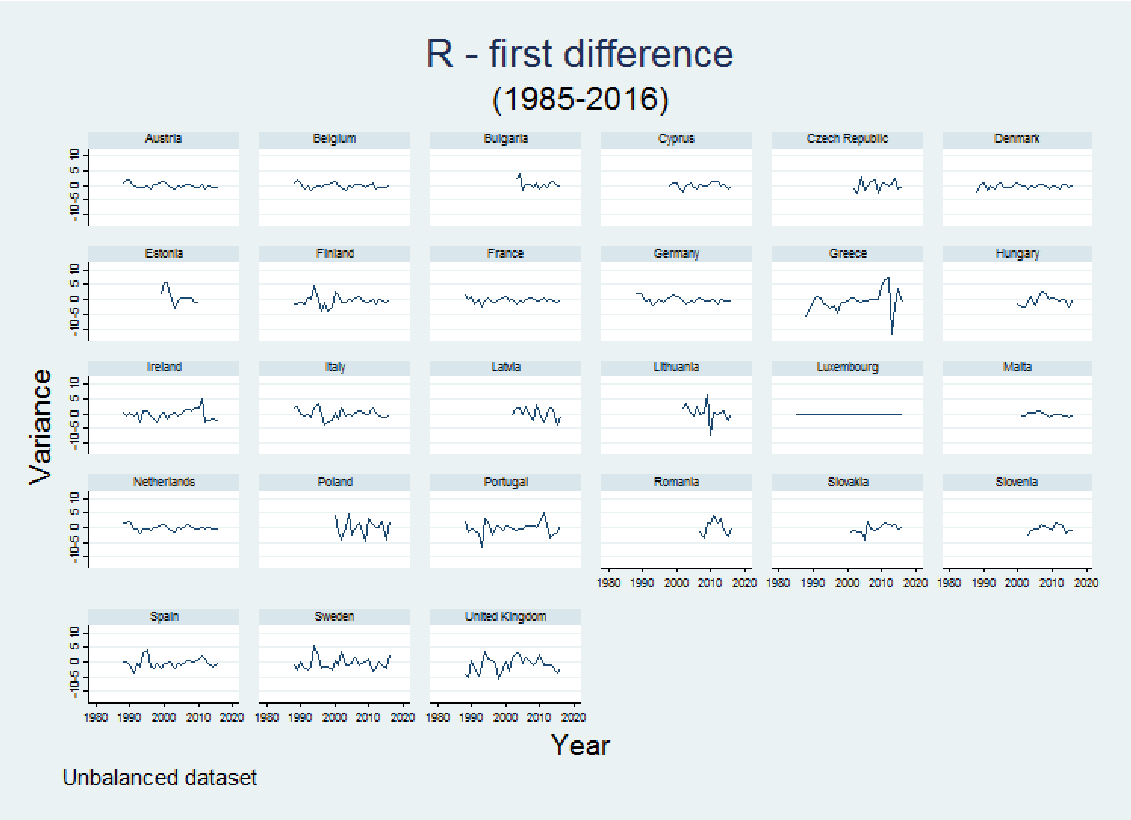

UB replacement rate
UBRR for EU27 (1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
UBRR
Year
Unbalanced dataset. Vertical line: start of net RR


UBRR - first difference
(1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Variance
-20 -10 0 10 20
1980 1990 2000 2010 2020
Year
Unbalanced dataset

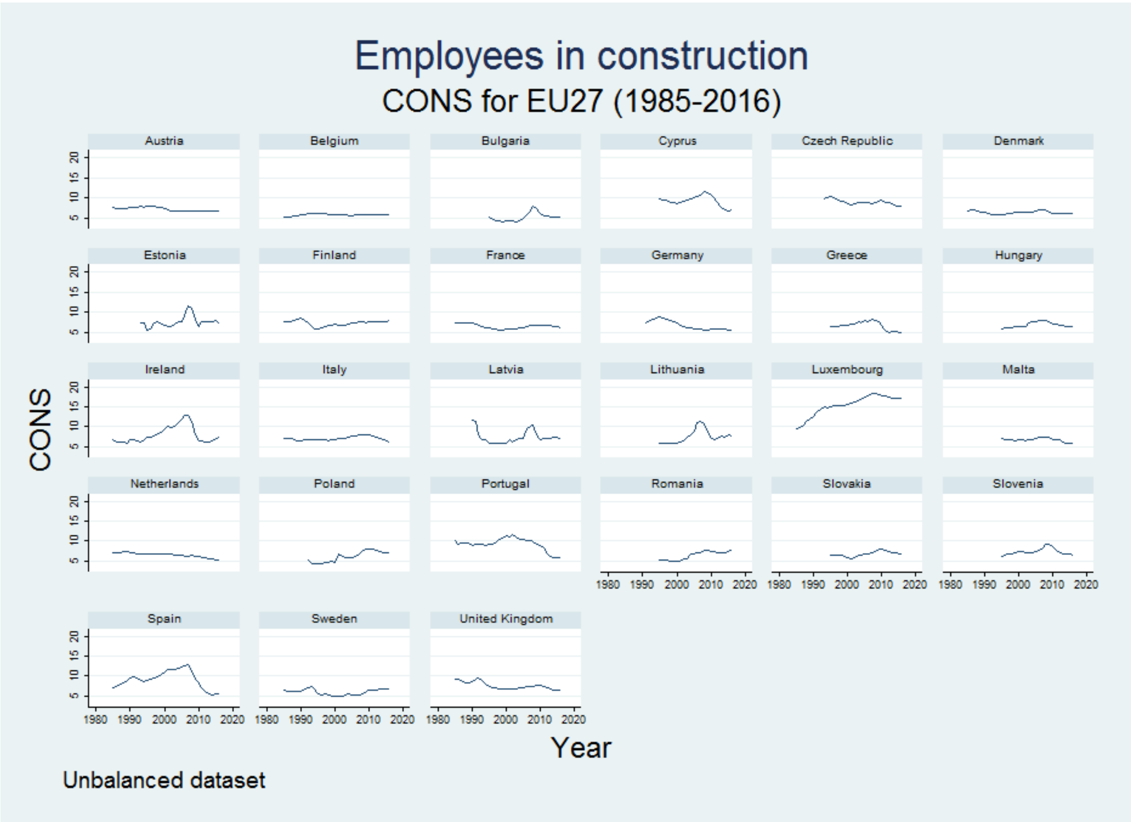

Total factor productivity
TFP for EU27 (1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
TFP
-10 0 10 20
1980 1990 2000 2010 2020
Year
Unbalanced dataset


TFP - first difference
(1985-2016)
Variance
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
-20 -10 0 10 20
1980 1990 2000 2010 2020
Year
Unbalanced dataset

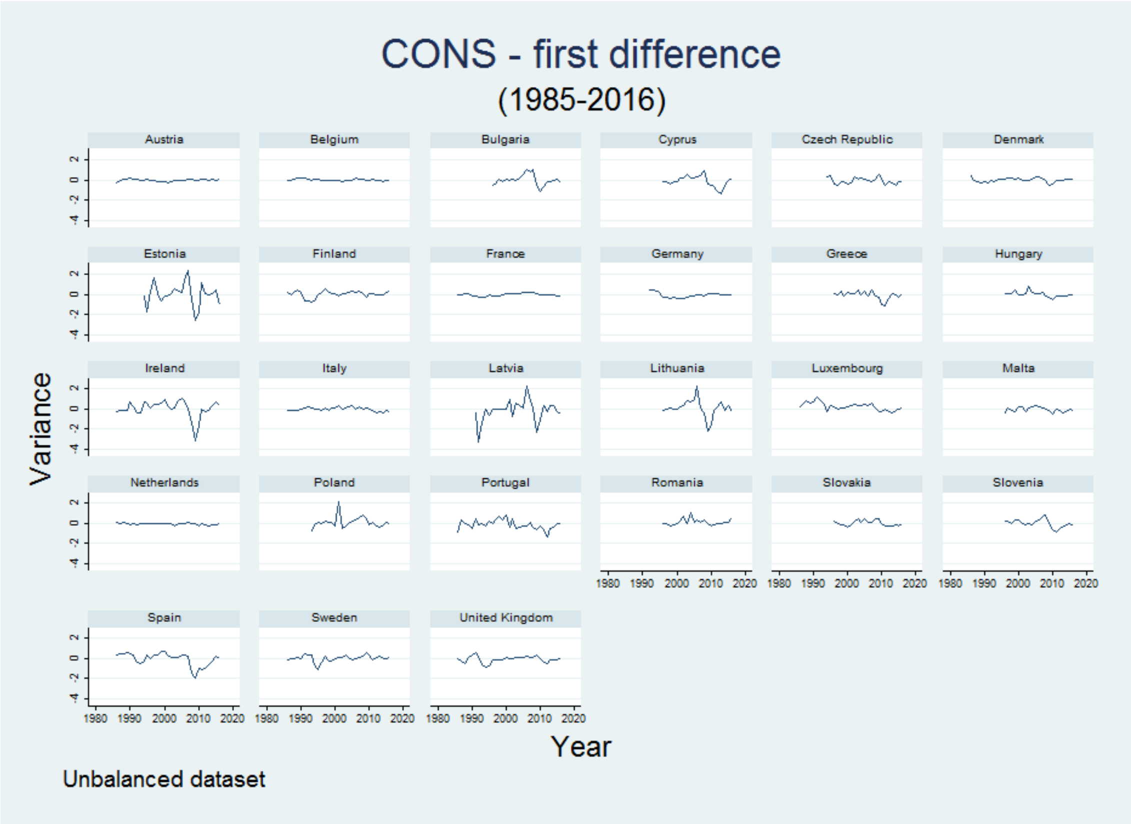

Real interest rate
R for EU27 (1985-2016)
R
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
-10 0 10 20 30
1980 1990 2000 2010 2020
Year
Unbalanced dataset



R - first difference
(1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Variance
Year
Unbalanced dataset



Employees in construction
CONS for EU27 (1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
CONS
Year
Unbalanced dataset


CONS - first difference
(1985-2016)
Austria
Belgium
Bulgaria
Cyprus
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Poland
Portugal
Romania
Slovakia
Slovenia
Spain
Sweden
United Kingdom
Variance
Year
Unbalanced dataset