Begging thy coworker – Is Europe's wage growth destined to slow further?

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Abstract

The pick up of European wage growth after the great financial crisis (GFC) remained excessively sluggish. This fuelled a debate about whether the Phillips curve had flattened and about alternative explanations for subdued wage growth. However, structural labour market aspects remained strangely absent from this discussion. This is where we contribute using EU-SILC data.

First, we find that the presence of temporary contracts in Europe's labour markets slows down aggregate wage growth due to the competition that temporary employees exert on permanent employees. Second, we demonstrate that the Phillips curve flattening after the GFC prevails in the EU even after controlling for the changing composition of workers. Third, we establish that labour market segmentation has been at least as important in slowing wage growth since the GFC as unemployment, i.e. the observed flattening of the Phillips curve.

JEL classification: J31, J42, J82

Keywords: Wage Growth, Labour Market Segmentation, Dual Labour Market Theory; Phillips Curve

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1 Introduction

After the great financial crisis (GFC), wage growth in Europe remained surprisingly slow; even after labour markets had started to recover. Given wage growth's crucial role in determining purchasing power, inflation and the tax base this became increasingly troublesome for policy makers. A rich debate ensued with a focus on the wage Phillips curve, i.e. the cyclical relationship between wage growth and labour market slack, i.e. unmet employment demands by potential workers.

In this paper, we demonstrate that one type of labour market segmentation – measured by the incidence of involuntary temporary employees – has been one of the most important drivers of the slow down in wage growth; including the slow down after the great financial crisis. Structural labour market aspects, thus, are key in understanding the contemporary development of wage growth; including at the aggregate level. This sheds new light on the macroeconomic debate that had mainly focused on cyclical properties of the Phillips curve. A large part of the debate had concentrated on whether and – if so – why the Phillips curve had flattened. In this paper, we show that the secular growth of less stable working arrangements is at least as important as the flattening of the Phillips curve in order to understand wage developments in Europe. Given the trend growth in temporary work arrangements, an important implication is that overall wage growth is likely to slow even *further* for the foreseeable future.

In the first section, we present a modeled synthesis of the debate about the flattening of the Phillips curve. In the second section, we demonstrate empirical evidence substantiating the existence of a flattened Phillips curve even when analysing a composition-corrected rate of wage growth. Our findings underline that the coexistence of permanent and temporary employees leads to competition-induced wage restraint at an aggregate level; a finding that is arguably more important in understanding wage dynamics than changes in the gradient of the Phillips curve. We finish by analyzing the trend of temporary employment and deducing an increasing dampening effect of aggregate wage growth in Europe.

2 What happened to wage growth after 2012? – A synthesis of the macroeconomic debate

2.1 The emerging picture in the literature

Did wage growth slow down at all after the GFC? Aren't wages *always* growing too slow from an employees' and too fast from an employers' point of view? The answer is no, following the macroeconomic literature. In a business cycle perspective[1] wage growth can be considered to be slow if the current rate is lower than it usually has been at the given level of labour market slack; most commonly measured by the unemployment rate. This Phillips curve interpretation of labour markets typically also considers inflation and productivity as key determinants of wage growth thereby linking the business cycle to the long run perspective of growth models. It is this view that dominates the macroeconomic debate.

After the GFC, wage forecasts based on historical relationship between wage growth and labour market slack, started to systematically *overshoot* realised wage growth, diverging from historical experiences. A flattening of this Phillips curve relationship (for high rates of unemployment) emerged as the most popular explanation for the period of depressed wage growth (2012-2017). Evidence of a flattening of the Phillips curve started to accumulate early after the crisis (Anderton and Boele, 2015). The period from 2012 onwards was identified as the starting point of disinflation driven by domestic factors such as wages (Ciccarelli and Osbat, 2017; Moretti et al., 2019). Nickel et al. (2019) find a large part of the slowdown in wage growth to be over-proportional and identify non-linearities of the Phillips curve as one of the many explanations for the protracted reaction of wages to labour market recovery. For a group of advanced economies this finding is supported by Arsov and Evans (2018) and it corroborates earlier findings by the IMF (2017).

Opposing this view Kiss and Van Herck (2019) find the decline in wage growth to be primarily

[1] An alternative approach would be to take the long run view. In the steady state setting of all major growth models, wage growth can be considered to be slow when it is below the inflation rate plus productivity as in this case the functional distribution of incomes is not constant, thereby yielding systemic instability (see Gächter et al.). This however, is a completely different time dimension than investigated in this paper.

driven by standard factors and identify the flattening as being not statistically significant. The latter result, however, is quite obviously driven by the choice of their time frame that already starts in 2010. This might also apply to the findings of Bonam et al. (2018) and Bulligan and Viviano (2016) who both chose 2008 as starting date for their analysis. Both papers investigate large euro area member economies and note that the flattening turns out to be robust only in the case of Germany. Bonam et al. (2018) even identify a steepening for some countries using an alternative rather unconventional indicator[2]. Bulligan and Viviano (2016) (for the pre-2016 period) seem to support these findings for Italy and France.

It may be possible to reconcile these apparently contradictory results. The different findings at the country level might be linked to the heterogeneous fate of the respective countries during the crisis (with Germany clearly faring best during the observation period). Assume for instance a behavioural shock occurs; such as e.g. a reduction in the reservation wage following a reform or a reduction in the bargaining power of employees. Theoretically, this shifts (the intercept of) the Phillips curve while not having a lasting impact on cyclical behaviour but the inter-temporal effect empirically might be picked up as a steepening of the slope; particularly in a time series setting. This reasoning appears to be underlined by the fact that most cross-country surveys find a flattening while some country specific time series surveys do not.

2.2 Hidden slack – Forms of underemployment and marginal attachment

If thus – overall – wage growth had experienced a negative shock after the GFC what was its nature? Why was wage growth depressed after the GFC in Europe? One important line of reasoning focuses on the correct identification of labour market slack. The major part of the debate concentrates on the question what labour market slack really is, or rather how it is best measured[3]. The idea leads to the conclusion that the headline unemployment rate (or the respective unemployment gap in the NAIRU terminology) has lost its accuracy in

[2]The alternate indicator they propose only checks for robustness and is based on an indicator that primarily appears to signal the shortage of technical competences (McGrath and Beehan, 2018).There is no clear case set out why this should be a better proxy for labour market slack than more conventional indicators.

[3]Another argument again focuses on the measure for inflation Ball and Mazumder (2020).

capturing the supply-overhang of labour.

The measure for unemployment needs to capture the shortness or abundance of labour supply as a prerequisite to establish a robust relationship between the inflation rate and the unemployment rate. If the measure for unemployment is incomplete, the Phillips curve loses its explanatory power for wage growth. Trying to capture this effect graphically, we depict a relationship between the unemployment rate and any given rate of total slack including hidden factors of labour supply. In the following, we call this the slack-unemployment relation (SUR) depicted in the South-East quadrant of figure 1. Any given rate of unemployment goes hand in hand with a larger rate of total slack; thus hiding excess labour supply.

Excess labour supply may be hidden via different avenues, such as discouraged worker effects, short-time working schemes and part-time work. Indeed, broader measures of labour-under-utilization, such as marginally attached workers, involuntary part-time employment and temporary workers have been lumped together with the unemployment rate in previous analyses. Unsurprisingly, these variables have increased more strongly during the recession than the unemployment rate as shown in Hurley and Partini (2017) at least relative to their trend before the crisis (ECB, 2017)[4]. In a key contribution Bell and Blanchflower (2019) derived an index for labour under-utilization for the UK that is constructed based on desired hours of work in order to capture the degree of underemployment. In a complimentary analysis, they demonstrate that this index improves the Phillips curve fit for Europe (and the US) (Bell and Blanchflower, 2021). The OECD (2018) supports this at least as regards composition effects of part-time workers. For advanced economies, Hong et al. (2018) find further evidence that involuntary part-time employment helps to explain wage developments, which is corroborated by the IMF (2017). Similarly, Zhang (2019) finds that broader cyclically adjusted measures for unemployment such as the hours gap or the non-employment gap improve the fit of the Phillips curve in the EU. Only the findings of Nickel et al. (2019) deviate somewhat. While they also use broader measures of slack, such as extensions of the

[4]This result might be driven by the wide spread introduction of short-time working schemes after their initial successes in Germany. The effect of these schemes is a reduction in the lay-off rate during the crisis as compared to the counterfactual but there also is evidence that their use hampers GDP and job growth in the recovery (Baller et al., 2018; Hijzen and Martin, 2013). It is possible that the resulting hike in involuntary part-time – really being nothing else but hidden excess supply – puts a drag on wage growth in the recovery.

unemployment rate by different aggregates of involuntary part-time- and marginally attached workers, their findings indicate that these broader measures are relevant for wage growth but perform equally well to the headline unemployment rate in Phillips curve estimations.

2.3 Non-linearities – Nominal wage resistance and the business cycle

The second line of reasoning is motivated by the traditional Keynesian assumption of downward rigidity (but upward flexibility) of nominal wages (see e.g. Dolado et al. (2003)). The main argument is that a recession warrants real wage cuts in order to clear the labour market; this is commonly understood as a situation in which the unemployment rate is brought down to its market clearing (or its natural or NAIRU) level. In the current situation however wage setters had been faced with a low-inflation environment. A veiled real devaluation of nominal wages by inflation thus became impossible making it way harder to bring labour markets into equilibrium in the face of downward nominal wages rigidity. The non-linearity thus is brought about by the zero lower bound; as symbolized by the dashed horizontal line in figure 1 in the upper right quadrant. According to this interpretation the critical years between 2012 and 2017 in the euro area simply show a movement along this non-linear element of the Phillips curve.

In the debate particularly the ECB and the Deutsche Bundesbank have propagated this view (ECB, 2015; Bundesbank, 2016) and for the euro area it has recently been supported by a DSGE modelling exercises (Iwasaki et al., 2021). It is also supported by the findings in Marotzke et al. (2017) based on a survey of 25 European countries for 2010-2013. This corresponds to the findings of ECB researchers who attest limited wage flexibility for Europe (Rusinova and Heinz, 2011; Rusinova et al., 2015). Indeed, in most euro area countries only very few firms had reported (nominal) wage cuts during the height of the crisis (Izquierdo et al., 2017) a fact that lends some support to the hypothesis of non-linearities. The results of the ECB's wage dynamics network also appear to point into the direction of nominal wage resistance during downward adjustments (Izquierdo et al., 2017). At the same time – the argument goes (Ciccarelli and Osbat, 2017) – excess capacities built up and led to labour hoarding, thereby resulting in excess employment at the prevailing wage level. If this is the case, wage growth will exhibit a delayed reaction to a decline in unemployment during the recovery.

2.4 A graphical synthesis of the main findings in the macroeconomic literature

There are three key findings of the macroeconomic literature. First, a substantial but not the entire part of the slowdown in wage growth can be explained by standard Phillips curve factors such as a reduction in inflation expectations, trend productivity growth and high conventional labour market slack. Second, there appears to be a non-linear element of the Phillips curve, that might be caused by downward wage rigidity. Third, our understanding of labour market slack should not rest on the headline rate of unemployment alone but might include broader measures of slack.

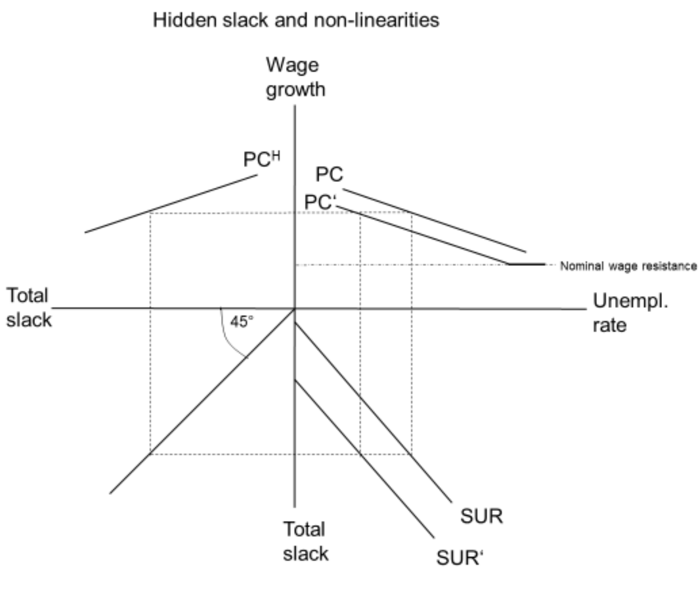


Figure 1: Synthesis of the main findings

We synthesized the major findings of the literature in a graphical model (figure 1). As long as hidden slack exists, any given rate of unemployment corresponds to a higher degree of total labour market slack as defined by the sum of unemployment plus hidden slack. This is illustrated in the lower right quadrant by the slack-unemployment ratio (SUR). A standard Phillips curve (PC) based on unemployment combined with the SUR leads to the hidden Phillips curve (PC^H), that is based on total slack. Inherently each given rate of wage growth is associated with a larger rate of total slack than the corresponding rate of unemployment. Labor market institutions and policies affect the ratio of unemployment to total slack. For instance, job seekers outside the labour force formally counted as being inactive or short-time workers during crises will shift the ratio of unemployment to total slack from SUR to SUR'. This again shifts the Phillips curve south and non-linearities will start to occur at lower levels of the unemployment rate

Our graphical synthesis yields a concise theoretical framework for the sometimes fraying debate about the sluggishness of wage growth in Europe. However, none of the contributions above are able to account for the observed flattening of the Phillips curve. Both approaches – hidden slack as well as non-linearities – imply a cyclical and thus somewhat transitory nature of the sluggishness of wage growth. Thus, wage growth can be expected to return as soon as unemployment (or broader slack) falls below a certain threshold. Below, however, we demonstrate that there are longer lasting developments that put a permanent drag on wage growth. These developments – we will show – are quantitatively at least as important as the post-crisis slow-down and have been of comparable significance to the flattening of the Phillips curve since the GFC.

3 Hidden structure – An extended explanation based on segmentation

3.1 Smoothing the cycle – Segmentation and composition effects

3.1.1 Segmentation and wage penalties

Neither labour markets nor wage setting institutions are homogeneous. It is well established that different kinds of employees suffer from wage penalties; that are systematically linked to certain key characteristics like place of birth (see e.g. Amo-Agyei (2020)), gender (see e.g.

Blau and Kahn (2017)) or temporary contracts (see e.g. Kahn (2016); Dias da Silva and Turrini (2015); Westhoff (2020); Pavlopoulos (2013)). As a logical corollary a change in the composition of the labour force will affect average and eventually aggregate wage levels and – in the making – transitionally also wage growth.

However, it is possible that there is a systematic relation between the business cycle and the incidence of temporary contracts. Hirsch (2016) and Gebel and Giesecke (2011), for instance, show that temporary agency workers have lower job stability than non-temporary workers suggesting that they are more likely to be layed-off during unfavourable economic conditions (e.g in a downturn). Apparently temporary employment is used to cushion firms against labour market fluctuations ((Draeger and Marx, 2017; Hijzen et al., 2017)). There is also a theoretical case why temporary employees might suffer excessively from labour demand shocks as the costs of separation tend to be smaller (Costain et al., 2010); an argument known as Insider-Outsider Theory (Lindbeck and Snower, 2002). For the case of Japan – that lives with a substantially deeper segmentation of its labour market than Europe for a long time – it can be shown that the existence of temporary labour is capable to account for the flattening of the Phillips curve (Aoyama et al., 2021). In Europe experiences made during the Covid-crisis support the view that the secondary labour market serves as an overflow basin for labour market fluctuations[5].

Temporary employees are likely to be the first ones to be laid off in crises and the first ones to be hired in recoveries. Thus, their incidence usually increases during recoveries – implying that the share of people suffering from a wage penalty from temporary employment contracts is increasing – which again puts a drag on aggregate wage growth. This is a simple, pure *composition effect*. If however, the composition of the labour force systematically changes over the business cycle not adjusting for the composition of employees potentially suffers from a substantial bias. Is the observed flattening of the Phillips curve nothing else than

[5]For instance the Italian response to the COVID-crisis included the so called Cura Italia decree. This decree suspended the right to dismiss employees for economic reasons. Adjustments to the labour force however were still possible given that according to OECD data 17% of all Italian employees held a temporary contract in 2019 (a fifth of which set to expire within three months, see OECD (2020), Box 2.8). This observation fits the picture described in Lombardi et al. (2021) who find that sinking bargaining power of employees has increased adjustments made along the extensive margin in Italy.

an over-interpretation of intra-labour market flows? As long as only the headline rate of aggregate wage growth is observed – as in most of the literature cited in section 2 – it is impossible to be certain about this issue. Therefore, we create a counterfactual rate of wage growth corrected for the employment composition effects.

3.1.2 Correcting for composition effects

To be able to adjust wage growth for changes in the employment composition, we aggregate the growth rate of wages from individual level data. We use all waves of the annual European Union Statistics on Income and Living Conditions (EU-SILC) personal files covering 2004 to 2018[6]. The target population examined are dependent workers. We use *gross employee cash or near cash income (PY010G)* as our main variable for wages since we are interested in the pre-tax labor income. We rely on the *number of hours usually worked per week in main job (PL060)* to compute hourly wage growth defined as the average annual change in nominal hourly wages. We compute aggregate measures at the country level using the (*personal cross-sectional weight (PB040)*.[7] EU-SILC combines demographic variables from the current year with wages from the previous year. Our analysis focuses on wage growth and we, therefore, use the year of the reported wage, i.e. one year prior to reported in EU-SILC.[8]

EU-SILC has been the established standard for cross-country income comparisons in Europe. A large effort is put on harmonisation of definitions and variables across countries, although some caveats apply due to national differences in data collection. Since its start in 2004, an increasing number of countries have shifted to rely on national registries to construct or correct the wage variables strengthening accuracy and reliability (for a detailed overview see Goedeme and Trindade (2020) and Lohmann (2011)). We carefully examine national partic-

[6]This implies that we have data for wages from 2003 to 2017 since all countries except the UK collect the wage of the previous year

[7]For a detailed discussion of representativity, in particular sampling design errors related to EU-SILC see Goedeme (2013); Zardo Trindade and Goedeme (2016).

[8]The income reference period for most of countries is the calendar year previous to the survey year with two exceptions: In Ireland the income reference period is the last twelve months. In the United Kingdom the current income is annualised and aims to refer the current calendar year, i.e. weekly estimates are multiplied by 52, monthly by 12 (Eurostat, 2018)

ularities in our data cleaning and aggregation procedure following Trindade and Goedeme (2019) on the income variables and GESIS (2021) in addition to the EU-SILC methodological guidelines and national quality reports to ensure a maximum of cross-country comparability. However, processing and aggregating individual level data always entails a series of small decisions that can affect the outcome and research should be transaparent about them. We document our aggregation procedure in detail in our annotated Stata code. Eurostat does not publish sufficient details on their procedure for data processing and aggregation that we could follow. To assess the validity of our aggregation, we compare the published aggregate of wages by Eurostat based on EU-SILC to our country aggregation of the individual level data. Since Eurostat does not publish an aggregate series for *gross* wages from EU-SILC but only for *net* wages, we use *net* wages (*net employee cash or near cash income (PY010N)* in EU-SILC) for comparison. Our aggregated series aligns closely with the officially published time series across Europe (appendix figure A.1 and figure A.2), although with two limitations. First, in 2009, several countries changed from survey to register data for documenting wages in EU-SILC resulting in some differences prior to the adjustment, most notably in the year of change (2009). As a result, alignment of the two series is substantially improved from 2010 onwards. Second, wage growth for Cyprus has an unreliable profile in *net* terms, although our series for *gross* wages in Cyprus is smoother (figure A.2).[9] Excluding both, the year 2009 and Cyprus, we obtain a correlation coefficient of 0.91 between our aggregated series and the officially published Eurostat data.

Our aim is to adjust for contributions of a changing employment composition over time to wage growth. The adjustment allows for clearer identification of the effects in the following country-level estimations. This is of particular relevance in our case since the main independent variable *the incidence of temporary employment* is the result of changes in the employment composition. Hence, we want to obtain a counterfactual measure for aggregate wage growth for a stable pseudo-workforce over time. To adjust wage growth for changes in the employment composition, we conduct *inverse probability weighting (IPW)*, first time

[9] Goedeme and Trindade (2020) indicate that Cyprus relies on surveys to collect income data but matches it with register data to correct for apparent mistakes and keeps extreme or outlying values in the data if they have been verified.

comprehensively explained by Rosenbaum and Rubin (1983), introduced to economics by DiNardo et al. (1996), and recently review by Fortin et al. (2011). We follow in the application the procedure as in Fessler et al. (2017) and use the Stata *teffects* command. IPW is typically used to estimate the counterfactual outcome when assignment is not random or all subjects in the population were assigned treatment. It removes confounding by re-weighting to create a pseudo-population in which the treatment is independent of the measured confounders. In our case, we use the year as treatment variable to re-weight our population weights and aggregate a counterfactual employment composition that is constant over time.

To create our stable counterfactual workforce, we first need to estimate the re-weighting factors for each year and replicate the analysis for each country. We predict the probability of treatment with our logit model, as in (1), pairing the base year t (2004 or earliest available) with each of the following years $t+n$:

$$\ln \frac{p}{1-p} = \beta_0 + \sum_{t=1}^{m} \beta_t X_t \tag{1}$$

where X_t is our set of controls including employment contract, gender, country of birth[10], educational attainment[11] and years of work experience[12]. We do not need to control for working time since our dependent variable for the macro estimations is aggregate wage growth per hour. We do not adjust for occupation (ISCO 2digit) and sector (NACE rev.2) as we would lose too many country-year observations due to missing data.

In a second step, we re-weight the cross-sectional weights for each individual observation using the propensity scores obtained by the logit estimation. For the base year (treated individuals) we keep the original weight $g_1 = g$, whereas for control individuals, we multiply the weight g with the inverse propensity score $g_{1+n} = g\frac{p(x)}{1-p(x)}$ simulating constant employment

[10]distinguishing between born inside and outside country of residence.

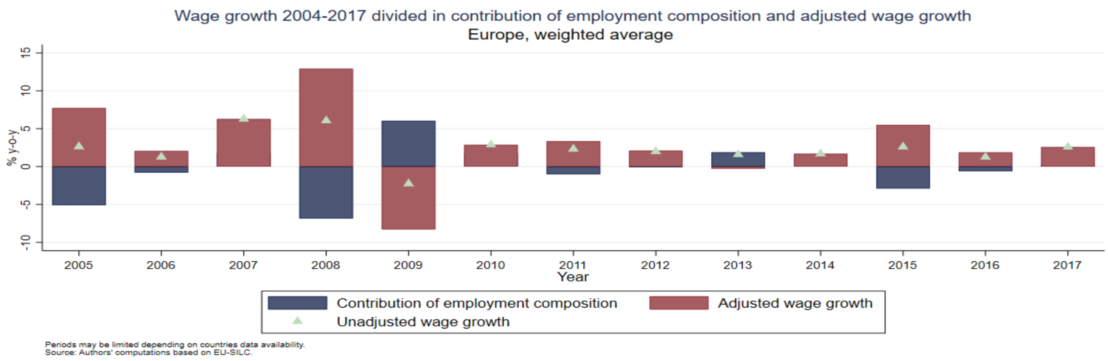
[11]ISCED clustered in the three groups low: pre-primary, primary and lower secondary education; middle: (upper) secondary education and post-secondary non tertiary education, and high: tertiary education.

[12]We use age as a proxy for work experience where data is missing (less than 10 % of the sample).

shares over time.[13] Finally, we aggregate the individual level data at the country year level to obtain our adjusted measure for aggregate wage growth, assuming constant employment shares over time.

The re-weighting procedure allows us to use a measure for wage growth that is not influenced by a changing composition of employment over time in respect to our controls. While employment composition contributions partially balance out over the business cycle (figure B.7), their impact on aggregate wages during economic recoveries and crises has been substantial (figure B.1). During the upswings in 2005 and 2015 changes in the employment composition depressed overall wage growth by 50% on average across Europe (figure B.3 and figure B.5). By contrast, during the crisis years 2009 to 2014 low-paid workers were over proportionally laid off and aggregate wage growth was elevated by changes in the employment composition (figure B.4).

Figure 2: Wage growth 2004-2017 in Europe divided in the contribution of employment composition and adjusted wage growth



3.2 Begging thy co-worker – Segmentation and the macro-economy

3.2.1 Assessing competition effects

Does a correction of composition effects eliminate all relevant effects of segmentation? Not at all. To the contrary a new and growing stream of literature points to further effects

[13]Note that it is not possible to fully rebalance continuous covariates with a semiparametric method, but we can eliminate a large part of the variation in individual worker characteristics over time with our re-weighting procedure.

of segmentation. That is – over an above their function as a buffer stock – temporary employees might also exert competitive pressure on permanent employees in a way that leads to increased wage restraint in exchange for job security of the latter. In fact, there is a theoretical case that the wage penalty of temporary employees might put permanent employees under competitive pressures (Koutentakis, 2008). If the work of permanent, more expensive employees can be done by flexible, cheaper employees, we expect the presence of temporary workers to exert a negative effect on wages of permanent workers. We call this the *competition effect* in the following.

Such interaction effects between different labour market segments have been established in empirical contributions. Damiani et al. (2018) show that reductions in employment protection legislation (EPL) for temporary workers tend to reduce wage shares in general, not only those of temporary workers. Bellani and Bosio (2019) find that average hourly wages of permanent employees are negatively affected by the incidence of temporary employees in a sample of European countries using EU-SILC. This is corroborated by Giuliano et al. (2017) who find for Belgium that the employment of temporary employees increases profits in (labour-intensive) service industries. However, effects are not equal along the income distribution. Weisstanner (2020), for instance, shows that deregulating flexible employment has a negative effect on the wage share of the lower and middle income groups while having a positive effect on the top group.

Given this evidence, it would be surprising if competition effects caused by changes in the incidence of temporary employees would have no aggregate effect on wage growth. In fact Ramskogler (2021) shows that overall, temporary employees do have a negative effect on aggregate (uncorrected) wage growth that even appears to increase after the GFC. Using EU SILC data allows us to isolate the wage growth of permanent employees from that of temporary employees. If a competition effect as defined above exits we should be able to identify a dampening effect of the incidence of temporary employment on the wage growth of permanent employees. Moreover, by netting out composition effects (caused by changes in temporary employment) we can asses the macroeconomic significance of potential competition effects on the overall aggregate wage growth.

The most widely used empirical model to study the cyclical drivers of wage growth is the wage Phillips curve. The traditional wage Phillips curve relates nominal wage growth to a measure of labor market slack. Additional determinants that are typically considered are (expected) inflation and labor productivity growth (see e.g. Nickel et al. (2019)). We will use such an augmented Phillips curve setup to study the impact of dual labour markets on nominal wage growth in Europe. We estimate a standard reduced form equation in a panel data frame-work of the form:

$$\dot{W}_{i,t} = \alpha_1 + \alpha_2 \mathrm{U}_{i,t} + \alpha_3 \mathrm{Prod.}_{i,t} + \alpha_4 \mathrm{Infl.}_{i,t} + \alpha_5 \mathrm{Invol.\ Temp}_{i,t} + \mu_i + \tau_t + \epsilon_{i,t} \qquad (2)$$

Our dependent variable is nominal wage growth obtained from EU-SILC data. As a benchmark, we will first study the dynamics of the unadjusted aggregate wage growth to represent the work horse Phillips curve model. In a second step, we will look at the impact from segmented labour markets on nominal wage growth of permanent employees and finally implement our main dependent variable, which is nominal wage growth net of composition effects ($\mathrm{W}_{i,t}$). While the bulk of studies estimating wage Phillips curves uses quarterly data[14], we have to stick to an annual frequency (as in the original contribution by Phillips (1958) or more recently in Kiss and Van Herck (2019)) as data to control for composition effects are only available on a yearly basis. Our sample includes 30 European countries (i) and ranges from $t = 2005, ..., 2017$, which leaves us with roughly 340 observations[15]. We intentionally choose a static representation as we do not observe any persistence in wage dynamics in our sample (likely due to the annual frequency of data). Moreover, as we are interested in the within-variability of the data, we consider the time-invariant country effects (μ_i) as fixed (and not random).

As a baseline, we use the most conventional labor market slack indicator, which is the headline unemployment rate $\mathrm{U}_{i,t}$, but consider also several other measures of labor market

[14]Examples are Bonam et al. (2021), Nickel et al. (2019) and Bulligan and Viviano (2017)

[15]Note that data for some countries are only available after 2005, such that the overall sample size is reduced to 341.

slack as a robustness check. Further, we control for the impact of labor productivity ($\text{Prod}_{i,t}$) on wages, which we measure as the growth rate of real output per employment, as well as for inflation ($\pi_{i,t}$). Empirical studies using quarterly wage growth data often employ (one quarter) lagged inflation implying backward-looking expectations (Ramskogler, 2021; Nickel et al., 2019; IMF, 2017). Given the annual frequency of our data, we assume a contemporaneous effect from inflation (measured as the annual change in the harmonized index of consumer prices) on nominal wage growth in our baseline setting[16].

Finally, we add to this rather standard Phillips curve specification a variable to identify the competition effect resulting from the presence of a segmented labor market. We measure the extend of labor market segmentation by the number of involuntary temporary employees as a share of the active working-age population ($\text{Temp}_{i,t}$). This indicator is a survey-based measure provided by Eurostat (based on the Labor Force Survey), which is collected since 2002 and is available for all countries in our sample. A detailed description of the measurement of all variables and their sources is included in table D.1 in the Appendix.

We start out presenting the result for the work horse Phillips curve model, which we summarize in column (1) of Table 1. The coefficient estimates have the expected signs and are statistically significant. An increase in labor productivity growth has a positive effect as it raises the demand for labor, which in turn puts upward pressure on wage growth. We also observe a positive impact from inflation with a regression coefficient standing around 1. Hence, an increase in the inflation rate transmits almost one to one into a rise of nominal wage growth[17]. In contrast, labour market slack is negatively associated with nominal wage growth. According to the point estimate, a one percentage point increase in the unemployment rate reduces nominal wage growth by 0.6 percentage points. This is also a common finding in the literature, reflecting that a larger share of job-less people diminishes

[16] We have also considered a survey-based measure capturing forward-looking inflation expectations provided by the European Commission (Exp. Infl.). As this variable is not available for two of our countries (Switzerland and Norway) and did not improve the explanatory power, we decided to stick to realized consumer price inflation.

[17] This finding likely is linked to the annual context of our estimations and corresponds to the results in Kiss and Van Herck (2019). While it is not very common in the literature using quarterly data, Rusinova et al. (2015) show that if 4 lags of inflation are considered in quarterly estimations the aggregate effect again accumulates to close to 0.9

Table 1: Identifying the competition effect

Indep. variable: unadjusted wage growth	work-horse PC	invol. Temp	time dummies	isolating Perm $\dot{W}$
	(1)	(2)	(3)	(4)
$Prod._t$	0.55***	0.59***	0.33**	0.37**
	(3.01)	(3.34)	(2.24)	(2.56)
$Infl._t$	0.99***	0.85***	0.51	0.51
	(3.49)	(2.81)	(1.09)	(1.11)
U_t	-0.59***	-0.65***	-0.49***	-0.48**
	(-3.02)	(-3.74)	(-2.80)	(-2.59)
$Invol.\,Temp_t$		-1.18***	-1.04***	-0.93***
		(-3.77)	(-3.30)	(-3.17)
Cons	6.22***	13.00***	11.66***	10.96***
	(3.53)	(5.65)	(3.87)	(3.83)
Model	FE	FE	FE	FE
TimeD	excl.	excl.	incl.	incl.
Weights	equal	equal	equal	equal
N	341	337	337	351

Two-tailed significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. T-statistics are reported in parenthesis.

the bargaining power of workers and puts downward pressure on wages.

In column (2) we add the explanatory variable of main interest, i.e. $Invol.\ Temp_t$. As expected, it is negatively associated with nominal wage growth and statistically highly significant. A rise in the share of involuntary temporary employees by one percentage point leads to a decrease in nominal wage growth by 1.2 percentage points. This resembles the findings in Ramskogler (2021), who establishes a significantly negative and causal effect from temporary employment on aggregate wage dynamics in Europe. Like in this paper, we have considered the *unadjusted* wage growth rate so far. Hence, the coefficient estimate might capture both, the potential composition isolated above *and* competition effects. However, before we alter our main dependent variable, we include time dummies in our model to control for common shocks that might have affected wage dynamics equally across countries over time, like the financial crises. In fact, a test of joint significance shows that the time dummies have high explanatory power. Apart from that, their inclusion reduces coefficient estimates of all variables, as we can see in column (3). This is particularly true for inflation, which even loses explanatory power. Obviously, price dynamics across countries have followed a very similar pattern over time. A possible common factor that could have determined prices across countries is certainly the oil price, which is known as being an important driver of consumer price dynamics.[18]

We will now alter our dependent variable in column (4) by considering the nominal wage growth of employees with permanent contracts only. This will allow us to estimate the competition effect, as we isolate that part of wage growth that cannot be affected by changes in relative weights between temporary and permanent employees. Compared to the estimates in column (3) all coefficient estimates remain broadly the same. Only the impact from temporary employment is slightly reduced but remains highly significant. This supports our thesis that the incidence of a segmented labour market has negative spill over effects on the dynamics of wages of employees with permanent contracts. Notably, our result is consistent with Bellani and Bosio (2019) who find that the density of temporary contracts within occupation and age-specific groups negatively affects average wages for permanent workers belonging to the same group[19].

3.2.2 The macroeconomic impact of competition effects

Having established the existence of a competition effect we now can proceed to investigate the macroeconomic significance of it. In how far does the segmentation of labour markets affect overall aggregate wage growth? Following up on our specification using unadjusted aggregate nominal wage growth in column (3) in Table 1, we re-estimate our model employing a wage growth variable net of composition effects arising from relative changes in contract types. The results are depicted in column (5) of Table 2. Two observations stand out. First, the estimates change only with respect to the variable of main interest, where the coefficient estimate drops from -1.04 to -0.90. Observing a reduction in the coefficient size is

[18] especially so in the period we are looking at (FIND CITATION, correlation is 0.47 in our sample, maybe use import prices as instrument in Endog-session as they are different across countries, use OECD data). Interestingly, the IMF makes use of this relationship and consider oil prices as an instrument for consumer price inflation in Phillips curve specifications (see e.g. IMF, 2017).

[19] Bellani and Bosio (2019) exploit EU-SILC data for 13 European countries in the period 2003 to 2010. The observation unit is based on 24 occupations and two different age groups. Temporary workers are classified as all individuals who are employed under a fixed-term contract.

very plausible, given that we have – by construction of the dependent variable – eliminated the composition effect. Second, and more importantly, the drop in the magnitude is not very pronounced. This indicates that the underlying mechanism that drives the negative relationship between segmentation labour markets and wage dynamics, is mainly a competition rather than a composition effect.[20]

Table 2: The economic significance of the competition effect

Indep. variable: adjusted wage growth	contract-corrected $\dot{W}$	all controls-corrected $\dot{W}$	beta coeff.	controlling country-size
	(5)	(6)	(7)	(8)
$Prod._t$	0.32**	0.28*	0.09*	0.07
	(2.26)	(1.78)	(1.78)	(0.26)
$Infl._t$	0.51	0.52	0.13	-0.09
	(1.13)	(1.10)	(1.10)	(-0.14)
U_t	-0.49***	-0.47***	-0.26***	-0.43**
	(-2.86)	(-2.97)	(-2.97)	(-2.57)
$Invol.\,Temp_t$	-0.90***	-0.92***	-0.42***	-1.02***
	(-2.93)	(-2.97)	(-2.97)	(-3.57)
Cons	11.07***	10.44***	-0.09	12.49***
	(3.80)	(3.51)	(-0.80)	(3.73)
Model	FE	FE	FE	FE
TimeD	incl.	incl.	incl.	incl.
Weights	equal	equal	equal	empl.
N	344	337	337	337

Two-tailed significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. T-statistics are reported in parenthesis.

In column (6) we employ nominal wage growth net of all composition effects (see also Micro Estimations). Interestingly, this has only an influence on the labour productivity estimate, which loses significance. This result is very intuitive, as some of the composition effects we control for, like age, skill and experience, are likely to affect average labour productivity developments. Therefore, they might be double counted to some extend, which is mirrored by a weaker t-statistic. Yet, turning back to our core variable, we do not observe any changes regarding the size or significance of the coefficient estimate. This allows us to conclude that there is a significant competition effect from involuntary temporary employees on aggregate

[20]Note also that the impact from temporary employees is of same magnitude as in specification (4) in Table 1, where we looked at wages of permanent workers only. Obviously, wage dynamics of permanent and overall employees (adding temporary employees) are very similar once composition effects are accounted for. This is very plausible, given that permanent workers make up 89% of all employees on average in our sample.

wage dynamics in Europe.

We conducted several robustness checks with respect to the measurement of labour market variables in Appendix C.1 that support our finding. Most notably, we show that it is *involuntary* temporary employment, which is driving the competition effect. Also, we demonstrate that the competition effect remains significant irrespective of which labour market slack indicator we use. In addition, we show that our results are not driven by one particular country by excluding one country at a time from the sample (see Table C.1 in Appendix C.2).

Finally, we want to assess the economic importance of segmented labour markets for wage dynamics in Europe. We do so by re-calculating specification (6) based on standardized variables, which allows us to rank the independent variables in terms of their strength in explaining wage growth. According to the resulting standardized (beta) coefficient estimates, which we present in column (7), an increase in temporary work by one standard deviation leads to a drop in nominal (compositional adjusted) wage growth by almost half a standard deviation. More importantly though, temporary employment turns out to be the most relevant determinant for wage growth followed by the unemployment rate. Taking into account the uncertainty surrounding the parameter estimates (a test on parameter equality is not rejected), we may conclude that unemployment and temporary work had been equally meaningful in explaining nominal wage growth in the period 2005-2017.

Another way to assess the economic importance of our result is to put more weight to countries that are larger. It could be the case that labour market segmentation is an important factor in driving wages in various small countries of Europe, but leaving aggregated (weighted) wage dynamics unaffected. Controlling for this possibility by employing frequency weights[21] in column (8) shows that segmented labour markets also matter when we control for the different size of labour markets across countries. The coefficient estimate even turns out to be slightly higher when the sample is re-weighted. Interestingly, the effect from labour productivity growth turns insignificant, which is not surprising given that the wage growth

[21] The relative weight of each country is based on the average number of employed persons during the overall sample period.

variable nets out some of the factors that determine labor productivity developments[22]. Finally, as the estimated sensitivity of wages to labour market segmentation as well as slack might be affected by potential endogeneity bias, we discuss this issue thoroughly in Appendix C.3.

To sum up, by correcting for composition-induced effects on wage growth, the results provided in Table 2 clearly demonstrate that competition between permanent and temporary employees have sizeable macroeconomic effects that are not only statistically but also economically significant.

3.3 The time after 2012

We have learnt in the previous subsection that labour market segmentation has been one of the most important determinants of nominal wage growth in Europe in the last 13 years. But does it also help to understand the observed slow-down in wage growth after 2012? Figure 3 shows the development of unemployment and involuntary temporary employment (both measured in % of the labor force) in Europe since 2002.[23] Focusing on the relationship between both series, one observation clearly stands out. Labour market segmentation has inversely mimicked the cyclical behaviour of the unemployment rate. This is also true for the period after 2012, where the unemployment rate was falling, while temporary employment started to increase

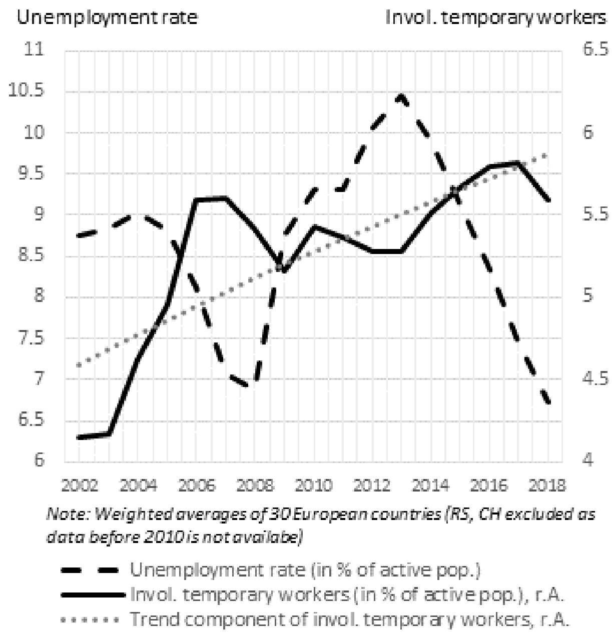


Figure 3: Labour market segmentation in Europe

[22] Also, excluding countries step-wise from the estimation reveals that the insignificant coefficient is highly driven by developments in Poland.

[23] The variables are weighted averages of 28 European countries. Due to the lack of data we excluded CH and RS in this illustration to draw a consistent picture of the development over time.

and kept growing until 2017. Recalling the significant negative impact from segmented labour markets on wage growth, we can hence conclude that the increase in involuntary temporary employment certainly had a dampening effect on wage growth in the latest recovery period.

However, the increase in the share of involuntary temporary employment was not exceptionally high compared to the recovery period before the financial crisis. From 2005, which is the beginning of our estimation period, up to 2006/2007 the rise in the temporary labour market segment was roughly of the same magnitude as the rise from 2013 to 2017. Hence, if we assume that the sensitivity of nominal wage growth to labour market segmentation was constant over the estimation period, the dampening effect from temporary employment could not have been particularly large in this specific period of sluggish wage growth.

Yet, what stands out from figure 3 though is that the rise in temporary employment in the recent recovery phase started from a higher level and reached an all time high in 2017. A plausible hypothesis would be that a higher share of temporary employees in the labor force reinforced the competition effect. Hence, another way to approach the question whether segmentation can help to understand the slow-down in wage growth in the recent recovery phase, would be to look whether the impact of temporary employment has increased since 2013. In table 3 we re-specify our model accordingly and allow for different slope parameters in order to isolate the effects after the crisis. Concretely, by interacting the unemployment rate and the incidence of temporary employees with a post-crisis dummy[24] we can assess whether the coefficients of the respective variables are subject to significant change after 2012.

Specification (8) in table 3 is a memo item and recalls our results (from table 2) when slope parameters are assumed to be constant over time. In column (9) we present estimates of the unrestricted model. We want to highlight two interesting findings. First and foremost, our results confirm the hypothesis that the competition effect has increased since 2013. The parameter estimate on the interaction term ($Invol.Temp_t * post\text{-}crisis$) signals that

[24] The dummy variable equals 1 for the years 2013 to 2017 and 0 for the period before. Note that we have experimented with other thresholds as well. It turned out that the break in slope parameters is most pronounced when the post-crisis period is defined from 2013 onwards.

Table 3: The competition effect in the post-crisis period 2013-2017

Indep. variable:	Unstand. coeff.		Standardized coeff.	
adjusted wage growth	(8)	(9)	(10)	(11)
$Prod._t$	0.07	0.04	0.02	0.01
	(0.26)	(0.14)	(0.26)	(0.14)
$Infl._t$	-0.09	-0.11	-0.02	-0.03
	(-0.14)	(-0.17)	(-0.14)	(-0.17)
U_t	-0.43**	-0.56***	-0.24**	-0.30***
	(-2.57)	(-3.03)	(-2.57)	(-3.03)
$U_t * post\text{-}crisis$		0.36***		0.25***
		(3.48)		(3.48)
$Invol.\,Temp_t$	-1.02***	-0.87***	-0.47***	-0.40***
	(-3.57)	(-3.24)	(-3.57)	(-3.24)
$Invol.\,Temp_t * post\text{-}crisis$		-0.47***		-0.21***
		(-3.03)		(-3.03)
Cons	12.49***	12.76***	-0.04	-0.02
	(3.73)	(3.87)	(-0.46)	(-0.11)
Model	FE	FE	FE	FE
TimeD	incl.	incl.	incl.	incl.
Weights	empl.	empl.	empl.	empl.
N	337	337	337	337

Two-tailed significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. T-statistics are not reported (so far, maybe place them beside coeff.estimates).

the sensitivity of wages with regard to temporary employment increased significantly by around 50%.[25] Second, the impact from unemployment on nominal wage growth has also changed since 2013 but in the opposite direction. According to the parameter estimates, the sensitivity of wage growth to the unemployment rate decreased by almost two-thirds.[26] When we look at the change in terms of standardized coefficients (to account for differences in the volatility of variables), which are displayed in column (11), the decrease amounts to more than 80%. In effect, the impact from unemployment becomes even insignificant in the latest recovery period[27], while the competition effect increased by around half, also in terms of standardized coefficients. Hence, we can conclude that after controlling for composition induced changes in the wage growth variable, the rise of temporary employment remains the

[25] Note that the effect from temporary employment in the second period amounts to -1.34 ($= -0.87 - 0.47$).

[26] Note that the interaction terms of inflation and labour productivity growth were not significantly different from zero. Therefore, we include those variables in their restricted form, i.e. a constant slope coefficient for the entire time span.

[27] The sensitivity of nominal wage growth with respect to the unemployment rate amounts to 0.05 ($= -0.30 + 0.25$) in the post crisis period, which is statistically not different from zero.

only factor of nominal wage growth in the period after 2012 registering a significant impact. Moreover, the overall impact from labour market segmentation on wage growth throughout the entire observation period (as displayed in column (10)) is significantly higher than the observed flattening of the unemployment rate.[28]

Yet, given the fact that we have employed nominal wage growth net of composition effects, the reduced sensitivity of wages with respect to the unemployment rate is an interesting result that adds to the debate on the Phillips curve flattening and supports the empirical findings in the literature that indicate a lower explanatory power of labor market slack measures in the post crisis period (e.g. Byrne and Zekaite (2020)). However, and contrary to our initial expectations, the incidence of temporary employment does not wipe out the dampening effect from unemployment.If this had been the case the interaction term that we use to control the flattening of the Phillips curve relationship (i.e. $U_t * post - crisis$) would have become insignificant. Instead, we observe a shift between labour market slack and segmentation in terms of their explanatory power. Comparing the dampening effect of unemployment (0.25) with the steepening effect of labour market segmentation (-0.21) in specification 11, it becomes evident that the increased sensitivity of nominal wage growth to temporary employment is statistically and economically of the same magnitude than the often debated flattening of the Phillips curve.[29] Hence, all in all the results in table 3 point to an important role of segmented labour markets in explaining wage dynamics in Europe, not only in general but particularly as regards the post crisis period.

What are the reasons for an increase in the competition effect of temporary employment after 2013. Two aspects are relevant here. Apart from the pro-cyclical feature of temporary employment, which we visualized in Figure 3, our data also confirm the general observation that there is a remarkable trend increase in temporary jobs (ILO, 2016), arguably driven

[28]A test of parameter equality confirms that the impact from temporary employment displaying a point estimate of -0.47 in specification (10) is of higher magnitude than the dampening effect from the unemployment rate in the post crisis period, which is estimated at 0.25 in specification (11). The corresponding test statistic for the equality of parameters (i.e. H0: $\hat{\beta}_{Invol.\ Temp}[10] + \hat{\beta}_{U*post\text{-}crisis}[11] = 0$) is $\chi^2(1) = 2.73$ with a p-value of 0.0985.

[29]The corresponding test statistic for the equality of parameters (i.e. H0: $\hat{\beta}_{Invol.\ Temp*post\text{-}crisis}[11] + \hat{\beta}_{U*post\text{-}crisis}[11] = 0$) is $F(1, 29) = 0.14$ with a p-value of 0.7122.

by the rise of the service sector Marx (2011). This trend increase might have potentially changed the general perception of these jobs. It has become more and more difficult to consider temporary employees as pure 'outsiders'. Rather temporary employees have become lower-strata-competitors and first empirical results along the occupational dimension point into this direction (Bellani and Bosio, 2019). The wide-spread fear of job loss during the crisis might have served as a behavioural catalyst leading to a behavioural shock yielding an internalisation of this into wage setting behaviour, and thus into wage schedules in general. Second, it is possible that temporary employment is a state dependent variable. The same absolute changes might have a different effect when there is a higher incidence of temporary employment than when there is a smaller incidence[30] Take for instance a reduction of the incidence of temporary employment by 1 percentage point. This accounts for a reduction of temporary employees by a quarter if the incidence stands at 4% but by only a twentieth if the rate is 20%; a difference that potentially will affect the perception of wage setters.

4 Conclusion

Is wage growth thus destined to slow further? In this paper we have summarized the rag rug of explanations for the period of subdued wage growth in Europe after the GFC. To do so we have presented a concise graphical exposition that allows to take a bird eye's view on the major findings of the literature.

More importantly however – trying to take the debate further – we demonstrated that competition between temporary and permanent employees in Europe has exerted a major downward pressure on aggregate wage growth over recent years; increasingly so after the GFC. By extrapolating the given trend of growing temporary employment, this allows us to point out some implications for the outlook of wage growth. Thus – to answer our introductory question – there are substantial signs that European wage growth indeed is destined to slow further. This seems to be the case in as far as temporary employment continues to in-

[30]Note that the non-linearities literature – implicitly – makes a similar point considering the rate of unemployment.

crease and given the current state of relations between the different labour market segments. Monetary policy and the fight against deflation thus might resemble increasingly the race between the rabbit and the hedgehog due to structural issues. Every labour recovery eventually pushes up involuntary employment above the pre-crisis level thereby further boosting competition-induced deflationary wage restraint; irrespective of the monetary stance.

Our analysis focused on aggregate wage growth at the country level, thereby combining a macro-level framework with evidence from the micro-level. To be very clear, we hereby only assessed the impact of temporary workers but due to data limitations not of other precarious employment, such as agency work, multi-party employment or dependent self-employment - all of which may have similar effects on overall wage growth. Future research would also be well advised to crave out the micro-mechanisms underpinning the aggregate trend to further assess the competition effect. Exploiting variation on the occupational, sectoral and regional level seems a promising avenue. Alternatively, the effect of policy-changes on the regulation of temporary contracts on aggregate wage growth could be exploited by quasi-experimental designs.

References

Amo-Agyei, S. (2020). The migrant pay gap: Understanding wage differences between migrants and nationals. *Discussion Papers.*

Anderton, R. and Boele, B. (2015). Downward wage rigidities in the euro area. *Discussion Papers*, (09).

Aoyama, H., Di Guilmi, C., Fujiwara, Y., and Yoshikawa, H. (2021). Dual labor market and the 'phillips curve puzzle'. *Discussion Papers*, (21006):1–15.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equation. *The Review of Economic Studies*, 58(2):277–297.

Arsov, I. and Evans, R. (2018). Wage growth in advanced economies. *Bulletin*, (1).

Ball, L. and Mazumder, S. (2020). A phillips curve for the euro area. *ECB - Working Paper Series*, (2354).

Baller, A., Gehrke, B., Lechthaler, W., and Merkl, C. (2018). Does short-time work save jobs? a business cycle analysis. *European Economic Review*, (84):88–122.

Bell, D. N. F. and Blanchflower, D. G. (2021). Underemployment in the united states and europe. *Industrial labor relations review*, 74(1):56–94.

Bell, David, N. F. and Blanchflower, David, G. (2019). The lack of wage growth and the falling nairu. *National Institute Economic Review*, (245):R40–R54.

Bellani, D. and Bosio, G. (2019). Knocking' on heaven's door? reframing the debate on temporary employment and wages: evidence from europe. *Socio-Economic Review*, (0):1–39.

Blau, F. and Kahn, L. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143.

Bonam, D., de Han, J., and van Limbergen, D. (2018). Time-varying wage phillips curves in the euro area with a new measure for labour market slack. *DNB Working Paper*, (587).

Bonam, D., de Han, J., and van Limbergen, D. (2021). Time-varying wage phillips curves in the euro area with a new measure for labour market slack. *Economic Modelling*, (96):157–171.

Bulligan, G. and Viviano, E. (2016). Has the wage phillips curve changed in the euro area. *Questioni di Economia e Finanza*, (355).

Bulligan, G. and Viviano, E. (2017). Has the wage phillips curve changed in the euro area. *IZA Journal of Labor Policy*, (6):R40–R54.

Bundesbank, D. (2016). Wage dynamics amid high euro-area unemployment. *Monthly Report - December*, (33).

Byrne, D. and Zekaite, Z. (2020). Non-linearity in the wage Phillips curve: Euro area analysis. *Economics Letters*, 186(C).

Ciccarelli, M. and Osbat, C. (2017). Low inflation in the euora area: Causes and consequences. *ECB – Occasional Paper Series*, (181).

Costain, J. S., Jimeno, J. F., and Thomas, C. (2010). Employment fluctuations in a dual labor market. *Banco de Espana Working Paper*, (1013).

Damiani, M., Pompei, F., and Ricci, A. (2018). Labour shares, employment protection and unions in european economies. *Socio-Economic Review*.

Dias da Silva, A. and Turrini, A. (2015). Precarious and less well paid? wage differences between permanent and fixed-term contracts across the eu. *IZA Policy Papers*, (105).

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64(5):1001–1044.

Dolado, Juan, J., María-Dolores, R., and Naveira, M. (2003). Are monetary-policy reaction functions asymmetric?: The role of nonlinearity in the phillips curve. *European Economic Review*, (49):485–503.

Draeger, V. and Marx, P. (2017). Do firms demand temporary workers when they face workload fluctuation? cross-country firm-level evidence. *ILR Review*, 70(4):942–975.

ECB (2015). Downward wage rigidity and the role of structural reforms in the euro area. *ECB Economic Bulletin*, (8/2015).

ECB (2017). Assessing labour market slack. *ECB Economic Bulletin*, (3).

Eurostat (2018). *EU-SILC Eurostat Quality Report*. Publication Office of the European Union, Luxembourg.

Fessler, P., List, E., and Messner, T. (2017). How financially vulnerable are CESEE households? An Austrian perspective on its neighbors. *Focus on European Economic Integration*, (2):58–79.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Chapter 1 - decomposition methods in economics. volume 4 of *Handbook of Labor Economics*, pages 1 – 102. Elsevier.

Gebel, M. and Giesecke, J. (2011). Labor market flexibility and inequality: The changing skill-based temporary employment and unemployment risks in europe. *Social Forces*, (1).

GESIS (2021). Zur missy-homepage metadata for official statistics. *GESIS Website*.

Giuliano, R., Kampelmann, S., Mahy, B., and Rycx, F. (2017). Short notice, big difference? the effect of temporary employment on firm competitiveness across sectors. *British Journal of Industrial Relations*, 55(2):421–449.

Goedeme, T. (2013). How much confidence can we have in eu-silc? complex sample designs and the standard error of the europe 2020 poverty indicators. *Social Indicators Research*, 110(1):89–110.

Goedeme, T. and Trindade, L. Z. (2020). MetaSILC 2015: A database on the contents and comparability of the EU-SILC income variables [Data file].

Hijzen, A. and Martin, S. (2013). The role of short time work shemes during the global financial crisis and early recovery: a cross-country analysis. *IZA Journal of Labor Policy*, (2).

Hijzen, A., Mondauto, L., and Scarpetta, S. (2017). The impact of employment protection on temporary employment: Evidence from a regression discontinuity design. *Labour Economics*, 46:64–76.

Hirsch, B. (2016). Dual labor markets at work: The impact of employers' use of temporary agency work on regular workers' job stability. *Industrial and Labour Relations Review*, 69.

Hong, G. H., Koczan, Z., Lian, W., and Nabar, M. (2018). More slack than meets the eye? recent wage dynamics in advanced economies. *IMF - Working Paper Series*, (50).

Hurley, J. and Partini, V. (2017). Estimating labour market slack in the european union. *Euorfound - Research Report*.

ILO (2016). *Non-standard employment around the world - Understanding challenges, shaping prospects*. International Labour Office, Geneva.

IMF (2017). Recent wage dynamics in advnace economies: Drivers and implitations. *World Economic Outlook - Chapter 2*, (2).

Iwasaki, Y., Muto, I., and Shintani, M. (2021). Missing wage inflation? estimating the natural rate of unemployment in a nonlinear dsge model. *European Economic Review*, 132:687–706.

Izquierdo, M., Francisco, J., Kosma, T., Lamo, A., Millard, S., Room, T., and Viviano, E. (2017). Labour market adjustment in europe during the crisis: microecnommic evidence from the wage dynamics network survey. *ECB – Occasional Paper Series*, (192).

Kahn, L. M. (2016). The structure of the permanent job wage premium: Evidence from europe. *Industrial Relations: A Journal of Economy and Society*, 55(1):149–178.

Kiss, A. and Van Herck, K. (2019). Short-term and long-term determinants of moderate wage growth in the eu. *IZA Policy Paper*, (144).

Koutentakis, F. (2008). The effect of temporary contracts on job security of permanent workers. *Economics Letters*, 101(3):220–222.

Lindbeck, A. and Snower, D. (2002). The insider-outsider theory: A survey. *Discussion Paper*, (534).

Lohmann, H. (2011). Comparability of eu-silc survey and register data: The relationship among employment, earnings and poverty. *Journal of European social policy*, 21(1):37–54.

Lombardi, M., Rigg, M., and Viviano, E. (2021). Bargaining power and the phillips curve: a micro-macro analysis. *BIS Working Papers*, (903).

Marotzke, P., Anderton, R., Bairrao, A., Berson, C., and Toth, P. (2017). Asymmetric wage adjustment and employment in european firms. *Working Paper Series – Wage Dynamics Network*, (2103).

Marx, P. (2011). The unequal incidence of non-standard employment across occupational groups: An empirical analysis of post-industrial labour markets in germany and europe,. *Discussion Paper*, (53521).

McGrath, J. and Beehan, J. (2018). A comparison of shortage and surplus occupations based on analyses of data from the european pulic employment services and labour force surveys.

Moretti, L., Onorante, L., and Saber, S. Z. (2019). Phillips curves in the euroa area. *Working Paper Series*, (2295).

Nickel, C., Bobeica, E., Gerrit, K., Lis, E., and Porqueddu, M. (2019). Understanding low wage growth in the euro area and european countries. *ECB – Occasional Paper Series*, (232).

OECD (2018). Decoupling of wages from productivity: what implications for public policies. *OECD Economic Outlook*, (2).

OECD (2020). Issue note 5: Flattening the unemployment curve? policies to support workers' income and promote a speedy labour market recovery. *OECD Economic Outlook*, (2).

Pavlopoulos, D. (2013). Starting your career with a fixed-term job: Stepping-stone or "dead end"? *Review of Social Economy*, 71(4):474–501.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom 1861-1957. *Economica, New Series*, (25):485–503.

Ramskogler, P. (2021). Labour market hierarchies and the macro-economy – do labour market dualities affect wage growth in europe? *Structural Change and Economic Dynamics*, 56:154–165.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, 9(1):86–136.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rusinova, D. and Heinz, F. (2011). How flexible are real wages in eu countries? a panel investigation. *ECB Working Paper Series*, (1360):1–32.

Rusinova, D., Lipativ, V., and Heinz, F. (2015). How flexible are real wages in eu countries? a panel investigation. *Journal of Macroeconomics*, 43:140–154.

Trindade, L. Z. and Goedeme, T. (2019). A new database on the contents and comparability of the income variables in eu-silc: Metasilc 2015. *International Journal of Microsimulation*, 12.

Weisstanner, D. (2020). Insiders under pressure: Flexible employment and wage inequality. *Journal of Social Policy*, pages 1–20.

Westhoff, L. (2020). Income differences between atypical and standard workers in european countries: Moving beyond average effects. *Barnett Papers in Social Research. Department of Social Policy and Intervention, University of Oxford.*

Wooldridge, J. M. (2009). *Introductory Econometrics: A Modern Approach*. South-Western.

Zardo Trindade, L. and Goedeme, T. (2016). Notes on updating the eu-silc udb sample design variables 2012-2014.

Zhang, Y. S. (2019). European wage dynamics and spillovers. *IMF Working Paper*, (2019/156).

A Appendix: EU-SILC data

A.1 Wage growth aggregated vs published (net)

Figure A.1: Net wage growth EU-SILC aggregated vs published by Eurostat

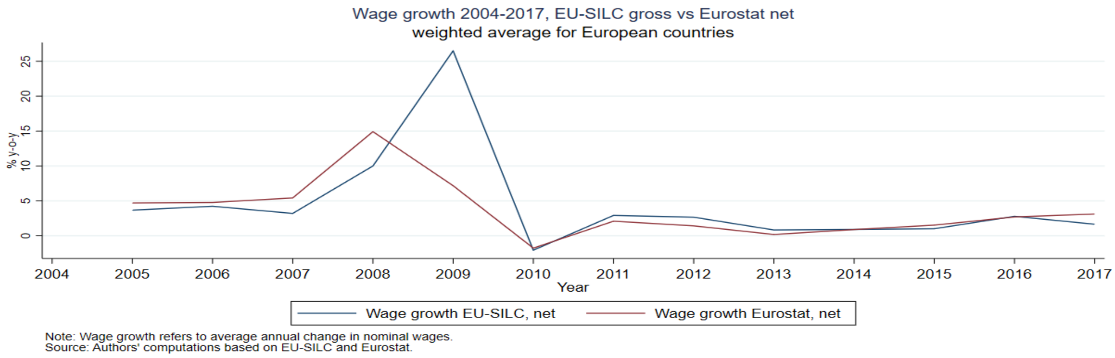
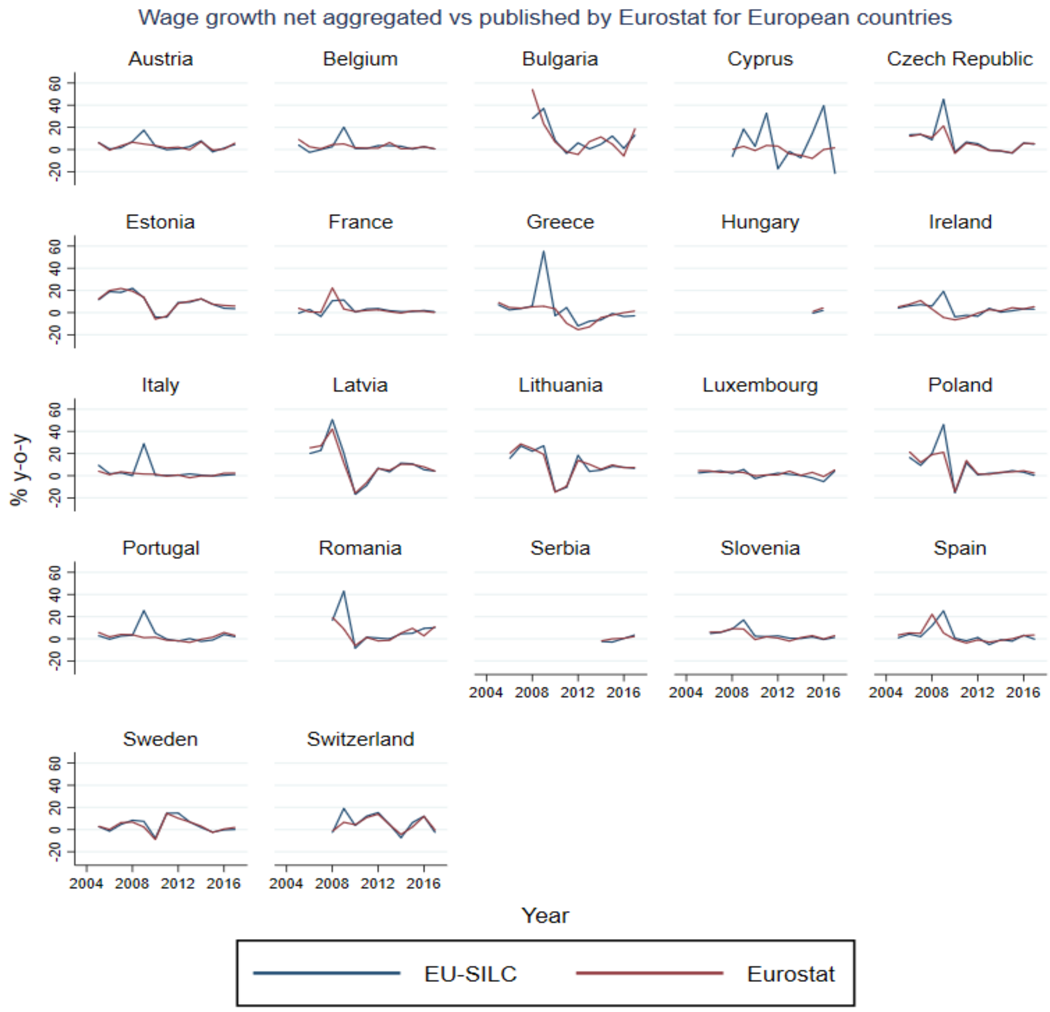


Figure A.2: Net wage growth EU-SILC aggregated vs published by Eurostat for countries with available data for net wages



Note: Wage growth refers to average annual change in nominal wages. Results are shown for all countries with available data for net wages.
Source: Authors' computations based on EU-SILC.

B Appendix: Micro Correction

B.1 Adjusted vs unadjusted wage growth

Figure B.1: Wage growth adjusted vs unadjusted in Europe

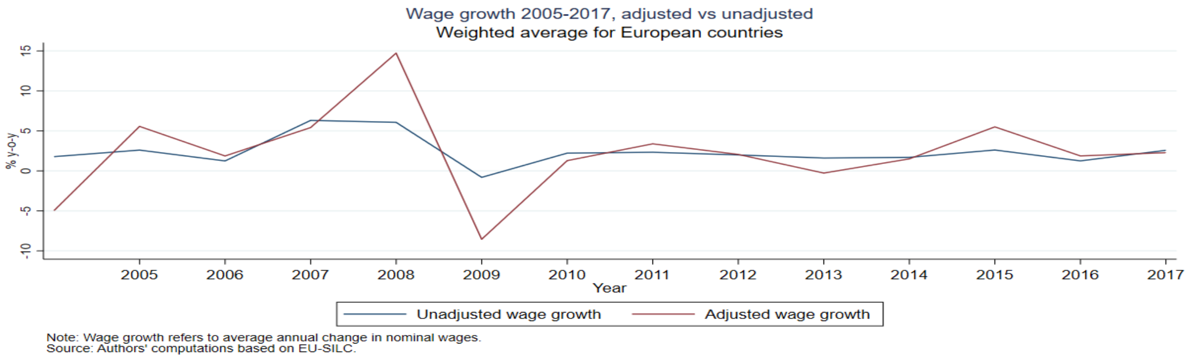
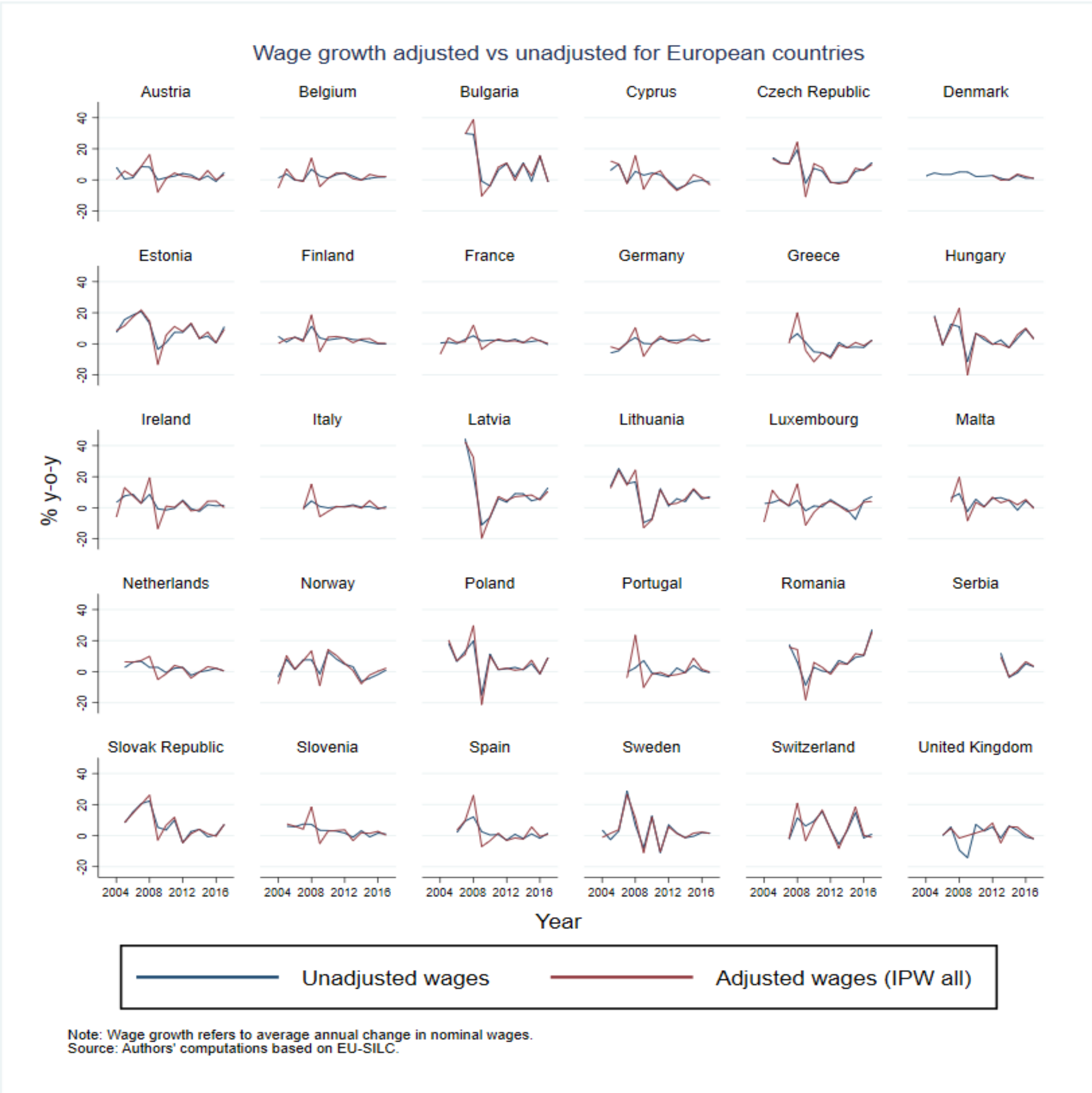


Figure B.2: Wage growth adjusted vs unadjusted for European countries



B.2 Contribution of employment composition and adjusted wage growth

Changes in the employment composition held back wage growth by around 50% and above in many countries during the economic upswings 2004-2008 (figure B.3) and 2015-2017 (figure B.5). By contrast, during the crisis period 2009-2014, wages for employed workers actually fell stronger than headline figures suggested. Contributions by the employment composition held up aggregate wages during the GFC because low-paid workers were over proportionally laid off (figure B.4). Without the positive contributions from changes in the employment composition, aggregate wage changes would have turned negative in many countries casting doubts on the nominal downward rigidity of overall pay packages. However, over the entire period observed 2004-2017, contributions from the changing employment composition balance out and are negligible in many countries with the United Kingdom as an outlier where wage growth was depressed by 50% (figure B.6). This is in line with our theoretical expectation and previous findings discussed in section 2. B.7 shows the results by country and year.

Figure B.3: Wage growth 2004-2008 divided in contribution of employment composition and adjusted wage growth

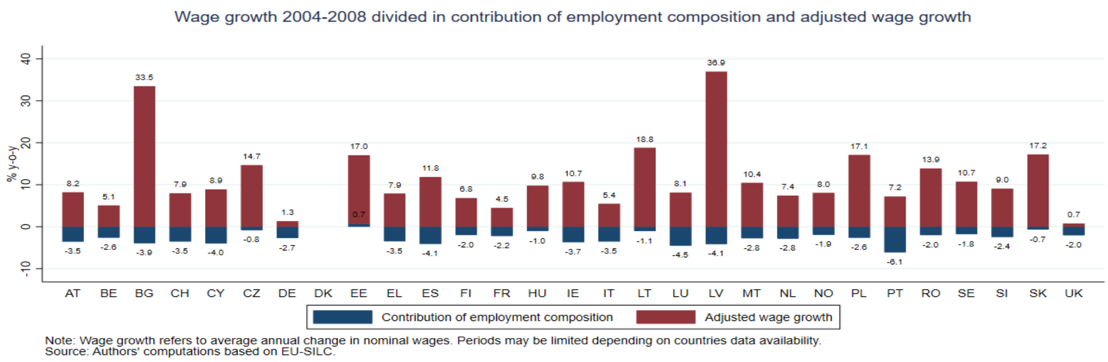


Figure B.4: Wage growth 2009-2014 divided in contribution of employment composition and adjusted wage growth

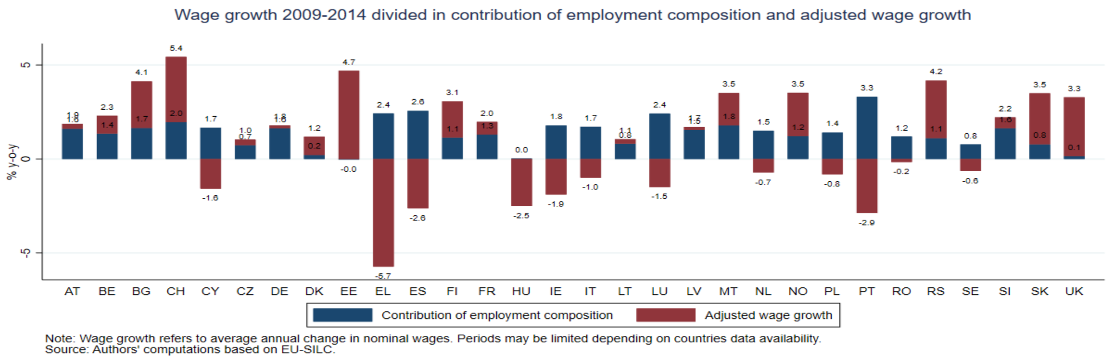


Figure B.5: Wage growth 2015-2017 divided in contribution of employment composition and adjusted wage growth

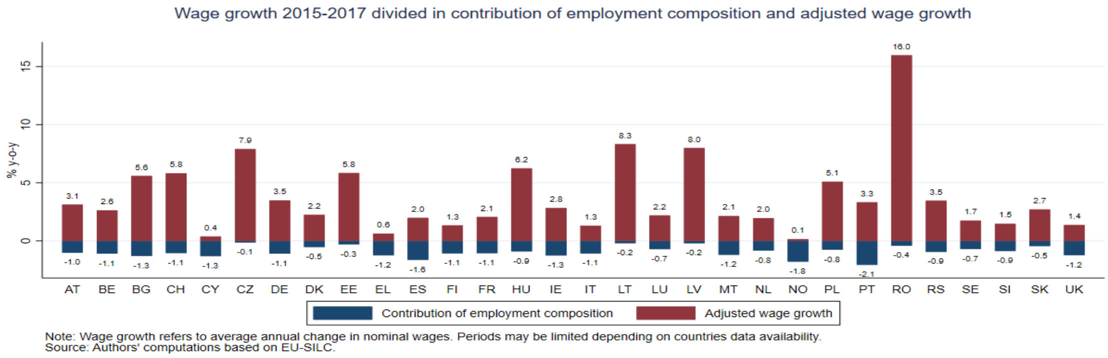


Figure B.6: Wage growth 2004-2017 divided in contribution of employment composition and adjusted wage growth

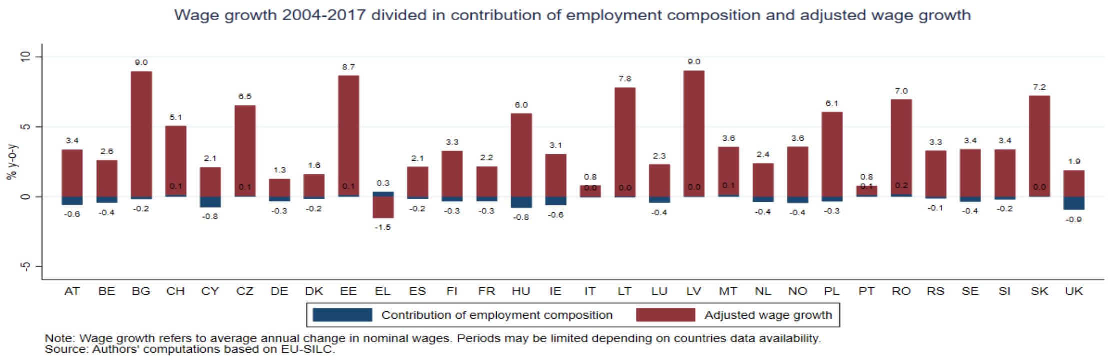
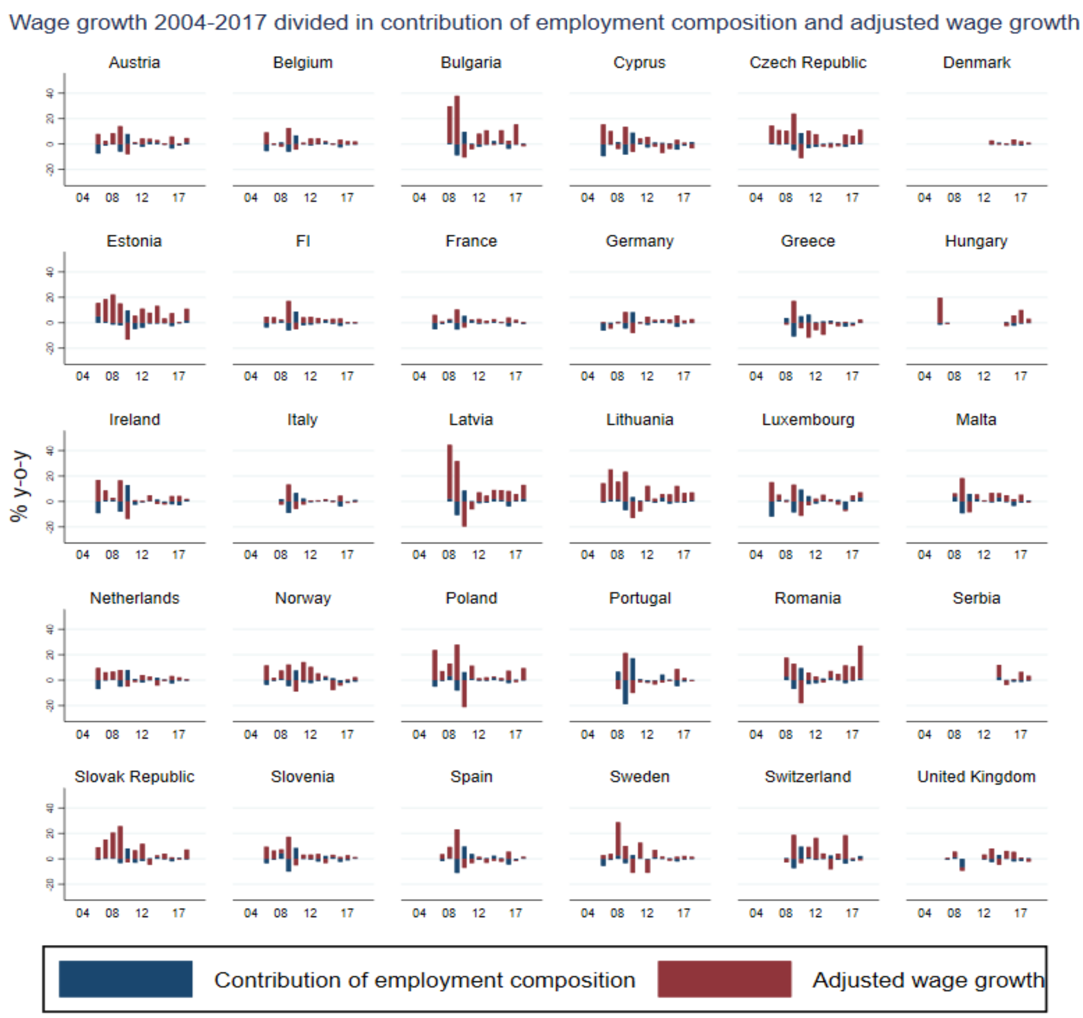


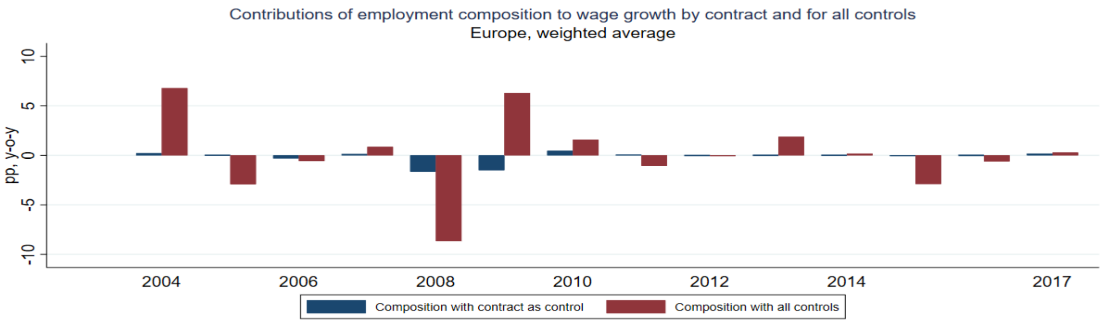
Figure B.7: Wage growth 2010-2017 divided in contribution of employment composition and adjusted wage growth for European countries



Note: Wage growth refers to average annual change in nominal wages. Periods may be limited depending on countries data availability.
Source: Authors' computations based on EU-SILC.

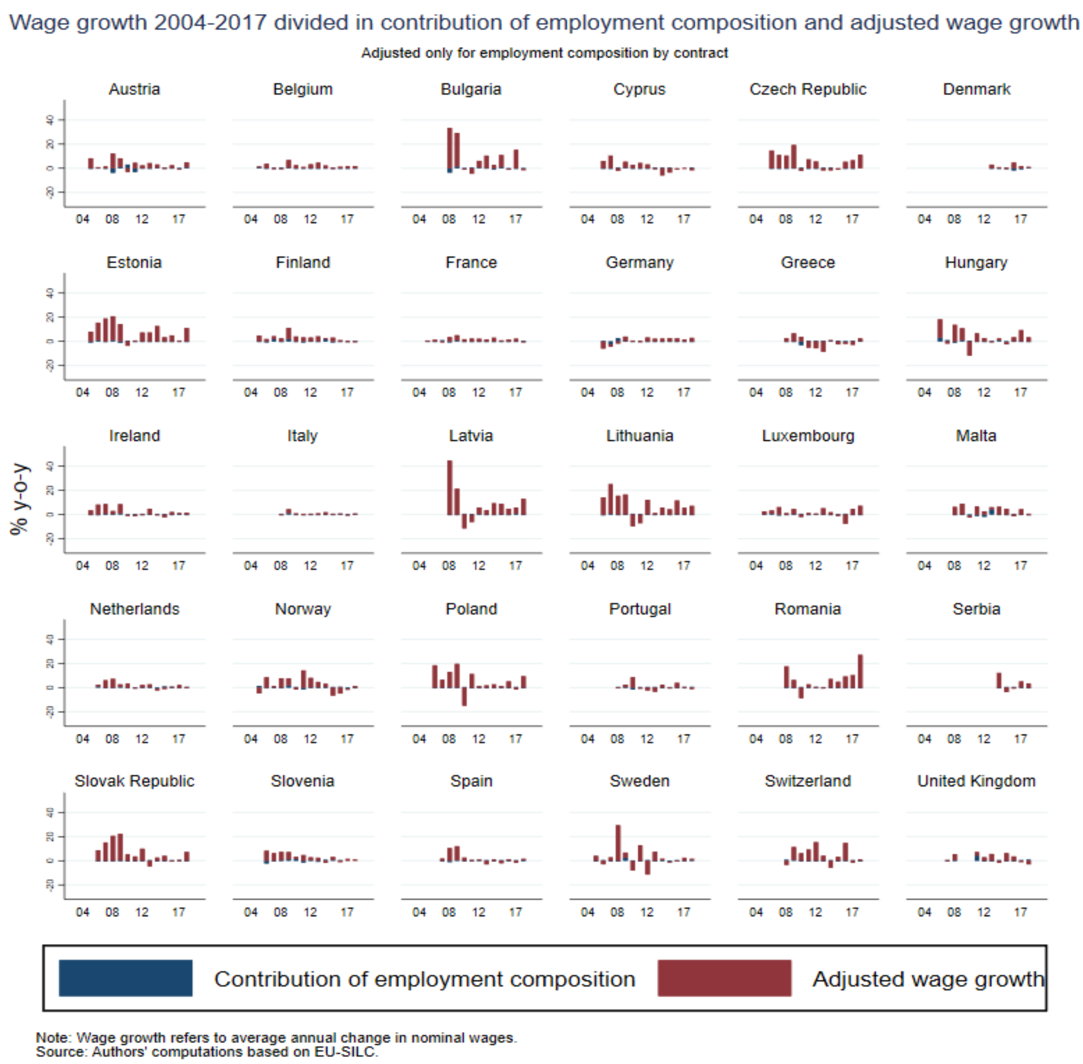
B.3 Contribution of employment composition by contract and all controls

Figure B.8: Contributions of employment composition to wage growth by contract and for all controls



Note: Wage growth refers to average annual change in nominal wages.
Source: Authors' computations based on EU-SILC.

Figure B.9: Adjusted wage growth and excluded contributions by employment composition changes controlling only for contract



C Appendix: Robustness

C.1 Measurement of labour market variables

We present several robustness checks with respect to the measurement of labour market variables. We start out by discussing our main independent variable. The literature analyzing the role of temporary work arrangements on wages mostly employ *overall* temporary employment to measure the degree of labour market segmentation ((Ramskogler, 2021; Bellani and Bosio, 2019)). In order to trace their findings, we recalculate specification (6) in Table 2 and consider both, the voluntary and involuntary temporary employees (in % of the labour force). We present the results in column (1) of Table C.1. As expected and in line with the literature, it turns out that *overall* temporary employment is a relatively good proxy for the extent of labor market segmentation in an economy. Compared to our baseline, the effect drops somewhat as does the t-static but the coefficient is still significantly different from zero. However, inserting both indicators separately at the same time into the model (i.e. involuntary and voluntary temporary employment), shows that it is clearly *involuntary* temporary work that determines wage dynamics (see column (2)). This underlines our narrative that it is a sub-ordinated class of employees exerting competitive pressure on overall wages. Hence, the crucial aspect in measuring labor market segmentation is to capture those temporary employees that would prefer to be employed on a permanent basis.

Another important check is to look whether temporary employment is indeed a feature of labour market segmentation rather than a form of economic slack. We therefore alter our specification in column (6) by considering a variety of alternative measures of labour market slack commonly employed in the literature, including different definitions of the unemployment rate, involuntary part-time workers and the unemployment gap (see columns 3 to 6 in Table C.1). None of those alterations changes our baseline findings.

Table C.1: The impact of temporary employment on adjusted wage growth: different measures for segmented labor market and slack

	segm. lab. market		slack measures			
	Pooling Temp.	Vol. Temp	U4 (incl. available)	U5 (incl. seeking)	Invol. Part-time	U-Gap
	(1)	(2)	(3)	(4)	(5)	(6)
$Prod._t$	0.28	0.28*	0.31*	0.22	0.18	0.29
	(1.68)	(1.74)	(1.89)	(1.27)	(0.96)	(1.63)
$Infl._t$	0.51	0.51	0.56	0.86**	0.77*	0.62
	(1.07)	(1.06)	(1.17)	(2.09)	(1.83)	(1.27)
U_t	-0.51***	-0.49***				
	(-2.89)	(-2.88)				
$Temp_t$	-0.61**					
	(-2.24)					
$Invol.\ Temp_t$		-0.94***	-0.82***	-0.70**	-0.93**	-1.08***
		(-2.90)	(-2.76)	(-2.39)	(-2.74)	(-3.35)
$Vol.Temp_t$		-0.21				
		(-0.72)				
$U4_t$			-0.35**			
			(-2.64)			
$U5_t$				-0.29**	-0.39**	
				(-2.08)	(-2.30)	
$Invol.\ Part._t$					0.66	
					(1.59)	
$U_t - NAWRU_t$						-0.64**
						(-2.72)
Cons	11.56***	11.57***	10.08***	7.95***	8.28***	8.02**
	(2.76)	(2.81)	(3.35)	(3.21)	(3.49)	(2.73)
Model	FE	FE	FE	FE	FE	FE
TimeD	incl.	incl.	incl.	incl.	incl.	incl.
Weights	equal	equal	equal	equal	equal	equal
N	341.00	337.00	332.00	310.00	304.00	312.00

Two-tailed significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. T-statistics are reported in parenthesis. Results are qualitatively the same if frequency weights are applied.

C.2 Country exclusion

Table C.1: Sensitivity of labour market segmentation to country exclusion

Country	Invol. Temp.	T-stat.	Country	Invol. Temp.	T-stat.
AT	-0.93 ***	-3.02	IT	-0.94 ***	-2.99
BE	-0.92 ***	-2.89	LT	-0.97 ***	-3.00
BG	-0.96 ***	-3.12	LU	-0.99 ***	-3.26
CH	-0.93 ***	-3.08	LV	-0.88 ***	-2.78
CY	-1.01 ***	-3.15	MT	-0.95 ***	-3.01
CZ	-0.89 ***	-2.82	NL	-0.94 ***	-3.02
DE	-0.88 ***	-2.84	NO	-0.93 ***	-2.99
DK	-0.92 ***	-2.98	PL	-0.85 **	-2.35
EE	-0.92 ***	-2.84	PT	-0.94 ***	-2.98
EL	-0.81 **	-2.42	RO	-0.78 **	-2.72
ES	-0.89 **	-2.55	RS	-0.92 **	-2.75
FI	-0.85 **	-2.75	SE	-0.95 ***	-3.03
FR	-0.90 ***	-2.87	SI	-0.89 ***	-2.89
HU	-1.02 ***	-3.23	SK	-0.74 **	-2.75
IE	-1.00 ***	-3.13	UK	-0.90 ***	-2.93

Notes: Two-tailed significance levels: $*$: 10% $**$: 5% $***$: 1%. Regression based on specification ...).

C.3 Endogeneity

Simultaneity bias arising from reverse causality between nominal wage growth and labour market slack can be a concern in our specification. Usually, this issue is approached by inserting the slack variable in its one-period lagged form into the model (see e.g. Ramskogler (2021); Byrne and Zekaite (2020); Nickel et al. (2019)). While this is certainly a valid approach when using quarterly data, it is not feasible in our case given the annual frequency of the data. Fortunately, in the case of reverse causality, the fixed-effect estimate of the impact from unemployment on wage growth would be downward biased rather than upward, as higher wage growth should cause higher labor market slack (IMF (2017); Wooldridge (2009)). The same logic applies to the segmentation measure. If wage growth accelerates it is presumable that employers increasingly demand temporary employees as they are cheaper and are associated with lower firing costs. Hence, it is very likely that our findings concerning the importance of temporary employment for wage growth are not mistaken even in the presence of reverse causality.

A standard approach to account for a potential simultaneity bias is to use instrumental variable techniques. As exogenous instruments are not at hand, neither for labour market slack nor for temporary employment, we use internal instruments, i.e. time lags of the variables in the model.

In particular, we employ the difference GMM estimator[31] (Arellano and Bond (1991); Blundell and Bond (1998)) and treat both variables as endogenous (by using the lagged levels of the variables as instruments).

Table C.1: The competition effect: controlling for potential endogeneity

Indep. variable:	memo item	reverse causality		ommitted vars
adjusted wage growth	(8)	(1)	(2)	(3)
$Prod._t$	0.07	-0.18	-0.18	-0.13
	(0.26)	(-0.74)	(-0.73)	(-0.41)
$Infl._t$	-0.09	-0.70	-0.27	-0.19
	(-0.14)	(-0.88)	(-0.32)	(-0.35)
U_t	-0.43**	-0.84*	-0.94**	-0.63***
	(-2.57)	(-1.72)	(-2.06)	(-6.00)
$Invol.\,Temp_t$	-1.02***	-1.61**	-1.76**	-0.65***
	(-3.57)	(-2.21)	(-2.24)	(-2.84)
EPL_t				-3.88**
				(-2.49)
TUD_t				0.96***
				(4.13)
CBC_t				-0.18***
				(-4.53)
Cons	12.49***	21.49***	16.76	11.44*
	(3.73)	(2.79)	(1.63)	(1.83)
Model	FE	GMM	GMM	FE
AR1		-2.30**	-2.22**	
AR2		0.71	0.88	
Hansen		15.45	15.16	
Hansen p-val		0.63	0.51	
TimeD	incl.	incl.	incl.	incl.
Weights	empl.	empl.	empl.	empl.
N	337	337	337	281

Two-tailed significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. T-statistics are reported in parenthesis. Specifications (1) and (2) are estimated by first difference GMM. We use the STATA command xtabond2 and employ the second level lag (up to 11 lags) of the endogenous variables as instruments. As the cross-section dimension is rather small (i.e. 30 countries), we use standard IV instruments rather than GMM-type instruments in order to limit the instrument count (by using the collapse option, see also Roodman (2009)). Specification (2) treats only U_t and $Invol.Temp_t$ as endogenous, while specification (3) assumes that all variables are endogenous except $Prod_t$. Column (3) is based on specification (8) and includes three institutional variables: employment protection legislation (EPL), trade union density (TUD) and collective bargaining coverage (CBC) (missing values imputed).

We summarize our results in Table C.1. As displayed in column (1) involuntary temporary employment and unemployment have the expected negative signs and are statistically significant. However,

[31] Note that our dependent variable is not persistent. This is why we choose a static representation and the difference rather than the system GMM estimator.

compared to the fixed effect estimation (see memo item (8)) we observe an increase in the coefficient estimate for both variables, which is more pronounced for U_t. Obviously, controlling for simultaneity has an effect on the estimates in the direction that we expected, i.e. labour market variables seem to be underestimated in a fixed-effects setting. A very similar result can be found in Bellani and Bosio (2019), who report an increase in the impact of temporary employment after controlling for reverse causality. Yet, the most relevant conclusion from the results presented in this robustness section is that the relative importance of labor market segmentation in driving wage growth does not change. More specifically, a test on parameter equality reveals that the coefficients of U_t and $Invol.\ Temp_t$ are of the same magnitude. This result also holds in a setting with standardized variables[32]. Hence, we can confirm our results that competition effects do exist and that they are at least as relevant as unemployment in driving wage growth in Europe.

In column (2) we add inflation to the set of endogenous variables. If firms increase prices as a result of increasing labour costs, reverse causality from wage growth to price inflation may occur. As our results show, controlling for potential endogeneity with respect to inflation does not have any significant influence on the estimation outcome. This might be related to the fact that a large part of consumer price dynamics is already captured by time dummies.

Finally, a potential source of endogeneity in our setting might occur due to omitted variables. So far, we have mainly controlled for the cyclical drivers of wage dynamics. However, institutional factors could have had an influence on wage growth as well, and – more importantly – also on the development of labour market segmentation. Generally, fixed effects models already tackle the problem of omitted variables to the extend that they capture time-invariant determinants of the independent variable. Hence, the influence from a country's individual institutional setting on the process of wage formation should to a large extend be captured by the so far presented model estimates. Still, although institutional changes evolve only slowly over time, these changes nevertheless could have had an influence on wage dynamics and on temporary employment. In order to control for changes in institutional settings we consider three different indicators provided by the OECD, namely trade union density (TUD), employment protection legislation (EPL), and collective bargaining coverage (CBC). The drawback of these indicators is that they are not available for all countries in our sample[33] and that they have gaps in the available time series, which would cut our sample size in half.

[32] Note that re-estimating the same specification on standardized variables yields coefficient estimates of -0.49 and -0.64 for U_t and $Invol.\ Temp_t$ respectively, which are statistically not different from each other.

[33] There is no data for Malta, Cyprus, Bulgaria and Romania.

Therefore, we impute[34] the missing values in the individual time series, which reduces our sample to 281 observations.

As shown in column (3), including institutional variables has only a modest impact on labour market segmentation. The coefficient estimate of $Invol.\ Temp_t$ remains negative and significant, but decreases by around one-third compared to specification (8). One reason for the smaller magnitude lies in the change of the sample (size). Re-estimating specification (8) based on the same sample size yields a coefficient estimate of -0.86, which is much closer to the observed coefficient in column (3). It is interesting to point out that the remaining difference in parameter estimates, albeit not large, stems from the inclusion of trade union density into the model equation. This might be related to the fact that in countries, where union density is rather low, the incidence of involuntary temporary employment is higher, which seems to dampen the effect from labour market segmentation on wage growth.

D Appendix: Variable measurement and sources

[34] We take the average of two values, the available value before and after the missing observation.

Table D.1: Variable measurement and sources

Abbrev.	Variable	Measurement	Source
Wage growth	Annual average change in nominal wages	Gross employee cash or near cash income (PY010G) / months employed (PL073+PL074) / hours worked (PL060) (separated for full time and part time) aggregated by using the personal cross-sectional weights (PB040)	EU-SILC
Prod.	Labour productivity growth	Nominal GDP/employment*100, annual change	Eurostat (naida_10_pe, naida_10_gdp)
Infl.	HICP Inflation	Annual average change of HICP	Eurostat (prc_hicp_aind)
Exp. Infl.	Inflation expectations	Monthly consumer survey asking for price trends over the next months, yearly average over 12 months	European Commission
U	Unemployment rate (U3)	Definition according to ILO, unemployed in % of active working age population (aged 15-74)	Eurostat (lfsa_urgan)
Invol. Temp	Involuntary temporary employment	Employees with a temporary contract who could not find a permanent job, in % of active working age population (aged 15-74)	Eurostat (lfsa_etgar, lfsa_eegais, lfsa_agan)
Temp	Temporary employment	Employees with a temporary contract, in % of active working age population (aged 15-74)	Eurostat (lfsa_etgadc, lfsa_agan)
Vol. Temp	Voluntary temporary employment	Temp − Invol. Temp	
U4	U4 Unemployment rate	Unemployed including discouraged workers (not seeking, but available)	Eurostat (lfsa_urgan, lfsa_sup_age)
U5	U5 Unemployment rate	Unemployed including discouraged and marginally attached workers (available, but not seeking)	Eurostat (lfsa_urgan, lfsa_sup_age)
NAWRU	Non-accelarating wage rate of unemployment	Estimates from a model-based approach, European Union, 2017.	European Commission
Invol. Part	Involuntary part-time employment	Share of involuntary part-time employees in labour force, in %	OECD Statistics
EPL	Employment protection legislation	Strictness of employment protection – individual and collective dismissals (regular contracts)	OECD Statistics
TUD	Trade union density	Union members in % of employees (administrative and survey data)	OECD Statistics
CBC	Collective bargaining coverage	Percentage of employees with the right to bargain	OECD Statistics