How far from full employment?
The European unemployment problem revisited

Meryem Gökten, Philipp Heimberger, Andreas Lichtenberger
(Vienna Institute for International Economic Studies)

Abstract
This paper analyzes deviations from full employment in EU countries compared to the US and the UK. We apply the Beveridge (full-employment-consistent) rate of unemployment (BECRU), derived from the relation between unemployment and vacancies. The BECRU is the amount of unemployment minimizing the nonproductive use of labor. Based on a novel dataset over 1970-2022, we find full employment episodes in selected EU countries (Germany, Sweden, Austria, Finland) during the 1970s. The European unemployment problem emerged in the 1980s and 1990s, as Beveridgean full employment gaps increased. Labor markets became tighter during the recovery from the Covid-19 crisis, but few countries hit full employment. Full employment gaps are informative, e.g. with regard to predicting the share of persons unemployed and not receiving education or vocational training. Panel regressions highlight that hysteresis, labor market institutions, structural factors, macroeconomic factors and political factors contribute to explaining full employment gaps.

Keywords: Full employment, unemployment, vacancies, EU, UK, USA.
JEL-codes: E24, E32, E6, J63, J64.

1. Introduction

Macroeconomists and policy-makers track closely whether the labor market is slack or overly tight, as this judgement affects whether macroeconomic policy measures should be expansionary or restrictive. While the level of unemployment at which an economy operates at full employment is non-observable, providing estimations is important when it comes to informing real-time macroeconomic policy debates. However, full employment estimates may also help shed light on historical labor market developments. In the 1980s and 1990s, high unemployment rates in European countries turned into a key policy challenge as economic research struggled for explanations (e.g. Bean 1994; Ljungqvist and Sargent 2008). While unemployment rates in many European countries rose so strongly that they markedly surpassed US levels, Figure 1 highlights that there were important differences across selected EU countries (e.g. Saint-Paul 2002; Blanchard 2006; Campos et al. 2023).

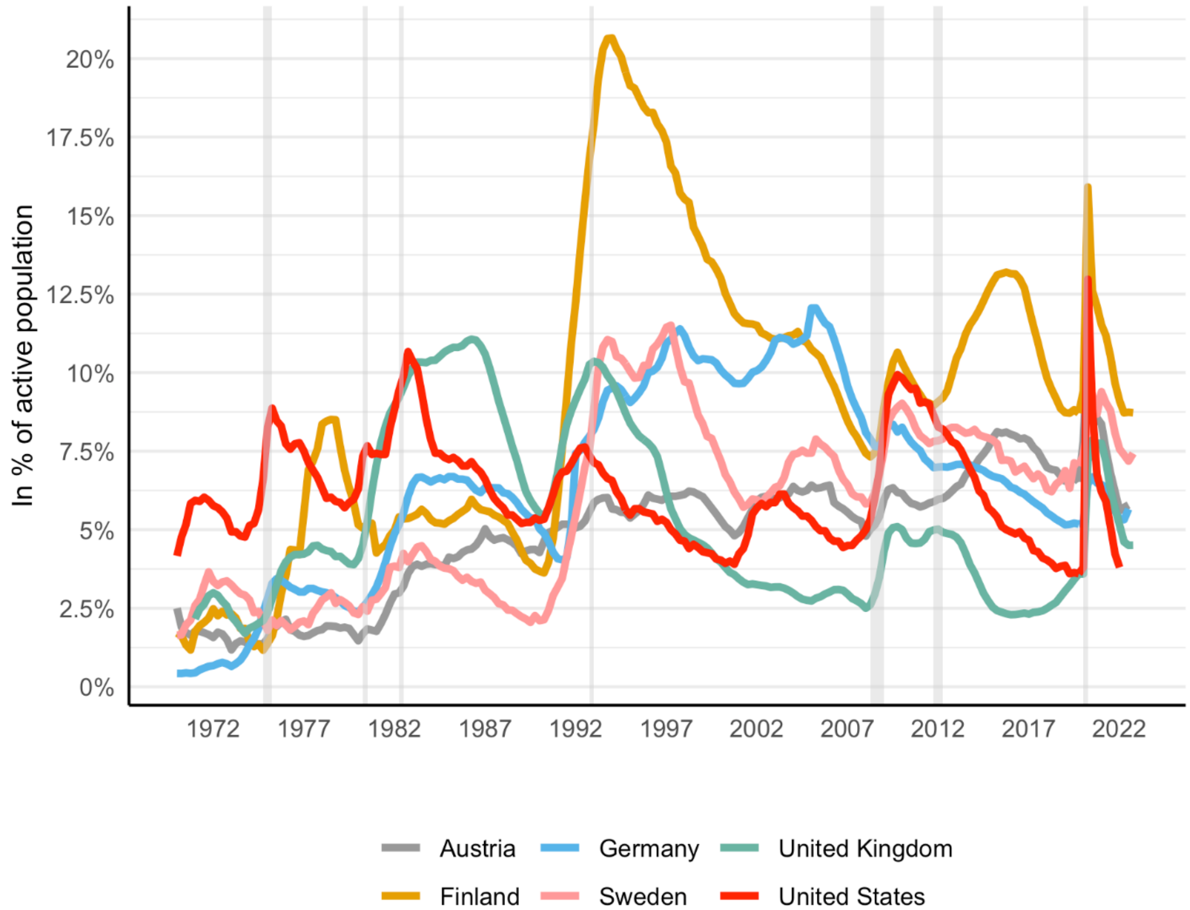

Figure 1: Unemployment rates, 1970-2022 (Source: OECD Registered Unemployed Dataset, Michaillat and Saez [2022]). Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991.

This paper utilizes a full employment concept derived from the Beveridge curve, i.e. the relationship between unemployment and vacancies. By building on recent contributions by Michaillat and Saez (2021, 2022) on the US case, we conceptualize full employment as the unemployment rate that minimizes the nonproductive use of labor in terms of both job seeking and recruiting. We call this the Beveridge (full-employment-consistent) rate of unemployment (BECRU). We contribute to the literature by using a novel quarterly data set for Germany, Austria, Sweden, Finland and the UK to complement existing data for the US; we analyze how much different countries deviate from full employment over the time period 1970-2022. To complement our analysis of the long panel datasest (high T and small N) with another sample including additional country data (smaller T and higher N), we further construct an extended quarterly dataset for 28 countries, including 26 EU countries plus the UK and the US over the shorter time period 2000-2022. We make the data set publicly available[1] and will provide regular updates to incorporate new data points that can inform research and policy-making. We argue that BECRU estimates are an informative measure of labour market slack, e.g. with regard to predicting the share of persons unemployed and not receiving education or vocational training. Our emphasis on the BECRU is in line with other recent studies that pick up on Beveridgean measures of labor market slack (e.g. Cerrato and Gitti 2022; Gäddnäs and Keränen 2023).

This paper sheds new light on how much EU countries deviate from full employment during the period of the European unemployment problem of the 1980s and 1990s in comparison to the US. We show how the historical data compares to recent developments, which have been characterized by debates over whether advanced economies reached full employment when recovering from the Covid-19 crisis; analyze how informative the Beveridgean full employemt gap estimates are; and provide econometric evidence on the explanatory factors (labor market institutions, structural factors, macroeconomic factors, political factors, hysteresis) of full employment gaps.

The rest of the paper is structured as follows: Section 2 discusses the theoretical background and derives the full employment gap from the relationship between unemployment and vacancies. Section 3 introduces new stylized facts on full employment gaps for EU countries in comparison to the UK and the US over 1970-2022. Section 4 presents the econometric analysis on the explanatory factors of full employment gaps. Section 5 discusses and concludes.

2. BECRU and full employment gaps: The Beveridge curve as the theoretical and empirical foundation

We derive our measure of the full employment gap from the Beveridge curve, i.e. the relation between unemployment and vacancies. While the concept can be traced back to Beveridge (1944), macroeconomists interested in understanding labor market developments have developed the Beveridge curve into an important organizing framework for their research (e.g. Nickell et al. 2003; Elsby et al. 2015). In using the relationship between unemployment and vacancies to derive a measure of labor market slack, we deviate from the approach of the non-accelerating inflation rate of unemployment (NAIRU), which conceptualizes how low the unemployment rate can go before inflation accelerates (e.g. Ball and Mankiw 2002; Galbraith 1997; Blanchard 2018), thereby linking the issue of labor market tightness to price stability concerns. We argue that the BECRU-related measure of labor market slack is informative, as it performs better than NAIRU unemployment gaps in predicting the share of persons unemployed and not receiving education or vocational training, and performs comparably with NAIRU gaps in predicting future inflation. BECRU estimates show more stability over time than NAIRU estimates. While the BECRU is based on thinking about labor market tightness in the vacancy-unemployment space, other approaches to conceptualizing full employment – e.g. via links to price stability, or by focusing on involuntary under-employment (e.g. Skidelsky and Gasperin 2021; Mason et al. 2021) – also have their merits. This paper develops the

[1] The dataset can be accessed via github: https://github.com/heimbergecon/fullemployment

argument that Beveridgean estimates of labor market slack should be taken into account by economists and policy-makers.

The Beveridge curve can be approximated by a rectangular hyperbola with the functional form $uv = k$, where u is the unemployment rate, v is the vacancy rate, and k is a constant. Hence, the Beveridge curve is negatively sloped: u and v are inversely related (e.g. Blanchard and Diamond 1989). This suggests that reducing vacancies and unemployment is not possible at the same time: in an economic downturn, many people are looking for jobs while there are few vacancies; but when the economy is in an upswing, there are more vacancies with fewer jobseekers. A reduction in unemployment allows more people to find a job; however, this also comes at a cost, as it forces companies to post more vacancies, which requires them to use more resources for recruiting at the expense of production.

The labor market operates at full employment when the vacancy-unemployment ratio is equal to 1 ($v = u$). When the vacancy-unemployment ratio is below 1 ($v < u$), the labor market is slack. And a vacancy-unemployment ratio higher than 1 ($v > u$) points to an overly tight labor market. Michaillat and Saez (2022) show that the "efficient" unemployment rate can be computed as the geometric average of the current unemployment rate and vacancy rate: $u^* = \sqrt{uv}$.[2] We label this the *Beveridge (full- employment-consistent) rate of unemployment*, in short: BECRU.[3] The BECRU is defined as the amount of unemployment minimizing the nonproductive use of labor in terms of both job seeking and recruiting. The BECRU is the solution to the social planner's problem of maximizing social welfare subject to the relationship between unemployment and vacancies. We decided for the acronym BECRU to offer an alternative acronym to the commonly used non-accelerating rate of inflation (NAIRU). The BECRU is a very useful measure as it can be computed based on observable data whereas the NAIRU relies on strong assumptions concerning non-observable variables and may suffer from estimation bias due to inherent problems with multi-variate statistical filtering models (e.g. Galbraith 1997; Heimberger and Kapeller 2017).

The full employment gap g derived from the Beveridge curve is the difference between actual unemployment and the BECRU: $g = u - BECRU$.[4] If $g = 0$, the economy is operating at the BECRU; if $g > 0$, the labor market is slack so that unemployment would need to fall to reach full employment; and if $g < 0$, the labor market is overly tight. In what follows, we use a new quarterly data set on the full employment gaps for EU countries and the UK in comparison with the US.

Since our focus on the European unemployment problem requires long time series, data availability for vacancy and unemployment rates is an issue. We are able to use quarterly data over the full time period 1970 to 2022 with unemployment rates and vacancy rates for five countries: Germany, Sweden, Austria, Finland and the UK. For the US, we use the data provided in Michaillat and Saez (2022). In total, this gives us our preferred country sample of six countries, driven by data availability with regard to vacancy data over the whole time period, which we use for the historical analysis.

[2] This formula is based on the assumptions that the Beveridge curve is a rectangular hyperbola and that the Beveridge elasticity is 1 (Michaillat and Saez 2022).
[3] We avoid the terminology of "efficiency" and rather stick with the label of the founder to avoid nurturing a constricting paradigm which tends to foreclude other epistemic approaches.
[4] Michaillat and Saez (2021) call g the Beveridgean unemployment gap.

We use Eurostat data from the 2000s onwards and OECD data for earlier decades. While the OECD obtains vacancy data from administrative records, Eurostat relies on labor force surveys. As data on registered vacancies often suffer from underreporting, we prefer the survey-based job vacancy data provided by Eurostat. However, for the period before the year 2000, we have to rely on registered OECD data. To account for potential underreporting of job vacancies in the OECD dataset from the 1970s to the 1990s, we adjust the data using predicted job vacancy values based on regressions of the OECD and Eurostat vacancy data; details are explained in appendix A.

To cover a larger group of EU member states for the period of 2000-2022, we supplement the data with information from national statistical offices. Despite some variations in data availability among countries, we are able to create a panel data set from 2000 to 2022 that covers 26 EU member states. We just have to exclude Denmark due to a lack of vacancy data. While the preferred dataset covering six countries over the period 1970-2022 allows us to analyze the European unemployment problem in historical perspective, the larger country sample over 2000-2022 provides additional valuable insights when it comes to understanding labor market slack in more recent years. It has to be noted, however, that vacancy data quality for some of the countries in the extended country sample is lower than for our preferred six countries sample, as some of the added countries may underreport the number of vacancies, so that our full employment gap estimates in the larger country sample have to be interpreted more cautiously.

Beveridge curves are subject to shifts over time and vary across countries, reflecting heterogeneity in matching efficiencies and labour market structures. The Beveridge curve captures changes in market tightness represented by the vacancy-unemployment ratio; it exhibits two key types of movements. First, changes in overall economic activity lead to movements along the Beveridge curve. During economic recessions, the curve slopes downward as the vacancy rate decreases and unemployment rises. Conversely, in economic booms, the curve slopes upward, with rising vacancy rates and decreasing unemployment, indicating cyclical labor market dynamics. Second, there can be structural shifts, represented by inward or outward movements of the curve, reflecting changes in matching efficiency or structural changes in the labor market, including structural changes regarding labor market institutions, policy interventions, technological advancements or shifts in the industry composition. The distance of the curve from the origin indicates labor market efficiency, i.e. how easily firms and workers can find suitable matches. An outward shift suggests reduced efficiency in finding matches, leading to higher unemployment for a given number of vacancies, while an inward shift implies improved matching efficiency, resulting in lower unemployment for a given number of vacancies (e.g. Blanchard and Diamond 1989; Ball and Mankiw 2002).

Shifts in the Beveridge curve, which are influenced by matching efficiency and structural changes, are more consistent and less prone to business cycle fluctuations than shifts observed in the Phillips curve. The Phillips curve is about the link between (wage) inflation and unemployment and does not directly account for search and matching efficiency in the labor market. Dickens (2008) makes the case that the Phillips curve is more susceptible to shifts and fluctuations than the Beveridge curve.

Figure 2 illustrates the unemployment and job vacancy rates for our preferred six country sample: Germany, Sweden, Austria, Finland, the UK, and the US, spanning the years from 1970 to 2022. The data points in the figure are distinguished by different colors to indicate four distinct time periods: 1970-1980 (low unemployment rates), 1980-2000 (emergence of the European unemployment problem), 2000-2019 (pre-Covid-19), and 2020-2022 (COVID-19 pandemic). While tendencies of downward-sloping curves are observed for most countries in the 1970s, the rise of unemployment rates in the 1980s and 1990s is associated with an outward shift or move to the right of the Beveridge curve. Between 2020 and 2022, Austria, Sweden, and the US witnessed an outward shift in their Beveridge curves, signaling a substantial decrease in matching efficiency since the COVID-19 outbreak. In contrast, Finland and the UK saw notable increases in vacancy rates while keeping unemployment relatively stable during the same period. Over the four periods, the curve for Austria shifted outwards, indicating a worsening in matching efficiency over time. Between 1970 and 2000, the curve for Germany remained stable. However, from 2000 to 2019, it shifted outwards, suggesting a decline in matching efficiency. During the COVID-19 period, Germany was the only country in our sample to experience an inward shift in the curve. Over time, the data for UK, Finland, and Sweden remained relatively stable over the different periods, showing no significant shifts in the respective Beveridge curve. In the case of the US, the Beveridge curve remained relatively stable until 2000. However, between 2000 and 2019, we observe an inward shift, suggesting a substantial improvement in matching efficiency during that period.

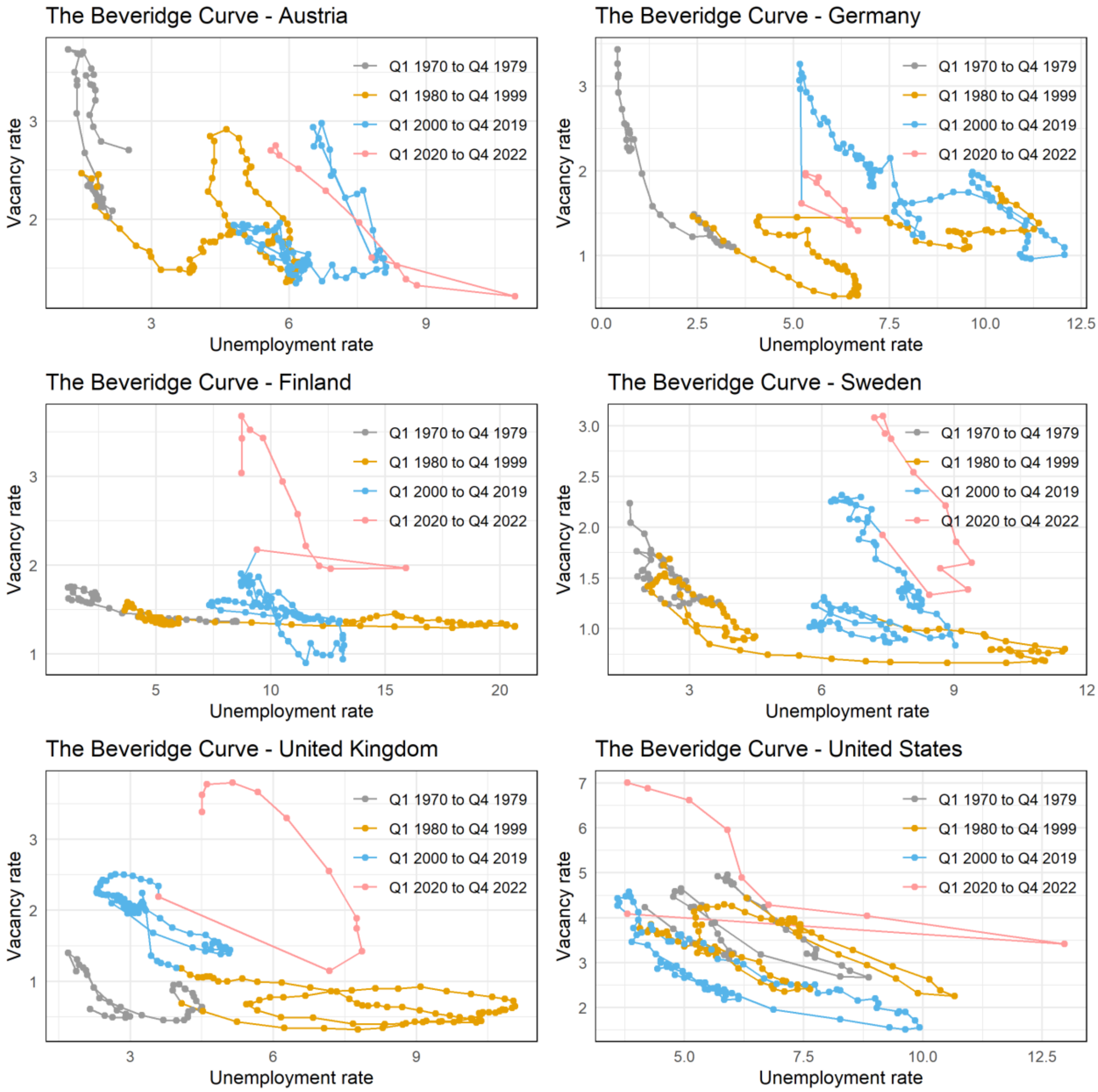

Figure 2: Beveridge Curve, 1970-2022 (Source: OECD Registered Unemployed Dataset, Michaillat and Saez [2022]; own calculations).

3. Revisiting the European unemployment problem: Stylized facts from a full employment perspective

Figure 3 shows BECRU estimates, which minimize the nonproductive use of labor in terms of both job seeking and recruiting, over the time period 1970-2022 for our six preferred countries. Figure 4 shows the Beveridge full employment gaps, i.e. the difference between actual unemployment and the BECRU. We can derive the following five major stylized facts.[5]

[5] Figure A 1 in appendix B provides additional information on unemployment rates and vacancy rates in Germany, Austria, Sweden, UK and USA over 1970-2022.

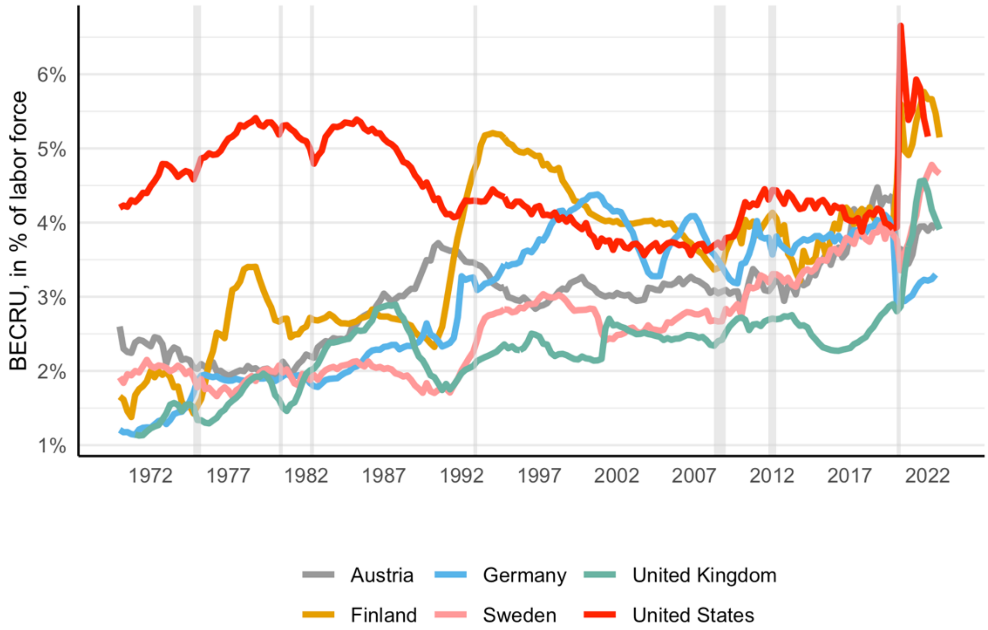

Figure 3: Beveridge (full-employment-consistent) rate of unemployment (BECRU), 1970-2022 (Source: OECD Registered Unemployed Dataset, Michaillat and Saez [2022]; own calculations).

Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991. The Beveridge full-employment consistent rate of unemployment (BECRU) is calculated as: $BECRU = \sqrt{uv}$.

1. The BECRU changes over time and shows different levels across countries. In Germany, Austria, Sweden and Finland, the BECRU was mostly below 2% during the 1970s; in the third quarter of 2022, it stood at 3.3%, 3.9%, 4.7% and 5.5%, respectively. The average BECRU of these three economies mostly increased during the late 1980s and 1990s. This was the period when the Beveridge curves in the EU countries of our sample shifted outward. In comparison, the BECRU of the US was on average significantly higher in the 1970s and 1980s, but actually decreased during the 1990s, a period during which the US Beverdige curve shifted inwards. The case of the UK falls somewhere in between: similarly to its European peers, the UK started with a lower BECRU in the 1970s; after a period of increasing rates in the 1980s, when the UK Beverdige curve initially shifted outwards, the BECRU stabilized and even dropped slightly in the 1990s and 2010s when the Beveridge curve shifted inwards (see Figure 2 for the Beveridge curves of individual countries).
2. Different from the UK and the US, all four EU countries recorded full-employment episodes during the 1970s, indicated by Beveridge full employment gaps below zero. For the EU countries (but not for the US), the 1970s is the period with the smallest distance of the Beverdige curve to the origin, which indicates the highest efficiency of firms and workers in finding suitable matches.
3. The European unemployment problem of the 1980s and 1990s emerges in terms of increasing full employment gaps in all four EU countries. The full employment gap in the US reached its highest level in the early 1980s and was close to zero in the late 1990s. While the full employment gap in the UK also came down below 2 percentage points in the fourth quarter of 1999, Germany, Sweden, Finland and Austria recorded full employment gaps of 6.0, 4.7, 4.3 and 2.2 percentage points, respectively.
4. While full employment gaps tend to rise during recessions and to decline during booms, the experience of EU countries in the 1980s and 1990s was characterized by non-

reversion of the full employment gap to the level it had at the end of the previous business cycle.

5. Full employment gaps initially increased during the first phase of the Covid-19 pandemic, which started in early 2020, given historically unprecedented changes in the Beveridge curve (e.g. Lubik 2021; Kiss et al. 2022). However, when recovery set in, labor markets in all six countries became significantly tighter, which is reflected in a substantial decline in full employment gaps. However, the US was the only country to hit full employment among the six countries covered in Figure 4, as the Beveridge full employment gap moved into negative territory. Notably, the US labor market was already overly tight during the economic upswing that preceded the outbreak of the pandemic (Michaillat and Saez 2022).

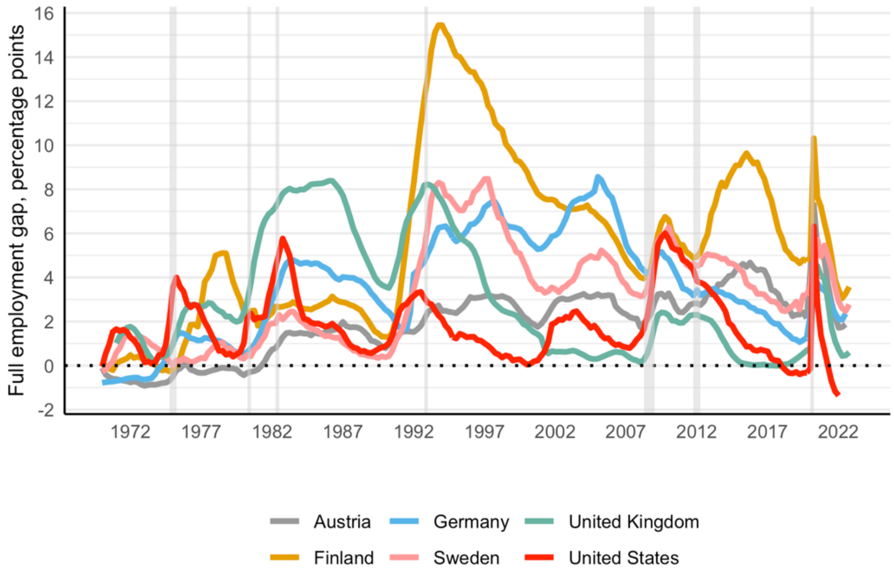

Figure 4: Beveridge full employment gap for six countries, 1970-2022 (Source: OECD Registered Unemployed and Job Vacancies Dataset and Michaillat and Saez [2022]; own calculations).

Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991. The Beveridge full employment gap (g) is calculated as $g = u - BECRU$.

Due to limited data availability, we were only able to show BECRU and full employment gap estimates over the full time period 1970-2022 for the six countries discussed above. However, Figure A 2 in Appendix B shows BECRU estimates over the time period 2000-2022 for a much larger set of 28 countries, including 26 EU countries plus the UK and the US.[6] While we are not able to analyze the European unemployment problem during the 1980s and 1990s for the extended country sample, the data nonetheless provide additional information about recent labor market developments and are further used as a robustness check for the regression estimation of our tested hypotheses. However, while the quality of the vacancy data for the preferred six countries is high, we note that vacancy data for some of the countries captured in extended country sample could be improved; full employment gaps have to be interpreted more cautiously in particular for the Southern and Eastern EU countries.

With this caveat in mind, Figure 5 shows full employment gaps for the extended country sample. The estimates confirm that the unemployment gap tends to increase during slumps and

[6] Denmark is the only EU country we were unable to include due to data limitations with regard to vacancy rates.

to fall during recoveries or booms. In particular, unemployment gaps increased during the slowdown following the financial crisis of 2007/2008, where the increase was much less pronounced in Continental and Nordic EU countries than in Eastern and Southern EU countries. The group of Southern EU countries experienced a severe push away from full employment during the Euro Crisis of 2011-2013.[7] There was a general move towards a reduction in labor market slack across the whole EU before the pandemic, followed by a spike in unemployment gaps when the Covid-19 crisis hit. When recovery set in, labor markets in virtually all the countries covered in Figure 5 became tighter, although to varying degrees. Our data suggest that Czechia and Netherlands are the only EU countries to hit the full employment-consistent rate of unemployment during the pandemic recovery, thereby joining the US.[8] For the Eurozone as a whole, we find that the population-weighted average of the full employment gap is still close to 4% at the end of 2022, while the US exhibits a negative full employment gap (see Table A 5 in the appendix). This suggests that there is significantly more slack in Eurozone labor markets than in the US. This is consistent with recent IMF work, which shows that the rise in core inflation in the Eurozone in 2022 is not driven by economic overheating, but by large headline shocks in the context of energy price increases – unlike in the US, where there is evidence that the labour market is overly tight (Dao et al. 2023).

[7] Figure A 3 in Appendix B shows the BECRU estimates with population-weights for Continental, Nordic, Southern, and Eastern EU countries as well as Anglo-American countries, respectively. Figure A 4 shows population-weighted full employment gaps for the different country groups.
[8] Luxembourg hit the BECRU before the pandemic in 2019, but we lack vacancy data for more recent quarters.

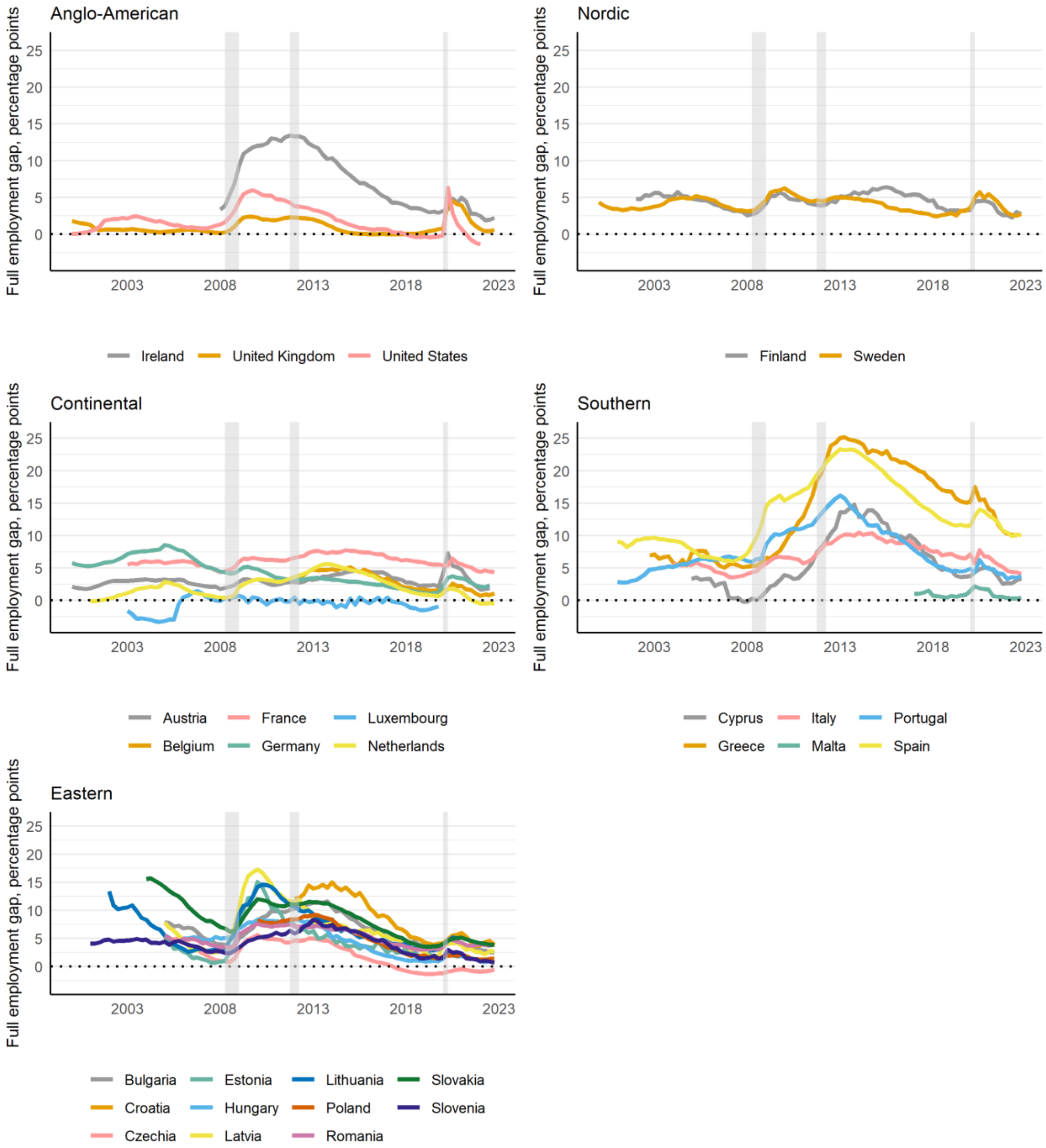

Figure 5: Beveridge full employment gap for the extended sample of 28 countries, 2000-2022 (Source: Eurostat, ISTAT, DARES and Michaillat and Saez [2022]; own calculations).

Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991. The Beveridge full employment gap (g) is calculated as $g = u - BECRU$. The classification of EU countries into Continental, Nordic, Southern and Eastern countries build on Arts and Gelissen (2002).

4. Are Beveridgean full employment gaps informative?

This section provides some first insights into whether our Beveridgean full employment gap estimates are informative, and how they compare with estimates of the NAIRU. Figure 6 compares actual unemployment rates, our BECRU estimates and the European Commission's NAIRU estimates for our preferred data sample of six countries over 1970-2022. Our BECRU estimates vary over time, but they move less than the NAIRU estimates, where the latter were produced by means of a multivariate Kalman filter with a Phillips curve relationship in the background (Havik et al. 2014). Our finding that the BECRU is more stable supports the theoretical observation that the Beveridge curves and related measures are less susceptible to shifts and fluctuations than Phillips-curve relationships (Dickens 2008). In the 1970s, NAIRU estimates in Germany, the UK, Sweden and the US were partly even lower than the BECRU estimates. However, the NAIRU estimates then increased more strongly in the 1980s and 1990s than the BECRU estimates. This implies that Beveridgean full employment gaps during the 1980s and 1990s are typically larger than NAIRU unemployment gaps, where the latter are given by the difference between actual unemployment and the NAIRU. In 2022, the US is the only country that shows a higher BECRU than NAIRU. This implies that for all countries shown in Figure 6 except for the US, the BECRU estimates currently point to more labor market slack than the NAIRU estimates.

Figure 6: Actual unemployment rate, BECRU and NAIRU estimates, 1970-2022 (Source: OECD, Eurostat, ISTAT, DARES and Michaillat and Saez [2022], AMECO; own calculations).

If the BECRU minimizes the non-productive use of labor, then we would expect a (close to) zero full employment gap to be related to a low share of youth who are unemployed and not receiving education or vocational training (Not in Education, Employment, or Training, NEET). This is indeed what we find when we look at Figure 7, which shows the development of NEET (left y-axis) and the Beveridgean full employment gap (right y-axis) over 2000-2021[9] for our preferred six country sample. For all countries but Austria and the UK, there is a strong positive relationship, and the data show that NEET is typically lowest when actual

[9] NEET data for the period 1970-1999 are unavailable.

unemployment is close to the BECRU. As Figure A 6 in the appendix shows, the correlation of NAIRU gap estimates with NEET is considerably weaker at the individual country level.

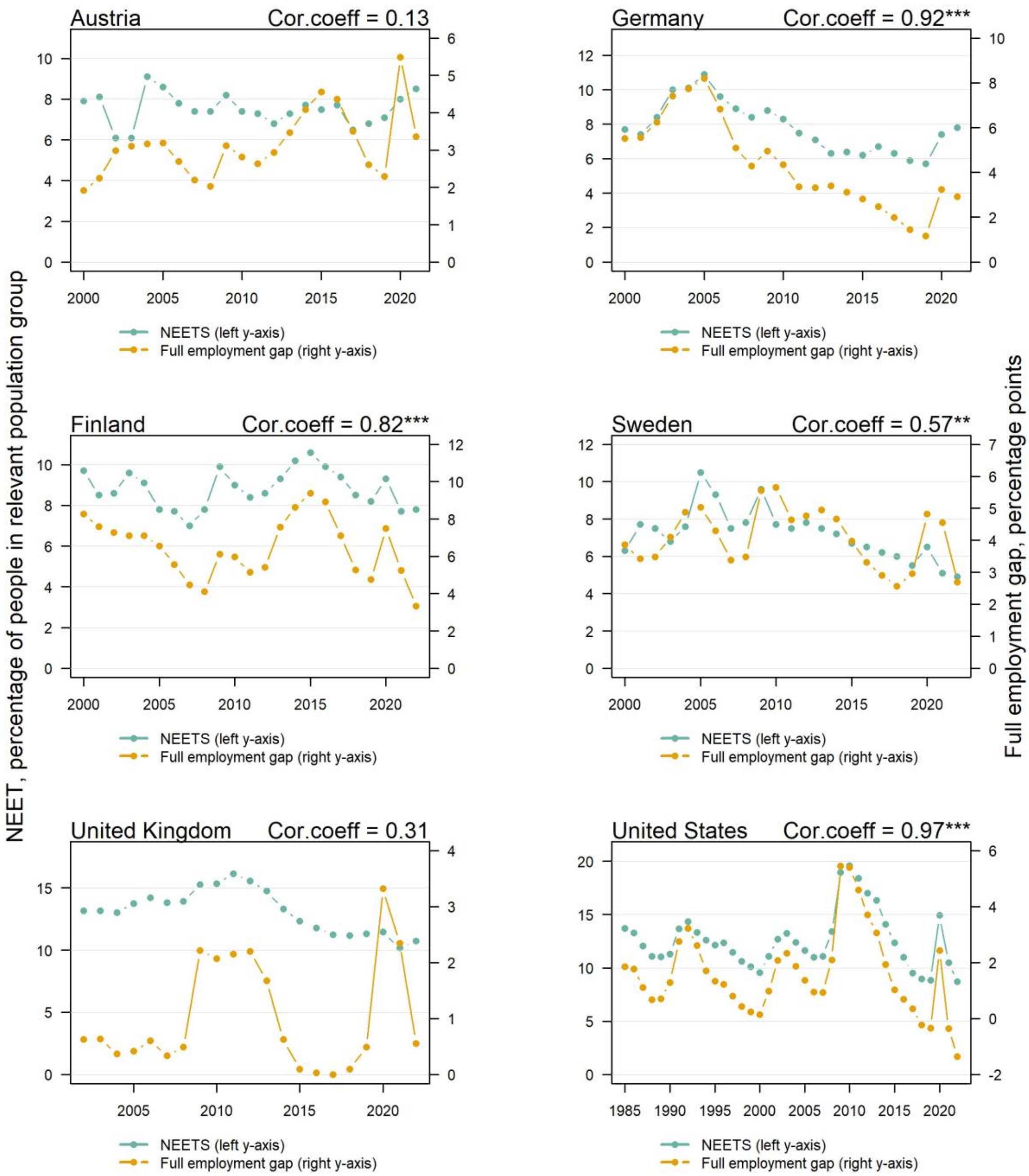

Figure 7: NEET rate and BECRU full employment gap estimates, 2000-2022 (Source: Eurostat, OECD, Michaillat and Saez [2022], ONS, and BLS; own calculations).

To investigate whether our full employment gap estimates do reasonably well in predicting NEET, we estimate the following panel model:

$$NEET_{i,t} = \alpha + \beta\, SLACK_{i,t} + \gamma\, ACTPOP_{i,t} + \zeta_i + \xi_t + \varepsilon_{i,t} \qquad (1)$$

where $NEET_{i,t}$ refers to NEET in country i and year t; $SLACK_{i,t}$ is the labor market slack measure, i.e. either the Beveridgean full employment gap (FEGAP) or the NAIRU unemployment gap (NAIRUGAP); $ACTPOP_{i,t}$ is the growth rate of the active population (aged between 15 and 64 years); ζ_i refers to country-fixed effects; ξ_t captures time-fixed effects; $\varepsilon_{i,t}$ is the error term.

We are interested in predicting NEET in the years running up to the Covid-19 crisis using different labor market slack measures, FEGAP and NAIRUGAP, and comparing the results. We use the period 2000-2014 as the training sample in our preferred dataset, and the 2015-2019 obervations for the out-of-sample forecast. Table 1 shows the panel regression results based on equation (1) for the training sample. We find that higher full employment gaps are significantly related to higher NEET (and vice versa); but this also holds for the NAIRU unemployment gap. We find that the adjusted R-squared is significantly higher for the model including the Beveridgean full employment gap compared to the NAIRU unemployment gap. We then estimate out-of-sample root mean squared error (RMSE) forecasts, which measure the average distance between the values predicted by the model and the actual values. We find that the RSME for model (1), including the full employment gap as a regressor, is 3.59, which is lower than the 4.33 for model (2). As a lower RSME suggests that a model performs better, our results suggest that the Beveridgean full employment gaps does better than the NAIRU unemployment gaps in predicting NEET. A graphical representation that compares the the fitted values of the different models with the NEET data can be found in Figure A 7 in appendix B.

Furthermore, if the BECRU were an informative measure, we would expect the Beveridgean full employment gaps to do reasonably well compared to NAIRU unemployment gaps in predicting inflation. To test this, we again run a panel regression model with country- and time-fixed effects, where we regress core inflation – i.e. headline inflation excluding the volatile components energy and food – on the labor market slack indicator, and further control for labor productivity growth, measured in terms of GDP per hours worked:

$$CINFL_{i,t} = \alpha + \beta\, SLACK_{i,t} + \gamma\, PROD_{i,t} + \zeta_i + \xi_t + \varepsilon_{i,t} \qquad (2)$$

In reference to Table 1 we see that results in model (3) show that higher full employment gaps are related to lower core inflation (and vice versa), although not significantly so; but this also holds for the NAIRU unemployment gaps in model (4) which also reflect a negative and insignificant coefficient. We then again estimate out-of-sample RSME values. We find that the RSME for model (3), including the full employment gap as a regressor, is 0.52, which is slightly above the 0.48 for model (4). The similarity of predicted values of the FEGAP and NAIRUGP estimates is also visualized in Figure A 8 in appendix B. Hence, our results suggest that the Beveridgean full employment shows a similar performance in predicting core inflation compared to NAIRU unemployment gaps.

The results presented in this section only provide some first, incomplete insights; future research needs to do more work to analyze how informative the Beveridgean full employment gaps based on BECRU estimates actually are, as this would be beyond the scope of this paper. However, our preliminary findings suggest that the Beveridgean full employment gap estimates are informative compared to NAIRU unemployment gaps when it comes to predicting NEET and core inflation.

Table 1: Predicting NEET and core inflation (covering the period 2000-2014)

	Dependent variable:			
	NEET		CINFL	
	(1)	(2)	(3)	(4)
FEGAP	1.040^{***}		-0.020	
	(0.202)		(0.076)	
NAIRU_gap		1.354^{***}		-0.103
		(0.310)		(0.090)
ACTPOP	-0.639^{***}	-0.574^{***}		
	(0.192)	(0.212)		
PROD			0.033	0.026
			(0.089)	(0.089)
Observations	88	88	88	88
R^2	0.690	0.599	0.007	0.027
Adjusted R^2	0.591	0.472	-0.309	-0.282
F Statistic (df = 2; 66)	73.433^{***}	49.330^{***}	0.219	0.925
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Estimates for the constant and for country-fixed and time-fixed effects are not shown for brevity. ***, ** and * refer to statistical significance at the 1%, 5% and 10% level, respectively. Cluster-robust standard errors are shown in parentheses.

5. Predictors of full employment gaps

5.1. Hypotheses and econometric model

In what follows, we discuss factors that may contribute to explaining full employment gaps. We formulate hypotheses based on theoretical considerations on how we expect these factors to be related to full employment gaps. The hypotheses are motivated by various strands of the literature on the European unemployment problem.

First, the European unemployment literature has highlighted the potential role of hysteresis, where higher unemployment persists even after the event that initially pushed unemployment upwards no longer plays a role. Blanchard and Summers (1986) argue that classical or New Keynesian macroeconomic theories struggle to explain the European unemployment problem in the 1970s and 1980s. An alternative explanation builds on hysteresis theory: an increase in unemployment rates or a move away from full employment can be persistent if the structural rate of unemployment shifts upwards (e.g. Ball and Onken 2022). We proxy for hysteresis in unemployment by including the lag of the full employment gap, where a statistically significant positive coefficient in the regressions would suggest that past values of the full employment gap correlate with full employment gaps contemporaneously, which would indicate persistence.[10] Another approach to accounting for hysteresis is to control for long-term unemployment. However, since data on long-term unemployment is not available for all six countries in our sample over the full time period (i.e., no data for some countries during the

[10] An additional benefit of including the lagged dependent variable is its technical feature of controlling for unobserved heterogeneity and endogeneity issues in panel data analysis.

1970s and 1980s), we do not include long-term unemployment in our baseline regression specification but include it as an additional explanatory variable in our robustness test section in Appendix D.

Second, we hypothesize that labor market institutions are significantly associated with full employment gaps. A voluminous literature has argued that rigid labor market institutions contribute to (persistently) high unemployment, which may help explain the rise in unemployment in many European countries from the 1970s to the 1990s (e.g. OECD 1994; Nickell 1997; Baccaro and Rei 2007). In this context, the role of employment protection legislation (EPL) has been analyzed prominently. The expectation based on the standard competitive model is that higher employment protection increases unemployment and, therefore, the full employment gap: resource costs rise due to a decline in the freedom to contract; insiders demand higher wages; the economy's ability to adjust to external shocks declines, which inhibits the reallocation of labor, thereby slowing job creation. However, the introduction of market imperfections may overturn this result (e.g. Heimberger 2021). The overall impact of EPL depends on the degree of wage flexibility, the labor demand function, labor turnover and other factors (e.g. Boeri 1999; Boeri and Jimeno 2005). We use the OECD's Employment Protection Index to measure the extent of job protection.[11] When it comes to the role of labor market institutions, trade unions also feature prominently. In this context, the power of organized labor in wage negotiations may not only affect business decisions but also how much governments focus on the political goal of reaching full employment (e.g. Pissarides 2006). One hypothesis is that a decline in labor power leads to a lower importance of full employment policies, thereby contributing to an increase in full employment gaps. However, insider-outsider theory (e.g. Lindbeck and Snower 2001) suggests the opposite prediction: if trade unions support the insiders (members) by pushing for higher wages and benefits, but undermine the interests of the outsiders (the unemployed or non-union members), then more powerful trade unions can be related to higher full employment gaps. We collect data on trade union density; higher union density proxies higher labor power, and vice versa (see Table 2). We do not account for other labor market institutions such as the unemployment benefit replacement rate due to problems with data coverage during the 1970s and 1980s.

Third, we formulate the hypothesis that structural factors contribute to explaining full employment gaps. Economic globalization promotes increased international competition between companies. It is ex ante unclear whether this leads to offshoring of jobs and larger full employment gaps, or whether higher integration across borders helps reduce full employment gaps. We measure economic globalization by using the KOF globalization index, which captures the dimensions of trade and financial globalization (Gygli et al. 2019). Another important structural factor that could affect full employment gaps is Total Factor Productivity (TFP) growth, which can potentially contribute to lowering unemployment if it raises output and employment, so that using the same amount of resources allows for producing more goods and services (e.g. Blanchard and Wolfers 2000). However, TFP growth may also induce job losses in some sectors of the economy, as more productive businesses produce the same amount of output with fewer employees, where the effect may also depend on the level of education and the flexibility of the labor market (e.g. Moreno-Galbis 2012). Furthermore, we consider that population developments may relate to labor market outcomes by using the growth rate of active population. The relationship between population growth and unemployment is complex, and might be positive or negative (e.g. Makarski et al. 2023). A larger active population will increase the labor supply, thereby increasing the competition for jobs, which may push up the

[11] For the period 1970-1984, we have to use the EPL indicator provided by Blanchard and Wolfers (2000), which we merge and make consistent with the OECD EPL index over 1985-2019.

full employment gap. However, a growing active population may also increase the demand for goods and services, thereby stimulating growth and reducing full employment gaps.

Fourth, we consider whether macroeconomic factors play a role. We hypothesize that higher capital accumulation is related with lower unemployment (and vice versa), which is akin to a short-run Keynesian demand relation. We measure capital accumulation as the ratio between real gross fixed capital formation and the real net capital stock (e.g. Heimberger et al. 2017). We also test whether a decline in public sector capital accumulation has a stronger or weaker impact on full employment gaps than private sector capital accumulation. Changes in capital accumulation are correlated with cyclical conditions. In our robustness test section in Appendix D, we also include a further regression specification that uses the output gap variable as an additional control variable for business cycle shifts. Furthermore, we account for the potential impact of inflation. Here, we would expect a negative relationship with full employment gaps if there were a trade-off between unemployment and inflation, as such a trade-off is often a modeling feature in the empirical literature (e.g. Nickell 1997).

Fifth, political forces can support an increase in employment levels or deemphasize full employment (Kalecki 1943). Political majorities in countries can be either more business or worker-oriented, with different implications for how high full employment ranks on governments' priority lists. We hypothesize that more left-leaning governments tend to emphasize full employment, while right-wing governments rather push for more conservative economic policies that prioritize goals such as fiscal discipline or price stability over full employment. We construct a variable for the left-right orientation based on data concerning the political inclination and majority relationships of governments on a scale ranging from zero (far right) to ten (far left).[12]

We specify the following baseline econometric model to test the hypotheses related to hysteresis, labor market institutions, structural factors, macroeconomic factors, and political factors:

$$FEGAP_{i,t} = \alpha + \beta\, H_{i,t-1} + \gamma\, L_{i,t-1} + \delta\, S_{i,t-1} + \theta\, M_{i,t-1} + \eta\, P_{i,t-1} + \zeta_i + \xi_t + \varepsilon_{i,t} \qquad (3)$$

$FEGAP_{i,t}$ is the Beveridge full employment gap in country i and year t; $H_{i,t-1}$ captures hysteresis in unemployment proxied by $FEGAP_{i,t-1}$, the lag of the dependent variable; $L_{i,t-1}$ is a vector with variables capturing lagged labor market institutions; $S_{i,t-1}$ includes lagged structural factors; $M_{i,t-1}$ refers to lagged macroeconomic regressors; $P_{i,t-1}$ refers to lagged political factors. We follow many studies in the empirical unemployment literature using lagged values for the control variables to "mitigate endogeneity concerns (though, admittedly, not solving them)" (Felbermayr et al. 2014). Furthermore, theoretical considerations suggest that labor market institutions, structural factors, macroeconomic factors and political factors may only affect full employment gaps with a lag. ζ_i refers to country-fixed effects, which we include to account for unmeasurable, time-invariant country-

[12] Data for the dimension of left-right leaning political majorities and governments were constructed by combining datasets from erdda (Bergman et al. 2019; Bergman et al. 2021; Hellström et al. 2021), parlgov (Döring et al. 2023), cpds (Armingeon et al. 2022), and v-party (Lindberg et al. 2022; Pemstein et al. 2020). The main outcome was the real value variable *LRG* (left-right dimension of the government based on parlgov data) that describes the political inclination of the current government and political majority. Data on political inclinations of European parties are taken from the parlgov dataset, and for the US we used information from the v-party dataset that presents evaluations on the political directions of each party. Information about the distribution of cabinet seats to the different parties is collected by the erdda dataset for European countries and by the cpds dataset for several democratic countries including the US.

specific characteristics; and $\varepsilon_{i,t}$ represents the error term. ξ_t are time-fixed effects, which capture time varying shocks that hit all countries. The groups of explanatory variables (H, L, S, M and P) correspond to the hypotheses formulated above;
Table 2 lists detailed definitions and data sources for all variables.

Table 2: Variables used in the regression analysis.

Variable	Abbreviation	Unit	Source
Full employment gap (difference between the actual unemployment rate and the BECRU in percentage points)	FEGAP	In percentage points of the labor force	OECD, Eurostat; own calculations.
1) Unemployment hysteresis (H)			
Lag of the full employment gap	$FEGAP_{t-1}$	In percentage points of the labor force	OECD, Eurostat; own calculations.
Long-term unemployment (+)	LTU	Share of long-term unemployed in total unemployment (in %)	OECD
2) Labor market institutions (L)			
Employment protection legislation (+)	EPL	Index for strictness of employment protection (individual and collective dismissals, regular contracts)	OECD for 1985-2019; IMF (2003) for 1970-1984
Trade union density (-)	UDENS	Share of employees that are union members (in %)	OECD
3) Structural factors (S)			
Economic globalization (-)	EGLOB	Economic globalization index (0-100)	KOF (Gygli et al. 2019)
Total Factor Productivity growth (-)	TFP	Total Factor Productivity (annual growth in %)	AMECO (Autumn 2022); own calculations.
Active population growth (~)	ACTPOP	Annual growth rate of the population aged 15 to 64 years (in %)	AMECO (Autumn 2022); own calculations.
4) Macroeconomic factors (M)			
Capital accumulation (-)	ACCU	Real gross fixed capital formation/real net capital stock * 100	AMECO (Autumn 2022); own calculations.
Public capital accumulation (-)	PUCA	Real gross fixed capital formation in the public sector/real net capital stock * 100	AMECO (Autumn 2022); own calculations.
Private capital accumulation (-)	PRCA	Real gross fixed capital formation in the private sector/real net capital stock * 100	AMECO (Autumn 2022); own calculations.
Inflation (-)	INFL	Consumer Price Index (annual growth rate)	OECD
Output gap (-)	OG	Difference between actual and potential output (in % of potential output)	AMECO (Autumn 2022).
5) Political economy (P)			
Left-right dimension of government (-)	LRG	Degree of the current government in being very right (0) to very left (10)	erdda, parlgov, cpds, and v-party; own calculations.
Time-sensitive dummies			
1980s dummy	EIGHTIES	Binary dummy set to 1 for all the years in the 1980s	Own calculations.
1990s dummy	NINETIES	Binary dummy set to 1 for all the years in the 1990s	Own calculations.
Financial crisis dummy	FINCRISIS	Binary dummy set to 1 for the years 2008/2009	Own calculations.
Welfare-state regimes			
Liberal welfare state dummy	LIB	Binary dummy set to 1 for US and UK	Own calculations.
Social democratic welfare state dumnmy	SOD	Binary dummy set to 1 for Sweden and Finland	Own calculations.
Conservative welfare state dummy	CON	Binary dummy set to 1 for Austria and Germany	Own calculations.

Notes: Own illustration. The signs in brackets indicate the expected sign, where (+) points to an expected positive relationship with full employment gaps, (-) suggests a negative correlation, and (~) indicates that there is no clear prediction.

An important question is how to estimate equation (3), which represents a dynamic panel data model. As we include both a lag of the dependent variable as well as country-fixed effects, using OLS could potentially bias the coefficient estimates (Nickell 1981). However, Judson and Owen (1999) use Monte Carlo simulations to show that the bias depends on T, the number of years in the panel. They argue that when $T > 30$, the bias can be ignored, as a least squares dummy variable estimator then performs at least as good as or better than GMM and other alternatives. This is important for our setting, since the annual dataset is characterized by $T = 50$ for our preferred six country sample (1970-2019). With our data structure of large T but small N, using a GMM estimator is not advisable. Hence, we follow the recommendation in Judson and Owen (1999) and estimate the fixed-effects model using OLS.

We conducted a series of pre-tests including a multi-collinearity analysis, unit root tests, cointegration tests (see appendix C), and further robustness checks (see appendix D). The results do not show any evidence of multi-collinearity or panel non-stationarity. In a further VECM specification of our baseline regression variables, we find further evidence that our dependent variable FEGAP is rather caused by our set of explanatory variables than the other way around. Furthermore the robustness checks applied to our dataset by including further variables and other time-specific dummies confirm our baseline regression results which are presented in the next sub-section below.

5.2. Results

Table 3 shows panel regression results. We include groups of explanatory variables from Table 2 in several steps, as this allows us to check whether the estimated coefficients are robust to controlling for other dimensions. Model (1) starts by accounting for hysteresis represented by the lag of the full employment gap. We find that the lagged value of the full employment gap is significantly associated with contemporaneous full employment gaps, which points to unemployment persistence. This is consistent with the hypothesis that hysteresis plays a role, which is also confirmed in appendix D where the inclusion of long-term unemployment as a regressor also shows a significant increase in the full employment gap.

Model (2) adds explanatory variables for labor market institutions. At first, employment protection legislation and trade union density are not significantly related to full employment gaps. This finding will change when including other control variables as described below.

Model (3) adds structural factors. It shows that higher Total Factor Productivity growth predicts lower full employment gaps. This suggests that, on average, an increase in TFP growth is related to a mitigation of the unemployment problem. We do not find a significant coefficient for economic globalization in column (3). However, higher active population growth is significantly related to lower full employment gaps. This suggests that the increase in labor supply and jobs competition due to a growing active population may, on average, be less important than the overall strengthening of demand for goods and services. While the point estimate of UDENS has increased and its standard error shrinked the coefficient has now turned more positive and highly significant: an increase in trade union density is positively related to full employment gaps. This is inconsistent with the prediction that more powerful trade unions, on average, are related to a stronger full employment focus. The result, however, may be rationalized with insider-outsider theory (Lindbeck and Snower 2001), where stronger unions serving the interests of their members (insiders) may even reduce employment opportunities for outsiders, as they rather fight for higher wages of current employees than higher employment levels.

Table 3: Regression results of our baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FEGAP_{t-1}$	0.928***	0.913***	0.937***	0.926***	0.911***	0.834***	0.979***
	(0.016)	(0.025)	(0.025)	(0.021)	(0.022)	(0.010)	(0.025)
EPL_{t-1}		0.162	0.401*	0.235	0.202	0.003	0.244*
		(0.162)	(0.216)	(0.217)	(0.228)	(0.233)	(0.144)
$UDENS_{t-1}$		0.021	0.029***	0.035***	0.038***	0.024***	0.021**
		(0.015)	(0.010)	(0.011)	(0.012)	(0.009)	(0.009)
TFP_{t-1}			-0.280***	-0.250***	-0.243***	-0.219***	-0.240***
			(0.047)	(0.048)	(0.048)	(0.043)	(0.062)
$EGLOB_{t-1}$			-0.012	-0.022	-0.026	0.031***	-0.044**
			(0.027)	(0.029)	(0.031)	(0.010)	(0.021)
$ACTPOP_{t-1}$			-0.125***	-0.127**	-0.125**	-0.143**	-0.139***
			(0.045)	(0.054)	(0.055)	(0.064)	(0.051)
$ACCU_{t-1}$				-0.054	-0.060	-0.091	0.026
				(0.060)	(0.051)	(0.088)	(0.035)
$INFL_{t-1}$				0.064*	0.064*	0.086***	0.056*
				(0.034)	(0.033)	(0.012)	(0.033)
LRG_{t-1}					-0.052**	-0.107***	-0.037
					(0.026)	(0.036)	(0.025)
EIGHTIES						-0.033	
						(0.209)	
NINETIES						0.547***	
						(0.182)	
FINCRISIS						0.649***	
						(0.219)	
SOD							-1.049**
							(0.442)
CON							-0.185
							(0.225)
Observations	311	297	294	294	294	294	294
R^2	0.870	0.878	0.909	0.911	0.912	0.898	0.938
Adjusted R^2	0.841	0.848	0.885	0.888	0.888	0.892	0.922
F Statistic	1,692.177*** (df = 1; 252)	570.730*** (df = 3; 239)	385.658*** (df = 6; 233)	296.875*** (df = 8; 231)	265.859*** (df = 9; 230)	202.362*** (df = 12; 276)	319.235*** (df = 11; 233)

Notes: Dependent variable: FEGAP. Details on the variables used are available in
Table 2. Estimates for the constant and for country-fixed effects are not shown for brevity. ***, ** and * refer to statistical significance at the 1%, 5% and 10% level, respectively. Cluster-robust standard errors are shown in parentheses.

Model (4) then adds macroeconomic factors. Capital accumulation is not significantly related to full employment gaps, which is inconsistent with the theoretical prediction that higher investment is related to a decline in full employment gaps. Notably, we find a positive and significant inflation coefficient. This suggests that, on average, there is no trade-off between inflation and full employment gaps.

To account for the role of political factors, model (5) controls for the left-right orientation of governments. We find that more left-leaning governments are associated with a decline in full employment gaps. This is consistent with the hypothesis that left governments put more emphasis on full employment than right governments.[13]

We further extend our baseline specifications of columns (1-5) by adding specific time-related dummies. Model (6) does not include year-fixed effects as in the previous specifications; instead, we now control for dummy variables for the 1980s, the 1990s and the financial crisis of 2008/2009, respectively. We include these variables to test for period-specific effects on full employment gaps. We find a positive and significant coefficient of the Nineties dummy and financial crisis dummy, respectively, whereas the coefficient of Eighties lacks significance. This suggests that there was something specific to how full employment gaps were affected during the 1990s and the financial crisis, when many advanced economies experienced a marked rise in unemployment. Importantly, coefficient estimates of the other control variables remain robust. The only major difference is that the coefficient of economic globalization turns positive and significant.

Finally, model (7) extends our baseline model by controlling for different welfare state regimes instead of country-fixed effects. The results suggest that, controlling for all the other confounding factors, the social democratic welfare states in our sample (Sweden and Finland) have lower average full employment gaps than the liberal welfare states (US and UK); the latter, however, do not show a significant difference to the conservative welfare regimes (Austria and Germany). It is notable that the variable measuring the left-right-dimension of government is now smaller in absolute size and loses significance. This suggests that the relationship of political partisanship with full employment gaps is moderated by the type of welfare state regime. Furthermore, the variable EGLOB switches sign, as it now indicates that an increase in economic globalization is related to decline in full employment gaps. This suggests that the results obtained for the EGLOB variable are sensitive to how we account for unobserved country characteristics. Regression results with individual country-specific dummies are further included in appendix D (see Table A 6). Its last column with all country dummies is equal to model (5) of the above regressions and while some individual country effects differ from above's welfare regime dummies the overall tendencies remain: conservative country types (AUT and DEU) do not differ significantly from the liberal type countries (GBR and USA), but social democratic country types (SWE and FIN) exhibit relatively lower average full employment gaps.

[13] The literature suggests that the ability of left governments to promote progressive social policies depends on trade union strength of workers (e.g. Korpi 2006). Hence, we also include an interaction term between the left-right political orientation of a government and the labor union density variable, but the regression results do not point to a significant interaction term. Results are available upon request.

Based on a cointegration analysis in appendix C (see Table A 4 and Table A 5) we find further evidence on the long-run relationship of variables in our analysis. Especially $FEGAP_{t-1}$, TFP_{t-1}, $INFL_{t-1}$, LRG_{t-1} show a strong and negative cointegration relationship with FEGAP, adding weight to the evidence supporting the relationship between them.

As a matter of further robustness checks, we carried out several additional regression strategies that can be found in appendix D. In one of the tests we adopted our regression approach of equation (3) by averaging our yearly data over a period of five years to account for business cycle dynamics (e.g. Romero and McCombie 2016). The results generally confirm the takeaway of the regression output of section 5, though some point estimates diminished while standard errors increased, leading to less and fewer significant coefficients regression results, which can be seen as a consequence of the reduction in the data variation through the averaging process (for more details see Table A 7). In another test we substituted the left-hand-side variable of equation (3) with the NAIRU gap (NAIRUGAP) to check for consistent correlations of reported explanatory variables. While we note some variations in the sign and size of coefficient estimates, we do not find major differences between the NAIRUGAP results of Table A 8 and FEGAP results of Table 3. Next, we include another set of regressions with additional regressors. Table A 9 shows that the effect sizes and statistical significance of estimators remain almost the same, contributing to the consistency of our estimation results. Additionally added/tested variables include (1) the output gap (OG) as an additional measure for business cycle shifts; (2) a different hysteresis measure, namely long-term unemployment (LTU); (3) a separation of the accumulated capital into a public (PUCA) and private (PRCA) rate; and (4) a different variable to measure the left-right share of governments (LRG_cp) which is based on cpds 'only' instead of parlgov data.[14] The biggest differences are reported in the case where LTU was included, which increased the standard errors for UDENS, TFP, ACTPOP and INFL and made them insignificant but also increased the point estimate of ACCU which turned out negative and significant. As mentioned above, the estimation with LTU is based on a significantly smaller sample size (225 instead of 294 observations) due to missing data on long-term unemployment for some countries in our sample; hence, the results are not directly comparable to our baseline specifications. The cases of the other models confirm our previously reported regression results also point to hysteresis: if workers remain unemployed for a longer time, it is more likely that current unemployment will go further up. Lastly, we also applied our regression approach of equation (3) to a bigger panel dataset of 28 countries, between 2000 and 2022. The results confirm the significant relations of $FEGAP_{t-1}$, $UDENS_{t-1}$, and TFP_{t-1} and additionally reflect a negative and significant association of $EGLOB_{t-1}$ and $ACCU_{t-1}$ with FEGAP (for more details see appendix D, Table A 10).

More generally, the conducted regressions and tests show consistent results regarding $FEGAP_{t-1}$ and $UDENS_{t-1}$ as being positively and significantly related to FEGAP, while EPL_{t-1} consistently shows insignificant coefficients (i.e., more rigid EPL is not significantly related with higher full employment gaps). For the TFP_{t-1} coefficients, which are mostly negative, though sometimes insignificant, we do find some deviations in their relation with FEGAP. $EGLOB_{t-1}$ mostly appears as insignificant though it also shows negative and significant point estimates (e.g. in cases of the short data panel as well as for the NAIRUGAP regressions); $ACTPOP_{t-1}$ is generally negatively signed and significant, although this is not a very robust

[14] Whereas parlgov lists the amount of seats of political parties in parliament and government, cpds only shows the government composition in percentage of total cabinet posts for three clusters, namely a right-wing, center and left-wing cluster. However, an advantage of the cpds data is that it is fully consistent since it contains data on all countries in our data set between 1960 and 2020. Parlgov on the other hand does not contain information on the USA regarding cabinet seats. Hence, US data for the LRG_pg variable were imputed with the help of cpds data.

relation; $INFL_{t-1}$ mostly appears with positive and a significant coefficients though some specifications reveal high standard errors with a loss in the significance of the results; LRG_{t-1} is generally negative and significant though as reported for the country-specific dummy regressions there appears to be unobserved heterogeneity within welfare regimes and across countries. For ACCU, we mostly find negative coefficients, but they are often not significant, although some regression specifications also reveal negative and significant point estimates for ACCU (e.g. regression with additional regressors or regressions with short panel data).

6. Conclusions

This paper has analyzed deviations from full employment in EU countries compared with the US and the UK. By building on seminal contributions by Michaillat and Saez (2021, 2022), we have relied on a full employment measure derived from the Beveridge curve, the relationship between unemployment and vacancies. We call this measure the Beveridge (full-employment-consistent) rate of unemployment (BECRU), which is the amount of unemployment that minimizes the nonproductive use of labor. Our work contributes to the literature by conceptualizing full employment via the BECRU and applying it to the European unemployment problem.

We have constructed a novel dataset with BECRU estimates covering four EU countries, the UK and the US over the time period 1970-2022. For a shorter time period (2000-2022), we have provided estimates for 26 EU countries plus the UK and the US. Based on this new data set, which is publicly available and will be regularly updated to facilitate further research,[15] we have derived a set of stylized facts. First, BECRU estimates differ across countries and can change over time. Second, EU countries experienced a marked rise in full employment gaps – defined as the difference between actual unemployment and the BECRU – in the 1980s and 1990s, as the European unemployment problem emerged. The years during the 1990s and the financial crisis of 2008/2009 appear as the periods with the strongest increases in full employment gaps. The full employment gaps in the US showed more wave-like patterns compared to the step-wise increases in full employment gaps of EU countries over time, which could be due to different labor market structures. Third, full employment gaps increased during the first phase of the Covid-19 crisis in 2020. But when recovery set in, labor markets in all countries became significantly tighter. However, our estimates suggest that Czechia and the Netherlands were the only EU countries to join the US in hitting full employment during the labor market recovery from the pandemic. Our analysis of selected EU countries (Germany, Austria, Sweden, Finland) suggests that the last historical record of full employment is to be found in the 1970s. Our analysis further suggests that the Eurozone and most individual member countries have recently experiencied significantly more labor market slack than conventional NAIRU and output gap estimates produced by organizations such as the European Commission suggest. The European Commission's NAIRU and output gap estimates point to comparably less slack during and after the Euro Crisis than our full employment gap estimates (e.g. Brooks and Fortun 2020; Heimberger and Kapeller 2017).

The final part of our paper has presented a regression analysis to shed light on the factors that contribute to explaining full employment gaps. We have formulated a set of hypotheses with regard to unemployment hysteresis, labor market institutions, structural factors,

[15] The dataset is available via: https://github.com/heimbergecon/fullemployment

macroeconomic factors, and political factors. We have tested these hypotheses by running panel regressions. We find that larger full employment gaps are, on average, significantly related to: larger full employment gaps in the past; an increase in trade union density; lower productivity growth; and more right-leaning governments.

A caveat with regard to full employment gaps based on the BECRU is that our estimates depend on the quality of the underlying vacancy data. Due to our interest in understanding full-employment gaps over the past five decades, our research approach is restricted by the availability of quality long-term time series. Previous studies have reported on the shortcomings of aggregate unemployment and vacancy data (e.g. Komlos 2021, and Fontanari et al. 2022). We argue that our preferred sample of six countries provides good quality vacancy data, but there could be underreporting of vacancies to an unknown degree, in particular for some of the countries in the extended country sample. Further improvements in the availability and reliability of the vacancy data would be helpful for further research. Furthermore, while the Beveridge full employment gap used in our study provides important information for researchers and policy-makers on whether labor markets are overall slack or tight, a notable limitation is that our approach does not deal with informal employment, underutilized labor (Komlos 2021; Fontanari et al. 2022), or the quality of jobs in the vacancy-unemployment space. The BECRU approach builds on a whole economy perspective, but this does not account for how different groups of labor market participants are affected. Extensions of our work, therefore, could aim at estimating full employment gaps by age, education and race, which may require an adapted methodology. Future research could also provide case studies for selected advanced economies and key periods (e.g. EU integration) to better understand full employment-supportive economic, political and institutional circumstances in comparison to environments characterized by larger full employment gaps. Finally, our framework could be extended to emerging-market economies and developing countries to allow for comparisons with advanced economies.

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Supplementary appendix (for online publication only)

Appendix A: Data sources

This appendix describes the data that are introduced in sections 2 through 4. Since our focus on the European unemployment problem requires long time series, data availability for vacancy and unemployment rates was an issue. We are able to construct time series over the full time period 1970 to 2022 for Austria, Germany, Finland, Sweden, and the UK. In addition, we use existing US data provided by Michaillat and Saez (2022).

Eurostat and OECD publish quarterly data on the stocks of unfilled job vacancies. The OECD Registered Unemployment and Job Vacancies dataset, a component of the MEI database, is a major source of information for both unemployment levels and job vacancies. The dataset offers a more comprehensive historical perspective, with data available from as early as the 1970s. In contrast, Eurostat's data only go back to 2000 and start even later for several countries. When comparing the data on the inventory of unfilled job vacancies between OECD and Eurostat, we found significant differences for Germany and Austria, with Eurostat estimates being notably higher. The primary reason for this discrepancy is the difference in data sources. While OECD obtains vacancy data from administrative records, Eurostat relies on labor force surveys. According to national statistics institutes (Destatis and Statistik Austria) and Eurostat, the administrative records collected by public employment services cover only a portion of the job market, with jobs requiring higher qualifications being less frequently reported to these services, as enterprises often do not anticipate finding suitable candidates there. Consequently, to account for the underreporting of job vacancies with higher qualifications in the OECD dataset, we use the Eurostat data from 2010 Q1 onwards and for the period between 1970 Q1 and 2009 Q4. Predicted job vacancy values, derived from regressing Eurostat on OECD data, are used for the adjustment of registered job vacancy levels. We exclude the time period of the pandemic from early 2020 onwards from the regression that we utilize for adjustment, as the pandemic represents a unique period with a significant increase in vacancies that could bias the results.

The quality of data concerning job vacancy statistics has been a point of concern in previous studies. Previous literature has already emphasized data quality issues in certain states due to varying definitions of job vacancies and distinct sampling practices. In the European Union, job vacancy statistics are compiled under the framework of Regulation 453/2008 and Eurostat, conducts data quality checks to ensure comparability and reliability throughout the dataset. However, the low job vacancy rates in certain Southern European countries, notably Spain, have been a subject of debate in the previous literature: While these low rates may initially imply limited employment prospects and economic stagnation, the literature also argues that the situation might stem from local customs and practices (Boscá et al. 2017). Particularly in Spain, the prevalence of distinct recruitment methods and the extensive reliance on temporary contracts can result in a reduced tally of formally reported job vacancies. This applies beyond Spain, highlighting the need to understand distinct labor market practices when interpreting job vacancy data across Member States and recognizing the potential for data discrepancies that could underestimate job vacancy rates due to these custom-induced variations. This concern is not relevant to our selected countries, as their labor markets and recruitment processes are notably consistent and transparent. Our primary concern lies in potential downward bias resulting from the underreporting of high-skill jobs in administrative data, a factor we have taken into consideration. The adjustment procedure for high-skill job vacancies, as identified through the labor force survey, significantly improves the comparability of registered vacancy data within the selected five countries. Subsequently, with this refinement, these five designated countries present data of high quality.

To calculate the vacancy rate, which is calculated as the stock of unfilled vacancies divided by the active population, and the unemployment rate, which is constructed by dividing the level of unemployed by the active population, we rely on the Active Population variable from the OECD Short-Term Labor Market Statistics dataset. While this dataset provides comprehensive quarterly statistics for most countries, the data for Sweden and Finland are only available from 1998 onwards. To ensure continuity in the dataset, we supplement the Swedish data with statistics on active population and unemployment levels from the Statistics Sweden's (SCB) Population by Labor Status database. To mitigate the impact of seasonal fluctuations on variables that were not originally available in seasonally adjusted values, we utilized a seasonal ARIMA model to adjust for seasonality in the data. Concerning Finland, OECD data is only available from 1998 onwards for the active population and from 1981 onwards for unemployment levels. To extend the dataset, we include archived OECD data obtained from FRED. Similar to the approach taken for adjusting vacancy data, we use predicted values to modify archived unemployment and the active population data to correspond with the more recent OECD observations.

To cover a larger group of EU member states over the period of 2000-2022, we supplement the data with information from other national sources such as ISTAT (The Italian National Institute of Statistics), and DARES (Ministry of Employment, Government of France). For France, we employ vacancy stock data from DARES, and for Italy, we use vacancy rate data from ISTAT. For the remaining EU member states, we obtain data on vacancy stock, unemployment levels, and active population from Eurostat. Despite variations in data availability across countries, we are able to create an unbalanced data series from 2000 to 2022 that covers 26 EU Member States (except for Denmark, which we have to exclude due to the lack of vacancy stock data).

Finally, the data on NEET, introduced in section 4, is derived from different sources. NEET refers to young people who are neither pursuing further education nor engaged in any employment or training activities. This data is typically expressed as a percentage within the corresponding age group. For EU Member States, the data is sourced from Eurostat, which offers annual NEET rate of individuals aged 15 to 24 years. In the UK, The Office for National Statistics (ONS) publishes quarterly statistics focused on NEET rate of individuals aged 15 to 24 years. For the US, data is gathered from the Bureau of Labor Statistics (BLS), which releases monthly data concerning the NEET rate of individuals aged 16 to 24 years. Since, the data from the US and UK are provided by monthly or quarterly reports, we aggregate the data to obtain annual figures.

Appendix B: Additional unemployment and vacancy rate charts

This appendix reports additional information and unemployment and vacancy rates as well as BECRU and full employment gap estimates.

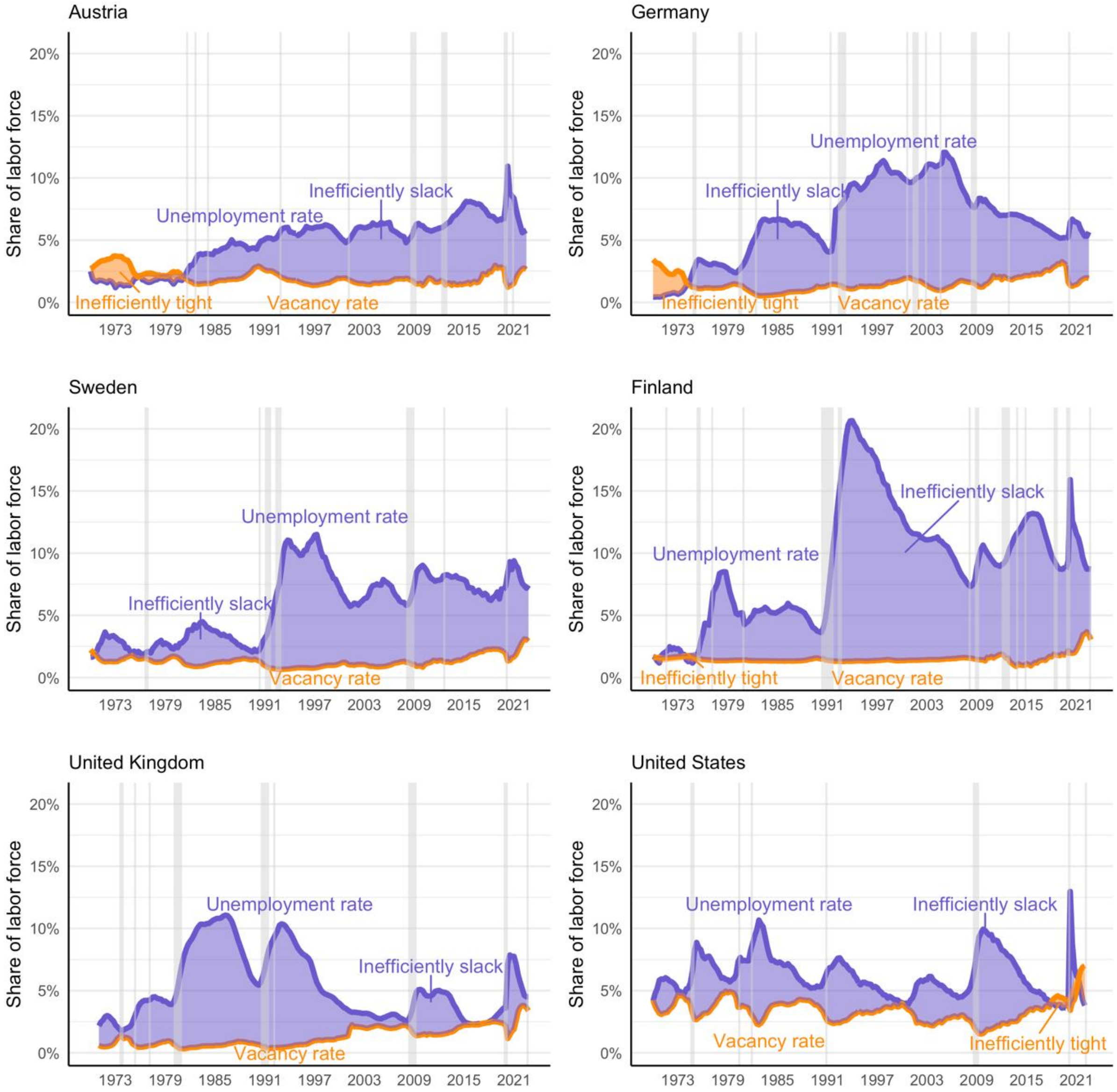

Figure A 1: State of labor market, 1970-2022 (Source: OECD, Registered Unemployed and Job Vacancies Dataset and Michaillat and Saez [2022]).

Notes: The grey areas in the figure indicate periods of recession in individual countries. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991. The labor market is considered inefficiently slack when the unemployment rate is higher than the vacancy rate (indicated by the purple shade), and inefficiently tight when the unemployment rate is lower than the vacancy rate (indicated by the orange shade).

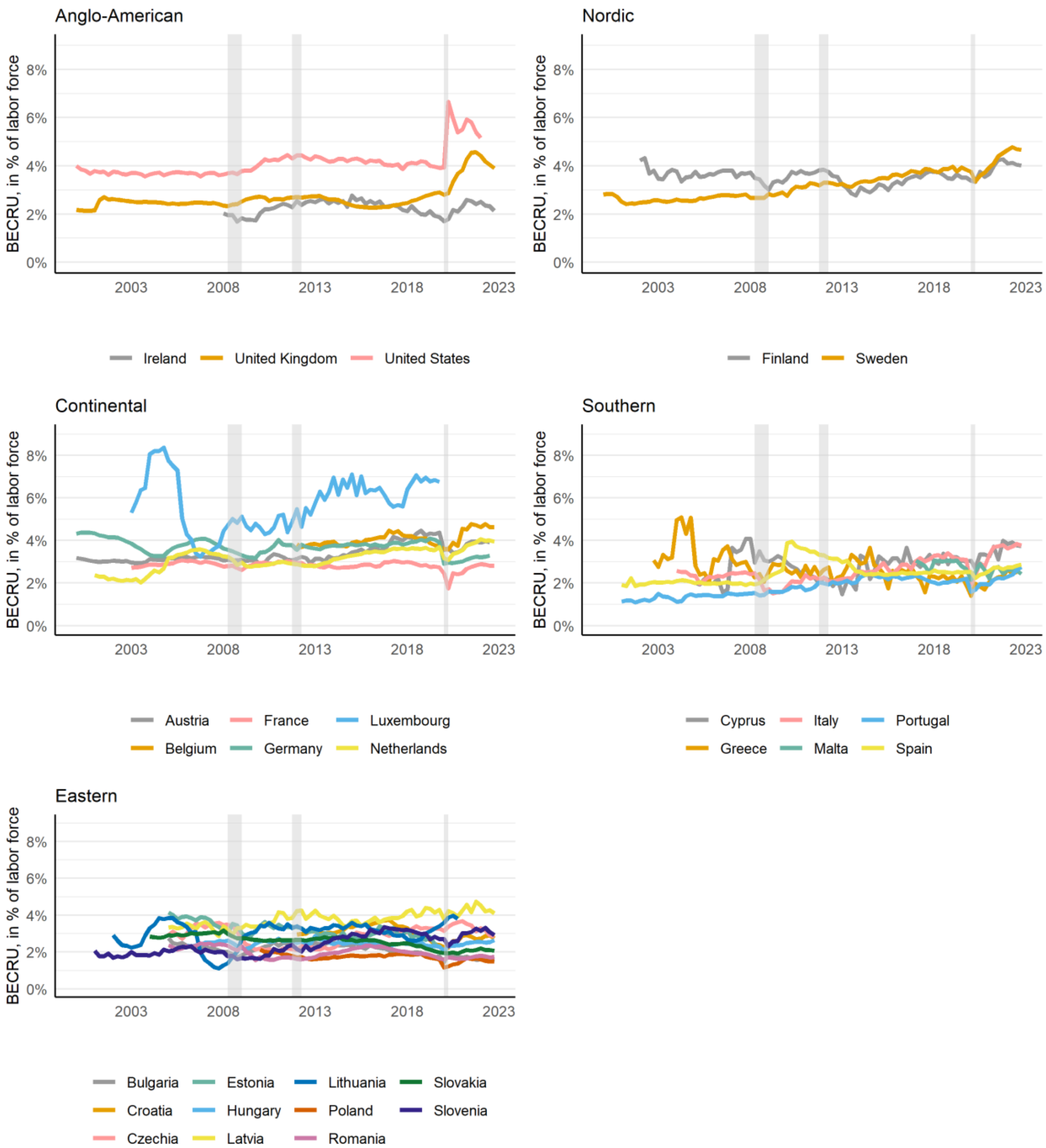

Figure A 2: BECRU estimates for the extended country sample, 2000-2022 (Source: Eurostat, ISTAT, DARES, and Michaillat and Saez [2022]).

Notes: The grey areas in the figure indicate periods of in the aggregated OECD Europe sample. The data for Germany are for West Germany until 1991. A recession is defined as two consecutive quarters of negative real GDP growth.

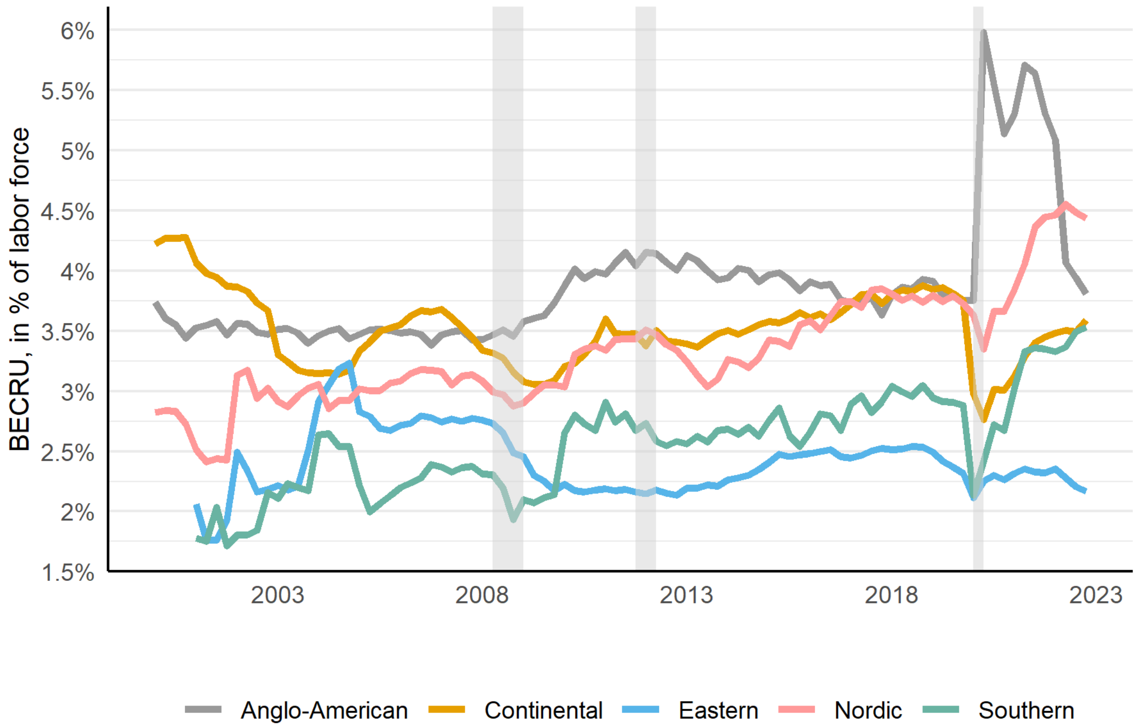

Figure A 3: Population-weighted BECRU estimates for different country groups, 2000-2022 (Source: Eurostat, ISTAT, DARES and Michaillat and Saez [2022]).

Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991. Continental: Austria, Belgium, France, Germany, Netherlands, Luxembourg. Nordic: Denmark, Finland, Sweden. Southern: Greece, Italy, Cyprus, Portugal, Spain, Malta. Eastern: Czechia, Bulgaria, Estonia, Croatia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia, Slovakia; Anglo-American: US, UK, Ireland.

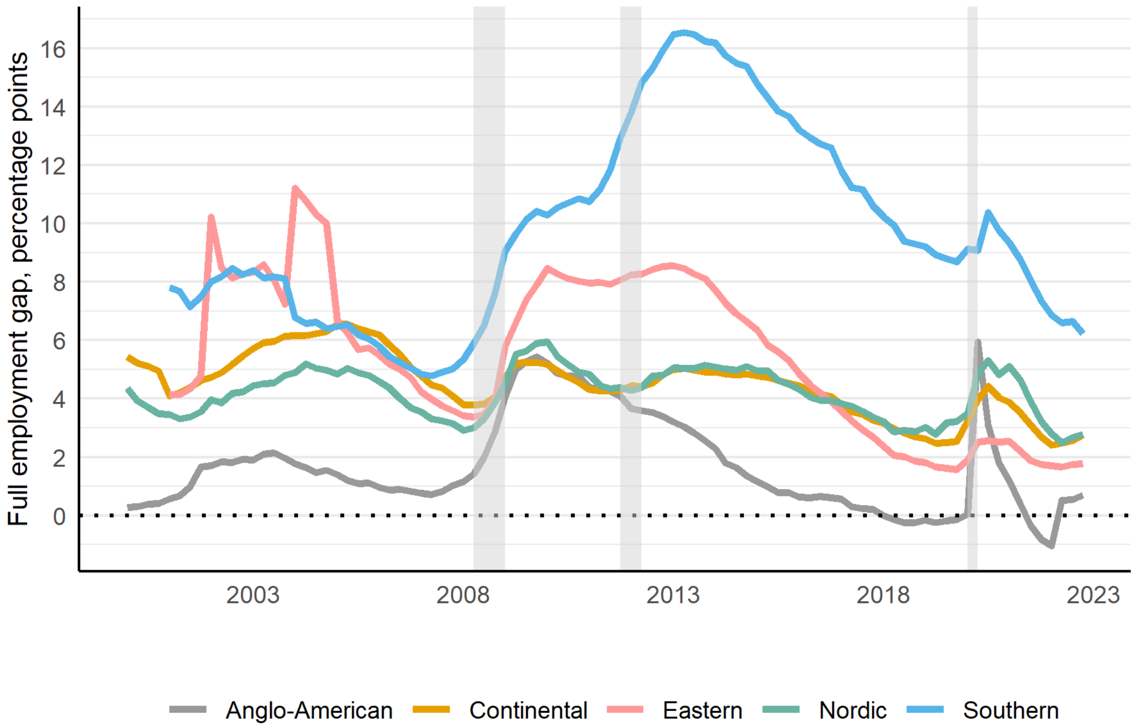

Figure A 4: Population-weighted full employment gaps for different country groups, 2000-2022 (Source: Eurostat, ISTAT, DARES and Michaillat and Saez [2022]).

Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The data for Germany are for West Germany until 1991. Continental: Austria, Belgium, France, Germany, Netherlands, Luxembourg. Nordic: Denmark, Finland, Sweden. Southern: Greece, Italy, Cyprus, Portugal, Spain, Malta. Eastern: Czechia, Bulgaria, Estonia, Croatia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia, Slovakia; Anglo-American: US, UK, Ireland. The Beveridge full employment gap (g) is calculated as $g = u - BECRU$.

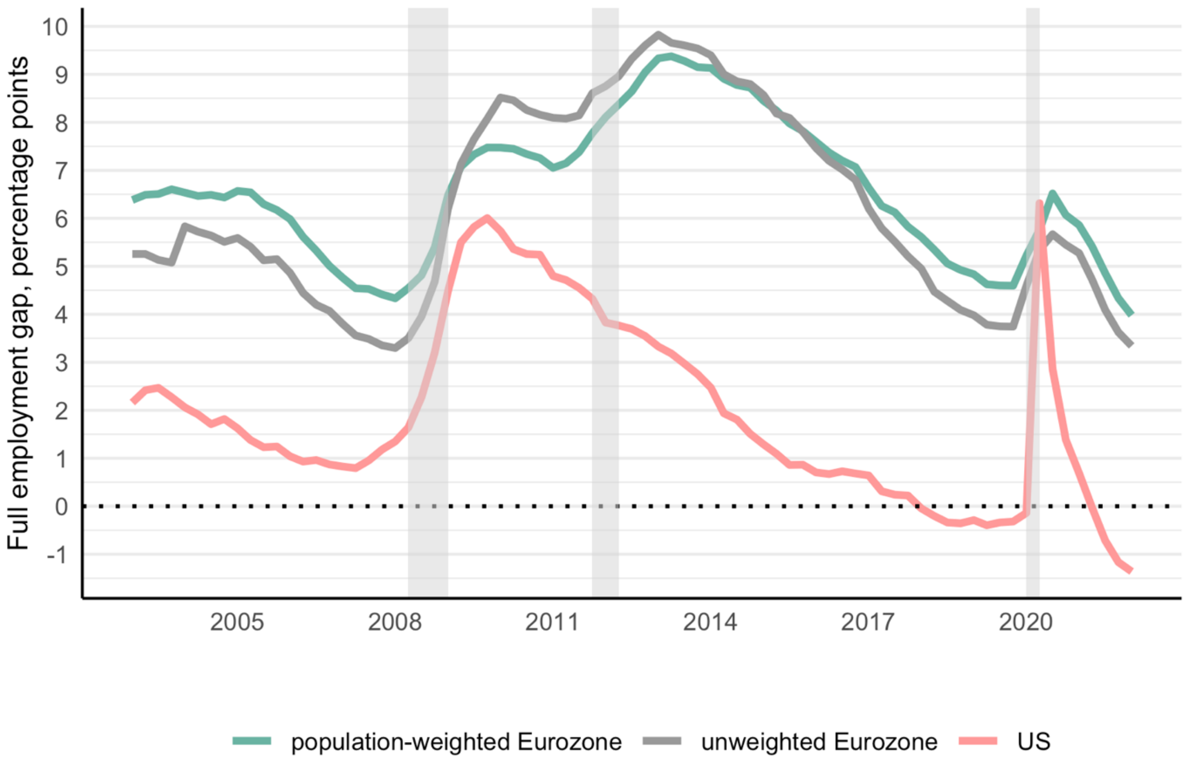

Figure A 5: Full employment gaps for the Eurozone and the US, 2000-2022 (Source: Eurostat, ISTAT, DARES and Michaillat and Saez [2022]).

Notes: The grey areas in the figure indicate periods of recession in the aggregated OECD Europe sample. A recession is defined as two consecutive quarters of negative real GDP growth. The Eurozone data show an average (either unweighted or population-weighted) for the 20 member countries of the Eurozone. The Beveridge full employment gap (g) is calculated as $g = u - BECRU$.

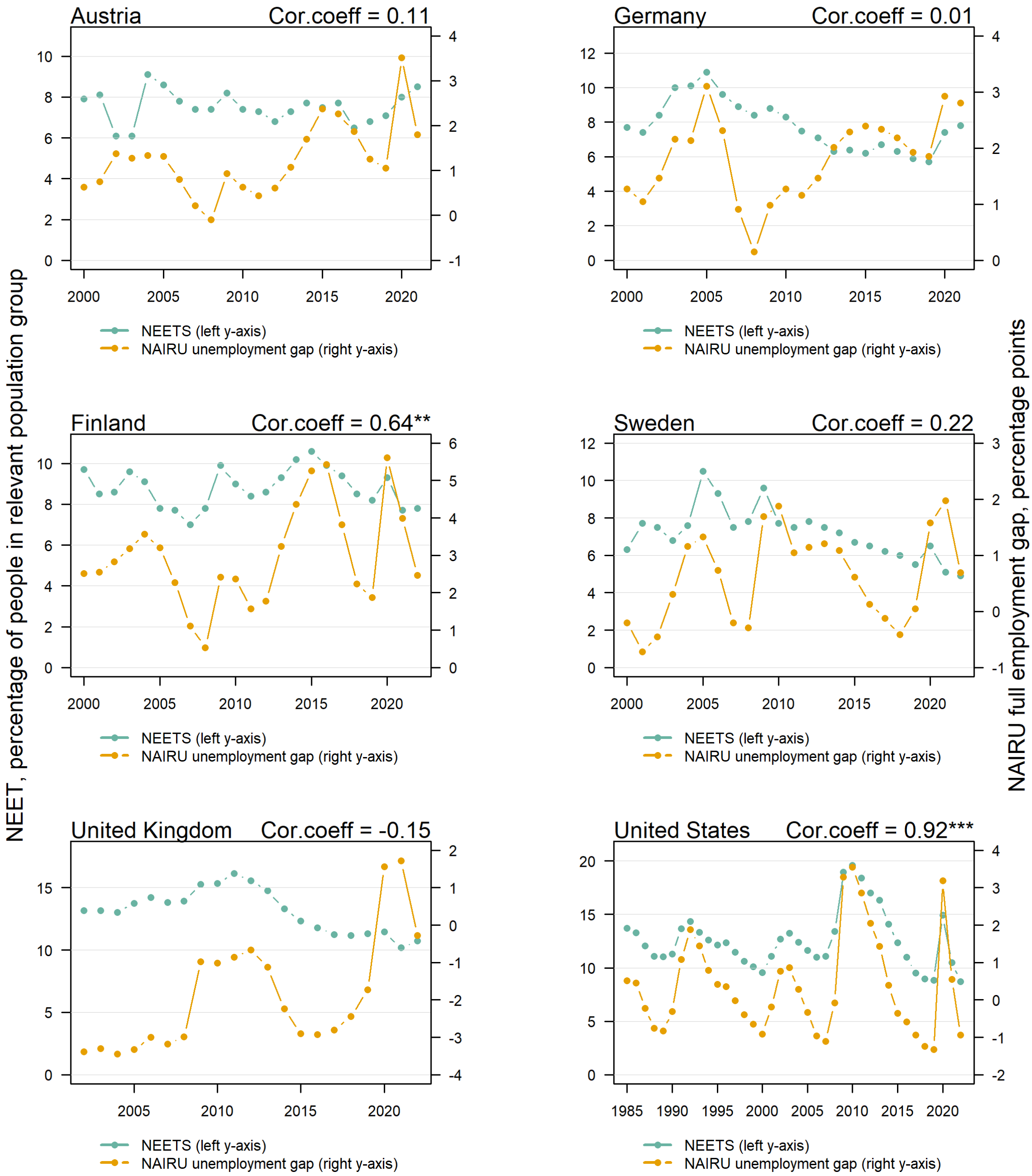

Figure A 6: NEET rate and NAIRU full employment gap estimates, 2000-2022 (Source: AMECO, Eurostat, OECD, Michaillat and Saez [2022], ONS, and BLS; own calculations).

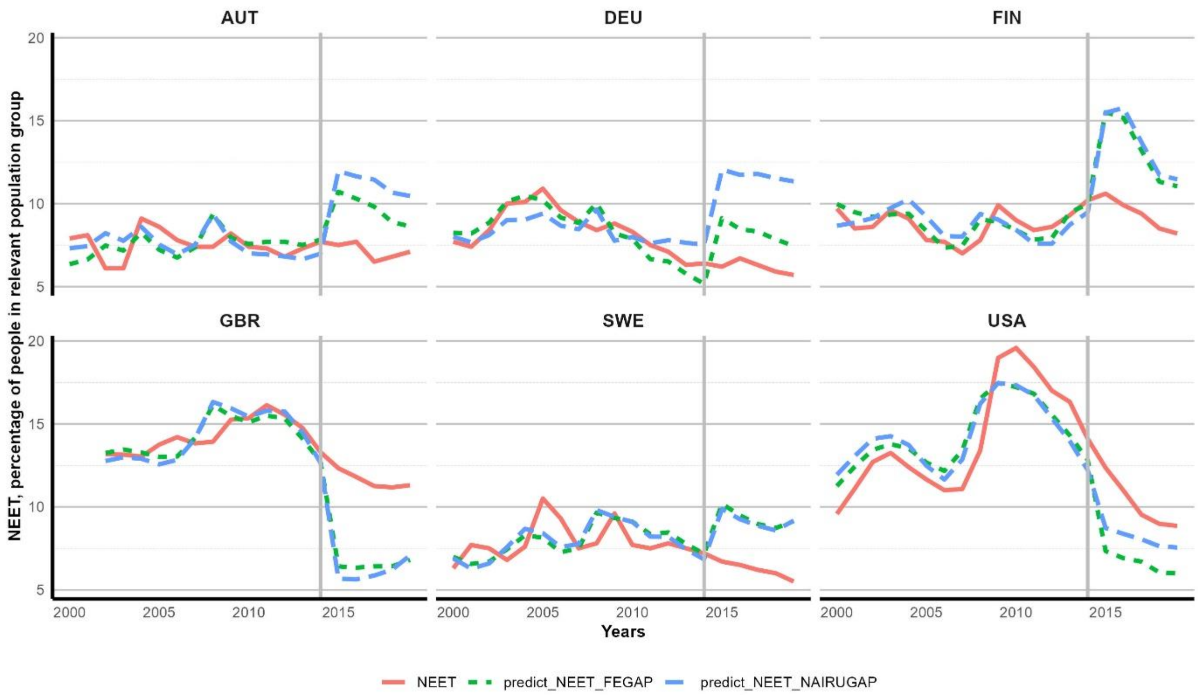

Figure A 7: Comparison of actual NEET data with in-sample (values between 2000 and 2014, i.e. left of vertical gray line) and out-of-sample predictions (right of vertical gray line) based on FEGAP and NAIRUGAP estimations

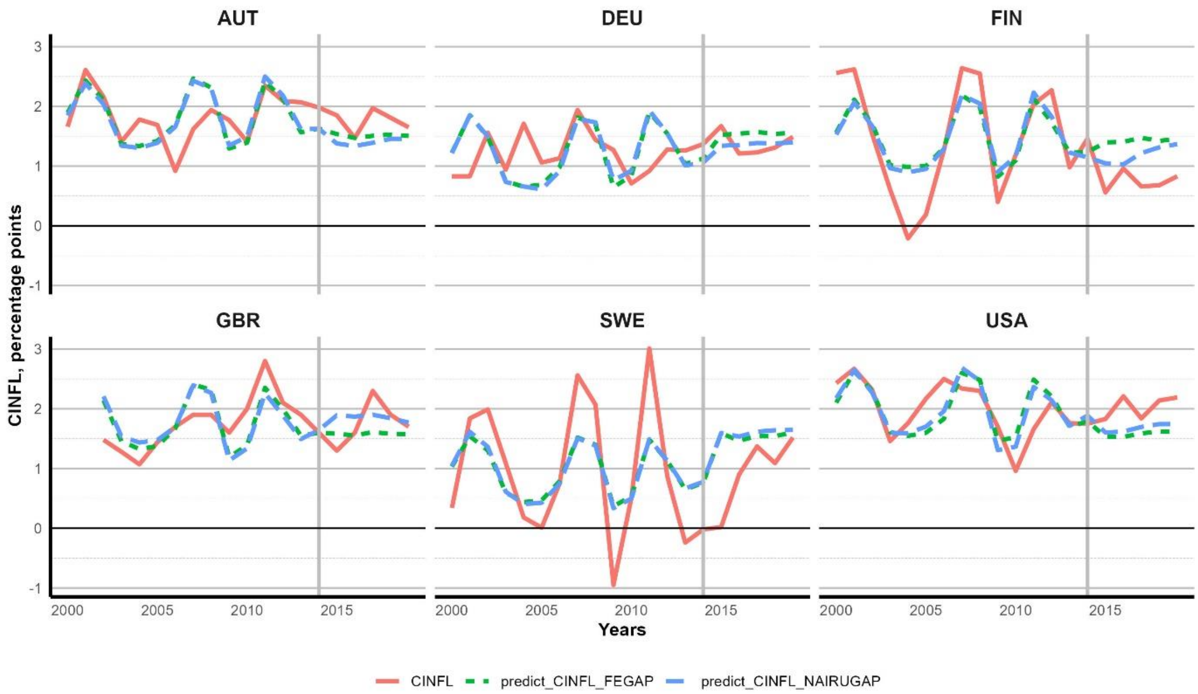

Figure A 8: Comparison of actual CINFL data with in-sample (values between 2000 and 2014, i.e. left of vertical gray line) and out-of-sample predictions (right of vertical gray line) based on FEGAP and NAIRUGAP estimations

Appendix C: Pre-testing

A) Checking for multi-collinearity

We perform a Spearman correlation analysis and compute the Variance Inflation Factor (VIF) to check for potential multi-collinearity of key variables in our baseline estimation setup. Spearman correlations among explanatory variables for our regressions are reported in Table A 1 and do not point to any evidence of considerable correlations, i.e. beyond 0.9 or -0.9. High correlations are found between ACCU and PRCA, 0.9, and between LTU and PUCA, -0.81, but since we are not including ACCU and its public and private sub-omponents (PUCA and PRCA) in the same model this is of no concern. The lagged FEGAP variable does not show any considerable correlation with other explanatory variables. Its high correlation with the dependent variable, 0.92, could potentially be a problem if the VIF is greater than 10; however, this is not the case. The VIF of the lagged FEGAP is between one and two for all econometric baseline specifications. VIF values based on the regression specifications as in section 5 (see Table 3) can be found in Table A 2 and only indicate signs of low to moderate correlation as they range between one and three. The highest VIF value recorded is 2.18 for EGLOB in the last baseline specification.

Table A 1: Spearman correlation analysis in a tabular form with values (upper table) and a graphical representation in the form of a correlation plot (lower table).

	FEGAP	lagFEGAP	EPL	UDENS	TFP	EGLOB	ACTPOP	ACCU	INFL	LRG_pg	LTU	PUCA	PRCA	OG
FEGAP	1	0.93	0.23	0.38	0.13	0.31	-0.46	-0.33	-0.36	-0.11	0.55	-0.32	-0.25	-0.4
lagFEGAP	0.93	1	0.19	0.34	0.29	0.35	-0.36	-0.25	-0.39	-0.05	0.62	-0.35	-0.16	-0.24
EPL	0.23	0.19	1	0.57	-0.05	0.19	-0.33	-0.42	-0.07	0.18	0.29	-0.45	-0.27	-0.13
UDENS	0.38	0.34	0.57	1	0.1	0.21	-0.26	-0.33	0.06	0.12	-0.01	-0.08	-0.35	-0.14
TFP	0.13	0.29	-0.05	0.1	1	-0.12	0.02	0.04	-0.03	0.04	0.15	-0.02	0.06	0.14
EGLOB	0.31	0.35	0.19	0.21	-0.12	1	-0.18	-0.06	-0.58	0.15	0.37	-0.44	0.09	0.09
ACTPOP	-0.46	-0.36	-0.33	-0.26	0.02	-0.18	1	0.18	0.27	-0.03	-0.39	0.25	0.08	0.37
ACCU	-0.33	-0.25	-0.42	-0.33	0.04	-0.06	0.18	1	0.08	-0.03	-0.24	0.37	0.91	0.4
INFL	-0.36	-0.39	-0.07	0.06	-0.03	-0.58	0.27	0.08	1	-0.24	-0.4	0.3	-0.03	0.15
LRG_pg	-0.11	-0.05	0.18	0.12	0.04	0.15	-0.03	-0.03	-0.24	1	0.02	0	-0.04	0.05
LTU	0.55	0.62	0.29	-0.01	0.15	0.37	-0.39	-0.24	-0.4	0.02	1	-0.78	0.04	-0.07
PUCA	-0.32	-0.35	-0.45	-0.08	-0.02	-0.44	0.25	0.37	0.3	0	-0.78	1	0	-0.1
PRCA	-0.25	-0.16	-0.27	-0.35	0.06	0.09	0.08	0.91	-0.03	-0.04	0.04	0	1	0.46
OG	-0.4	-0.24	-0.13	-0.14	0.14	0.09	0.37	0.4	0.15	0.05	-0.07	-0.1	0.46	1

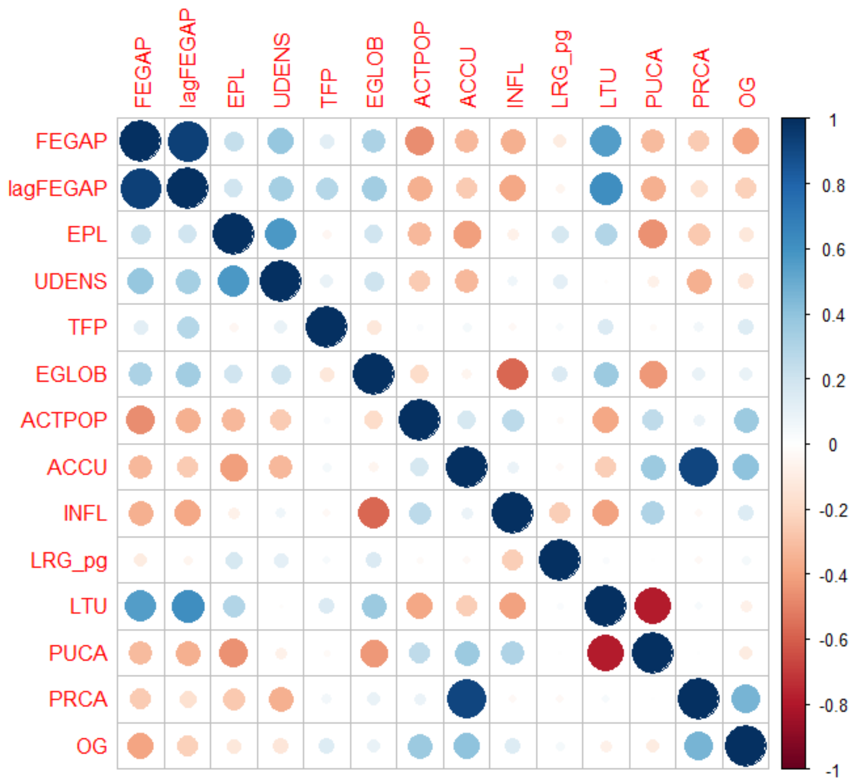

Table A 2: VIF results for explanatory variables of our econometric baseline regression specifications

Model	lag(FEGAP)	EPL	UDENS	TFP	EGLOB	ACTPOP	ACCU	INFL	LRG_pg
(2)	1.08	1.44	1.48						
(3a)	1.50	1.76	1.61	1.13	1.59				
(3b)	1.51	1.78	1.64	1.14	1.60	1.11			
(4a)	1.77	2.08	1.68	1.18	1.68	1.11	1.39		
(4b)	1.89	2.08	1.88	1.20	2.18	1.11	1.39	1.93	
(5a,b)	1.99	2.11	1.93	1.21	2.18	1.11	1.39	1.95	1.14

B) Testing for unit roots

Results of several unit-roots tests that we applied to our panel dataset variables are depicted in Table A 3. In the first run (1) we applied the Levin Lin Chu (LLC) test which assumes in its H_0 that each time series contains a unit root, and in its H_a that each time series is stationary. In addition to its restrictive Null the LLC further assumes cross-sectional indepence (which would imply, for instance, that Austria's EGLOB is independent of Germany's). As a second unit root test (2) we run the Im, Pesaran and Shin test (IPS) which is more flexible than the LLC test, as its H_a allows some individuals to have a unit root (i.e. allowing for heterogenous coefficients). A third test (3) that we run is the Maddala Wu (MW) test, which is a Fisher-type test that combines p-values from tests based on ADF regressions per individual available. In contrast to the IPS test, which assumes asymptotic validity regarding the amount of N individuals going to infinity, the Fisher test depends on T going to infinity (Maddala & Wu 1999). Since our data set has the format of a long time series with few cross-sectional units, it is worthwhile to add the MW test to our battery of unit root tests. Lastly, we also run the Advanced Dickey-Fuller

(ADF) test for each variable and country for matters of completeness; it only tests for unit roots on a country level for the single time series variables and is not as reliable as the other tests for a panel dataset. As Table A 3 shows the IPS , LLC, and MW test report stationarity (or at least weak stationarity) for all variables. In case of UDENS we have a non-stationary result for the LLC test but since we do find evidence of stationarity in the IPS and MW tests as well as cointegration with other variables and also find panel data analysis in the literature that also uses the union density rate (see Rumler & Scharler 2011), we argue that the UDENS variable as a rate variable can be used.

Table A 3: Unit root tests for key variables of our econometric baseline regression specifcations

<table>
<tr><th>Variable</th><th>(1) LLC test results[16]</th><th>(2) IPS test results[17]</th><th>(3) MW testing[18]</th><th>(4) ADF test results[19]</th><th>Result</th></tr>
<tr><td>FEGAP</td><td>p < 0.01, stat</td><td>p < 0.01, stat</td><td rowspan="9">p < 0.01, stat</td><td>p > 0.10, non-stat</td><td>Stationary</td></tr>
<tr><td>EPL</td><td>p < 0.01, stat[20]</td><td>p < 0.01, stat[20]</td><td>p > 0.10, non-stat (except DEU, FIN, USA)</td><td>Stationary</td></tr>
<tr><td>UDENS</td><td>p > 0.10, non-stat</td><td>p < 0.10, weakly stat</td><td>p > 0.10, non-stat</td><td>Weakly stationary</td></tr>
<tr><td>TFP</td><td>p < 0.01, stat</td><td>p < 0.01, stat</td><td>p < 0.01, stat</td><td>Stationary</td></tr>
<tr><td>EGLOB</td><td>p < 0.01, stat</td><td>p < 0.10, weakly stat</td><td>p > 0.10, non-stat (except GBR)</td><td>Weakly stationary</td></tr>
<tr><td>ACTPOP</td><td>p < 0.01, stat</td><td>p < 0.01, stat</td><td>p < 0.01, stat (except SWE)</td><td>Stationary</td></tr>
<tr><td>ACCU</td><td>p < 0.01, stat</td><td>p < 0.01, stat</td><td>p > 0.10, non-stat</td><td>Stationary</td></tr>
<tr><td>INFL</td><td>P < 0.01, stat</td><td>p < 0.01, stat</td><td>p > 0.10, non-stat (except SWE, USA)</td><td>Stationary</td></tr>
<tr><td>LRG_pg</td><td>p < 0.01, stat</td><td>p < 0.01, stat</td><td>p > 0.10, non-stat (except FIN)</td><td>Stationary</td></tr>
</table>

C) Testing for cointegration

If time series variables are not stationarity they can still show a stable long-term relationship together, i.e. be cointegrated with each other, which can impact the model estimation. The panel specific stationarity tests (LLC and IPS) did not report any non-stationarity, so there is no strict requirement for co-integration tests. However, we include a battery of co-integration tests for matters of completeness and also to check on the variables that were individually reported as non-stationary by the ADF test. Table A 4 shows the resuls of the cointegration tests: (1a) the Pedroni test does not show a strong sign of co-integration for a first set of explanatory variables and hence does not speak against applying a FE model to level variables of our panel data set. Applied to an additional set of variables (1b) where some country time series variables turned out as non-stationary processes we do find cointegration relations. Additionally, (2) with a rank of four the trace-based Johansen test shows evidence of at most four co-integrating relationships. Since the Pedroni test is a panel specific cointegration test, its results should be trusted more than the outcome of the Johansen test, which was primarily

[16] H_0 is that all individuals follow a unit root process, and H_a is that all individuals are stationary

[17] H_0 is that all individuals follow a unit root process, and H_a is that some individuals can have a unit root, while somce can be stationary

[18] H_0 is that all individuals follow a unit root process, and H_a is that some individuals can have a unit root, while somce can be stationary

[19] The Advanced Dickey-Fuller (ADF) test results report the p-value for the lag coefficient (γ) for a trend based ADF regression specification, being $\Delta y_t = \gamma y_{t-1} + a_0 + a_2 t + \epsilon_t$. The null hypothesis represents a non-stationary outcome ($\gamma = 0$). The tests were run on each time series variable per country and unless otherwise stated test results hold for all country cases.

[20] Due to time series issues with the data variation of the EPL variable the test was carried out on a subsample that excluded the USA

developed for time series data and stacks the panel data into a long format to treat it as a time series.

Table A 4: Cointegration tests for variables used in the baseline econometric specification

#	Variables	Tests	Test statistics	Test conclusions
(1a)	FEGAP, TFP, EGLOB, INFL, LRG_pg	Pedroni (1999) [H0: no cointegration][21]	Panel ν -1.104: $p > 0.10$ Panel ρ 1.382: $p > 0.10$ Panel t_{par} -4.861: $p < 0.01$ Panel $t_{non\text{-}par}$ 0.256: $p > 0.10$ Group ρ 2.613: $p < 0.01$ Group t_{par} 2.143: $p < 0.05$ Group $t_{non\text{-}par}$ 1.703: $p < 0.10$	Little vidence for co-integration. Most test statistics do not reject the null of no-cointegration
(1b)	FEGAP, EPL, UDENS, EGLOB, ACCU, INFL	Pedroni (1999) [H0: no cointegration][22]	Panel ν -2.952: $p < 0.01$ Panel ρ 2.017: $p < 0.05$ Panel t_{par} -19.813: $p < 0.01$ Panel $t_{non\text{-}par}$ 0.799; $p > 0.10$ Group ρ 3.187: $p < 0.01$ Group t_{par} 2.236: $p < 0.05$ Group $t_{non\text{-}par}$ 2.698: $p < 0.01$	Some vidence for co-integration. Most test statistics reject the null of no-cointegration
(2)	All baseline variables	Johansen test based on the *trace* test [H0: no cointegration]	$r <= 5$: $p > 0.10$ $r <= 4$: $p < 0.05$ $r <= 3$: $p < 0.01$ $r <= 2$: $p < 0.01$ $r <= 1$: $p < 0.01$ $r = 0$: $p < 0.01$	At most 4 cointegrating relationships present among baseline variables

With a rank of $r^{trace} = 4$ the Johansen test suggests considering the first four eigenvalues and their corresponding eigenvectors in terms of determining the cointegration structure in our datset. The eigenvalues represent the strength of the cointegration relationships and the eigenvectors the actual cointegration relations among the variables. Eigenvalues are $\lambda_1^{trace} = 0.389$, $\lambda_2^{trace} = 0.265$, $\lambda_2^{trace} = 0.174$ and $\lambda_4^{trace} = 0.170$, and eigenvector results with the direction and magnitude of the relationships between the variables in the cointegration relationship are depicted in Table A 5. Some variables that showed a significant relationship already in the regression table with baseline specifications (see Table 3) also indicate a robust long-term connection between explanatory variables and the dependent variable. FEGAP shows a strong and negative long-run relationship with TFP (-17.860).

[21] The Pedroni test is based on 7 test statistics. Assuming asymptotic convergence to normality, the test is conducted by comparing the test statistics to z-scores ($z_{\alpha/2=5\%} = 1.64$, $z_{\alpha/2=2.5\%} = 1.96$, $z_{\alpha/2=0.5\%} = 2.58$)

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Table A 5: Cointegration results based on eigenvectors of the Johansen test for the trace- (r=4)

	EV_1^{trace}	EV_2^{trace}	EV_3^{trace}	EV_4^{trace}
Variable names	**FEGAP.l2**	**EPL.l2**	**UDENS.l2**	**TFP.l2**
FEGAP.l2	1.00000000	1.00000000	1.00000000	1.00000000
EPL.l2	-1.05616770	3.74147297	3.74147297	0.80056069
UDENS.l2	0.10818026	-0.10687185	-0.10687185	-0.12060328
TFP.l2	-17.86036957	2.06521933	2.06521933	0.25841690
EGLOB.l2	-0.29226496	0.46286501	0.46286501	0.12735233
ACTPOP.l2	-0.59623647	13.50956660	13.50956660	-1.11188026
ACCU.l2	4.13639657	1.59790817	1.59790817	-0.21987658
INFL.l2	0.29868465	0.76468201	0.76468201	1.00964702
LRG_pg.l2	0.83789833	1.10483283	1.10483283	2.55843034
Trend.l2	-0.03351275	0.02743625	0.02743625	0.01592474

Note: We indicate that the Johansen test was carried out with a lag order of K=2 by putting '.l2' to the variables

Based on the trace- and eigen-type Johansen test specifcations we run a VECM model following the general VECM panel equation (A2) which allows us to detect long-run and short-run error corrections, as well as checking for reverse causality.

$$\Delta Y_{i,t} = \alpha_i + \sum_{k=1}^{p} \beta_i \Delta Y_{it-k} + \sum_{k=0}^{q} \delta_i \Delta X_{it-k} + \sum_{k=1}^{q} \phi_i ECT_{it-k} + \mu_{i,t} \qquad \textit{(A1)}$$

In equation (A2), the first two terms with the sum operators and differenced variables, $\sum_{k=1}^{p} \beta_i \Delta Y_{it-k} + \sum_{k=0}^{q} \delta_i \Delta X_{it-k}$, reflect the short-run error corrections, while ECT_{it-1} is the error-correction term of lag order one and stands for the long-run correction $ECT_{it-1} = \epsilon_{it-1} = Y_{it-1} - \beta_{0i} - \beta_{1i} X_{it-1}$ (lagged OLS residuals from long run model), and ϕ reflects the speed of adjustment.

The results show that for the trace-type VECM we find $ECT_{it-1} = -0.060$ (the error correction term which is associated with lag order one), $ECT_{it-2} = 0.118$, $ECT_{it-3} = 0.001$, and $ECT_{it-4} = 0.023$ but only the first two are significant. The first ECT term being negative indicates a stabilizing force in the error correction process (indicating that the dependent variable adjusts by 6.0% downwards when it is above the equilibrium and 6.0% upwards when it is below the equilibrium); the second ECT term being positive indicates a destabilizing force in the error correction process, leading to increases in the dependent variable above the equilibrium and decreases below the equilibrium. Another noteworthy observation regarding reverse causality is that while lagged coefficients of explanatory variables show significance in explaining ΔFEGAP ($FEGAP_{t-1}$, TFP_{t-1}, $INFL_{t-1}$, LRG_{t-1}), we find a significant relationship in $FEGAP_{t-1}$ explaining ΔTFP and ΔINFL but in no other cases. This slightly supports the hypothesis that FEGAP is determined by the explanatory variables rather than the other way around.

Appendix D: Robustness checks

A) Using country-specific dummies:

In the following Table A 6 we collect regression results with individual country-specific dummies. In order to visualize the individual country effects the regressions were run with time-fixed effects only. Its last column (7) with all country dummies is basically equal to model (5) of Table 3. While some individual country effects differ from the welfare regime dummies the overall tendencies remain. Most estimates remain unchanged in their sign and significance (FEGAP, EPL, TFP, EGLOB, ACTPOP, ACCU and INFL). Slightly different effects are found for UDENS and LRG with reduced point estimates.

B) Using 5-year data averages:

As argued in Section 5 we followed an approach in the empirical literature (e.g. Felbermayr et al. 2014) of using lagged variables as an identification strategy of our explanatory variables. In addition, we now average our data over the time course of 5 years, which is the time period of a business cycle, to account for business cycle effects and complement our analysis with an additional identification strategy. The estimation equation that we apply is shown in equation (A3) and only differs from equation (3) in terms of averaging data over 5 years.

$$\widetilde{FEGAP}_{i,t} = \alpha + \beta\, \widetilde{H}_{i,t-1} + \gamma\, \widetilde{L}_{i,t-1} + \delta\, \widetilde{S}_{i,t-1} + \theta\, \widetilde{M}_{i,t-1} + \eta\, \widetilde{P}_{i,t-1} + \zeta_i + \xi_t + \varepsilon_{i,t} \qquad (A3)$$

The regression results are reported below in Table A 7 and generally confirm our regression results of section 5, though quite some point estimates became attenuated and while standard errors increased, leading to less and fewer significant coefficients. E.g. point estimates for the FEGAP5 coefficient shows values in the range of 0.281 and 0.686 instead of 0.834 and 0.979 as in Table 3. Coefficients where the sign was remained but standard errors changed include UDENS5 (still positive point estimates but higher standard errors), TFP5 (still negative sign while standard errors increased), INFL5 (still positive point estimates and fewer significant results), and LRG5 (remaining its negative point estimate, though standard errors relatively increase). Most other insignificant coefficients also remained the sign of their point estimates and remained insignificant, like EPL5 (still positive but insignificant point estimates), ACCU5 (still negative but insignificant point estimates). Insignificant results are reported for the EGLOB5 variable, while the standard errors even increase beyond the effect size of the respective point estimates. The ACTPOP5 variable remains the sign of its point estimate but with increasing standard errors no more significant results are obtained. In case of the dummy variables we find that for the 1980s and 1990s dummies, as well as the SOD5 dummy the signs were remained (though some standard errors changed). The biggest recorded change now is that the FINCRISIS shows a significant positive coefficient, which seems theoretically sound, though through the data averaging over a period of five years it can't be ruled out that the estimator is confounded by the three anticipating years (2005, 2006, 2007). The regression results also confirm that the social democratic welfare regimes are associated with lower full employment gaps, while no significant difference can be observed between liberal and conservative regimes in terms of their effect on full employment gaps.

Table A 6: Regression results for country dummies

	Dependent variable:						
	FEGAP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FEGAP_{t-1}$	0.966^{***}	0.962^{***}	0.924^{***}	0.934^{***}	0.964^{***}	0.967^{***}	0.911^{***}
	(0.018)	(0.025)	(0.016)	(0.013)	(0.018)	(0.019)	(0.022)
EPL_{t-1}	0.088^{***}	0.073	0.036	0.032	0.084	0.180^{***}	0.202
	(0.031)	(0.081)	(0.034)	(0.041)	(0.066)	(0.063)	(0.230)
$UDENS_{t-1}$	0.001	0.002	0.010^{***}	-0.0004	0.001	0.001	0.038^{***}
	(0.002)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.012)
TFP_{t-1}	-0.239^{***}	-0.239^{***}	-0.245^{***}	-0.246^{***}	-0.239^{***}	-0.241^{***}	-0.243^{***}
	(0.060)	(0.061)	(0.054)	(0.056)	(0.063)	(0.057)	(0.049)
$EGLOB_{t-1}$	-0.011	-0.010	-0.015^{**}	-0.002	-0.009	0.003	-0.026
	(0.010)	(0.011)	(0.007)	(0.010)	(0.015)	(0.019)	(0.032)
$ACTPOP_{t-1}$	-0.141^{***}	-0.138^{**}	-0.141^{***}	-0.140^{***}	-0.140^{***}	-0.144^{***}	-0.125^{**}
	(0.049)	(0.053)	(0.048)	(0.046)	(0.046)	(0.045)	(0.056)
$ACCU_{t-1}$	0.014	0.019	-0.088^{*}	-0.049	0.016	0.026	-0.060
	(0.020)	(0.019)	(0.053)	(0.049)	(0.019)	(0.029)	(0.052)
$INFL_{t-1}$	0.052^{**}	0.052^{**}	0.050^{**}	0.045^{**}	0.052^{**}	0.054^{***}	0.064^{*}
	(0.022)	(0.021)	(0.020)	(0.020)	(0.023)	(0.020)	(0.033)
LRG_{t-1}	-0.037	-0.039	-0.041^{**}	-0.039^{*}	-0.037^{*}	-0.035	-0.052^{**}
	(0.023)	(0.024)	(0.021)	(0.020)	(0.023)	(0.024)	(0.027)
DCOU_AUT	0.028						-0.924^{*}
	(0.051)						(0.506)
DCOU_DEU		0.054					-0.446
		(0.167)					(0.589)
DCOU_SWE			-0.524^{***}				-2.422^{***}
			(0.065)				(0.634)
DCOU_FIN				0.335^{***}			-1.790^{***}
				(0.128)			(0.651)
DCOU_GBR					-0.025		-0.637^{*}
					(0.130)		(0.329)
DCOU_USA						0.421	
						(0.311)	
Observations	294	294	294	294	294	294	294
R^2	0.936	0.936	0.939	0.937	0.936	0.937	0.941
Adjusted R^2	0.920	0.920	0.923	0.922	0.920	0.921	0.925
F Statistic	344.836^{***} (df = 10; 234)	344.899^{***} (df = 10; 234)	358.917^{***} (df = 10; 234)	350.765^{***} (df = 10; 234)	344.792^{***} (df = 10; 234)	346.575^{***} (df = 10; 234)	263.710^{***} (df = 14; 230)
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A 7: Regression table for 5-year averaged data

	Dependent variable:						
	FEGAP5						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FEGAP5 $_{t-1}$	0.568***	0.486***	0.409***	0.357***	0.281***	0.281	0.686***
	(0.098)	(0.131)	(0.104)	(0.074)	(0.092)	(0.169)	(0.071)
EPL5 $_{t-1}$		1.053**	1.973	1.006	1.106	0.902	0.231
		(0.434)	(1.555)	(1.568)	(1.688)	(1.282)	(0.619)
UDENS5 $_{t-1}$		0.090	0.107	0.139*	0.172**	0.128*	0.025
		(0.059)	(0.087)	(0.073)	(0.077)	(0.064)	(0.050)
TFP5 $_{t-1}$			-0.576***	-0.439*	-0.309	-0.392*	-0.146
			(0.200)	(0.239)	(0.354)	(0.204)	(0.278)
EGLOB5 $_{t-1}$			0.134	0.072	0.032	0.106	-0.062
			(0.152)	(0.142)	(0.148)	(0.073)	(0.085)
ACTPOP5 $_{t-1}$			-0.304	-0.277	-0.274	-0.149	-0.476
			(0.472)	(0.562)	(0.570)	(0.592)	(0.592)
ACCU5 $_{t-1}$				-0.274	-0.311	-0.167	-0.081
				(0.402)	(0.386)	(0.382)	(0.301)
INFL5 $_{t-1}$				0.318*	0.325**	0.260	0.251
				(0.159)	(0.143)	(0.164)	(0.232)
LRG5 $_{t-1}$					-0.254*	-0.140	-0.056
					(0.138)	(0.152)	(0.168)
EIGHTIES						-0.977*	
						(0.488)	
NINETIES						1.232*	
						(0.709)	
FINCRISIS						-0.111	
						(1.378)	
SOD							-0.370
							(1.984)
CON							0.471
							(1.220)
Observations	59	56	54	54	54	54	54
R^2	0.342	0.403	0.453	0.506	0.520	0.586	0.645
Adjusted R^2	0.091	0.136	0.122	0.155	0.152	0.390	0.431
F Statistic	21.806*** (df = 1; 42)	8.559*** (df = 3; 38)	4.556*** (df = 6; 33)	3.966*** (df = 8; 31)	3.609*** (df = 9; 30)	4.242*** (df = 12; 36)	5.460*** (df = 11; 33)
Note:							*p<0.1; **p<0.05; ***p<0.01

C) Using the NAIRU gap instead of the FEGAP variable:

To check for the consistency of our regression results of Table 3 regarding the full employment gap (FEGAP) we now regress the NAIRU gap (NAIRUGAP) on the selection of our variables. The estimation equation that we apply is shown in equation (A4) and only differs from equation (3) in terms of the left-hand-side variable, which shows the NAIRU gap (NAIRUGAP) instead of the FEGAP:

$$NAIRUGAP_{i,t} = \alpha + \beta\, H_{i,t-1} + \gamma\, L_{i,t-1} + \delta\, S_{i,t-1} + \theta\, M_{i,t-1} + \eta\, P_{i,t-1} + \zeta_i + \xi_t + \varepsilon_{i,t} \qquad (A4)$$

Results in Table A 8 do not hint at large differences between the two tables. The most notable observable deviation can be found in the behavior of the EGLOB variable which is negative and significant through columns (4-7) in the NAIRUGAP case, but only reflects a negative and significant coefficient in model (7) of the FEGAP case. While the signs of the EGLOB coefficients are positive in both regression tables, it is the lower standard errors that yields positively significant results in the NAIRUGAP case. This could be explained in the sense that the relation of the FEGAP-EGLOB variable appears similar though slightly noisier in the NAIRUGAP-EGLOB case. Another set of deviations are reported for the time- and country-specific regression models (6) and (7) which go back again to unobserved country and time characteristics. In model (6) the EGLOB coefficient in the FEGAP turns positive and significant, the UDENS coefficient in the NAIRUGAP cases loses its significance, and the FINCRISIS coefficient in the NAIRUGAP case also shows up positive and significant. For model (7) in the NAIRUGAP case the EPL coefficient gains while the LRG loses its significance.

Table A 8: Regression table for NAIRU gap estimates

	Dependent variable:						
	NAIRUGAP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NAIRUGAP $_{t-1}$	0.834***	0.823***	0.861***	0.855***	0.837***	0.797***	0.892***
	(0.029)	(0.031)	(0.028)	(0.040)	(0.038)	(0.041)	(0.033)
EPL $_{t-1}$		-0.011	0.190	0.046	0.029	-0.098	0.057
		(0.152)	(0.123)	(0.117)	(0.153)	(0.129)	(0.069)
UDENS $_{t-1}$		0.014	0.027***	0.032***	0.036***	0.006	0.019***
		(0.010)	(0.005)	(0.008)	(0.008)	(0.007)	(0.006)
TFP $_{t-1}$			-0.242***	-0.216***	-0.206***	-0.211***	-0.197***
			(0.047)	(0.050)	(0.050)	(0.045)	(0.060)
EGLOB $_{t-1}$			-0.021**	-0.032**	-0.040***	0.022***	-0.041***
			(0.010)	(0.013)	(0.015)	(0.004)	(0.009)
ACTPOP $_{t-1}$			-0.093***	-0.096***	-0.095***	-0.149***	-0.108***
			(0.024)	(0.028)	(0.027)	(0.049)	(0.022)
ACCU $_{t-1}$				-0.048	-0.040	-0.040	0.014
				(0.054)	(0.048)	(0.104)	(0.025)
INFL $_{t-1}$				0.059**	0.058**	0.075***	0.051**
				(0.025)	(0.023)	(0.018)	(0.020)
LRG $_{t-1}$					-0.073***	-0.088***	-0.075***
					(0.013)	(0.031)	(0.016)
EIGHTIES						-0.056	
						(0.184)	
NINETIES						0.355***	
						(0.109)	
FINCRISIS						0.404	
						(0.275)	
SOD							-0.503**
							(0.241)
CON							0.247
							(0.189)
Observations	311	297	294	294	294	294	294
R^2	0.696	0.710	0.770	0.777	0.782	0.733	0.879
Adjusted R^2	0.627	0.641	0.711	0.717	0.722	0.717	0.848
F Statistic	578.055*** (df = 1; 252)	195.313*** (df = 3; 239)	130.343*** (df = 6; 233)	100.541*** (df = 8; 231)	91.707*** (df = 9; 230)	63.231*** (df = 12; 276)	154.009*** (df = 11; 233)
Note:							*p<0.1; **p<0.05; ***p<0.01

D) Adding regressors:

We add further regressors to check the robustness of our baseline regression specification. Table A 9 below compares the results of the benchmark regression (0) with additional regression specifications (1-4). Regressions with the following additional variables are used in our robustness checks:

- (1): We add the output gap (OG) as an additional control variable for the effects of business cycle shifts on the full employment gap. Similar to the inflation measure we would also expect a negative relationship between output gap and the full employment gap, since the full employment gap will decrease in times of expansions and increase in times of recessions. While the standard error for the OG coefficient is high and we do not find a significant result for its point estimate, adding the variable does not change the sign or significance of other baseline regression variables.
- (2): As another indicator for unemployment hysteresis we add long-term unemployment (LTU). Notably, the data for LTU are not equally available between 1970 and 2019 for the countries in our data set, which significantly reduces the number of observations for the panel regression (drop in the number of observations from 294 to 225). Therefore, we include LTU as an additional robustness check but do not use it in our baseline regression. If the lagged dependent variable is dropped, regression results suggest that LTU is positively associated with the full employment gap (2). Nevertheless, coefficient signs of $FEGAP_{t-1}$ and LTU in their separate regressions indicate that there is a hysteresis effect of higher unemployment rates: if workers remain unemployed for a longer time, it is more likely that current unemployment will go further up and not go down. A policy-minded conclusion of this finding would be to specifically target the long-term unemployed to sustainably reduce overall unemployment rates.
- (3): Instead of using the aggregated value for capital accumulation, we include public capital accumulation (PUCA) as the ratio between real gross fixed capital formation of general government and the real net capital stock, and the private capital accumulation rate (PRCA) as the ratio between real gross fixed capital formation of the private sector and the real net capital stock. Results of our baseline regressors do not change. Both, PRCA and PUCA, are negatively though insignificantly associated with FEGAP and hence mirror the behavior of their aggregated variable ACCU.
- (4): Besides the political variable that we use in our baseline regressions, which are based on the parlgov data (LRG = LRG_pg), we also have information on the left-right inclination of governments based on the cpds dataset (left-right dimension of the government based on cpds data, LRG2 = LRG_cp) that we use for sensitivity checks. To adjust it to the zero-to-ten scale, we constructed a weighted sum, weighting the cabinet seat share of left-wing parties by multiplying it with one, center parties with five, and right wing parties with nine. While the original parlgov and cpds data use a left-to-right-wing scale, i.e. higher numbers indicating a more right-leaning government, we use an inverted scale for our LRG_pg and LRG_cp where 1 is the score for a very right-leaning party and 9 the score for a very left-leaning government. Results for the political inclination appear only partly robust: more left-leaning governments (or their interactions with union strength) are associated with lower full employment gaps, though standard errors are high and hence results not significant.

Table A 9: Regression results for testing additional regressors

	Dependent variable:				
	FEGAP				
	(1)	(2)	(3)	(4)	(5)
FEGAP $_{t-1}$	0.911***	0.914***		0.908***	0.915***
	(0.022)	(0.022)		(0.021)	(0.027)
EPL $_{t-1}$	0.202	0.214	-0.506	0.161	0.206
	(0.228)	(0.208)	(1.568)	(0.232)	(0.240)
UDENS $_{t-1}$	0.038***	0.038***	0.129*	0.040***	0.036***
	(0.012)	(0.013)	(0.077)	(0.012)	(0.011)
TFP $_{t-1}$	-0.243***	-0.246***	-0.203	-0.243***	-0.246***
	(0.048)	(0.043)	(0.133)	(0.048)	(0.049)
EGLOB $_{t-1}$	-0.026	-0.025	0.160	-0.025	-0.022
	(0.031)	(0.032)	(0.157)	(0.031)	(0.030)
ACTPOP $_{t-1}$	-0.125**	-0.129***	-0.106	-0.128**	-0.126**
	(0.055)	(0.049)	(0.100)	(0.055)	(0.056)
ACCU $_{t-1}$	-0.060	-0.063	-0.977*		-0.063
	(0.051)	(0.052)	(0.495)		(0.050)
INFL $_{t-1}$	0.064*	0.064*	0.164	0.065*	0.067*
	(0.033)	(0.033)	(0.196)	(0.033)	(0.035)
LRG $_{t-1}$	-0.052**	-0.052*	-0.350***	-0.050*	
	(0.026)	(0.028)	(0.120)	(0.030)	
OG $_{t-1}$		0.010			
		(0.029)			
LTU $_{t-1}$			0.116***		
			(0.029)		
PRCA $_{t-1}$				-0.057	
				(0.053)	
PUCA $_{t-1}$				-0.143	
				(0.181)	
LRG2 $_{t-1}$					-0.023
					(0.021)
Observations	294	294	225	294	294
R^2	0.912	0.912	0.615	0.912	0.912
Adjusted R^2	0.888	0.888	0.464	0.888	0.888
F Statistic	265.859*** (df = 9; 230)	238.330*** (df = 10; 229)	28.553*** (df = 9; 161)	238.575*** (df = 10; 229)	264.723*** (df = 9; 230)
Note:					*p<0.1; **p<0.05; ***p<0.01

E) Running main regression specification on a larger sample of countries with a shorter time scale:

We run the same regression approach from section 5 on a different dataset that includes 28 countries (26 EU member states, plus the UK and the US) for a time between 2000 and 2022. Results are shown in Table A 10 below. What we find is that the lagged FEGAP variable is continuously and significantly associated with an increase in FEGAP. Lagged EPL shows a slightly positive tendency in its relation to FEGAP but no significant results. The result of the lagged UDENS variable is less clear regarding its relation to the FEGAP but in the complete regression specification of column (5) we also find a positive and significant outcome. The lagged TFP coefficient is mostly negative and (weakly) significant but also mirrors the results of the longer panel data. $INFL_{t-1}$ shows generally positive point estimates and also a significant result in model (4), yet, model (5) that includes all basic regression variables is not significant

– as well as the time and welfare regime specific regressions. Results that deviate from our observations of section 5 are that $EGLOB_{t-1}$ as well as $ACCU_{t-1}$ show a significantly negative outcome and the political LRG, as well as the ACTPOP variable a null outcome regarding their relation with FEGAP. In addition, the newer time-specific dummies show that the financial crisis of 2008 and 2009 as well as the Covid crisis are positively and significantly related with an increase in FEGAP.

Table A 10: Regression table based on short panel data

	Dependent variable:						
	FEGAP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FEGAP_{t-1}$	0.744^{***}	0.814^{***}	0.829^{***}	0.795^{***}	0.904^{***}	0.927^{***}	0.973^{***}
	(0.053)	(0.065)	(0.057)	(0.051)	(0.043)	(0.055)	(0.038)
EPL_{t-1}		0.231	0.110	0.442	0.016	0.391	0.306^{**}
		(1.287)	(1.023)	(0.753)	(0.396)	(0.395)	(0.149)
$UDENS_{t-1}$		-0.0004	-0.002	-0.027	0.146^{**}	0.020	0.007^{*}
		(0.034)	(0.035)	(0.024)	(0.071)	(0.023)	(0.004)
TFP_{t-1}			-0.178^{*}	-0.159^{**}	-0.072^{*}	-0.088^{**}	-0.049
			(0.103)	(0.066)	(0.041)	(0.041)	(0.035)
$EGLOB_{t-1}$			-0.036	-0.204^{***}	-0.449^{***}	-0.329^{***}	-0.036^{**}
			(0.123)	(0.066)	(0.115)	(0.071)	(0.017)
$ACTPOP_{t-1}$			-0.006	-0.005	-0.115	-0.070	-0.198
			(0.209)	(0.139)	(0.248)	(0.165)	(0.158)
$ACCU_{t-1}$				-0.344^{***}	-0.139^{***}	-0.135^{***}	0.026
				(0.118)	(0.041)	(0.033)	(0.039)
$INFL_{t-1}$				0.224^{***}	0.176	0.181	0.171
				(0.084)	(0.160)	(0.149)	(0.199)
LRG_{t-1}					0.032	0.066	0.072
					(0.070)	(0.069)	(0.074)
FinancialCrisis						1.466^{***}	
						(0.502)	
EuroCrisis						0.515	
						(0.327)	
CovidCrisis						2.713^{***}	
						(0.382)	
DCLU_SOD							-0.311
							(0.253)
DCLU_CON							-0.189
							(0.199)
DCLU_MED							0.031
							(0.591)
Observations	515	299	267	267	185	185	185
R^2	0.641	0.743	0.763	0.812	0.893	0.903	0.966
Adjusted R^2	0.602	0.699	0.713	0.770	0.864	0.889	0.959
F Statistic	828.846^{***} (df = 1; 464)	245.381^{***} (df = 3; 254)	117.959^{***} (df = 6; 220)	117.502^{***} (df = 8; 218)	134.099^{***} (df = 9; 144)	124.548^{***} (df = 12; 160)	358.035^{***} (df = 12; 153)
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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