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Wages, compositional effects and the business cycle

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Abstract

During the Great Recession, unemployment increased substantially across several euro area countries, with wages exhibiting a muted response. As low skilled workers lose their jobs first during a recession, the remaining employed workers result in a relatively more skilled employment pool. This change in the composition of the employed workers inflates the aggregate wage mechanically, even in the case of no actual pay rises. This paper uses individual level data to control for the effect of changes in the composition of workers on wages and wage cyclicality. We find that compositional effects are highly correlated with the severity of the business cycle, being significant in countries where employment losses were larger. Thus, the results partially explain the muted response of the observed wages to the business cycle, as wages decreased more than what the aggregate numbers suggest during the downturn, a picture that is reversed somewhat during the recent recovery.

JEL codes: J30, E32

Keywords: Wages, Compositional effects, Wage cyclicality

Non-technical summary

During the years of the Great Recession, the unemployment rate increased significantly across some euro area countries, reaching a peak of around 27% in Spain and Greece in 2013. At the same time, wages in the euro area exhibited a muted response to labour market conditions. Wages remained stable or even increased during the crisis. When the economy showed signs of recovery since 2013, wages showed some lag in their reaction to this positive juncture. This observation has raised questions regarding the proper functioning of the euro-area labour market and its ability to absorb and adjust to negative shocks. It also poses a "puzzle" with respect to the responsiveness of wages to the business cycle.

Several explanations have been provided for the muted response of wages to the business cycle, but little emphasis has been put until recently on the role of changes in employment characteristics in affecting wages. Business cycle fluctuations inevitably affect the composition of the employed force, as job losses are not randomly distributed across skill levels and other labor characteristics. In the case that these job losses are concentrated on the lower end of the skill distribution, average aggregate productivity can change across years. In turn, if wages are a function of the productivity of the employed labor, then such a change in average productivity will mechanically bias the observed average wages upwards. Changes in the aggregate wages that are solely a result of the changes in the composition of the employed labor force are called compositional effect. This compositional effect has recently received some attention in the economic literature, as it tends to be highly correlated with the business cycle, leading to a muted response of the aggregate wage. As a result, if we fail to take into account compositional changes, the observed aggregate wages tend to be upward biased during downturns and downward biased during recoveries.

This idea is not new as early studies focusing on the role of changing labour force on wage elasticities are available for the 70s and the 80s in the United States. The results of those studies paint a mixed picture regarding the size of the effect, with the compositional effect being counter-cyclical, biasing upward aggregate wages during recessions. For the euro area, few studies for selected countries regarding the first couple of years of the Great Recession conclude that the compositional effects were large during 2009-2011, masking the true degree by which wages fell during the rising unemployment period. In this paper, we use individual level data to control for the effect of workers heterogeneity and changes in the composition of the employed labor force on wages and wage cyclicality. We provide results for all the euro-area members in a unified framework and for the whole period of the Great Recession as well as the period of the subsequent recovery until 2018. This makes our conclusions more robust, comparable and heterogeneous across countries, compared to the sporadic evidence provided by the recent few studies.

We find a significant compositional effect especially in countries where employment losses were more severe. In these countries, actual wage growth would have fallen more, during the recession, compared to what official aggregate wage statistics indicate. On the other hand, during the recovery the sign of the compositional effect has reversed, especially during 2015-2017, providing some explanation for the "missing" wage growth. The compositional effect in Germany and France remained small, as job losses were contained. Hence, the compositional effect is correlated with the direction and the severity of the business cycle.

Once the size of the compositional effect has been estimated, a measure of wage growth free of compositional effect is constructed. We use the aggregate wages from National Accounts data, our individual data, and the adjusted measure of wages to estimate the wage elasticity in a simple wage Phillips curve framework. We find that the adjusted measure of wage growth responds more to unemployment compared to the unadjusted measure and the measure obtained from the National Accounts data, suggesting that the existing compositional effect partially explains the muted response of the observed wages to the business cycle. Aggregate wages actually fall (increase) more during recessions (expansions) once the compositional effect is accounted for. These results are robust to the inclusion of industry effects in the analysis. Additionally, we explore and quantify the contribution of different components of the compositional effect: education and experience tend to have the most significant contribution in driving the bias in wage growth.

From a policy point of view, it would be important to estimate the compositional effects and the impact on wage growth during the recession (recovery) in an effort to explain the missing wage deflation (inflation) in the euro-area. Moreover, the compositional effect is highly correlated with the severity of the business cycle, leading to differential effects across countries. These differences indicate that wage moderation might have more significantly contributed to the degree of re-balancing of the euro area, a fact that might be understated by the use of official aggregate wage data.

1 Introduction

Since the beginning of the Great Recession in 2007, the responsiveness of inflation to the business cycle has been greatly diminished. During the downturn inflation did not fall, whereas during the subsequent recovery years inflation did not pick up to the extend expected, leading to the "puzzle" of missing dis-inflation and inflation. One strand of the literature has focused on the "anchored expectations" hypothesis to explain this puzzle. Bernanke [2010] proposes as an explanation the inflation stabilization achieved by the credibility of modern central banks and the anchoring of inflation expectations. Another strand of the literature has focused on the flattening of the Philips curve which was pointed out by International Monetary Fund [2013]. However, many have questioned the lack of structural changes in the economy that would justify such a result (e.g. Coibion and Gorodnichenko [2015]). Finally, attention was drawn on developments in the labour markets and the missing pass-through from wages to inflation.

During the first phase of the euro area crisis, wage growth did not fall significantly, despite the large losses in employment observed across several euro area economies. Furthermore, wage growth did not pick up quickly after 2013, when employment growth started to improve steadily across euro-area labor markets. This observation has raised questions regarding the proper functioning and the ability of the euro area labour market to absorb and adjust to negative shocks and poses a "puzzle" with respect to the responsiveness of wage growth to the business cycle. Furthermore, since the covid-19 pandemic outbreak, officially reported aggregate wage patterns were considered unreliable, with the case of the US providing an example where wage growth increase up to 8% in April 2020.[1]

Several explanations have been considered for this apparent irresponsiveness of wages to labour market conditions. Alternative explanations mainly focus on downwards wage rigidities (e.g. Holden and Wulfsberg [2008], Babecký et al. [2010], Radowski and Bonin [2010], Hall and Krueger [2012], Fabiani et al. [2015], Adamopoulou et al. [2016], Adamopoulou et al. [2019]). However, from their nature downward wage rigidities are asymmetric to the business cycle and are failing to explain the muted response in the upturn of the cycle unless we impose additional assumptions.[2] On the other hand, little attention has been paid until recently, to the compositional effect caused by significant changes in employment concentrated on the lower end of the skills distribution, as an

[1] See BLS data release on real average hourly earnings on January 19, 2021 and the related US CPI data.

[2] Related to the existence of downward wage rigidities is the phenomenon of pent-up wage deflation as an explanation of the slow recovery in wage growth (Yellen [2014], Daly and Hobijn [2014]). During a downturn firms are faced with constraints in their ability to cut compensation per hour, due to binding wage contracts. As the recovery starts, firms might find it unnecessary to increase wages to attract workers as wages remained higher than equilibrium wages during the recession. This results in observed slow rise in wages as the recovery strengthens. However, recent research (Peneva and Rudd [2017]), does not strongly support the existence of pent up wage deflation during the recent economic recovery in the US.

explanation for the muted reaction of wages to the business cycle. As job losses affect mostly low skilled and younger workers, average wages are mechanically inflated, not due to actual pay rises, but because the remaining workers were already paid higher due to their relatively higher skill profile.[3] This bias is even more significant in the euro area as changes in employment were severe and evidently different across countries, not only biasing aggregate wage figures, but also distorting cross-country wage growth comparisons at the aggregate level. Since the covid-19 pandemic outbreak, the discussion regarding its effect on the composition of employment and consequently on wage growth both in the US and Europe has become even more prevalent. In the US job losses have disproportionately concentrated on low income workers (Crust et al. [2020]), whereas in major euro area member states the sectors mostly affected are those with higher shares of lower paid, younger and female workers (Fana et al. [2020]). These changes in the composition of employment can be currently pushing up artificially wage growth. Additionally, this type of wage miss-measurement can lead to a decreased correlation between wages and prices due to attenuation bias. Hence, this could provide an explanation why recent studies (Heise et al. [2020]) find a weakened link between wages and inflation.

This paper estimates the size of compositional effects with a focus on worker heterogeneity using individual worker-level data for the euro area. The study most closely related to this paper is Verdugo [2016], who finds that compositional effects were significant in countries that faced largest employment losses. However, the dataset used in Verdugo is incomplete and covers only up to the first two years of the Great Recession period. This paper utilises the most recent data of the EU-SILC dataset to provide estimates across all euro area member states, including the first years of the recent euro area recovery in a unified framework. The importance of this is threefold: **(i)** the estimates provided refer to the whole crisis period and provide some evidence for the start of the recent recovery, **(ii)** the inclusion of all member states provides more heterogeneity and robustness of the results, **(iii)** we use a common methodology offering reliable cross-country comparisons.

We demonstrate that the compositional effect, is counter-cyclical and significantly dampens the wage growth profile during the cycle. Compositional effects have been large in countries that faced the largest employment losses, like Spain, Italy, Greece and Portugal. When constructing a wage series adjusted for compositional effects, the adjusted wages seem to have fallen more than observed wages in these countries during the downturn. In contrast, in countries like Germany and the France, compositional effects were relatively small. In the more recent recovery period, compositional effects have reduced in size and even changed sign. In countries like Spain and Italy they have turned negative, biasing downwards wage growth since the unemployment gap has been reducing. In the rest of the euro area countries with smaller employment losses during

[3] In this paper low skilled workers refers to workers with low values of observable characteristics such as low education and low experience. Moreover, as shown in the histograms in Section 3.2 the workers we refer to as low skilled turn out to be also lower paid.

the first years of the crisis, the compositional effects remained insignificant and close to zero.

Furthermore, the current paper sheds some light to the sources of this compositional effect based on observable individual characteristics. Education and experience tend to have the most significant contribution in driving the compositional effect on wage growth. The estimation followed in the paper allows to create a series for wage growth free of compositional effects, which can be used in a standard wage Phillips curve analysis to assess the cyclicality of wage growth free of compositional effects. The results show that the measure of wage growth free of compositional effects is more responsive to the business cycle than the observed aggregate wage measure and that since the recovery, wage growth might have been underestimated in the euro area.

From a policy point of view, it would be important to estimate the impact of the compositional effects on wage growth during the recovery in an effort to explain the "missing" wage cyclicality in the euro area. Moreover, it would be interesting to consider that the true extent of wage re-balancing can be significantly larger than what the aggregate data suggest.

The rest of the paper is structured as follows: Section 2 reviews the existing literature on the response of wages and the existence of compositional changes over the cycle. Section 3 provides an illustration and descriptive evidence on the size and direction of the compositional effects that have occurred since the beginning of the crisis in 2007. Section 4 describes the data and the estimation procedure. Section 5 presents the main results and Section 6 concludes.

2 Wage Cyclicality and Compositional Effects

The cyclical behaviour of wages has been extensively studied in the economic literature and part of the debate has focused on possible sources of bias that could explain early findings of an ambiguous relationship with the business cycle. More specifically, wages exhibit less volatility over time than most theoretical models predict and are modestly correlated with the business cycle, on an aggregate level. On the other hand, studies based on disaggregated data have reached the conclusion that wages are more procyclical. This naturally leads to either question our theoretical models or try to identify sources of bias that distort the measurement of aggregate wage growth and its relation to the business cycle.

Two main sources of bias have been identified in the literature **i)** compositional bias due to worker heterogeneity or **ii)** due to firm heterogeneity which includes changes in the composition and quality of jobs. Moreover, aggregation can suffer from a selection bias, as individuals that remain in employment might have different unobservable skills, even if the observable skills are the same.[4]

[4] In a nutshell, it is well documented in the micro empirical literature that workers that get displaced

Aggregate hourly wage data are constructed as a weighted average of the hourly wage levels across the different population groups in employment, weighted by hours worked. The use of aggregate wage data leads to a bias, as they rely on the assumption that the composition of the labour force, i.e. the respective group weights based on hours worked remain the same over the business cycle. This is unrealistic because as individual characteristics and productivity vary over the cycle, changes in the composition of the employed force that are correlated with the business cycle can bias the measurement of aggregate wages. Stockman [1983] argues that the employment of less educated and less experienced workers is much more variable over the cycle. This implies that in times of recoveries real wages are averaged over a group with lower earnings, as the employment of less educated and experienced workers tends to increase disproportionately in an upturn. In contrast, in times of recessions, real wages are averaged over a group with higher earnings as the employment of less skilled workers is hurt most. Thus, aggregate real wage statistics give more weight to low skill workers during expansions than during recessions. These movements in the employment of different groups impose a counter-cyclical bias on aggregate real wages.

Focusing on the bias arising from worker heterogeneity, early studies have shown that the impact of changes in the composition of the employed labour force can be sizeable leading to counter-cyclical effect on the measured aggregate wages. This was brought into attention by the early studies (see Coleman [1984], Barsky and Solon [1989], Blank [1990], Kydland and Prescott [1993]) which used individual-level data for the US to quantify the bias in aggregate wage measurement.[5] Most studies (Bils [1985], Barsky and Solon [1989], Solon et al. [1994], Hines et al. [2001]) do so by focusing on a group of individuals working continuously throughout the sample, controlling in this way for compositional effects. For the period 1966-1980, Bils [1985] finds that a percentage point rise in the unemployment rate is associated with a decrease in real wages of between 1.5 and 2 percent. Aggregating the individual data for the same period also yields very pro-cyclical aggregate real wage leading to a decrease of 1.66 percent. On the other hand, Solon et al. [1994] for the period 1967 to 1987 find that the cyclicality of real wages based on micro data is two times larger than the one estimated using aggregate data: 1.3 percentage points increase in the former case versus 0.6 in the latter. Hines et al. [2001] find also that wages are pro-cyclical: a 1 percentage point rise in the unemployment rate brings a 1.29 percentage point decline in hourly real wages, indicating a small magnitude of compositional effects when compared with the estimates from aggregate data. Studies based on workers continuously employed in the sample, exclude those individuals moving in and out of employment. Keane et al. [1988] emphasize the selection bias that can result from changing composition of the workforce, stemming from those moving in and out of the labour force. An aggregate wage remains still pro-cyclical, when corrected for

receive lower wages for a persistent period of time (e.g. Stevens [1997]).

[5] For an early survey of the role of compositional effects on wage cyclicality see Abraham and Haltiwanger [1995].

both observed and unobserved heterogeneity. The importance of compositional effects in affecting wage sensitivity to the business cycle is recognised by country specific studies (Anger [2011], Peng and Siebert [2008], Haefke et al. [2013], De la Roca [2014]) that use methods to correct the wage series used for the presence of compositional changes, without providing an estimate for the size of the effect.

More recent studies focusing on the period of the Great Recession have also attributed significant role to compositional effects in biasing average aggregate wages. Verdugo [2016] quantifies the compositional bias for eight euro area countries, finding that the real wage is pro-cyclical; a one percent increase in the unemployment rate yields a reduction in real wages between 0.6 and 1 percent. The compositional effects are found to be important during the Great Recession, especially for countries that were hit more severely by the crisis. Studies for Italy (D'Amuri [2014], Adamopoulou et al. [2016]) and Spain (Puente and Galán [2014], Orsini [2014]) indicate that compositional effects amplified the increase in aggregate wages during the recent recession. Daly et al. [2012] adopt a similar analysis using U.S. data, finding that the wage effect turns out to be pro-cyclical, while the compositional effect behaves in a counter-cyclical manner. The large effect of the changing labour force comes through the part-time employment, whose share grew dynamically during the 2007-2008 recession. Elsby et al. [2013] indicate that compositional effects tend to be more prevalent in the US than the UK, in a study of real wage behaviour in recent recession episodes. Blundell et al. [2014] confirm that over the period 2007-2012 in the UK compositional effects introduce a counter-cyclical bias that is small compared to the negative contribution from the falling returns in worker characteristics.

Turning to the bias arising from firm heterogeneity, the main source of compositional bias is the fact that industry composition may change over the business cycle. Okun et al. [1973] demonstrated that if some industries offer a premium to workers and if these industries are at the same time more cyclically sensitive, then workers tend to switch into these high paying jobs during booms and switch out during recessions. However, the nature of this source of compositional bias is different than that arising from worker heterogeneity, as it partially encompasses a part of the wage growth effect that we would like to capture. This is the case if the tendency to switch into high paying industries/ firms/ jobs during an expansion is viewed as a general process common for all types of workers (Abraham and Haltiwanger [1995], Barsky and Solon [1989]). In that case, while compositional bias based on worker heterogeneity is purely a statistical artifact of aggregation, compositional bias due to industry shifts (while keeping the skills of the workers the same) refer to rents to workers that are part of their own decision during the wage determination process, and as such should not be used to correct aggregate wages for their effect. On the other hand, if such changes in industry composition are considered to create job opportunities for only specific types of workers, changing the distribution of types of workers in an economy, then a pro-cyclical bias is introduced in aggregate real wages that we should account for. Studies such as Abraham and Haltiwanger [1995] refer to estimates, which show that real aggregate wages corrected for industry effects are less pro-cyclical or even become counter-cyclical compared to cases where real wages are not corrected for industry effects. The explanation provided for these results is that in certain high wage industries in the manufacturing sector, employment shares are pro-cyclical, adding a pro-cyclical bias in aggregate real wages. Barsky and Solon [1989] show that real wage data dis-aggregated by industry tend to be less pro-cyclical compared to aggregate real wages.

Firms differ in their hiring, firing and wage practices, and their composition might change over the cycle. Workers that are hired, fired or promoted over the cycle are not randomly selected. Thus, the matching quality of new hires can rise (or fall) in recession, or firms might hire less (or more) low-skilled workers in a recession than an expansion, introducing a counter-cyclical (or pro-cyclical) bias in real aggregate wages, respectively.[6] For instance, Carneiro et al. [2012] use individual level data for Portugal over 1986-2007 and account for changes in the composition of worker, firms and job characteristics. They find an elasticity of -1.6, but real wages become more pro-cyclical, with an elasticity of -2.2 once changes in the composition are included. Therefore, ignoring changes in worker, firm and job characteristics over the cycle, introduces a counter-cyclical bias; low skill/ paid workers represent a higher share of the workforce in expansions than in recessions.

Apart from the bias arising from changes in worker or industry composition, some studies like Bils [1985] and Keane et al. [1988] argue that another problem with the use of aggregate data is that they can suffer from selection bias. The selection bias arises when the assumption that the relationship between real wages and the business cycle is the same for all individuals does not hold. Indeed, research has shown that this assumption does not hold and that workers who move in and out of the work force differ systematically in their characteristics and wage levels, and they also tend to have more pro-cyclical employment shares and wages, compared to other groups, for instance the continuously employed (Bils [1985], Keane et al. [1988], Solon et al. [1994], Carneiro et al. [2012], Devereux [2001], Devereux and Hart [2006]). Therefore, these groups affect both the composition of employment and aggregate wage cyclicality even after accounting for composition. That is because their specific wage growth profile differs from the average worker adding a second order bias once included in the labor force.[7]

[6] Matching quality can rise or fall during a recession. According to Davis and Haltiwanger [1990] during a recession, workers can accept jobs that endure less (lower matching quality) or employers make better matches because they face a larger pool of applicants (higher matching quality). Bowlus [1995] showed empirically that the first effect prevails in the USA data, implying a pro-cyclical bias in aggregate wages, whereas if the second effect prevails then a counter-cyclical bias in aggregate wages is introduced.

[7] The way selection bias is estimated rests on the assumption that unobservable factors affecting wage levels are correlated with the unobservable factors affecting labour market participation decisions. The size and the direction of selection bias depends on the magnitude and the sign of the correlation. Bils [1985] and Barsky and Solon [1989] indicate that this correlation is most probably positive, leading to an underestimation of the true wage procyclicality, while Keane et al. [1988] estimate the correlation to be

It is unclear if it is optimal to remove the compositional bias due to industry shift (Abraham and Haltiwanger [1995]), while controlling for compositional bias based on worker heterogeneity. In other words, if the compositional bias based on changes in worker characteristics is removed, what is left should essentially be part of the wage growth determination process, even if that means that some effect arising from cyclical changes in the composition of industries might be included. Finally, regarding the selection bias, we would need data on the wages of those that leave the labour force as done in Bils [1985], by using the most recent wage of the non-employed or a panel data structure to control for the unobservable characteristics. The first information is also not available in EU-SILC, however we have used a sample and methodology to control to some extend for the potential existence of selection bias as explained later in Section 4 of the paper.

Given that the literature on wage aggregation and compositional changes originates in the mid to late 80's, the question is why so little attention has been paid to it and why it resurfaces now. We argue that the relative size of these compositional effects depends on three factors: i) the size of the changes in employment, ii) how asymmetric these changes are and how this asymmetry is affected by the business cycle and iii) the base skill distribution of the employed.[8] Focusing on the first point it can be argued that the size of the Great Recession and the recovery afterwards has lead to large changes in employment. However, one can argue that we have experienced sizeable recessions before, therefore why is the effect more pronounced now? To answer this we need to compare the base skill distribution during the 80's and today. During the 80's a large part of the labour force consisted of low to medium skilled workers.[9] On the contrary now, the workforce is more evenly divided between skill levels with high skilled workers reaching up to 50%. Given this, it can easily be demonstrated numerically that the same absolute loss of employment on the low end of the skill distribution today will have a higher percentage impact on the growth of the aggregate wage, as compared to the past.

3 Illustrating the Compositional Effect

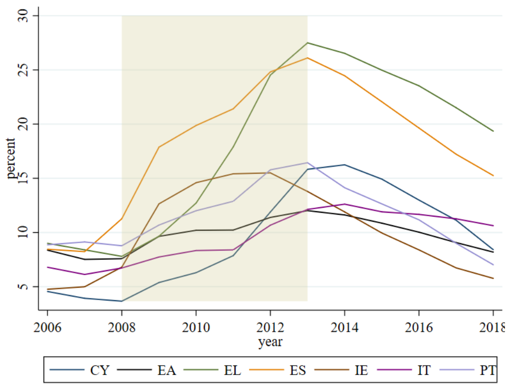
In this section we first discuss the theoretical sources and importance of compositional effects on wage growth. Furthermore, we empirically demonstrate the key idea using euro area micro data, by focusing on an illustrative example during the first years of the

negative, overestimating true wage procyclicality. However, as indicated in the study of Abraham and Haltiwanger [1995] the results of Keane et al. [1988] are not robust to changes in their specification. Blank [1990] finds no evidence of such correlation in the data used. She explains this absence of correlation as follows: she uses a wage measure where annual total earnings are divided by annual hours worked. This measure includes more individuals that might have been unemployed during some period in the year. Bils [1985] and Keane et al. [1988] exclude more non employed individuals as they include individuals that were employed when interviewed at a particular week over two consecutive years.

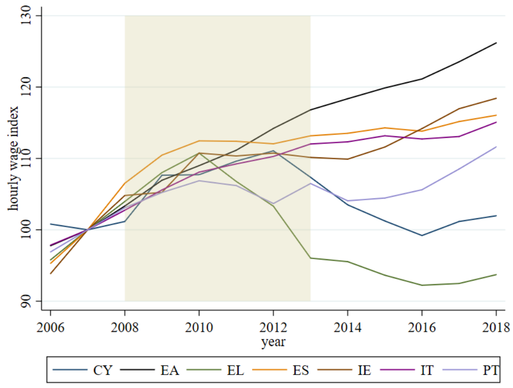
[8] The base skill distribution refers to the relative ratio between high and low skilled workers in the economy.

[9] See Barro and Lee [1996].

Figure 1: Unemployment and wage trends in selected euro area countries



(a) Unemployment rate



(b) Hourly wages

Note: ECB and Authors' calculations. Hourly compensation based on employees expressed as index with base year 2007.

crisis and the subsequent recovery.

3.1 Aggregation and Wages

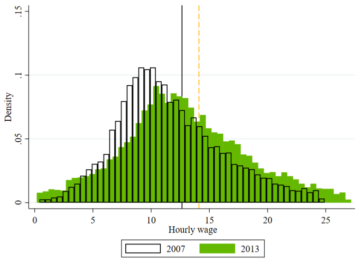
Market participation is a discrete choice and in turn employment is a discrete outcome. Workers decide whether to work or not at a given wage and firms decide whether to employ a worker or not. However, that impacts the structure of aggregate wages given that wages are observed only for matches that materialize and that changes over time.[10] In detail, there are two key issues to focus on. Firstly, the question is what is causing the growth in aggregate wages between two periods: is it either due to the increase of individual wages or due to low wage individuals that choose (or are forced) to leave employment? A second issue is whether each of these causes is systemically correlated with economic activity and in what way. This raises the question which aggregate wage growth we are interested in estimating. Are we interested in a wage growth that tracks the change in skills and average productivity or the returns to these skills? The question has no obvious answer and depends on how we are modelling economic activity.[11] However, it becomes more obvious if we are trying to estimate the responsiveness of wages to the economic cycle. In detail, if we are interested in estimating the direct effect of inflation and inflation expectations on wages, then it can be argued that what we ideally would like to know is the increases in individual wages over time.

[10] For a detail discussion of aggregation issues see Blundell and Stoker [2005] and Stoker [2008].

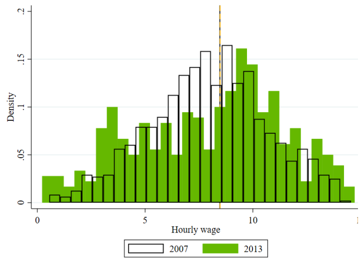
[11] For example if we are trying to track the overall labor share in a country we might be interested in the first one, however if we try to estimate wage inflation (essentially following wage prices) then we need to keep the skill set constant. This is similar to having a fixed basket price index versus an expenditure index for inflation.

Figure 2: Unconditional and Conditional Wage Distributions

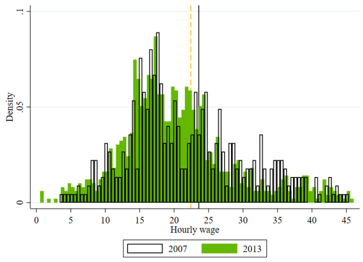
Focusing on the Downturn



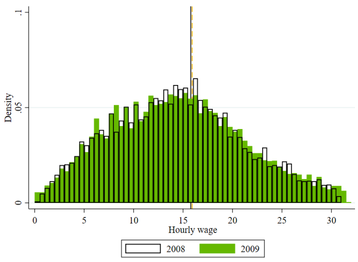
(a) Unconditional Italy



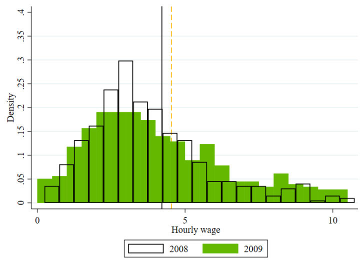
(b) Low Skilled Italy



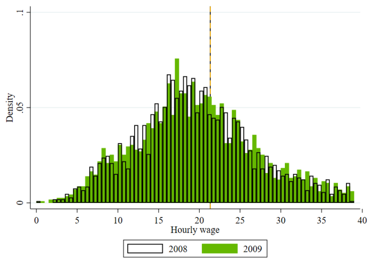
(c) High Skilled Italy



(d) Unconditional Germany

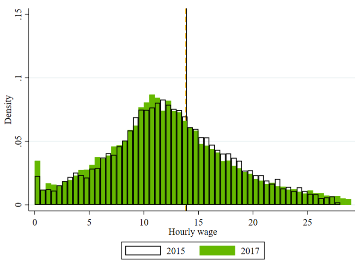


(e) Low Skilled Germany

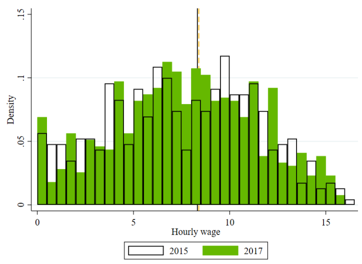


(f) High Skilled Germany

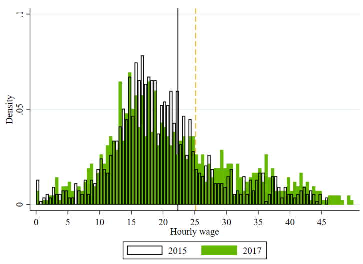
Focusing on the Recovery



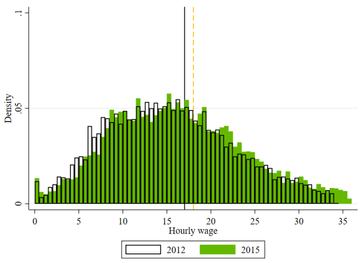
(g) Unconditional Italy



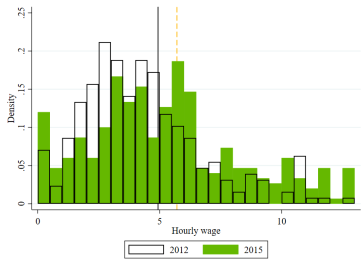
(h) Low Skilled Italy



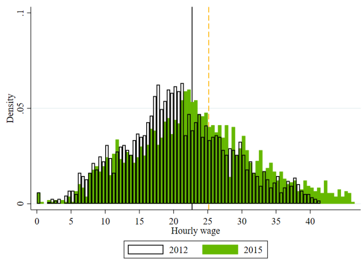
(i) High Skilled Italy



(j) Unconditional Germany



(k) Low Skilled Germany



(l) High Skilled Germany

Note: To produce the conditional distributions we use different combinations of values of education and experience, as proxies for low and high skilled workers. Low skilled workers refer to workers with low education and up to ten years of work experience. High skilled workers refer to workers with high education and more than 20 years of work experience. The black line represents the mean of the wage distribution in white (first year in each panel's legend) and the red dotted line the mean of the wage distribution in green (second year in each panel's legend). In each panel the upper 5 percent quantile of the distribution has been truncated, for visualisation purposes, while the means are calculated including all the available data. Source: EU-SILC and Authors' calculations.

3.2 Means and Wage Distributions

During the Great Recession the limited responsiveness of wage growth to the business cycle has raised questions in the literature. The graphic representation of aggregate wage and unemployment dynamics helps to put into perspective the wage-unemployment puzzle in the euro area described in the previous sections. As presented in figure 1a and 1b, in the euro area the unemployment rate rose from 7.28% in March 2007 to 12.09% in April 2013, while wages remained elevated. The aggregate wage figures suggest that even in countries like Spain and Italy, where the unemployment rate increased by almost 15 percentage points and more than doubled respectively, wage growth hardly responded. In the rest of the countries, the unemployment rate almost doubled. At the same time, nominal wages increased especially during 2008-2010. Since 2013, the recovery in nominal wages has been particularly slow. The increasing wages during the first phase of the crisis (2008-2010), and their relatively flat profile observed since the start of the recovery in 2013, have led researchers to believe in a potential breakdown of the empirical relationship between wage growth and unemployment in the euro area.

However, the assessment of aggregate wage developments crucially depends on the correct measurement of the aggregate wage taking into account the changes in the employed labour force characteristics. Figure 2, panel (a) depicts the unconditional wage distribution in Italy during the downturn.[12] We observe that between 2007 and 2013 in Italy the wage distribution appears to have shifted to the right, indicating an increase in the average aggregate wage. However, if we condition on the skill level[13] we can observe that, in reality, the wage distribution has shifted to the left between 2007 and 2013 for both low and high skilled workers, indicating a decreasing nominal wage (panels (b) and (c)). This observation shows that it is possible to have an increase in the wage in the overall wage distribution, and a decrease within in each skill category. This is known as the Simson paradox. Focusing on the subsequent recovery, panels (g), (h) and (i) show that while the unconditional wage distribution has marginally shifted to the left between 2015 and 2017, resulting in a marginally decreasing average aggregate wage, the average wages of low and high skilled individual workers have increased.

This purely descriptive evidence demonstrates the existence of a compositional effect: as the skill distribution of the employed in each economy is changing, it affects the unconditional wage distribution, given that the support of the distribution is also changing. To make this point more concrete, the Appendix presents the percentages of the employed attributed to worker characteristics and their evolution over time in each

[12] The choice of Italy and Germany is merely made to illustrate the concept of compositional effects in one country with high employment movements and a country with low employment movements. The choice of the time periods is based on the unemployment developments (peak and troughs). In Italy, the unemployment rate steadily increased between 2007-2013, and kept falling steadily since 2014, mirroring changes in employment patterns. In Germany, the unemployment rate increased marginally during 2008-2009, and kept decreasing since then.

[13] Low skilled workers refer to workers with low education and up to ten years of work experience. High skilled workers refer to workers with high education and more than 20 years of work experience.

of the 19 euro area countries. Focusing on the level of education, we can observe that in Italy, there was a significant increase in the percentage of employed workers with a university degree from around 14 percent in 2007 to around 23 percent in 2013 (Table 14 in the Appendix). Likewise, the percentage of more experienced workers, i.e. those with more than 20 years' experience, increased by 12 percentage points over the same period. This is the underlying reason why we observe the discrepancy between the unconditional and the conditional wage distributions in Figure 2. That is, in the unconditional distribution we have a higher percentage of high skilled workers being part of the employed workforce in 2013 compared to 2007. This combined with the fact that high skilled workers also tend to receive, on average, higher wages than those of low skilled (panels (b) and (c), Figure 2), leads to an increase in aggregate average wage (panel (a), Figure 2). This is the case even though the average wage of high skilled workers has declined (panel (c), Figure 2). Since 2013, the pattern seems to have reversed in Italy. The share of high skilled workers (workers with high education and experience above 20 years) has been declining, while the share of low skilled workers has been increasing (Table 14). This is translated into a marginal fall in aggregate average wage (panel (g), Figure 2), even though wages in the two skill categories have been increasing. This implies that the aggregate average wage may be overestimated before 2013 and underestimated since 2013, as a result of changes in the composition of the employed labour force.

The picture in several euro area countries, where unemployment also increased the most since the crisis, is somehow similar to the one described for Italy.[14] For instance, in Greece, by conditioning on the skill level, we observe a reduction in the average aggregate wage until 2013, compared to a more moderate reduction in the mean wage of the unconditional distribution. During the downturn, in Ireland, Portugal and Spain, the overall wage slightly increased, whereas the conditional mean wages of high skilled workers remained stable or even declined. Again, these patterns are explained by the fact that the share of employees with a higher level of education and experience increased between 2007/2008 and 2012/2013 (Tables 12, 13, 20 and 23). Despite the observed changes in the mean wages in both high and low skilled groups, the relatively higher wage level of the highly educated and experienced workers keeps the overall mean wage mechanically elevated.

This pattern is observed, although to a lesser degree, in countries with more modest cyclical changes in the employed labour force. In Germany, the unconditional wage distribution seems to have shifted marginally to the right between 2008 and 2009 (panel (d), Figure 2). However, when we condition on the skill level, we can observe a moderate growth in the average wage for low skilled workers, while the average wage of high skilled has remained constant (panels (e) and (f), Figure 2). During 2012-2015, the unconditional distribution has shifted slightly to the right, with average wages of low and high skilled categories increasing by more (panels (j), (k) and (l), Figure 2). In a nutshell,

[14] Demonstrating relatively high differences in their unconditional and conditional distributions.

in Germany, it is also possible to observe different patterns in wage growth in each skill category compared to the overall wage growth (resulting from the unconditional wage distribution). This discrepancy in unconditional and conditional wage distributions can be explained, as in the case of Italy, by the fact that the weights of each category of characteristics in the employed labour force have changed.

In a similar vein, in Austria, France and Finland, countries with small employment losses and a short-lived crisis, the conditional wage distributions have remained relatively stable between 2008 and 2010, indicating small changes in nominal wages and resembling the case of Germany presented above. The compositional effect is expected to be relatively small as the changes in the composition of the employed labour, in terms of education and experience, were much smaller in France and Austria, compared to countries like Greece, Ireland, Italy, Spain, and Portugal (Tables 5 and 10). This combined with small changes in wages across the different groups result in a minimal upward bias to aggregate wages.

To sum up, the analysis of the descriptive statistics demonstrates that when we account for skill level and other worker characteristics, there are significant differences across euro-area countries, which are correlated with the severity of the business cycle. In the next section we will describe our methodology on how we use individual level data to estimate the size of the compositional effect.

4 Estimating the Compositional Effects

In this section, we firstly describe the data sources used in our analysis. Secondly, we compare our data with other aggregate data sources and describe a methodology of choosing an optimal weighting scheme to minimize the distance between data sources. Finally, we conclude the section by describing the methodology used to estimate the size and direction of the compositional effects.

4.1 The Data

To estimate the effect on wages due to changes in the composition of the employed force, we use the detailed micro data on income and living condition dataset (EU-SILC) from Eurostat.[15] The EU-SILC data start in 2003 which was the pilot year. In the current paper we have used the cross-sectional dataset and the analysis starts from 2008. The latest wave used is the 2019 wave, however, not all countries report data for the final year (2018).[16] Each individual reports information on its annual gross income

[15]The EU-SILC dataset is available in a cross-section and a longitudinal version. The longitudinal version follows individuals over 4 waves; however, it contains slightly less observations and data on major euro area countries (mainly Germany) are missing.

[16]This is the case for Italy and Ireland, as at the time that this analysis took place only data until 2017 were available (see country tables in the Appendix).

and hours worked for the year prior to the survey. In total, the cross-sectional sample includes almost 7.2 million observations.

In the EU-SILC data, no variable directly measures hourly wage. However, given the information provided it can be constructed. The variables used, to construct the hourly wage, are the gross income, the main economic activity and the hours worked per week in the main economic activity for the year prior to the survey.[17] Furthermore, information on the main economic activity is also provided monthly, and as such we know for how many months each individual has been in each economic state. We utilized several different sample criteria but the results reported in this paper refer to a sample including employees between 16-65 years old for which their employment status belongs to one of the following categories: employees that are full-time employed throughout the year, part-time employed throughout the year, partially part-time employed throughout the year, partially full-time employed throughout the year, individuals switching between one specific status of employment and unemployment during the year.[18] Each worker is identified in one of these categories based on information provided by their monthly economic status. For each worker in each status we have information on how many months the individual spent in employment and on the hours worked per week. This sample has the advantage that it suffers less from the selection bias reported in Section 2 as it does not exclude people moving in and out of employment, as happened in several previous micro studies.[19] The annual nature of our depended variable also mitigates this.[20] In all our calculations and aggregation of variables, we use survey weights and weights based on hours worked to preserve the representativeness of the sample in each period. Other main variables used are education, experience, age, gender and nationality.[21]

To check the representativeness of the EU-SILC data we compare them with data from National Accounts (NA) on hourly compensation of employees. The purpose is to make a direct comparison between aggregated hourly compensation data based on

[17] Main economic activity can be working part-time or full-time either as self-employed or employee along with several other cases such as unemployed, retired e.t.c

[18] For people switching between unemployment and being an employee is straight forward how to calculate the annual hourly wage given that we have information on how many months the individual spent in employment or unemployment during that year. Hence, we calculate the months spent employed which given the hours per week gives us the overall hours worked in the year. The yearly hours together with the yearly income provide enough information to calculate the hourly wage. We repeat the same procedure both for part-time and full-time employees. However, we exclude individuals switching between part-time and full-time employment as the hours worked per week are only defined for the main activity. Thus it is not recoverable if the worker has switched between jobs with different hours. Smaller sample including only full-time employed throughout the year and part-time employed throughout the year was used and the results were similar.

[19] For instance, Verdugo [2016] used only the hourly wage for employees which have been working full time the whole year, thus suffering from sample selection problems. For other studies raising this point see discussion in Section 2.

[20] See discussion in Blank [1990] and Barsky and Solon [1989] on this point.

[21] These are included as dummies representing different categories. The categories included are defined as follows: (i) three categories for education: low (individuals with primary education), medium (tertiary education), high (college degree) (ii) four categories for experience: 0-3 years, 4-10 years, 11-20 years, over 20 years (iii) four categories for age: 16-34, 35-44, 45-54, over 55 years old (iv) two categories for gender: male or female and (v) two categories for nationality: nationals or immigrants.

Table 1: Percentage improvement in absolute distance between NA and EU-SILC

	sample including:		
	full-timers	full- and part-timers	full-, part-timers and partially unemployed
weights based on:			
hours and survey	−10.7	−11.7	−14.6
hours	−9.2	−10.3	−11.4
survey	−3.0	−4.2	−0.1
none	0.0	−3.2	−1.8

Note: Percentage decline in absolute distance of annual hourly wage growth between NA and EU-SILC data of different combinations of weighting schemes and samples compared to the reference combination. The reference combination of sample and weighting scheme is the one where the absolute distance is the maximum among the 12 potential combinations. In our case this is achieved when the sample includes only full-time workers and no weights are used. For instance, -3.0 means that using a sample of only full-timers and only survey weights improves the absolute distance by 3.0 percent compared to using the same sample and no weights. Source: EU-SILC and Authors' calculations.

the EU-SILC and the data most widely used based on the National Accounts. For the National Accounts data there is no single survey source and single population concept across the member states[22], and sources for each country vary, hence the resulting data could be subject to variations in methodology. Therefore, it is important to keep this in mind when comparing wage data from National Accounts with wage aggregated data from the EU-SILC, which is a common survey conducted across countries. This implies that the data sources and the concept of population used in each dataset differ from each other. On the other hand, the way income is reported in EU-SILC does not include social security contributions. As will be shown below, this difference in definitions does not affect the comparability of both datasets in terms of growth rates.[23]

The EU-SILC dataset offers alternative ways to aggregate the individual data within each country using different weighting schemes. This can impact the way they emulate the National Accounts data. According to the National Accounts, country (euro area) wide aggregates are based on the use of appropriate sector (country) weights usually based on hours worked. In the EU-SILC, we could account for both the survey sampling weights and the hours worked weights by each individual to mimic the aggregation method used in the National Accounts. For completeness, we tested four ways of weighting the individual data: no weights, survey (or sampling) weights, weights based on hours

[22] In its website for National Accounts metadata, Eurostat mentions regarding the data sources "Countries use many sources to compile their National Accounts, among them administrative data from government, population censuses, business surveys and household surveys. No single survey can hence be referred to. Sources vary from country to country and may cover a large set of economic, social, financial and environmental items, which need not always be strictly related to National Accounts. In any case, there is no single survey source for National Accounts." Regarding data collection "Data in ESA2010 are transmitted via SDMX which introduced standardised codes. National Accounts combine data from many source statistics. Techniques of data collection vary widely, depending on the compilation approach, the source statistics available, the particular account in the system of accounts, the timeliness of data release and other factors."

[23] Moreover, according to the National Accounts compensation of employees is defined as "the total remuneration, in cash or in kind, payable by an employer to an employee in return for work done by the latter during the accounting period. Compensation of employees consists of wages and salaries, and of employers' social contributions."

worked of each individual and a combined weight of survey and hours worked weights. We worked with three different samples of individuals: individuals working only full-time throughout the year, individuals working only full-time or part-time throughout the year, and individuals in the second sample plus partially full-timers or part-timers and individuals switching between full-time or part-time and unemployment status. We end up with 12 potential combinations of weighting schemes and sample types. The combination of weighting scheme and sample from the EU-SILC, to be used throughout the analysis, is decided by minimizing the distance between National Accounts and EU-SILC aggregate data. The minimization algorithm works as follows: For each country, year and combination of weights and sample:

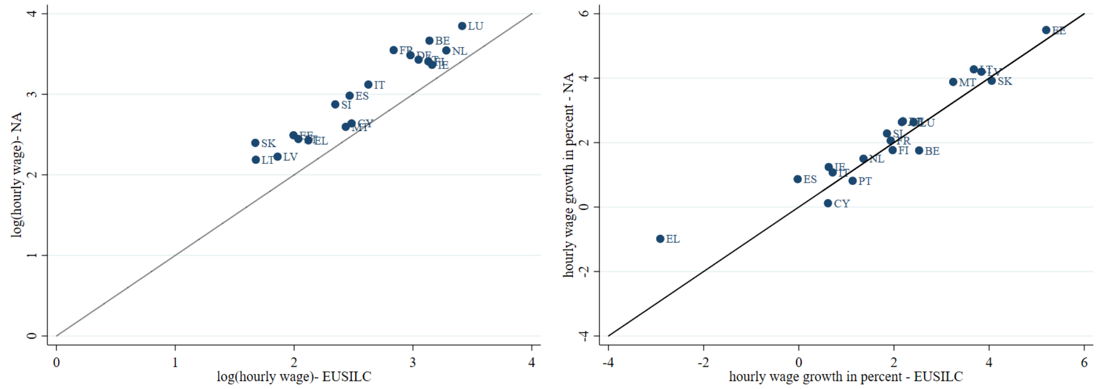
1. Calculate the annual growth rate of hourly compensation for the National Accounts aggregate data and the annual growth rate of the aggregate data series from the EU-SILC dataset for each of the years 2008-2018.
2. Calculate the absolute difference between the annual growth rates from the National Accounts and the EU-SILC aggregate data for each year available.
3. Calculate a simple average of the absolute differences for the years 2008-2018 and we end up with a measure of average absolute distance between the growth rates of the two datasets for each country. We have 19 such measures, one for each country.
4. Calculate a simple or weighted average of the 19 country measures.
5. Compare with previous result and keep the minimum
6. Repeat for all 12 combinations of weighting scheme and sample type.

Our analysis indicates that the minimum distance is achieved when using the combined survey and hours worked weights and the sample that includes both full-timers, part-timers and partially unemployed. The results are presented in Table 1 which shows the comparative improvement in the distance between the two datasets due to different weighting and sample choices. According to Table 1 using the aggregate wage measure based on the combined weight and the most complete sample from the EU-SILC diminishes the absolute distance between NA and EU-SILC by 14.6%, the largest decline among all the 12 combinations presented in the table.

Focusing on the optimal aggregation the EU-SILC data are compared to the National Accounts aggregates. Figure 3a shows a simple scatter plot of hourly compensation levels from National Accounts against that based on the EU-SILC for 2018 [24] and it can be inferred that the levels of hourly compensation and the rankings of countries are

[24] For Ireland and Italy data are available up to 2017, so the wage levels of 2017 and average growth rates for the period 2008-2017 are used in the scatter plots.

Figure 3: Hourly wages, National Accounts versus EU-SILC



(a) Hourly wage levels in 2018 **(b)** Hourly wage growth, average 2008-2018

Source: National Accounts and EU-SILC data from Eurostat.
Note: Authors' calculations.

similar based on both datasets.[25] Most importantly, Figure 3b shows a scatter plot of the average annual growth rates of hourly compensation based on National Accounts against those based on the EU-SILC. The fact that most pairs are clustered close to the 45-degree line indicate that the annual growth rates are, on average, similar in both datasets for most countries. This makes evident that in terms of growth rates aggregate EU-SILC hourly wage data render some similarity to the ones based on National Accounts data.

4.2 How to estimate the compositional changes

The main rationale behind any type of estimation of such a bias is that there are always at least two sources of aggregate wage growth. The first is the change in the returns to a specific level of productivity or skill level, which we will call wage inflation. The second is the change in the average productivity level or skill set.[26] The combination of the two gives us the change in the aggregate wage figures. To be able to achieve this decomposition we need to use individual level data which will allow us to estimate both.

Although there are several different methods of decomposing the wage growth, they are all based on the logic we already described. Differences between approaches are more related to data availability and structure. In detail, when longitudinal data are available, we could additionally control for changes in the unobservable productivity component. On the other hand, using repeated cross sectional data, we could only correct for changes in the observable characteristics such as education level, experience,

[25] This can be seen as the dots are close to the 45-degree line. The dots are systematically clustered slightly above the 45-degree line, as the compensation data based on National Accounts include social security contributions, a relatively constant percent of total compensation, which is not included in the income variable reported in the EU-SILC.

[26] There is also a third term, which in our analysis tends to be negligible and represents changes in returns that are associated with changes in the aggregate skills distribution.

gender, age and nationality.

For the estimation we used an Oaxaca-Blinder decomposition [Blinder, 1973, Oaxaca, 1973], a method commonly used to study labour market outcomes by different groups (e.g. poor vs rich, gender, race etc.). In our case the different groups are the different years of employed people i.e. the changes in the composition of the employed labour force from one year to another.

The goal is to estimate the change in nominal wages due to either a compositional effect or due to changes in the structural returns to labour between two subsequent years and thus create a hypothetical measure of aggregate wages free of compositional effects. In order to achieve that, we define two consecutive years as two groups of employed individuals (group t and group $t+1$). Thus the difference on the mean wage can be written as:

$$\Delta E(Y) = E(Y_{t+1}) - E(Y_t) \tag{1}$$

Given a liner model:

$$Y_T = X_T'\beta_T + \epsilon_T, \quad E(\epsilon_T) = 0 \quad T \in (t, t+1) \tag{2}$$

Thus assuming that $E(\epsilon_T) = 0$ we can rewrite equation (1) as:[27]

$$\Delta E(Y) \quad = \quad \underbrace{[E(X_{t+1}) - E(X_t)]'\beta_t}_{\text{Compositional Effect}} + \underbrace{E(X_t)'(\beta_{t+1} - \beta_t)}_{\text{Returns to Skills}} - \underbrace{[E(X_{t+1}') - E(X_t')(\beta_{t+1} - \beta_t)}_{\text{Interaction Term}} \tag{3}$$

The first term on the right hand side of equation (3) is the compositional effect or what in the literature is called the endowment effect (E), as it measures the differences in predicted wages, if only the composition of the employed labour force has changed. The second term is what we call the coefficient effect (C), which measures the difference in predicted wages (or the returns to the covariates), if the skill-set of the employed labour force is held constant. Finally, the last term is the interaction effect (I), which accounts for the fact that differences in skills and returns co-exist.

In this approach employed for the estimation of the wage returns, we use typical mincerian regressions including as covariates observable skills.[28] However, we abstain from including more aggregate controls that are direct outcomes of the observable skills such as industry dummies. This is because when we are interested in wage growth, we are interested in principal in the return to individual workers over the business cycle and not changes in industry characteristics, which are part of the market structure and thus the wage determination process. In detail, the fact that an individual leaves job A and goes to job B, and given the choice is rational that means that she must earn at least as much, in expectation[29], in job B as she would at the same point in time get in

[27] The proof is included in the Appendix.

[28] Which include education, experience, age, gender and nationality as dummy categories explained in footnote 21.

[29] In principal the worker will compare the wage she will get in job B to the wage in job A, taking

job A. To sum up, the literature in firm specific compositional effect is less conclusive, because as explained in Section 2 the effect on real wages can be either pro-cyclical or counter-cyclical. However, in principal this should not be clearly classified as a pure bias but rather as a partial explanation of wage cyclicality, which is the reason why we exclude the changes in firm/industry characteristics from our choice covariates.[30,31] Furthermore, there is an econometric argument on why we should not include as co-variates outcomes of our explanatory variables, as they would bias our estimates. For instance, including as a covariate if the type of job is a blue collar or a white collar job will bias the return of education, as being a blue or white collar worker is an outcome of education among other things.[32]

Another point to consider regarding the current analysis is that changes in the composition of employed workers can be driven by short-run fluctuations and longer-term trend developments in worker characteristics. One such characteristic is the education structure of employees: this can be affected by trend developments, as more recent cohorts of workers entering the labour force tend to be more educated than the older cohorts, but also by cyclical developments, such as less educated workers tend to be the first to lose their job during a downturn. A similar argument can be made for other worker characteristics such as age and experience. While a long-term positive trend in education or age would by default be present at any point in time, this might be dominated by the size of short-term fluctuations in the compositional effect caused by changes in the worker characteristic. Hence, during a recession the short run fluctuations might be so negative, that they tend to inflate the (long run) compositional effect, while during an upturn they tend to deflate it. Thus, compositional effects tend to be larger in size during a recession, and more muted during an upturn.

As a final note, our sample and approach allow us to use several proxies such as education that are highly correlated with unobserved skill characteristics that might affect labour market participation decisions. Also as noted earlier, the use of the full sample including the continuously employed, but also partially full-timers and partially part-timers, as well as movers in and out of employment and unemployment statuses, diminishes any effect of selection bias. Finally, we also use annual measures of individual hourly wages, that tend to mitigate the selection bias problem as described in the literature (e.g. Blank [1990] and Barsky and Solon [1989]).

also into account the time that she might potentially spent unemployed in each of the two jobs, thus her expected wage.

[30] See discussion on industry compositional bias in Section 2.

[31] Results including industry effects are discussed in the next section and included in the Appendix as a robustness test.

[32] For details see Angrist and Pischke (2009) and their discussion on bad controls.

5 Results

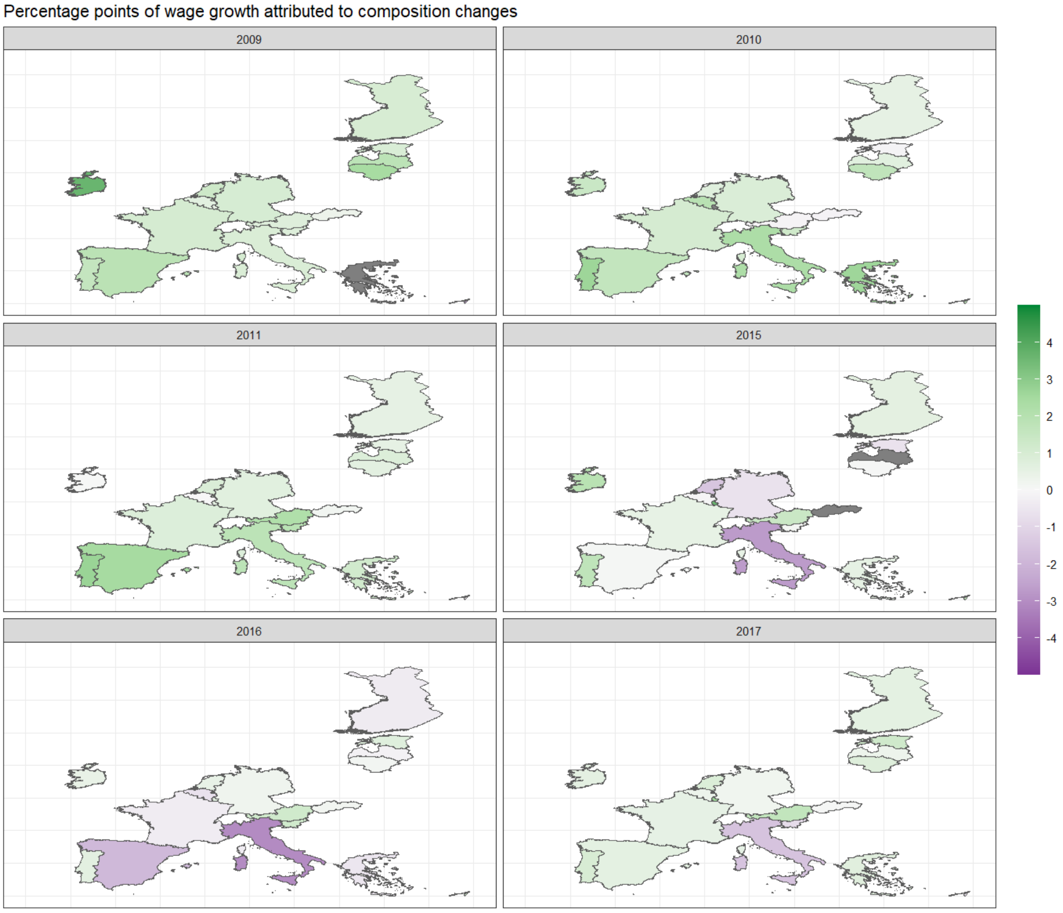
In the current section we discuss the main results of our paper. Compositional effects are driven by changes in the employment pool, and as such significant impact of compositional effects on aggregate wages is expected in countries with large employment changes. Hence, we begin by reporting the estimates for the compositional effects in countries faced with high employment losses early in the crisis and we continue with the rest of the euro area. Moreover, a discussion on the main drivers of the compositional effect is provided. Finally, results of a wage cyclicality analysis when compositional effects are accounted for are presented.

5.1 Estimates of compositional effects

Regarding the euro area, our results indicate that the compositional effect is countercyclical. As can be seen in Figure 4, the compositional effects tend to be positive during the years of the downturn (2008-2013) across the euro area countries (most countries are shaded in green). Since the start of the recovery, the compositional effect is estimated to be less positive or even turns negative in some countries (shaded in purple in Figure 4). Given this simple observation, aggregate wage growth tends to be over-reported during a downturn and under-reported during a recovery due to the presence of compositional effects.

The size of the compositional effect in aggregate wages differs across euro area countries and is correlated with the severity of the business cycle. Our results indicate that the compositional effect tends to be higher in some countries that faced larger cyclical employment movements early in the crisis. The magnitude of the compositional effect in these countries is estimated to be on average 2 to 3 times larger compared to that in the countries that have not experienced high employment losses. Table 2 shows the evolution of the observed aggregate wage growth and the wage growth free of compositional effects, as well as their difference i.e. the estimated compositional effect in the euro area countries that experienced the largest employment losses. In particular, the compositional effect is estimated to be positive, highest and prolonged in Italy, Spain and Portugal during the downturn 2008-2013/2014, (Table 2). Greece also seems to have experienced a positive and significant compositional effect during 2010-2013. In Ireland, the bias in wages is large and significant mainly during 2008-2009. For these countries the difference between the observed aggregate wage growth and the wage growth free of compositional effects is estimated to be positive and, thus, the wage growth free of composition effects seems to be significantly lower than what is suggested by the observed wage growth figures (Table 2). In other words, Table 2 shows that these are the countries that have experienced the largest wage reductions, indicating that due to positive compositional effects, actual aggregate wage statistics understate the the actual degree of wage reduction; net wage growth has fallen more than actual wage growth.

Figure 4: Compositional effects in the euro area over time



Note: Percentage points of wage growth attributed to compositional effects. Calculations are performed using the EU-SILC dataset.

In fact, these results are also in line with the descriptive statistics in Appendix A2, which showed an increasing share of high-skilled workers and a decreasing share of low skilled workers in employment since 2007, pulling up mechanically the average observed aggregate wages.

Since the start of the recovery in the euro area in 2013, the compositional effect has decreased in size and even changed sign in the countries with the largest employment losses in the beginning of the crisis (Table 2). The compositional effect has declined and even becomes negative and significant in Italy and to a lesser extend Spain. In Portugal, the bias in wages has remained positive but is much smaller since 2013, while in Greece and Ireland, it is mostly closer to zero and insignificant. These patterns indicate that since 2013 the observed wage growth might suffer from a lower positive bias, and in countries like Italy and Spain the compositional effect even turns negative, implying that wage growth would actually be higher than observed. Table 14 and Table 23 show that there is a change in employment flows since 2014, with the share of low skilled workers rising and that of high skilled workers declining, keeping the observed aggregate

Table 2: Wage growth and compositional effects: High unemployment countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
IT	Comp. Effect	2.0***	0.9**	2.3***	1.8***	2.1***	1.6***	1.4***	−2.7***	−3.1***	−1.6***	-
	Wage growth	1.8	0.0	2.5	1.0	1.8	0.8	1.2	−4.2	−0.9	−0.8	-
	Net Wage growth	−0.2	−0.9	0.2	−0.9	−0.2	−0.7	−0.2	−1.5	2.2	0.8	-
ES	Comp. Effect	3.7***	1.9***	1.6***	2.5***	2.1***	1.1**	0.9	0.1	−1.9***	0.6	−1.7***
	Wage growth	13.0	3.3	−1.4	4.1	−1.1	−1.9	−2.7	1.8	−7.9	2.4	−1.5
	Net Wage growth	9.3	1.4	−3.0	1.7	−3.2	−3.0	−3.5	1.7	−6.1	1.9	0.2
IE	Comp. Effect	3.1***	3.6***	1.4	0.0	1.1	−0.2	1.1	1.9**	0.4	0.6	-
	Wage growth	7.7	0.0	0.6	−1.1	1.6	−1.3	−2.1	3.6	0.7	0.8	-
	Net Wage growth	4.6	−3.7	−0.8	−1.2	0.5	−1.1	−3.2	1.7	0.3	0.2	-
PT	Comp. Effect	3.0***	1.6	2.7***	2.7***	3.2***	2.1***	1.2	1.7***	0.6	1.0*	0.5
	Wage growth	2.7	7.5	−0.2	−2.1	−2.7	2.4	−0.9	2.8	1.2	0.6	6.5
	Net Wage growth	−0.3	5.9	−2.9	−4.8	−5.9	0.3	−2.1	1.0	0.6	−0.4	6.0
EL	Comp. Effect	-	-	2.6***	1.2	2.8***	1.5**	0.0	0.5	−0.5	0.7*	−0.4
	Wage growth	6.6	−2.0	−1.0	−7.5	−7.7	2.3	−1.8	−2.7	−3.3	6.3	−4.9
	Net Wage growth	-	-	−3.6	−8.7	−10.4	0.8	−1.8	−3.2	−2.8	5.6	−4.5
CY	Comp. Effect	1.0	−2.7**	1.8	−0.5	1.6	1.5	0.4	1.7	1.3	−0.5	−0.9
	Wage growth	6.6	−0.2	4.8	1.1	−1.4	−4.6	−3.6	−0.5	1.8	1.1	2.0
	Net Wage growth	5.6	2.5	3.0	1.6	−3.0	−6.1	−4.0	−2.2	0.5	1.6	3.0

Note: The table reports the estimated compositional effect in percentage points and wage growth in percent. The net wage growth is a measure of wage growth free of compositional effects defined as the difference between the observed wage growth and the estimated compositional effect. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. Calculations are performed using the EU-SILC dataset.

wage growth artificially lower, since low skilled workers also tend to be lower paid.

Table 3 shows that early in the crisis (2008-2010) in the rest of the euro area countries, the compositional effect is found to be positive and of a smaller magnitude and duration than that reported in Table 2. The most notable positive and significant compositional effects are spotted in the cases of Slovenia and France, whereas in cases like Belgium, Finland, Germany and Slovakia, the positive compositional effect is mainly significant during 2008-2009/2010. Since then the compositional effects turn out to be small and insignificant in the rest of the euro area countries (Table 3).

We perform some sensitivity analysis by including industry effects in our analysis. Industry effects are included in two ways.[33] First, industry effects are treated as part of the compositional effects with the results presented in Tables 26 and 27. Secondly, industry effects are introduced in equation (2) but are not accounted as part of the compositional effect, with results presented in Tables 28 and 29. Introducing industry effects in our analysis does not alter our results significantly. The estimates of the compositional effects differ only marginally in terms of size and retain their significance (see summary Tables 30 and 31). Compositional effects remain highest in countries where employment losses were largest during the crisis.

5.2 Decomposition of the compositional effects

Worker specific characteristics such as education, experience, age, gender and nationality influence individual worker productivity and wage. They can have a differential impact

[33]Industry effects are included as sector dummies based on NACE (Rev.2) classification variables included in the EU-SILC.

Table 3: Wage growth and compositional effects

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
AT	Comp. Effect	1.2	0.8	−0.1	2.2***	0.4	3.1***	0.6	1.4*	1.2	1.7**	−1.5*
	Wage growth	6.2	2.3	2.9	3.2	4.1	2.5	0.5	4.6	−0.2	1.6	5.5
	Net Wage growth	5.0	1.5	3.1	1.0	3.7	−0.6	−0.1	3.2	−1.4	−0.1	7.0
BE	Comp. Effect	−0.3	0.7	1.9***	0.0	0.8	−0.1	1.6***	−0.1	−0.6	0.3	−0.7
	Wage growth	6.7	3.0	1.7	3.2	4.3	2.5	0.8	0.7	0.9	2.1	2.5
	Net Wage growth	7.0	2.4	−0.2	3.2	3.6	2.6	−0.9	0.8	1.6	1.8	3.3
DE	Comp. Effect	−0.6	1.0*	0.9	0.7	−0.1	−0.9	0.0	−0.6	0.3	0.2	0.5
	Wage growth	3.9	−0.2	2.4	2.6	2.8	1.3	2.8	2.1	2.1	3.3	4.6
	Net Wage growth	4.5	−1.2	1.5	1.9	2.8	2.1	2.8	2.7	1.9	3.1	4.1
EE	Comp. Effect	0.4	0.9	−0.1	0.5	−0.2	0.2	0.7	−0.6	0.7	1.2**	0.2
	Wage growth	10.1	−0.7	−0.6	7.5	6.9	3.8	6.2	4.7	0.0	14.4	3.5
	Net Wage growth	9.8	−1.6	−0.5	7.0	7.1	3.6	5.5	5.3	−0.8	13.1	3.3
FI	Comp. Effect	2.3***	1.0**	0.5	0.5	0.8*	−1.0**	−0.1	0.6	−0.4	0.6	0.0
	Wage growth	40.5	3.9	2.7	3.7	4.2	−2.2	2.0	0.8	0.7	0.3	2.3
	Net Wage growth	38.2	2.8	2.2	3.1	3.5	−1.2	2.1	0.2	1.1	−0.3	2.3
FR	Comp. Effect	1.1***	1.1***	1.1***	0.8**	0.7**	0.3	0.7*	0.5	−0.3	0.5	0.2
	Wage growth	3.1	1.2	2.8	2.4	1.5	0.3	4.4	1.0	1.1	0.0	4.5
	Net Wage growth	2.0	0.2	1.7	1.5	0.8	0.0	3.7	0.5	1.5	−0.6	4.3
LT	Comp. Effect	−0.6	2.4***	1.7**	0.6	1.0	−1.6**	0.2	0.0	0.2	0.8	0.3
	Wage growth	14.7	−19.2	−1.4	13.1	2.6	4.8	−0.2	10.3	7.5	6.8	9.1
	Net Wage growth	15.2	−21.7	−3.1	12.5	1.6	6.4	−0.4	10.2	7.3	6.0	8.8
LU	Comp. Effect	2.7***	0.5	1.8*	0.6	1.7*	0.3	−4.6***	3.7***	0.7	2.7***	1.8**
	Wage growth	7.4	1.1	2.6	1.9	5.2	0.8	−5.4	0.0	4.9	−1.6	11.6
	Net Wage growth	4.6	0.6	0.9	1.3	3.5	0.4	−0.8	−3.7	4.2	−4.2	9.8
LV	Comp. Effect	2.5***	1.8***	0.7	0.8	−0.6	1.1*	0.6	0.3	−0.2	0.3	1.4**
	Wage growth	19.7	−12.1	−5.1	7.3	3.9	8.4	9.4	5.2	4.7	11.0	6.6
	Net Wage growth	17.1	−13.9	−5.8	6.4	4.5	7.3	8.8	4.9	4.9	10.7	5.2
MT	Comp. Effect	1.6**	0.6	1.4**	1.0	1.1*	2.6***	0.4	0.9	0.9	−0.8	0.5
	Wage growth	4.1	1.3	4.7	3.4	4.8	5.7	3.4	−0.3	3.7	−0.6	4.7
	Net Wage growth	2.5	0.7	3.3	2.4	3.6	3.1	3.0	−1.2	2.8	0.1	4.2
NL	Comp. Effect	0.8	1.3**	0.7	0.9	1.5***	1.1*	1.5**	−1.5***	0.5	0.9	0.5
	Wage growth	5.5	2.6	0.1	3.4	1.8	−1.6	3.3	−3.3	1.0	3.0	1.8
	Net Wage growth	4.7	1.3	−0.7	2.5	0.3	−2.7	1.8	−1.8	0.5	2.1	1.3
SI	Comp. Effect	−0.1	0.8	1.3*	1.9**	1.3*	1.6**	0.7	0.1	1.2*	−0.8	1.1*
	Wage growth	6.7	2.8	4.0	2.5	0.4	0.6	1.7	0.0	1.1	1.4	4.4
	Net Wage growth	6.9	2.0	2.8	0.6	−0.9	−1.0	0.9	−0.1	−0.2	2.2	3.3
SK	Comp. Effect	1.6***	0.3	−0.1	0.2	0.0	0.4	−0.2	−0.3	0.2	0.0	0.1
	Wage growth	21.3	5.3	3.8	9.5	−4.2	3.5	5.1	−1.7	0.8	7.8	12.1
	Net Wage growth	19.7	4.9	3.9	9.3	−4.3	3.0	5.3	−1.4	0.6	7.7	12.0

Note: The table reports the estimated compositional effect in percentage points and wage growth in percent. The net wage growth is a measure of wage growth free of compositional effects defined as the difference between the observed wage growth and the estimated compositional effect. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. Calculations are performed using the EU-SILC dataset.

on the compositional effect. To examine the importance of each characteristic for the compositional effect, Table 24 and Table 25 in the Appendix show the decomposition of the compositional effect estimates by worker characteristics over time.

In the countries faced with highest employment losses (Table 24), the compositional effect is mainly driven by changes in the education profile of the employed. Compositional changes with respect to age and experience also tend to be important contributors and indicate that job losses were concentrated in the younger and less experienced workers or that the job-finding rate of that category was lower. The importance of the combination of experience and age compared to education differs across countries. In

Italy, changes in the aggregate profile of education and experience are the most significant contributors, followed by age. The effect is estimated to be positive up to 2014, as the employed labour force becomes more educated and more experienced and job losses in Italy were unequally distributed and more concentrated on the lower end of the skill distribution. Additionally, as the age profile of the employed workers is increasing (Table 14) and given that older workers tend to be better compensated, that also tends to bias the aggregate wage upwards. In Portugal, Greece and Ireland, education is the dominant force behind the positive and significant compositional effect in aggregate wages, whereas in Spain experience and age also play an important role. Since 2014, the impacts become negative and significant mainly in Italy and Spain, with the less educated, less experienced workers entering employment.[34]

In the rest of the euro area countries, the effects of education and experience are dominant, even though small and often insignificant (Table 25). These countries were not faced with the largest job losses and pressure to adjust their imbalances, resulting in small changes in the composition of labour over time since the crisis and indiscernible contributions from worker specific characteristics.

To sum up, compositional changes in employment tend to bias the aggregate wage growth in the euro area and the effect seems to be correlated with the size of the business cycle. Hence, the aggregate wage figures are found to be upward biased during the crisis, a trend which seems to get reversed during the recent recovery, with the bias being larger in countries with the largest employment losses during the crisis. In the next section, we will illustrate how the existence of compositional effects could explain the muted response of wages to changes in the labour market conditions observed during the crisis and the more recent recovery period.

5.3 Wage Cyclicality in Light of the Compositional Effect

Given the importance of the compositional effect in some countries, it would be of interest to see if it can explain the missing wage dis-inflation (inflation) during the recent recession (expansion). In the rest of the section, we demonstrate that some part of the muted wage cyclicality can be explained by the presence of compositional effects.

As described in the introduction, one of the puzzles encountered during the Great Recession and the subsequent recovery is the "missing" response of wages to the business cycle. The presence of compositional effects could partially explain this puzzle. The main reason is that the compositional effect tends to be counter-cyclical, effectively reducing the response of aggregate wages to the cycle. We provide some evidence of this hypothesis by estimating the elasticity of aggregate wages to the unemployment rate, using aggregate wage data from the National Accounts (NA), aggregate wage data

[34]Interestingly, in Italy since 2015 the contribution of nationality also became significant. A possible explanation is that a significant number of non-Italian nationals with lower average wage found a job. Hence, with those workers present in the employment pool, the observed wage growth is biased downwards (Table 24 and 14).

from our micro data (EU-SILC) and our wage measure free of compositional effects as the dependent variables. Our estimation relates wage growth to a measure of slack, in particular unemployment.[35] The equation is specified below:

$$w_{c,t} = \alpha_0 + \alpha_1 U_{c,t} + \alpha_2 U_{c,t-1} + \alpha_3 \pi_{c,t-1} + \epsilon_{c,t} \tag{4}$$

In equation (4), $w_{c,t}$ denotes annual wage growth in country c at time t[36], $U_{c,t}$ and $U_{c,t-1}$ stand for unemployment in country c at time t and its lag, as well as $\pi_{c,t-1}$ as lagged inflation rate. Year fixed effects are also included. Extra regressions controlling for country specific effects and productivity growth are also reported in Table 4.

Wage cyclicality is obscured when aggregate wages based on National Accounts are considered, while it is found to be higher when a wage measure free of compositional effects is employed (Table 4). In columns (1), (4), (7) of Table 4, that refer to National Accounts data, the elasticity of aggregate wages to the cycle is estimated around -0.8 to -0.9 percent. In all the cases, the aggregate wage measure based on micro data is more responsive to changes in unemployment compared to the aggregate wages published in the National Accounts (columns (2), (5) and (8), Table 4). The wage measure free of compositional effects is responding the most to the unemployment rate compared to the other two aggregate wage measures (columns (3), (6) and (9), Table 4). In all cases the measure free of compositional effects is around 15 to 40 percent more responsive to the unemployment rate. Even though these regressions are just indicative, they are still helpful as a benchmark among alternative measures of wage growth, in an analysis of wage cyclicality. This verifies our priors that the compositional effect is highly counter-cyclical and that the wages constructed from micro data and free of compositional effects respond significantly more to the unemployment rate.

[35] We generally follow the specification by Galí [2011], which relates to a structural interpretation.

[36] Our dependent variable is hourly wage growth constructed as follows: for each year and country we calculate a national annual hourly wage as a weighted average of the hourly wages across all workers in that year and country. As weights we use the combined weight based on survey weights for each individual worker available in the EU-SILC and on a weight based on hours worked of each individual constructed using data available in the EU-SILC. Finally, the annual wage growth of the national hourly wage is calculated.

Table 4: Wage Phillips Curve Equations, aggregate versus free of compositional effects

	Dependent Variable								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Wages NA	Wages EU-SILC	Net Wages	Wages NA	Wages EU-SILC	Net Wages	Wages NA	Wages EU-SILC	Net Wages
$U_{c,t}$	-0.81^{***}	-1.11^{***}	-1.36^{***}	-0.76^{***}	-0.89^{***}	-1.12^{***}	-0.88^{***}	-0.92^{***}	-1.15^{***}
	(0.24)	(0.32)	(0.29)	(0.19)	(0.27)	(0.24)	(0.21)	(0.25)	(0.24)
Controls							✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country Dummies				✓	✓	✓	✓	✓	✓
Observations	205	205	205	205	205	205	205	205	205

Note: The dependent variable is change in log of aggregate nominal wages. Net wages refer to wage growth free of compositional effects. We have used the specification that is consistent with Galí [2011] structural model including unemployment, the first lag of unemployment and inflation. In the last three columns productivity growth is also included. Robust standard errors clustered at the country level are reported in parentheses, significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimation over 2008-2018.

6 Conclusions

Policy debate has focused on the so called wage cyclicality puzzle, especially with respect to the responsiveness of wages to unemployment. In the current paper we use euro area individual level data and provide evidence regarding a potential explanation to this puzzle: the role played by compositional effects over the business cycle. As we demonstrated in the paper, the observed aggregate wage growth tends to be biased upwards due to the presence of positive compositional effects, especially in the countries that have experienced high employment losses during the downturn. Since the start of the recovery, the bias has reduced in size and even turned negative in some countries.

The importance of the compositional effect for policy is therefore threefold. First, it provides a possible explanation for the missing wage growth cyclicality. Several estimations of wage elasticity to unemployment demonstrated that some part of the missing wage cyclicality is explained by the compositional effect. The elasticity of wages seems to be significantly higher when accounting for the compositional effect. Hence, it seems that the traditional wage Philips curve relationship is still relevant as long as we take into account the compositional effect.

Secondly, it offers an indication of possible lower than expected observed aggregate wage growth during an economic recovery. The perception that during an economic recovery wage growth will start picking up only when the slack has reduced sufficiently might be flawed by the mere fact that the slack is reducing in an asymmetric way across skill levels. This is creating a negative compositional effect and obscures any ongoing increase in wage growth.

Finally, the asymmetric size of compositional effects across countries with differences in their cyclical positions introduces extra difficulty in cross country comparisons. For this purpose, the construction of harmonised wage measures that account for compositional effects should be seriously considered. The size of these effects needs to be accounted for during any assessment of wage pressures both in relation to the point of the business cycle and the true degree of wage moderation in the euro area.

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Appendix

A.1 Oaxaca-Blinder Decomposition

Given a liner model:

$$Y_T = X_T'\beta_T + \epsilon_T, \quad E(\epsilon_T) = 0 \quad T \in (t, t+1) \tag{5}$$

Thus assuming that $E(\epsilon_T) = 0$ we can rewrite equation (1) as:

$$\begin{aligned}
\Delta E(Y) &= E(X_{t+1})'\beta_{t+1} - E(X_t)'\beta_t \\
&= E(X_{t+1})'\beta_{t+1} - E(X_t)'\beta_t + E(X_{t+1})'\beta_t - E(X_{t+1})'\beta_t \\
&= [E(X_{t+1} - E(X_t)]'\beta_t + E(X_{t+1})'\beta_{t+1} - E(X_{t+1})'\beta_t \\
&= [E(X_{t+1} - E(X_t)]'\beta_t + E(X_{t+1})'\beta_{t+1} - E(X_{t+1})'\beta_t \\
&+ E(X_t)'\beta_{t+1} - E(X_t)'\beta_{t+1} + E(X_t)'\beta_t - E(X_t)'\beta_t \\
&= [E(X_{t+1} - E(X_t)]'\beta_t + E(X_t)'(\beta_{t+1} - \beta_t) + [E(X_{t+1}') - E(X_t')](\beta_{t+1} - \beta_t) \quad (6)
\end{aligned}$$

In the first step we assume that both $E(\epsilon_t) = 0$ and $E(\epsilon_{t+1}) = 0$ or they are equal to each other. In the second step we add and subtract $E(X_{t+1})'\beta_t$. In the second to last line we add and subtract $E(X_t)'\beta_t$ and $E(X_t)'\beta_{t+1}$.

A.2 Descriptives By Age, Education, Gender, Experience and Nationality

A.2.1 Austria

Table 5: Composition of Employed in Austria During 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	31.78	31.60	30.50	28.93	28.43	28.26	27.95	28.21	28.74	28.52	28.01	26.64	25.59	26.16
	Age 35-44	30.78	30.69	30.70	30.91	29.99	29.02	26.96	25.01	24.62	24.96	24.74	24.43	23.89	23.98
	Age 45-54	27.66	28.44	29.14	30.10	31.15	31.77	32.15	33.05	33.05	32.16	32.22	31.69	31.02	29.89
	Age Over 55	9.787	9.27	9.66	10.06	10.42	10.95	12.94	13.73	13.59	14.35	15.04	17.25	19.50	19,97
Education	Low	16.16	14.13	13.16	13.26	14.17	14.26	12.27	12.35	11.89	11.39	10.08	9.08	9.80	9.41
	Medium	65.76	68.00	68.89	66.96	65.19	65.41	66.80	66.21	54.99	55.50	54.60	54.17	52.64	52.77
	High	18.08	17.87	17.95	19.77	20.65	20.33	20.93	21.45	33.11	33.11	35.32	36.75	37.56	37.82
Gender	Male	55.74	55.55	54.79	53.70	54.18	53.06	53.86	54.37	53.64	53.40	52.95	52.18	51.59	52.36
	Female	44.26	44.45	45.21	46.30	45.82	46.94	46.14	45.63	46.36	46.60	47.05	47.82	48.41	47.64
Experience	0-3 Years	8.00	8.50	8.36	7.76	7.05	7.20	6.22	6.12	6.62	6.10	6.13	5.62	4.66	6.10
	4-10 Years	17.02	17.16	16.32	15.29	15.56	15.53	16.04	15.76	15.52	15.31	14.97	14.90	14.46	15.29
	11-20 Years	29.35	29.01	28.96	27.75	27.02	26.20	25.23	25.49	25.25	25.99	25.84	24.79	25.36	25.04
	Over 20 Years	45.63	45.32	46.36	49.20	50.36	51.07	52.50	52.62	52.61	52.59	53.06	54.69	55.52	53.57
Nationality	EU	1.73	2.08	2.68	3.27	3.76	3.51	3.22	3.61	4.05	5.14	5.65	5.92	6.14	7.30
	Local	92.19	91.87	91.96	91.58	91.73	91.43	92.01	91.64	90.96	89.54	89.56	89.84	88.89	88.14
	Other	6.08	6.05	5.36	5.15	4.51	5.06	4.77	4.75	4.99	5.33	4.79	4.24	4.96	4.56

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.2 Belgium

Table 6: Composition of Employed in Belgium During 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	30.56	30.97	30.17	29.60	29.21	28.30	27.12	27.46	27.20	26.34	26.39	28.30	26.90	27.14
	Age 35-44	31.96	31.76	30.79	30.62	29.52	29.39	29.18	28.52	28.24	28.22	29.34	25.71	27.18	26.65
	Age 45-54	28.14	26.74	27.73	27.79	28.02	28.32	29.18	28.67	28.09	29.71	28.10	27.64	27.36	26.89
	Age Over 55	9.34	10.53	11.32	11.99	13.24	13.99	14.52	15.35	16.46	15.73	16.17	18.35	18.55	19.32
Education	Low	16.71	14.98	18.50	22.19	19.64	15.20	15.87	14.82	14.19	12.22	12.00	12.67	12.47	12.05
	Medium	38.58	40.28	38.58	35.18	35.88	38.09	37.01	36.40	35.73	37.22	34.48	33.69	33.35	34.87
	High	44.71	44.75	42.92	42.63	44.48	46.71	47.12	48.78	50.08	50.56	53.52	53.65	54.18	53.08
Gender	Male	53.84	52.84	53.30	53.09	52.44	51.59	51.02	51.06	50.67	51.09	51.08	50.39	51.30	50.28
	Female	46.16	47.16	46.70	46.91	47.56	48.41	48.98	48.94	49.33	48.91	48.92	49.61	48.70	49.72
Experience	0-3 Years	7.52	9.46	8.04	7.91	9.15	7.44	7.90	7.50	9.47	6.83	8.69	9.69	9.64	10.47
	4-10 Years	20.01	21.30	20.22	19.76	20.01	18.04	18.12	18.93	18.26	17.84	18.64	19.28	18.87	19.34
	11-20 Years	28.99	27.97	28.34	28.43	28.19	29.48	29.13	28.98	28.42	27.68	28.95	27.23	28.46	27.44
	Over 20 Years	43.48	41.27	43.40	43.90	42.65	45.04	44.85	44.58	43.86	47.65	43.72	43.80	43.04	42.76
Nationality	EU	5.76	5.72	5.76	6.11	6.20	6.43	6.97	7.26	7.38	8.16	8.34	8.34	8.09	7.91
	Local	92.44	92.78	92.95	90.54	92.24	91.92	90.32	90.46	90.19	89.27	88.74	88.47	88.73	88.75
	Other	1.80	1.50	1.29	3.36	1.56	1.65	2.71	2.28	2.43	2.57	2.93	3.19	3.18	3.34

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.3 Cyprus

Table 7: Composition of Employed in Cyprus during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	33.92	31.95	31.09	28.04	28.88	29.02	31.47	29.87	29.16	28.06	26.26	24.97	24.15	25.73
	Age 35-44	27.57	26.39	26.36	27.09	27.66	26.48	26.61	27.59	28.68	28.17	28.37	28.54	28.53	26.35
	Age 45-54	24.57	26.64	26.93	28.39	27.76	27.40	26.11	25.61	24.59	25.67	25.93	26.05	25.13	25.11
	Age Over 55	13.93	15.02	15.62	16.48	15.70	17.09	15.80	16.93	17.57	18.10	19.43	20.44	22.19	22.82
Education	Low	24.15	23.54	23.36	22.04	21.66	19.88	18.00	17.57	16.23	15.33	14.91	14.23	14.62	14.80
	Medium	42.60	41.24	41.26	41.42	42.53	42.15	42.35	41.09	40.88	41.64	42.34	41.61	40.96	41.95
	High	33.25	35.22	35.38	36.54	35.81	37.97	39.64	41.35	42.88	43.02	42.75	44.16	44.41	43.24
Gender	Male	53.28	52.66	50.88	51.08	50.14	49.42	49.09	48.89	48.36	48.02	48.78	49.84	50.05	50.71
	Female	46.72	47.34	49.12	48.92	49.86	50.58	50.91	51.11	51.64	51.98	51.22	50.16	49.95	49.29
Experience	0-3 Years	9.85	9.82	10.16	9.48	10.55	10.63	9.51	8.29	8.06	8.11	8.97	10.06	10.97	11.45
	4-10 Years	21.39	19.52	18.83	17.08	16.64	16.82	19.48	19.26	19.23	18.23	15.99	14.47	14.24	14.48
	11-20 Years	28.23	27.93	27.56	28.07	27.34	25.66	26.78	27.00	28.28	28.78	28.18	27.65	26.26	24.86
	Over 20 Years	40.53	42.73	43.45	45.37	45.47	46.88	44.23	45.46	44.43	44.88	46.86	47.82	48.53	49.22
Nationality	EU	5.87	6.05	7.50	6.37	7.55	8.08	9.99	10.06	10.76	10.55	10.75	11.14	10.53	10.20
	Local	85.80	86.50	85.61	86.25	83.49	83.08	80.44	80.46	80.40	80.57	81.23	81.26	81.54	81.76
	Other	8.32	7.45	6.89	7.38	8.96	8.84	9.57	9.48	8.84	8.88	8.02	7.60	7.93	8.04

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.4 Estonia

Table 8: Composition of Employed in Estonia during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	27.77	28.00	27.59	21.68	23.95	24.66	25.27	26.53	26.12	24.96	23.62	23.44	23.64	23.22
	Age 35-44	25.06	24.79	24.51	25.75	26.05	25.27	25.21	24.85	23.13	22.40	22.05	21.92	21.71	22.39
	Age 45-54	28.68	28.75	28.76	31.38	29.77	27.70	27.35	26.74	27.41	26.63	26.82	26.70	25.95	25.98
	Age Over 55	18.49	18.46	19.13	21.19	20.23	22.37	22.17	21.88	23.34	26.01	27.51	27.93	28.70	28.41
Education	Low	11.08	11.51	11.59	10.04	9.57	9.85	9.39	10.11	12.90	13.10	12.52	12.31	11.90	11.52
	Medium	60.72	60.76	58.73	56.62	55.53	55.66	56.47	56.41	51.87	49.22	49.31	48.15	48.25	48.32
	High	28.21	27.74	29.67	33.33	34.89	34.50	34.14	33.49	35.23	37.69	38.17	39.54	39.85	40.16
Gender	Male	49.55	50.06	49.48	47.89	47.72	48.52	49.62	49.72	48.94	49.38	49.06	48.42	48.70	48.17
	Female	50.45	49.94	50.52	52.11	52.28	51.48	50.38	50.28	51.06	50.62	50.94	51.58	51.30	51.83
Experience	0-3 Years	11.66	11.33	10.85	6.65	8.28	8.22	8.43	9.36	9.06	8.62	9.47	8.75	8.08	7.86
	4-10 Years	13.45	13.30	13.61	13.26	14.59	15.26	15.26	16.33	16.05	15.34	14.95	14.99	14.32	14.23
	11-20 Years	24.46	25.59	24.50	25.59	24.97	24.76	24.32	23.87	22.69	22.26	23.18	22.70	23.18	23.79
	Over 20 Years	50.43	49.79	51.04	54.51	52.16	51.77	51.98	50.44	52.20	53.78	52.40	53.57	54.42	54.12
Nationality	EU	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Local	87.07	87.05	87.16	87.79	89.78	88.94	88.52	89.88	89.63	90.09	90.43	90.66	91.06	90.92
	Other	12.93	12.95	12.84	12.21	10.22	11.06	11.48	10.12	10.37	9.91	9.57	9.34	8.94	9.08

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.5 Finland

Table 9: Composition of Employed in Finland during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	17.78	16.90	17.60	20.14	18.65	17.95	17.34	17.05	20.15	19.89	19.46	19.37	18.69	18.31
	Age 35-44	26.03	25.05	23.89	23.31	23.32	24.45	22.58	22.86	22.82	22.63	24.30	23.91	23.95	24.27
	Age 45-54	33.88	33.85	33.10	33.05	33.29	33.61	34.93	34.88	32.09	31.24	29.69	29.65	29.83	29.65
	Age Over 55	22.31	24.19	25.41	23.51	24.73	23.98	25.15	25.21	24.95	26.24	26.56	27.07	27.52	27.78
Education	Low	17.37	17.12	16.91	11.00	8.71	8.75	8.26	7.37	7.53	7.68	6.15	5.75	4.92	4.71
	Medium	43.54	43.68	44.25	42.00	40.97	40.61	40.06	39.28	39.61	39.50	39.98	39.95	39.41	39.32
	High	39.08	39.20	38.84	47.00	50.32	50.64	51.68	53.35	52.86	52.82	53.87	54.30	55.67	55.97
Gender	Male	54.77	55.56	55.13	50.11	47.57	48.35	48.11	48.23	47.36	47.74	48.28	47.50	47.78	47.77
	Female	45.23	44.44	44.87	49.89	52.43	51.65	51.89	51.77	52.64	52.26	51.72	52.50	52.22	52.23
Experience	0-3 Years	-	-	-	-	-	-	-	-	8.46	7.78	7.00	7.01	7.16	6.95
	4-10 Years	-	-	-	-	-	-	-	-	16.04	15.97	16.03	15.92	15.84	16.07
	11-20 Years	-	-	-	-	-	-	-	-	25.34	25.84	27.68	27.54	27.33	26.91
	Over 20 Years	-	-	-	-	-	-	-	-	50.16	50.42	49.29	49.53	49.67	50.07
Nationality	EU	0.64	0.59	0.70	0.90	1.02	0.84	1.00	1.02	1.06	1.22	1.12	1.29	1.55	1.59
	Local	98.81	98.96	98.65	98.54	98.46	98.53	98.45	98.36	98.28	98.09	97.86	97.60	97.20	96.99
	Other	0.55	0.44	0.64	0.56	0.52	0.62	0.56	0.62	0.67	0.69	1.02	1.11	1.25	1.42

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.6 France

Table 10: Composition of Employed in France during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	27.33	27.96	28.74	27.73	26.98	26.65	26.04	24.76	24.28	23.11	22.84	22.16	22.21	22.48
	Age 35-44	30.37	30.14	29.69	29.33	28.65	27.78	28.52	28.59	27.72	27.72	26.50	25.57	25.50	24.65
	Age 45-54	29.84	29.17	28.70	29.07	29.73	30.17	28.80	29.99	30.03	30.60	31.20	31.84	31.01	31.20
	Age Over 55	12.46	12.73	12.87	13.87	14.63	15.40	16.64	16.65	17.97	18.57	19.45	20.43	21.28	21.68
Education	Low	21.85	20.70	20.29	19.22	17.90	15.13	14.34	13.62	14.82	14.29	14.03	15.28	14.40	14.47
	Medium	47.93	47.18	46.90	46.61	46.50	48.62	47.55	47.77	45.39	45.00	45.06	44.74	44.19	44.29
	High	30.22	32.11	32.82	34.17	35.60	36.25	38.12	38.61	39.79	40.71	40.91	39.98	41.41	41.24
Gender	Male	52.22	51.66	51.26	51.30	50.74	51.06	51.16	50.79	49.97	49.47	49.99	49.72	49.67	50.28
	Female	47.78	48.34	48.74	48.70	49.26	48.94	48.84	49.21	50.03	50.53	50.01	50.28	50.33	49.72
Experience	0-3 Years	11.73	11.63	11.19	8.84	7.82	-	-	-	7.22	6.46	6.77	7.07	7.12	7.28
	4-10 Years	17.75	18.65	19.07	19.70	19.25	-	-	-	15.30	14.72	14.03	13.48	13.51	13.73
	11-20 Years	25.66	25.36	25.34	26.77	26.67	-	-	-	29.75	30.12	29.72	28.62	27.90	26.41
	Over 20 Years	44.85	44.36	44.39	44.70	46.26	-	-	-	47.73	48.70	49.47	50.83	51.46	52.58
Nationality	EU	2.10	2.09	2.12	2.11	1.94	1.80	1.79	1.64	1.57	1.89	1.88	1.95	1.91	1.96
	Local	95.47	96.07	96.10	96.01	96.19	96.17	96.20	96.51	96.43	96.27	96.09	95.81	95.94	95.57
	Other	2.43	1.85	1.78	1.88	1.87	2.03	2.01	1.86	2.00	1.84	2.03	2.24	2.16	2.47

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.7 Germany

Table 11: Composition of Employed in Germany during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	17.49	20.45	21.18	21.15	20.86	20.18	19.74	19.16	18.16	17.53	18.57	18.55	17.85	16.65
	Age 35-44	32.28	30.69	29.54	27.54	26.18	25.45	24.31	23.06	20.95	20.18	19.21	18.92	19.56	19.90
	Age 45-54	32.76	31.59	30.88	32.07	32.53	32.32	33.05	33.68	34.63	34.41	33.08	31.80	31.05	30.26
	Age Over 55	17.46	17.26	18.39	19.24	20.43	22.05	22.90	24.09	26.26	27.88	29.14	30.73	31.54	33.19
Education	Low	7.48	8.23	8.36	8.51	8.80	7.42	6.92	6.92	7.43	7.29	8.01	7.35	6.81	6.59
	Medium	51.01	50.99	51.58	54.65	52.03	54.46	54.00	53.99	56.93	56.87	56.21	57.03	56.71	56.89
	High	41.51	40.78	40.06	36.84	39.17	38.12	39.08	39.09	35.64	35.84	35.78	35.62	36.49	36.52
Gender	Male	51.19	50.26	50.93	51.33	51.30	51.24	50.49	49.88	49.68	49.31	48.66	48.85	48.58	48.75
	Female	48.81	49.74	49.07	48.67	48.70	48.76	49.51	50.12	50.32	50.69	51.34	51.15	51.42	51.25
Experience	0-3 Years	-	6.93	6.58	6.49	5.64	5.21	5.27	5.27	5.27	5.06	5.32	5.36	5.19	4.84
	4-10 Years	-	12.06	13.03	12.61	12.72	11.88	11.08	10.78	10.81	10.99	11.32	10.56	10.41	9.80
	11-20 Years	-	25.98	24.57	23.81	23.12	21.83	21.92	21.70	20.26	19.97	20.13	19.59	19.59	19.75
	Over 20 Years	-	55.03	55.82	57.09	58.52	61.08	61.73	62.25	63.66	63.98	63.23	64.49	64.81	65.61
Nationality	EU	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Local	97.99	97.88	97.99	97.99	97.90	97.71	97.24	96.90	96.80	96.80	95.98	96.32	96.28	96.40
	Other	2.01	2.12	2.01	2.01	2.10	2.29	2.76	3.10	3.20	3.20	4.02	3.68	3.72	3.60

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.8 Greece

Table 12: Composition of Employed in Greece during 2007-2018

By	Category	Year											
		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	26.04	30.13	30.54	28.94	25.04	24.54	24.90	24.87	23.33	21.81	20.49	20.80
	Age 35-44	30.49	32.13	31.13	30.96	33.33	33.01	32.35	31.82	30.96	30.79	30.32	28.70
	Age 45-54	26.26	26.19	26.79	29.84	30.87	31.18	30.80	30.65	31.80	32.16	32.20	31.73
	Age Over 55	17.20	11.55	11.53	10.27	10.76	11.26	11.95	12.65	13.91	15.24	16.99	18.77
Education	Low	31.97	20.66	21.36	19.19	18.72	14.62	14.19	13.60	13.91	14.07	14.54	15.95
	Medium	39.96	42.71	43.85	43.71	44.13	43.39	42.26	44.06	44.15	45.04	45.25	44.54
	High	28.07	36.63	34.79	37.10	37.15	41.99	43.56	42.34	41.93	40.89	40.21	39.52
Gender	Male	59.42	55.69	54.41	55.36	55.40	54.75	55.64	55.11	55.23	55.65	55.60	43.62
	Female	40.58	44.31	45.59	44.64	44.60	45.25	44.36	44.89	44.77	44.35	44.40	45.57
Experience	0-3 Years	-	-	7.89	8.21	6.93	6.90	6.54	6.66	6.79	7.77	8.30	8.24
	4-10 Years	-	-	23.61	22.11	21.68	22.01	19.62	20.14	19.09	18.96	17.21	17.14
	11-20 Years	-	-	31.70	32.53	32.57	33.72	32.79	32.57	32.32	34.01	33.18	31.00
	Over 20 Years	-	-	36.81	37.14	38.82	37.37	41.04	40.63	41.80	39.26	41.31	43.62
Nationality	EU	1.12	1.40	1.77	1.27	1.62	1.37	1.19	1.15	0.94	0.79	1.08	1.12
	Local	93.14	90.94	90.65	92.47	91.79	92.71	93.13	92.85	92.97	93.35	92.89	92.83
	Other	5.74	7.66	7.58	6.26	6.59	5.92	5.68	6.00	6.09	5.86	6.03	6.05

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.9 Ireland

Table 13: Composition of Employed in Ireland during 2005-2017

By	Category	Year												
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Age	Age 16-34	24.81	30.44	30.10	30.78	29.94	30.90	30.18	29.93	28.87	26.61	24.61	23.69	25.77
	Age 35-44	26.02	24.66	23.44	23.78	27.91	29.10	30.76	31.67	30.53	30.96	30.35	30.17	28.80
	Age 45-54	28.80	26.30	25.35	25.28	24.03	22.74	23.28	23.38	24.15	24.11	26.91	26.10	26.59
	Age Over 55	20.37	18.59	21.11	20.16	18.11	17.27	15.78	15.02	16.44	18.32	18.13	20.04	18.84
Education	Low	31.29	27.32	27.06	22.17	20.05	17.67	16.74	14.72	14.81	13.52	13.16	12.10	11.12
	Medium	34.86	35.88	35.62	34.41	32.13	29.62	30.12	30.28	30.18	30.41	29.47	30.04	28.77
	High	33.84	36.80	37.32	43.42	47.82	52.71	53.14	55.00	55.02	56.07	57.36	57.86	60.11
Gender	Male	56.88	48.96	48.10	49.38	48.06	47.35	46.06	46.12	47.15	47.66	48.43	48.39	48.12
	Female	43.12	51.04	51.90	50.62	51.94	52.65	53.94	53.88	52.85	52.34	51.57	51.61	51.88
Experience	0-3 Years	-	10.70	9.50	7.30	4.84	6.23	5.40	5.24	6.78	7.51	7.14	7.30	7.75
	4-10 Years	-	15.53	16.08	17.97	17.67	18.71	17.98	17.81	17.10	14.66	12.90	12.94	13.83
	11-20 Years	-	24.20	23.44	26.58	29.99	31.93	33.69	34.05	32.64	30.85	29.72	29.13	28.15
	Over 20 Years	-	49.58	50.98	48.15	47.50	43.13	42.93	42.89	43.48	46.98	50.24	50.63	50.27
Nationality	EU	4.01	5.32	6.06	8.74	8.36	10.35	11.69	12.03	11.23	10.95	11.02	10.17	10.00
	Local	94.15	92.49	92.01	88.13	87.76	85.95	85.17	85.68	87.29	87.14	87.15	87.97	87.76
	Other	1.84	2.19	1.93	3.14	3.88	3.70	3.14	2.29	1.48	1.91	1.83	1.86	2.24

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.10 Italy

Table 14: Composition of Employed in Italy during 2006-2017

By	Category	Year											
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Age	Age 16-34	28.51	27.18	26.01	24.93	23.26	21.38	19.69	18.85	17.32	18.75	18.83	19.32
	Age 35-44	31.87	32.32	31.87	31.08	30.96	30.26	30.31	28.74	28.24	26.98	26.08	24.72
	Age 45-54	28.48	29.06	29.82	31.06	31.72	33.00	32.86	32.89	33.41	33.14	32.43	31.62
	Age Over 55	11.14	11.44	12.30	12.93	14.06	15.36	17.14	19.52	21.04	21.14	22.66	24.35
Education	Low	35.81	34.36	32.66	32.48	30.55	28.31	25.95	25.41	24.48	26.04	26.91	27.64
	Medium	51.10	51.70	50.71	50.83	50.32	52.32	54.15	51.51	50.52	51.15	51.58	51.86
	High	13.09	13.94	16.63	16.69	19.14	19.37	19.90	23.08	25.01	22.82	21.51	20.50
Gender	Male	56.74	56.61	56.10	56.46	54.55	54.50	53.84	53.27	53.53	54.11	53.57	52.97
	Female	43.26	43.39	43.90	43.54	45.45	45.50	46.16	46.73	46.47	45.89	46.43	47.03
Experience	0-3 Years	6.78	6.65	4.92	4.78	4.52	5.68	5.39	4.83	4.72	5.86	8.65	11.29
	4-10 Years	24.84	24.71	24.49	23.42	21.84	17.81	15.97	15.41	14.28	15.49	17.42	17.72
	11-20 Years	31.61	31.37	33.73	33.20	33.04	30.75	30.83	30.74	29.34	29.66	29.89	28.67
	Over 20 Years	36.77	37.27	36.86	38.60	40.60	45.76	47.81	49.02	51.67	48.99	44.04	42.33
Nationality	EU	0.60	1.62	1.90	1.93	1.93	2.25	2.03	2.30	2.33	2.88	3.56	3.86
	Local	94.58	94.26	94.20	93.91	94.32	93.83	93.88	93.33	93.43	91.92	90.50	89.70
	Other	4.82	4.12	3.90	4.16	3.75	3.92	4.09	4.37	4.24	5.20	5.94	6.44

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset

A.2.11 Latvia

Table 15: Composition of Employed in Latvia during 2006-2018

By	Category	Year												
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	28.75	28.53	27.58	26.63	24.81	24.16	23.36	23.33	23.60	23.76	23.10	21.97	19.88
	Age 35-44	25.33	23.44	23.56	24.50	25.22	24.54	23.75	22.81	22.74	23.14	22.48	21.88	21.27
	Age 45-54	25.06	26.38	27.33	29.22	28.53	28.07	27.81	27.72	27.01	25.60	24.98	25.06	25.05
	Age Over 55	20.86	21.65	21.53	19.65	21.44	23.23	25.08	26.14	26.65	27.50	29.44	31.09	31.09
Education	Low	13.78	14.60	11.77	10.82	10.76	9.826	10.30	8.05	8.24	8.12	7.98	7.35	6.54
	Medium	61.86	59.44	57.74	56.60	55.66	55.19	55.14	56.55	56.09	55.76	55.45	55.48	55.15
	High	24.37	25.96	30.49	32.58	33.57	34.98	34.56	35.40	35.67	36.12	36.57	37.17	38.31
Gender	Male	47.44	47.66	43.93	44.75	44.85	44.77	45.10	45.85	46.49	46.36	46.07	45.94	46.94
	Female	52.56	52.34	56.07	55.25	55.15	55.23	54.90	54.15	53.51	53.64	53.93	54.06	53.06
Experience	0-3 Years	8.72	8.57	7.49	6.82	6.86	6.46	6.93	6.31	6.92	6.90	7.07	5.65	4.54
	4-10 Years	16.03	16.11	16.63	16.07	15.50	15.69	15.61	14.85	14.54	15.02	13.71	14.14	13.18
	11-20 Years	23.91	23.46	23.16	24.92	24.26	23.01	22.48	22.20	23.15	23.14	23.42	23.22	21.87
	Over 20 Years	51.34	51.86	52.71	52.19	53.38	54.85	54.98	56.64	55.39	54.94	55.80	56.99	60.40
Nationality	EU	-	-	-	-	-	-	-	-	-	-	-	-	-
	Local	84.64	84.87	85.34	85.15	84.24	85.10	85.58	85.91	86.69	87.48	86.89	87.22	87.49
	Other	15.36	15.13	14.66	14.85	15.76	14.90	14.42	14.09	13.31	12.52	13.11	12.78	12.51

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset

A.2.12 Lithuania

Table 16: Composition of Employed in Lithuania during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	22.27	23.85	22.50	20.57	18.71	16.89	16.66	14.87	17.31	17.48	17.14	17.90	19.19	17.50
	Age 35-44	27.00	24.85	24.89	23.33	22.84	21.57	20.79	20.82	20.60	20.25	19.20	18.48	18.00	17.59
	Age 45-54	31.92	30.97	31.79	33.35	34.66	36.92	36.35	35.49	33.42	33.49	32.16	30.77	28.61	28.57
	Age Over 55	18.82	20.33	20.83	22.75	23.78	24.62	26.21	28.83	28.66	28.78	31.50	32.84	34.19	36.33
Education	Low	6.06	5.69	5.23	6.86	5.83	4.93	4.45	3.81	3.28	3.63	3.74	3.32	3.37	3.28
	Medium	60.87	60.55	60.57	59.43	55.83	55.12	54.38	54.42	57.57	57.48	57.32	57.05	54.45	54.25
	High	33.07	33.76	34.20	33.71	38.34	39.95	41.17	41.77	39.15	38.89	38.94	39.63	42.17	42.47
Gender	Male	48.67	49.42	49.13	47.50	45.04	44.87	45.55	46.76	47.55	48.17	47.14	46.08	45.80	45.06
	Female	51.33	50.58	50.87	52.50	54.96	55.13	54.45	53.24	52.45	51.83	52.86	53.92	54.20	54.94
Experience	0-3 Years	8.01	9.35	8.71	8.25	-	-	-	-	6.61	6.11	5.23	5.83	6.06	5.43
	4-10 Years	12.14	11.63	11.61	11.32	-	-	-	-	10.96	11.36	11.54	12.29	12.41	12.12
	11-20 Years	25.34	23.58	24.12	22.28	-	-	-	-	19.64	19.24	19.14	18.67	19.74	19.97
	Over 20 Years	54.51	55.44	55.56	58.15	-	-	-	-	62.79	63.29	64.09	63.21	61.79	62.47
Nationality	EU	0.01	0.05	0.09	0.05	0.03	0.03	0.03	0.01	0.05	0.05	0.08	0.07	0.07	0.02
	Local	99.14	99.24	99.40	99.48	99.53	99.50	99.25	99.42	99.25	99.34	99.41	99.45	99.42	99.38
	Other	0.77	0.71	0.51	0.47	0.44	0.47	0.72	0.57	0.70	0.60	0.51	0.48	0.51	0.60

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.13 Luxembourg

Table 17: Composition of Employed in Luxembourg during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	39.77	39.34	40.08	35.56	32.49	31.06	29.65	29.23	29.23	34.06	30.11	28.58	28.54	25.29
	Age 35-44	30.44	30.56	31.42	31.92	32.60	31.84	31.68	30.79	29.49	25.36	25.89	25.64	25.58	27.22
	Age 45-54	21.85	21.50	20.13	23.22	24.99	26.91	27.88	28.05	29.34	29.29	31.54	31.84	31.52	31.63
	Age Over 55	7.95	8.60	8.38	9.29	9.91	10.19	10.78	11.93	11.94	11.29	12.45	13.94	14.36	15.85
Education	Low	34.23	35.53	35.74	34.18	34.35	32.62	32.21	29.18	29.23	30.87	28.56	26.75	25.24	22.17
	Medium	34.58	32.19	30.66	33.84	35.90	37.82	38.02	39.69	38.20	40.98	38.87	39.27	37.59	37.14
	High	31.19	32.27	33.60	31.98	29.75	29.56	29.77	31.13	32.57	28.14	32.58	33.98	37.17	40.69
Gender	Male	58.80	58.32	57.50	58.05	56.90	56.32	55.35	54.49	54.45	54.88	54.60	53.28	52.80	52.03
	Female	41.20	41.68	42.50	41.95	43.10	43.68	44.65	45.51	45.55	45.12	45.40	46.72	47.20	47.97
Experience	0-3 Years	9.22	8.65	8.94	7.48	7.49	7.16	7.57	8.68	8.41	11.19	9.03	7.61	6.81	6.90
	4-10 Years	24.66	24.74	24.85	22.53	19.58	18.74	17.39	18.15	17.30	20.97	19.58	18.78	17.81	16.51
	11-20 Years	28.37	28.84	30.50	30.39	30.22	30.33	30.90	28.34	28.68	26.53	27.01	24.92	25.73	27.79
	Over 20 Years	37.75	37.77	35.71	39.60	42.71	43.77	44.14	44.84	45.61	41.31	44.38	48.69	49.65	48.80
Nationality	EU	53.99	57.31	60.55	52.81	46.82	44.59	42.52	37.69	39.77	39.14	43.83	45.99	44.20	46.30
	Local	42.13	38.31	34.64	43.13	48.66	51.42	53.06	57.54	55.10	55.69	50.89	48.08	50.34	47.09
	Other	3.88	4.38	4.80	4.06	4.52	3.99	4.41	4.78	5.14	5.17	5.28	5.92	5.46	6.61

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.14 Malta

Table 18: Composition of Employed in Malta during 2006-2018

By	Category	Year												
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	42.14	44.65	44.21	42.71	41.62	41.54	41.37	40.95	39.74	39.25	37.39	36.64	35.49
	Age 35-44	21.40	21.08	21.60	22.40	23.47	23.94	23.68	23.73	24.33	24.62	25.30	25.53	26.18
	Age 45-54	23.93	23.93	24.69	23.37	23.23	22.54	22.29	22.49	22.70	21.75	22.38	22.00	22.67
	Age Over 55	12.52	10.34	9.506	11.52	11.68	11.98	12.67	12.82	13.23	14.38	14.93	15.83	15.65
Education	Low	54.15	54.59	50.12	50.94	47.88	47.03	46.28	42.33	41.15	39.79	38.12	39.10	38.33
	Medium	27.31	25.85	29.84	28.79	29.46	28.79	28.12	29.61	29.92	30.21	31.91	32.10	32.71
	High	18.54	19.56	20.05	20.26	22.66	24.18	25.60	28.06	28.92	29.99	29.97	28.80	28.96
Gender	Male	66.25	64.48	63.05	62.21	60.85	60.53	60.08	60.02	59.08	58.32	57.59	57.78	57.74
	Female	33.75	35.52	36.95	37.79	39.15	39.47	39.92	39.98	40.92	41.68	42.41	42.22	42.26
Experience	0-3 Years	12.70	14.10	13.42	12.01	11.84	11.17	10.36	9.94	10.56	9.93	8.95	9.97	7.81
	4-10 Years	22.41	22.33	21.33	20.94	20.52	20.91	21.40	20.57	19.66	19.74	19.27	19.47	19.19
	11-20 Years	24.76	25.05	25.49	26.39	26.84	26.55	26.44	27.71	27.67	27.00	26.36	25.57	25.59
	Over 20 Years	40.12	38.53	39.76	40.66	40.80	41.37	41.80	41.78	42.12	43.33	45.42	44.98	47.41
Nationality	EU	1.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Local	98.07	98.07	97.95	97.74	98.04	97.71	97.48	97.34	96.80	96.48	96.46	96.47	95.15
	Other	0.70	1.93	2.05	2.26	1.96	2.29	2.52	2.66	3.20	3.52	3.54	3.53	4.85

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset

A.2.15 Netherlands

Table 19: Composition of Employed in Netherlands during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	24.13	21.49	20.58	20.77	19.58	19.96	19.21	17.98	16.42	15.30	17.38	18.00	16.62	17.03
	Age 35-44	32.69	33.01	31.33	30.21	29.27	27.61	26.35	24.52	24.15	23.73	22.42	21.45	21.21	20.25
	Age 45-54	29.60	30.19	30.82	31.08	32.03	31.86	32.76	33.35	32.65	31.83	31.46	31.18	31.52	30.89
	Age Over 55	13.58	15.31	17.27	17.93	19.12	20.57	21.68	24.15	26.78	29.14	28.74	29.37	30.65	31.84
Education	Low	20.31	19.53	18.60	17.00	16.55	15.95	15.69	14.95	13.97	12.83	14.39	14.48	14.72	15.20
	Medium	44.21	44.35	43.88	43.94	43.35	42.81	41.81	41.07	40.38	39.40	39.75	39.54	38.32	37.69
	High	35.48	36.13	37.52	39.06	40.10	41.24	42.51	43.98	45.66	47.77	45.86	45.97	46.96	47.11
Gender	Male	55.35	54.48	54.15	53.15	52.84	52.58	52.17	51.96	52.08	52.56	51.60	51.17	52.57	52.94
	Female	44.65	45.52	45.85	46.85	47.16	47.42	47.83	48.04	47.92	47.44	48.40	48.83	47.43	47.06
Experience	0-3 Years	10.27	6.52	5.47	4.34	3.66	4.12	4.09	3.17	3.57	2.99	3.89	3.85	4.02	3.72
	4-10 Years	21.61	20.47	18.97	18.80	16.80	16.39	15.67	14.22	13.84	12.42	12.92	13.02	12.73	11.97
	11-20 Years	31.90	33.63	33.75	35.00	34.85	33.29	32.51	32.26	30.85	30.24	28.64	28.09	26.81	25.87
	Over 20 Years	36.23	39.38	41.81	41.86	44.69	46.20	47.73	50.35	51.74	54.35	54.55	55.04	56.43	58.44
Nationality	EU	0.80	0.82	0.87	0.92	0.92	0.88	1.02	1.10	1.08	1.12	1.42	1.46	1.42	1.53
	Local	98.94	98.92	98.82	98.78	98.77	98.84	98.73	98.65	98.71	98.61	98.23	98.22	98.27	98.02
	Other	0.27	0.26	0.31	0.31	0.31	0.28	0.25	0.24	0.21	0.28	0.35	0.32	0.31	0.45

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.16 Portugal

Table 20: Composition of Employed in Portugal during 2006-2018

By	Category	Year												
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	31.78	31.15	29.41	27.85	28.27	26.34	24.38	22.75	21.21	20.51	20.09	19.68	19.60
	Age 35-44	26.90	24.55	26.50	28.09	27.44	29.09	29.70	30.67	31.65	30.64	29.21	27.03	25.16
	Age 45-54	27.51	27.81	28.93	29.09	28.73	28.83	29.57	28.85	28.99	29.52	29.50	29.90	30.11
	Age Over 55	13.81	16.49	15.15	14.96	15.56	15.74	16.35	17.72	18.15	19.34	21.19	23.39	25.13
Education	Low	68.31	68.96	66.43	63.17	59.92	58.27	54.96	53.70	51.78	49.98	49.48	48.86	47.57
	Medium	17.39	16.83	17.96	20.28	21.84	22.30	23.87	24.02	25.30	25.73	26.52	26.71	27.70
	High	14.29	14.20	15.61	16.55	18.25	19.42	21.17	22.28	22.91	24.29	24.00	24.42	24.73
Gender	Male	51.78	52.41	51.71	49.62	49.56	48.60	47.82	47.99	47.62	47.42	47.87	48.18	48.03
	Female	48.22	47.59	48.29	50.38	50.44	51.40	52.18	52.01	52.38	52.58	52.13	51.82	51.97
Experience	0-3 Years	8.99	8.90	8.30	7.66	8.16	6.10	4.82	5.42	5.53	5.71	6.22	6.91	7.17
	4-10 Years	16.51	15.93	15.82	15.01	14.94	13.05	12.27	11.78	11.00	10.20	9.89	9.29	9.73
	11-20 Years	25.15	23.46	23.51	23.71	23.36	23.53	24.69	25.41	25.62	24.58	23.86	22.25	20.33
	Over 20 Years	49.35	51.71	52.37	53.62	53.54	57.32	58.22	57.39	57.84	59.51	60.03	61.56	62.77
Nationality	EU	0.20	0.32	0.45	0.57	0.62	0.45	0.38	0.43	0.48	0.48	0.55	0.49	0.58
	Local	97.89	97.61	98.04	97.76	97.64	97.59	97.74	98.02	97.97	98.09	98.37	98.27	97.91
	Other	1.91	2.07	1.51	1.68	1.74	1.96	1.88	1.55	1.55	1.44	1.08	1.25	1.51

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset

A.2.17 Slovakia

Table 21: Composition of Employed in Slovakia during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	33.96	33.52	34.85	32.63	31.91	29.63	30.15	28.37	28.66	28.00	27.78	27.84	26.89	25.45
	Age 35-44	25.10	23.84	23.36	23.87	23.74	24.74	24.14	26.35	26.87	27.53	27.51	26.56	26.11	24.42
	Age 45-54	30.88	31.44	29.80	30.26	30.36	31.12	30.23	29.15	28.06	26.52	26.11	25.24	26.07	27.20
	Age Over 55	10.05	11.21	11.99	13.24	13.99	14.51	15.49	16.13	16.41	17.95	18.60	20.36	20.93	22.93
Education	Low	3.01	3.09	2.87	2.22	2.94	3.09	2.81	2.31	2.38	2.43	3.21	3.40	3.54	3.60
	Medium	77.22	76.01	77.21	74.88	72.49	71.76	71.01	71.39	70.20	70.74	71.04	71.02	71.40	70.59
	High	19.77	20.90	19.92	22.90	24.58	25.15	26.17	26.30	27.41	26.84	25.75	25.58	25.06	25.81
Gender	Male	51.18	51.10	50.88	50.48	50.13	49.58	49.74	49.63	49.51	50.28	50.30	50.54	49.95	49.01
	Female	48.82	48.90	49.12	49.52	49.87	50.42	50.26	50.37	50.49	49.72	49.70	49.46	50.05	50.99
Experience	0-3 Years	8.54	8.95	11.37	9.05	9.16	10.23	11.62	11.78	12.36	11.99	12.08	11.00	8.99	7.87
	4-10 Years	17.04	16.93	17.46	17.19	17.37	15.81	15.67	14.86	15.03	15.90	14.79	15.68	15.95	15.67
	11-20 Years	22.44	21.37	21.77	21.36	21.30	21.92	22.10	23.22	23.43	23.91	24.81	22.94	22.67	21.53
	Over 20 Years	51.98	52.74	49.40	52.40	52.17	52.04	50.61	50.14	49.18	48.20	48.32	50.37	52.39	54.93
Nationality	EU	0.20	0.17	0.20	0.25	0.27	0.19	0.13	0.22	0.20	0.20	0.15	0.15	0.12	0.18
	Local	99.63	99.70	99.78	99.72	99.67	99.78	99.82	99.76	99.74	99.78	99.84	99.82	99.85	99.76
	Other	0.17	0.13	0.02	0.03	0.06	0.03	0.05	0.02	0.05	0.02	0.02	0.03	0.03	0.06

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.18 Slovenia

Table 22: Composition of Employed in Slovenia during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	31.10	30.85	30.10	29.83	28.93	29.06	27.33	26.16	23.89	23.38	22.70	23.32	23.88	23.19
	Age 35-44	27.93	26.96	27.31	27.48	27.79	27.70	28.04	28.12	29.02	28.11	27.91	27.91	26.92	26.41
	Age 45-54	33.16	33.45	33.41	32.85	32.98	33.43	33.49	34.92	34.53	34.05	33.84	32.87	32.75	32.22
	Age Over 55	7.81	8.74	9.18	9.84	10.31	9.81	11.14	10.80	12.56	14.46	15.55	15.90	16.45	18.18
Education	Low	15.00	15.91	15.42	14.73	13.42	12.38	11.76	10.58	10.64	9.82	8.71	8.86	8.34	7.49
	Medium	66.20	59.19	59.29	59.96	59.61	59.11	57.37	57.13	56.22	56.26	56.82	55.49	55.70	55.33
	High	18.81	24.90	25.29	25.31	26.97	28.51	30.87	32.30	33.14	33.93	34.47	35.65	35.96	37.18
Gender	Male	51.20	51.11	51.57	52.46	52.05	52.45	52.03	51.90	52.75	53.02	53.01	52.73	52.14	52.03
	Female	48.80	48.89	48.43	47.54	47.95	47.55	47.97	48.10	47.25	46.98	46.99	47.27	47.86	47.97
Experience	0-3 Years	8.33	9.64	8.68	9.12	8.62	9.48	8.95	8.19	7.31	7.91	8.47	7.65	9.47	9.00
	4-10 Years	16.92	16.33	17.29	15.74	17.39	18.85	17.60	18.95	17.66	16.95	17.35	16.49	15.96	15.18
	11-20 Years	24.50	22.75	23.43	25.33	25.16	26.13	27.09	26.03	27.65	26.62	25.45	26.13	25.43	26.49
	Over 20 Years	50.25	51.27	50.60	49.81	48.83	45.54	46.35	46.83	47.38	48.51	48.73	49.73	49.14	49.33
Nationality	EU	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Local	-	-	-	-	-	-	-	-	97.07	96.99	96.92	96.93	96.29	95.75
	Other	-	-	-	-	-	-	-	-	2.93	3.01	3.08	3.08	3.71	4.25

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.2.19 Spain

Table 23: Composition of Employed in Spain during 2005-2018

By	Category	Year													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	Age 16-34	35.09	33.96	33.77	30.17	27.74	25.51	23.08	21.54	20.95	20.33	19.22	18.60	18.93	19.89
	Age 35-44	29.98	29.16	28.58	29.01	29.78	29.54	30.10	29.86	29.42	29.03	29.46	29.31	28.92	27.48
	Age 45-54	23.82	24.64	25.59	27.35	28.33	29.79	30.45	30.80	31.70	31.21	31.00	31.19	30.86	31.10
	Age Over 55	11.10	12.24	12.07	13.47	14.15	15.16	16.38	17.80	17.94	19.42	20.32	20.90	21.29	21.53
Education	Low	42.16	40.58	38.71	36.10	35.71	34.47	33.35	32.07	32.36	31.05	30.23	30.47	29.99	31.10
	Medium	24.26	24.25	24.41	24.08	23.71	24.42	24.08	24.57	23.06	23.92	24.38	24.39	24.12	24.54
	High	33.58	35.17	36.88	39.82	40.57	41.10	42.57	43.35	44.58	45.03	45.39	45.13	45.89	44.36
Gender	Male	58.21	57.02	54.61	53.35	52.81	52.81	52.83	51.65	51.81	51.12	51.14	51.31	51.68	52.21
	Female	41.79	42.98	45.39	46.65	47.19	47.19	47.17	48.35	48.19	48.88	48.86	48.69	48.32	47.79
Experience	0-3 Years	10.36	9.78	9.56	7.69	6.32	5.06	4.77	4.65	4.21	4.74	5.31	5.74	5.89	6.15
	4-10 Years	23.10	22.27	22.95	21.55	20.95	19.33	17.98	17.08	16.91	14.31	12.72	13.03	12.93	14.01
	11-20 Years	29.38	28.76	29.10	29.80	29.98	32.11	31.39	31.19	32.48	31.93	31.69	32.97	31.79	31.15
	Over 20 Years	37.16	39.19	38.39	40.96	42.75	43.50	45.86	47.08	46.40	49.02	50.28	48.26	49.39	48.68
Nationality	EU	0.57	0.70	1.90	1.99	1.95	2.24	1.91	1.83	2.18	2.25	2.16	2.66	2.63	2.61
	Local	94.57	93.82	92.98	93.75	93.99	94.16	94.25	94.35	94.48	94.60	94.25	92.92	92.74	91.69
	Other	4.87	5.48	5.12	4.26	4.06	3.60	3.84	3.82	3.34	3.15	3.58	4.43	4.63	5.70

Note: Numbers reported as percentages. The descriptives include full-timers, part-timers and partially unemployed employees and are calculated using the EU-SILC dataset.

A.3 Wage growth and compositional effects: High unemployment countries

Table 24: Compositional Effect and Decomposition by Year

		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
IT	Total	2.0***	0.9**	2.3***	1.8***	2.1***	1.6***	1.4***	−2.7***	−3.1***	−1.6***	-
	Education	1.3***	0.2	1.5***	0.6**	1.1***	1.1***	0.7**	−1.1***	−0.5**	−0.4	-
	Age	0.3***	0.4***	0.4***	0.5***	0.3***	0.1*	0.2**	−0.1	0.1	0.1	-
	Experience	0.5***	0.4**	0.5***	0.9***	0.8***	0.6***	0.5**	−1.0***	−2.1***	−0.9***	-
	Gender	−0.1	0.0	−0.1*	−0.1	−0.1	−0.1	0.1	0.0	−0.1	0.0	-
	Nationality	0.0	0.0	0.0	−0.1	−0.1	−0.2	0.0	−0.5***	−0.4**	−0.3**	-
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
ES	Total	3.7***	1.9***	1.6***	2.5***	2.1***	1.1**	0.9	0.1	−1.9***	0.6	−1.7***
	Education	1.6***	0.7*	0.2	1.1**	1.0**	0.4	0.4	0.2	−0.4	0.3	−0.7*
	Age	1.0***	0.6***	0.6***	0.5***	0.6***	0.2	0.2	0.2	0.1	0.0	−0.1
	Experience	0.9***	0.7***	0.7***	0.9***	0.4*	0.3	0.4	−0.1	−1.0***	0.2	−0.6*
	Gender	−0.3**	−0.2	0.0	0.0	−0.2	0.1	−0.1	−0.1	−0.1	0.1	0.0
	Nationality	0.4**	0.1	0.2	0.0	0.2	0.1	0.0	−0.2	−0.5***	−0.1	−0.4**
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
IE	Total	3.1***	3.6***	1.4	0.0	1.1	−0.2	1.1	1.9**	0.4	0.6	-
	Education	3.8***	2.6***	2.3***	0.3	0.8	0.1	0.6	0.7	0.5	1.1*	-
	Age	−0.1	0.3	0.2	0.1	0.1	0.2	0.2	0.8**	0.1	−0.4	-
	Experience	0.1	0.9**	−0.5	0.2	0.1	−0.5*	0.1	0.4	−0.1	−0.2	-
	Gender	0.0	−0.2	−0.1	−0.1	0.1	0.0	0.1	0.1	0.0	0.0	-
	Nationality	−0.7***	0.0	−0.4	−0.5*	−0.1	0.0	0.0	0.0	0.0	0.1	-
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
PT	Total	3.0***	1.6	2.7***	2.7***	3.2***	2.1***	1.2	1.7***	0.6	1.0*	0.5
	Education	2.6***	1.6*	2.6***	1.6*	2.1**	1.4*	1.1	1.5**	0.1	0.6	0.4
	Age	0.3	0.2	0.0	0.2	0.3*	0.5**	0.1	0.2*	0.4**	0.5***	0.3**
	Experience	0.2	0.3	−0.1	1.1***	0.8***	0.1	0.0	0.1	−0.1	0.0	−0.1
	Gender	−0.1	−0.5*	0.0	−0.3	−0.1	0.0	0.0	−0.1	0.2	0.0	0.0
	Nationality	0.1	−0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	−0.1
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
EL	Total	-	-	2.6***	1.2	2.8***	1.5**	0.0	0.5	−0.5	0.7*	−0.4
	Education	-	-	1.5**	0.1	2.5***	0.5	−0.1	−0.1	−0.3	0.0	−0.6**
	Age	-	-	0.3	0.6**	0.2	−0.1	0.1	0.5***	0.3**	0.4***	0.1
	Experience	-	-	0.1	0.7*	−0.1	0.8**	0.0	0.2	−0.6***	0.4**	0.2
	Gender	-	-	0.1	0.0	−0.1	0.1	0.0	0.0	0.0	0.0	−0.1
	Nationality	-	-	0.6***	−0.2	0.3	0.1	0.0	0.0	0.1	−0.1	0.0
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
CY	Total	1.0	−2.7**	1.8	−0.5	1.6	1.5	0.4	1.7	1.3	−0.5	−0.9
	Education	0.4	−0.3	1.5**	1.2*	1.0*	1.0*	0.0	0.1	0.8	0.3	−0.7
	Age	0.1	−0.1	0.1	−0.3*	0.3	0.1	0.2	0.3	0.2	0.0	−0.3
	Experience	0.5	−0.1	0.1	−0.3	0.6*	0.1	0.3	0.3	−0.1	−0.8	−0.1
	Gender	0.0	−0.4	−0.2	−0.1	−0.1	−0.1	−0.1	0.2	0.2	0.1	0.1
	Nationality	0.0	−1.8***	0.2	−1.0*	−0.3	0.4	0.0	0.8	0.2	0.0	0.0

Note: The table presents contributions in percentage points. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. The calculations are performed using the EU-SILC dataset.

A.4 Wage growth and compositional effects: Rest of euro area countries

Table 25: Compositional Effect and Decomposition by Year

		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
AT	Total	1.2	0.8	−0.1	2.2***	0.4	3.1***	0.6	1.4*	1.2	1.7**	−1.5*
	Education	0.5	0.1	−0.2	1.0**	0.1	4.1***	0.2	1.2**	0.9*	0.2	0.0
	Age	0.3	0.2	0.2	0.3*	0.1	−0.2	0.0	0.2	0.3	0.5**	−0.1
	Experience	0.7	0.6	0.1	0.7*	0.2	−0.6	0.6	0.2	0.0	1.2***	−1.3***
	Gender	−0.2	0.0	−0.1	0.1	0.1	−0.1	0.0	−0.1	−0.1	0.0	0.1
	Nationality	−0.1	0.0	−0.1	0.0	0.0	−0.1	−0.2	0.0	0.2	−0.2*	−0.1
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
BE	Total	−0.3	0.7	1.9***	0.0	0.8	−0.1	1.6***	−0.1	−0.6	0.3	−0.7
	Education	−0.5	0.7**	1.1***	0.2	0.6*	0.5	0.4	0.9**	−0.2	0.2	−0.2
	Age	0.1	0.2*	0.1	0.2*	0.0	0.0	0.1	0.0	0.0	0.1	0.0
	Experience	0.2	−0.5**	0.9***	−0.3	0.0	−0.5**	1.1***	−0.9***	−0.4*	0.0	−0.3
	Gender	0.0	0.0	−0.1	−0.1	0.0	−0.1	0.1	0.0	−0.1	0.0	−0.1
	Nationality	−0.1	0.2***	0.0	−0.1	0.1	−0.1	0.0	0.0	0.0	0.0	0.0
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
DE	Total	−0.6	1.0*	0.9	0.7	−0.1	−0.9	0.0	−0.6	0.3	0.2	0.5
	Education	−0.7**	0.3	0.2	0.5	0.0	−1.0***	0.0	−0.2	0.2	0.3	0.2
	Age	0.1	0.0	0.1	0.0	0.0	0.1	0.0	−0.1*	−0.1	0.1	0.1
	Experience	0.0	0.7**	0.6*	0.2	0.0	0.2	0.0	−0.3	0.1	0.0	0.3
	Gender	0.0	0.0	0.0	−0.1	−0.1	−0.1	−0.1	−0.1	0.0	−0.1	0.0
	Nationality	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
EE	Total	0.4	0.9	−0.1	0.5	−0.2	0.2	0.7	−0.6	0.7	1.2**	0.2
	Education	1.3***	0.6	0.0	0.0	−0.4	0.6	0.7	0.2	0.6	0.3	0.3
	Age	−1.2***	0.3	−0.2	0.2	0.2	−0.2	−0.7***	−0.4*	0.2	−0.2	0.0
	Experience	0.8***	−0.3	0.0	−0.1	−0.4*	0.0	0.4	−0.4	0.0	1.0***	0.1
	Gender	−0.7*	−0.1	0.2	0.4	0.1	−0.3	0.3	−0.1	−0.2	0.1	−0.2
	Nationality	0.2	0.5***	−0.2	−0.1	0.2	0.0	0.0	0.1	0.1	0.0	0.0
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
FI	Total	2.3***	1.0**	0.5	0.5	0.8*	−1.0**	−0.1	0.6	−0.4	0.6	0.0
	Education	2.3***	1.4***	0.3	0.5	0.6*	−0.1	−0.1	0.6*	−0.1	0.5*	0.1
	Age	0.0	0.3**	0.1	0.2	0.1	−0.6***	0.0	0.0	0.0	0.1	0.0
	Experience	-	-	-	-	-	-	-	-	-	-	-
	Gender	−0.1	−0.7***	0.2	−0.1	0.1	−0.2	0.1	0.1	−0.2	0.0	−0.1
	Nationality	0.0	0.0	0.0	0.0	0.0	−0.1*	−0.1	−0.1	−0.1	−0.1	−0.1
		Year										
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
FR	Total	1.1***	1.1***	1.1***	0.8**	0.7**	0.3	0.7*	0.5	−0.3	0.5	0.2
	Education	0.6*	0.8**	0.9***	0.7**	0.4	0.3	0.5*	0.1	−0.5*	0.5	0.0
	Age	0.6***	0.4*	0.2	0.1	0.4*	0.2	0.2	0.4*	0.3	0.1	0.2
	Experience	-	-	-	-	-	-	-	-	-	-	-
	Gender	−0.1	−0.1	0.0	0.0	−0.1	−0.2	−0.1	0.0	−0.1	0.0	0.1
	Nationality	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	0.0	0.0	0.0

Table 25 continued in the next page

Continuation of Table 25
Compositional Effect and Decomposition by Year

	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
LT	Total	−0.6	2.4***	1.7**	0.6	1.0	−1.6**	0.2	0.0	0.2	0.8	0.3
	Education	−0.4	3.1***	1.0	0.4	0.6	−1.3*	0.2	0.1	0.5	1.2*	0.2
	Age	0.3**	0.2	0.6*	0.1	0.2	−0.5*	−0.1	0.1	−0.1	−0.3	0.3
	Experience	-	-	-	-	-	-	-	-	-	-	-
	Gender	−0.4	−0.9**	0.1	0.1	0.2	0.2	0.2	−0.2	−0.2	0.0	−0.1
	Nationality	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	0.0
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
LU	Total	2.7***	0.5	1.8*	0.6	1.7*	0.3	−4.6***	3.7***	0.7	2.7***	1.8**
	Education	−0.5	−1.0	0.3	0.3	0.9	0.8	−2.1***	2.9***	0.7	1.3*	2.9***
	Age	0.7**	0.3	0.3*	0.1	0.1	0.1	−0.6**	0.8***	0.3	0.0	0.6*
	Experience	0.7**	0.6	0.5	−0.1	−0.3	0.2	−1.9***	1.0***	1.1***	0.7**	−0.2
	Gender	0.2	−0.2	−0.1	−0.1	−0.1	0.0	0.0	0.0	0.0	0.0	−0.1
	Nationality	1.6***	0.8**	0.7**	0.4	1.1***	−0.7*	0.0	−1.0**	−1.3***	0.6	−1.3***
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
LV	Total	2.5***	1.8***	0.7	0.8	−0.6	1.1*	0.6	0.3	−0.2	0.3	1.4**
	Education	3.6***	1.4**	0.8	0.7	−0.3	0.8	0.3	0.3	0.2	0.5	1.2*
	Age	−0.3	−0.1	−0.3*	−0.2	−0.3	−0.2	0.0	0.1	−0.5	−0.5	−0.8**
	Experience	0.3	0.4	0.3	0.1	−0.2	0.2	0.0	−0.2	0.2	0.4	0.7**
	Gender	−1.1***	0.2	0.0	0.0	0.1	0.1	0.3	0.0	−0.1	−0.1	0.3
	Nationality	0.1	0.0	−0.1	0.1	0.0	0.0	0.0	0.1	−0.1	0.0	0.0
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
MT	Total	1.6**	0.6	1.4**	1.0	1.1*	2.6***	0.4	0.9	0.9	−0.8	0.5
	Education	1.3**	0.1	1.2*	0.8	0.6	2.2***	0.8	0.8	0.6	−0.6	0.0
	Age	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.0	0.1	0.0	0.2
	Experience	0.3	0.6*	0.2	0.1	0.5*	0.4	−0.2	0.2	0.3	−0.2	0.4*
	Gender	−0.1	−0.1	−0.1	0.0	−0.1	0.0	−0.2	−0.1	−0.1	0.0	0.0
	Nationality	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
NL	Total	0.8	1.3**	0.7	0.9	1.5***	1.1*	1.5**	−1.5***	0.5	0.9	0.5
	Education	0.4	0.5	0.7	0.8	0.5	0.9*	0.9*	−0.7	0.5	0.2	−0.1
	Age	0.2	0.3	−0.1	0.1	0.3*	0.2	0.5*	−0.4*	0.0	0.3	0.1
	Experience	0.2	0.6***	0.2	0.1	0.7***	0.0	0.3*	−0.3*	0.0	0.0	0.3
	Gender	0.0	0.0	−0.1	0.0	0.0	0.0	−0.1	−0.1	−0.2	0.3	0.2
	Nationality	0.0	0.0	0.0	−0.1	0.0	0.0	−0.1	0.0	0.1	0.1	0.0
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
SI	Total	−0.1	0.8	1.3*	1.9**	1.3*	1.6**	0.7	0.1	1.2*	−0.8	1.1*
	Education	−0.3	1.4**	1.5**	1.1	1.3*	0.5	0.5	0.2	1.2*	−0.5	1.0
	Age	0.0	−0.1	0.1	0.3*	0.1	0.2	0.1	0.0	0.2	−0.1	0.1
	Experience	−0.1	−0.3	−0.4**	0.4*	0.0	0.5*	0.0	−0.1	0.3	−0.3	0.2
	Gender	0.2	−0.2	0.1	0.1	−0.1	0.4*	0.1	0.0	−0.5**	0.0	−0.1
	Nationality	-	-	-	-	-	-	-	-	-	-	-
	By Category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
SK	Total	1.6***	0.3	−0.1	0.2	0.0	0.4	−0.2	−0.3	0.2	0.0	0.1
	Education	1.3***	0.4	0.0	0.5	0.1	0.4	−0.3	−0.4	0.0	−0.2	0.1
	Age	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	−0.1	−0.1
	Experience	0.3***	0.0	−0.1	−0.3**	−0.1	−0.1	0.0	0.1	0.3**	0.4***	0.1
	Gender	−0.1	−0.1	−0.1	0.0	0.0	0.0	0.2	0.0	0.0	−0.1	−0.1
	Nationality	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: The table presents contributions in percentage points. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. The calculations are performed using the EU-SILC dataset.

A.5 Wage growth and compositional effects: industry effects included in the compositional effect

Table 26: Wage growth and compositional effects: High unemployment countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
IT	Comp. Effect	0.9**	0.8*	2.3***	1.6***	2.0***	1.3***	1.4***	−3.1***	−2.8***	−1.8***	-
	Wage growth	1.8	0.0	2.5	1.0	1.8	0.8	1.2	−4.2	−0.9	−0.8	-
	Net Wage growth	0.9	−0.7	0.2	−0.7	−0.1	−0.4	−0.1	−1.1	1.9	1.0	-
ES	Comp. Effect	3.3***	2.2***	1.4**	2.3***	1.8***	0.3	1.0	0.0	−2.0***	0.5	−2.0***
	Wage growth	13.0	3.3	−1.4	4.1	−1.1	−1.9	−2.7	1.8	−7.9	2.4	−1.5
	Net Wage growth	9.7	1.1	−2.7	1.8	−2.9	−2.2	−3.6	1.8	−5.9	2.0	0.5
IE	Comp. Effect	3.3***	4.0***	0.5	−0.2	1.3	−0.2	0.3	1.9**	0.1	0.3	-
	Wage growth	7.7	0.0	0.6	−1.1	1.6	−1.3	−2.1	3.6	0.7	0.8	-
	Net Wage growth	4.4	−4.0	0.1	−1.0	0.2	−1.0	−2.4	1.7	0.7	0.5	-
PT	Comp. Effect	3.0***	1.5	2.8***	2.9***	3.5***	1.5*	1.2	1.4**	0.1	0.9	0.3
	Wage growth	2.7	7.5	−0.2	−2.1	−2.7	2.4	−0.9	2.8	1.2	0.6	6.5
	Net Wage growth	−0.3	6.1	−3.0	−5.0	−6.1	0.9	−2.1	1.4	1.1	−0.3	6.2
EL	Comp. Effect	-	-	2.3**	1.1	2.7***	0.9	−0.3	0.7	−0.8*	0.6	−0.6
	Wage growth	6.6	−2.0	−1.0	−7.5	−7.7	2.3	−1.8	−2.7	−3.3	6.3	−4.9
	Net Wage growth	-	-	−3.3	−8.6	−10.3	1.3	−1.4	−3.4	−2.6	5.7	−4.3
CY	Comp. Effect	1.4	−2.9**	1.6	−1.2	1.2	1.7	0.1	2.1	1.2	−1.2	−1.0
	Wage growth	6.6	−0.2	4.8	1.1	−1.4	−4.6	−3.6	−0.5	1.8	1.1	2.0
	Net Wage growth	5.2	2.7	3.2	2.3	−2.7	−6.3	−3.7	−2.7	0.6	2.3	3.0

Note: The table reports the estimated compositional effect in percentage points and wage growth in percent. The net wage growth is a measure of wage growth free of compositional effects defined as the difference between the observed wage growth and the estimated compositional effect. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. Calculations are performed using the EU-SILC dataset.

Table 27: Wage growth and compositional effects: Rest of euro area countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
AT	Comp. Effect	1.4	1.3	−0.6	1.9**	0.4	3.3***	0.6	1.3	1.2	2.1**	−1.9**
	Wage growth	6.2	2.3	2.9	3.2	4.1	2.5	0.5	4.6	−0.2	1.6	5.5
	Net Wage growth	4.8	0.9	3.5	1.3	3.7	−0.8	−0.2	3.3	−1.4	−0.5	7.4
BE	Comp. Effect	0.0	0.4	1.3***	0.2	0.7	−0.2	1.5***	0.0	−0.8	0.3	−0.5
	Wage growth	6.7	3.0	1.7	3.2	4.3	2.5	0.8	0.7	0.9	2.1	2.5
	Net Wage growth	6.8	2.6	0.4	3.0	3.6	2.7	−0.7	0.7	1.7	1.8	3.1
DE	Comp. Effect	0.1	1.2*	0.5	1.6***	−0.1	−1.9***	0.1	−1.0*	0.1	0.5	0.4
	Wage growth	3.9	−0.2	2.4	2.6	2.8	1.3	2.8	2.1	2.1	3.3	4.6
	Net Wage growth	3.8	−1.4	1.9	0.9	2.9	3.2	2.7	3.1	2.0	2.8	4.2
EE	Comp. Effect	−0.4	1.1	−0.1	0.8	−0.3	0.1	0.8	−0.6	0.5	1.3**	0.4
	Wage growth	10.1	−0.7	−0.6	7.5	6.9	3.8	6.2	4.7	0.0	14.4	3.5
	Net Wage growth	10.6	−1.7	−0.5	6.7	7.2	3.6	5.4	5.2	−0.5	13.1	3.2
FI	Comp. Effect	12.2***	0.9	1.5**	−0.1	0.6	−1.2***	0.0	0.5	−0.3	0.7*	0.0
	Wage growth	40.5	3.9	2.7	3.7	4.2	−2.2	2.0	0.8	0.7	0.3	2.3
	Net Wage growth	28.3	3.0	1.2	3.7	3.6	−1.1	2.0	0.3	1.0	−0.4	2.3
FR	Comp. Effect	−2.0	2.3***	1.0**	0.5	0.2	−0.7	0.7	0.5	1.2***	0.4	0.5
	Wage growth	3.1	1.2	2.8	2.4	1.5	0.3	4.4	1.0	1.1	0.0	4.5
	Net Wage growth	5.0	−1.1	1.8	1.9	1.3	0.9	3.7	0.5	−0.1	−0.5	4.0
LT	Comp. Effect	−0.7	2.4***	1.6*	0.6	0.9	−1.7**	0.1	−0.1	0.3	1.0	0.4
	Wage growth	14.7	−19.2	−1.4	13.1	2.6	4.8	−0.2	10.3	7.5	6.8	9.1
	Net Wage growth	15.4	−21.6	−2.9	12.5	1.7	6.5	−0.3	10.4	7.2	5.9	8.7
LU	Comp. Effect	3.0***	0.0	1.6*	0.8	2.5***	0.1	−5.2***	3.9***	0.2	2.5***	2.5**
	Wage growth	7.4	1.1	2.6	1.9	5.2	0.8	−5.4	0.0	4.9	−1.6	11.6
	Net Wage growth	4.4	1.2	1.0	1.2	2.7	0.7	−0.2	−3.9	4.7	−4.1	9.1
LV	Comp. Effect	2.6***	1.7**	1.0	1.0	−0.8	1.0	0.3	0.4	−0.1	0.6	1.4*
	Wage growth	19.7	−12.1	−5.1	7.3	3.9	8.4	9.4	5.2	4.7	11.0	6.6
	Net Wage growth	17.1	−13.8	−6.1	6.3	4.7	7.4	9.1	4.7	4.8	10.4	5.2
MT	Comp. Effect	1.5**	1.2	0.5	0.3	0.9	2.7***	0.4	0.8	1.0	−0.9	0.4
	Wage growth	4.1	1.3	4.7	3.4	4.8	5.7	3.4	−0.3	3.7	−0.6	4.7
	Net Wage growth	2.5	0.1	4.2	3.1	3.9	3.0	3.0	−1.1	2.7	0.3	4.3
NL	Comp. Effect	0.6	0.9	0.5	1.0	1.8***	1.3*	2.0***	−1.8***	0.4	0.6	0.5
	Wage growth	5.5	2.6	0.1	3.4	1.8	−1.6	3.3	−3.3	1.0	3.0	1.8
	Net Wage growth	4.8	1.7	−0.4	2.5	0.0	−2.9	1.3	−1.5	0.6	2.4	1.3
SI	Comp. Effect	−0.4	0.6	1.3	2.1***	1.4*	1.5*	0.7	0.4	1.1	−1.0	1.4*
	Wage growth	6.7	2.8	4.0	2.5	0.4	0.6	1.7	0.0	1.1	1.4	4.4
	Net Wage growth	7.1	2.2	2.7	0.5	−1.1	−0.9	0.9	−0.3	0.0	2.4	3.1
SK	Comp. Effect	1.6***	0.2	−0.1	0.2	0.2	0.3	−0.3	−0.3	0.2	0.1	0.1
	Wage growth	21.3	5.3	3.8	9.5	−4.2	3.5	5.1	−1.7	0.8	7.8	12.1
	Net Wage growth	19.6	5.1	3.9	9.2	−4.4	3.2	5.4	−1.3	0.6	7.6	12.0

Note: The table reports the estimated compositional effect in percentage points and wage growth in percent. The net wage growth is a measure of wage growth free of compositional effects defined as the difference between the observed wage growth and the estimated compositional effect. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. Calculations are performed using the EU-SILC dataset.

A.6 Wage growth and compositional effects: industry effects not included in the compositional effect

Table 28: Wage growth and compositional effects: High unemployment countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
IT	Comp. Effect	1.7***	0.8**	1.9***	1.6***	1.8***	1.5***	1.3***	−2.3***	−2.7***	−1.3***	-
	Wage growth	1.8	0.0	2.5	1.0	1.8	0.8	1.2	−4.2	−0.9	−0.8	-
	Net Wage growth	0.0	−0.8	0.5	−0.7	0.0	−0.6	0.0	−1.9	1.8	0.5	-
ES	Comp. Effect	2.9***	1.6***	1.5***	2.0***	1.7***	0.9**	0.7	0.1	−1.5***	0.5	−1.4***
	Wage growth	13.0	3.3	−1.4	4.1	−1.1	−1.9	−2.7	1.8	−7.9	2.4	−1.5
	Net Wage growth	10.1	1.7	−2.9	2.1	−2.8	−2.8	−3.4	1.7	−6.4	2.0	−0.1
IE	Comp. Effect	2.8***	3.4***	1.1	0.1	1.0	−0.2	1.0	1.6**	0.3	0.5	-
	Wage growth	7.7	0.0	0.6	−1.1	1.6	−1.3	−2.1	3.6	0.7	0.8	-
	Net Wage growth	4.9	−3.4	−0.5	−1.2	0.6	−1.1	−3.0	2.0	0.4	0.3	-
PT	Comp. Effect	2.5***	1.3	2.2***	2.5***	2.8***	1.8***	1.0	1.5**	0.6	0.9*	0.4
	Wage growth	2.7	7.5	−0.2	−2.1	−2.7	2.4	−0.9	2.8	1.2	0.6	6.5
	Net Wage growth	0.2	6.2	−2.4	−4.6	−5.5	0.6	−2.0	1.3	0.6	−0.3	6.0
EL	Comp. Effect	-	-	2.0***	1.1	2.1***	1.3**	0.0	0.5	−0.5	0.6**	−0.3
	Wage growth	6.6	−2.0	−1.0	−7.5	−7.7	2.3	−1.8	−2.7	−3.3	6.3	−4.9
	Net Wage growth	-	-	−3.0	−8.7	−9.7	1.0	−1.8	−3.2	−2.9	5.7	−4.6
CY	Comp. Effect	1.0	−2.0**	1.3	−0.5	1.3	1.0	0.4	1.3	1.1	−0.4	−0.8
	Wage growth	6.6	−0.2	4.8	1.1	−1.4	−4.6	−3.6	−0.5	1.8	1.1	2.0
	Net Wage growth	5.6	1.9	3.5	1.6	−2.7	−5.6	−4.0	−1.9	0.7	1.5	2.8

Note: The table reports the estimated compositional effect in percentage points and wage growth in percent. The net wage growth is a measure of wage growth free of compositional effects defined as the difference between the observed wage growth and the estimated compositional effect. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. Calculations are performed using the EU-SILC dataset.

Table 29: Wage growth and compositional effects: Rest of euro area countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
AT	Comp. Effect	1.1	1.0	−0.2	2.0***	0.3	3.1***	0.6	1.4*	1.1	1.7**	−1.5*
	Wage growth	6.2	2.3	2.9	3.2	4.1	2.5	0.5	4.6	−0.2	1.6	5.5
	Net Wage growth	5.1	1.3	3.2	1.3	3.8	−0.6	−0.1	3.2	−1.3	−0.1	7.0
BE	Comp. Effect	−0.2	0.6	1.8***	0.1	0.7	−0.1	1.6***	−0.2	−0.6	0.3	−0.6
	Wage growth	6.7	3.0	1.7	3.2	4.3	2.5	0.8	0.7	0.9	2.1	2.5
	Net Wage growth	6.9	2.5	0.0	3.1	3.6	2.5	−0.9	0.8	1.6	1.8	3.2
DE	Comp. Effect	−0.6	1.0*	0.9*	0.7	0.0	−0.8	0.0	−0.6	0.2	0.2	0.5
	Wage growth	3.9	−0.2	2.4	2.6	2.8	1.3	2.8	2.1	2.1	3.3	4.6
	Net Wage growth	4.5	−1.2	1.6	1.9	2.8	2.0	2.8	2.7	1.9	3.1	4.1
EE	Comp. Effect	0.4	0.9	−0.2	0.5	−0.2	0.2	0.6	−0.6	0.7	1.2**	0.2
	Wage growth	10.1	−0.7	−0.6	7.5	6.9	3.8	6.2	4.7	0.0	14.4	3.5
	Net Wage growth	9.7	−1.6	−0.5	7.0	7.0	3.6	5.5	5.3	−0.7	13.2	3.4
FI	Comp. Effect	0.8*	0.9	1.2**	0.3	0.7*	−0.9***	0.0	0.6	−0.3	0.6	0.0
	Wage growth	40.5	3.9	2.7	3.7	4.2	−2.2	2.0	0.8	0.7	0.3	2.3
	Net Wage growth	39.7	3.0	1.5	3.4	3.5	−1.3	2.1	0.2	1.1	−0.2	2.3
FR	Comp. Effect	2.7***	1.1***	1.0***	0.2	1.3***	−0.4	0.8*	0.6*	0.1	0.5	0.2
	Wage growth	3.1	1.2	2.8	2.4	1.5	0.3	4.4	1.0	1.1	0.0	4.5
	Net Wage growth	0.4	0.2	1.8	2.2	0.2	0.6	3.6	0.4	1.0	−0.5	4.3
LT	Comp. Effect	−0.5	2.3***	1.6**	0.6	0.8	−1.5**	0.2	0.1	0.2	0.7	0.3
	Wage growth	14.7	−19.2	−1.4	13.1	2.6	4.8	−0.2	10.3	7.5	6.8	9.1
	Net Wage growth	15.2	−21.6	−2.9	12.5	1.7	6.3	−0.4	10.2	7.3	6.1	8.8
LU	Comp. Effect	2.3***	0.3	1.4*	0.4	1.2	0.4	−4.1***	3.3***	1.0	2.3***	1.7**
	Wage growth	7.4	1.1	2.6	1.9	5.2	0.8	−5.4	0.0	4.9	−1.6	11.6
	Net Wage growth	5.1	0.9	1.2	1.5	4.0	0.4	−1.3	−3.3	3.8	−3.8	9.9
LV	Comp. Effect	2.3***	1.7***	0.6	0.8	−0.6	1.1*	0.6	0.3	−0.1	0.3	1.3**
	Wage growth	19.7	−12.1	−5.1	7.3	3.9	8.4	9.4	5.2	4.7	11.0	6.6
	Net Wage growth	17.4	−13.7	−5.7	6.5	4.5	7.3	8.8	4.9	4.9	10.7	5.3
MT	Comp. Effect	1.4**	0.6	1.2*	0.9	1.1*	2.4***	0.4	0.9	0.8	−0.7	0.5
	Wage growth	4.1	1.3	4.7	3.4	4.8	5.7	3.4	−0.3	3.7	−0.6	4.7
	Net Wage growth	2.7	0.7	3.5	2.4	3.7	3.3	3.0	−1.2	2.9	0.1	4.2
NL	Comp. Effect	0.6	1.1**	0.4	0.8	1.7***	1.1*	1.5**	−1.5***	0.4	0.7	0.7
	Wage growth	5.5	2.6	0.1	3.4	1.8	−1.6	3.3	−3.3	1.0	3.0	1.8
	Net Wage growth	4.8	1.5	−0.3	2.6	0.1	−2.7	1.8	−1.8	0.6	2.3	1.2
SI	Comp. Effect	−0.1	0.6	1.2	1.9***	1.2*	1.5*	0.8	0.2	1.3*	−0.8	1.3**
	Wage growth	6.7	2.8	4.0	2.5	0.4	0.6	1.7	0.0	1.1	1.4	4.4
	Net Wage growth	6.9	2.2	2.9	0.6	−0.8	−0.8	0.8	−0.1	−0.2	2.2	3.2
SK	Comp. Effect	1.4***	0.3	−0.1	0.1	0.1	0.4	−0.1	−0.3	0.1	0.1	0.1
	Wage growth	21.3	5.3	3.8	9.5	−4.2	3.5	5.1	−1.7	0.8	7.8	12.1
	Net Wage growth	19.8	4.9	3.9	9.3	−4.3	3.1	5.2	−1.4	0.6	7.6	12.0

Note: The table reports the estimated compositional effect in percentage points and wage growth in percent. The net wage growth is a measure of wage growth free of compositional effects defined as the difference between the observed wage growth and the estimated compositional effect. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Numbers might not add up due to rounding. Calculations are performed using the EU-SILC dataset.

A.7 Compositional effects: summary table

Table 30: Compositional effects: High unemployment countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
IT	Comp. Effect[a]	2.0***	0.9**	2.3***	1.8***	2.1***	1.6***	1.4***	−2.7***	−3.1***	−1.6***	-
	Comp. Effect[b]	0.9**	0.8*	2.3***	1.6***	2.0***	1.3***	1.4***	−3.1***	−2.8***	−1.8***	-
	Comp. Effect[c]	1.7***	0.8**	1.9***	1.6***	1.8***	1.5***	1.3***	−2.3***	−2.7***	−1.3***	-
ES	Comp. Effect[a]	3.7***	1.9***	1.6***	2.5***	2.1***	1.1**	0.9	0.1	−1.9***	0.6	−1.7***
	Comp. Effect[b]	3.3***	2.2***	1.4**	2.3***	1.8***	0.3	1.0	0.0	−2.0***	0.5	−2.0***
	Comp. Effect[c]	2.9***	1.6***	1.5***	2.0***	1.7***	0.9**	0.7	0.1	−1.5***	0.5	−1.4***
IE	Comp. Effect[a]	3.1***	3.6***	1.4	0.0	1.1	−0.2	1.1	1.9**	0.4	0.6	-
	Comp. Effect[b]	3.3***	4.0***	0.5	−0.2	1.3	−0.2	0.3	1.9**	0.1	0.3	-
	Comp. Effect[c]	2.8***	3.4***	1.1	0.1	1.0	−0.2	1.0	1.6**	0.3	0.5	-
PT	Comp. Effect[a]	3.0***	1.6	2.7***	2.7***	3.2***	2.1***	1.2	1.7***	0.6	1.0*	0.5
	Comp. Effect[b]	3.0***	1.5	2.8***	2.9***	3.5***	1.5*	1.2	1.4**	0.1	0.9	0.3
	Comp. Effect[c]	2.5***	1.3	2.2***	2.5***	2.8***	1.8***	1.0	1.5**	0.6	0.9*	0.4
EL	Comp. Effect[a]	-	-	2.6***	1.2	2.8***	1.5**	0.0	0.5	−0.5	0.7*	−0.4
	Comp. Effect[b]	-	-	2.3**	1.1	2.7***	0.9	−0.3	0.7	−0.8*	0.6	−0.6
	Comp. Effect[c]	-	-	2.0***	1.1	2.1***	1.3**	0.0	0.5	−0.5	0.6**	−0.3
CY	Comp. Effect[a]	1.0	−2.7**	1.8	−0.5	1.6	1.5	0.4	1.7	1.3	−0.5	−0.9
	Comp. Effect[b]	1.4	−2.9**	1.6	−1.2	1.2	1.7	0.1	2.1	1.2	−1.2	−1.0
	Comp. Effect[c]	1.0	−2.0**	1.3	−0.5	1.3	1.0	0.4	1.3	1.1	−0.4	−0.8

Note: The table reports the estimated compositional effect in percentage points. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Calculations are performed using the EU-SILC dataset.
[a]Estimates without industry effects.
[b]Estimates when industry effects are included in the compositional effects.
[c]Estimates when industry effects are not included in the compositional effects.

Table 31: Compositional effects: Rest of euro area countries

country		Year										
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
AT	Comp. Effect[a]	1.2	0.8	−0.1	2.2***	0.4	3.1***	0.6	1.4*	1.2	1.7**	−1.5*
	Comp. Effect[b]	1.4	1.3	−0.6	1.9**	0.4	3.3***	0.6	1.3	1.2	2.1**	−1.9**
	Comp. Effect[c]	1.1	1.0	−0.2	2.0***	0.3	3.1***	0.6	1.4*	1.1	1.7**	−1.5*
BE	Comp. Effect[a]	−0.3	0.7	1.9***	0.0	0.8	−0.1	1.6***	−0.1	−0.6	0.3	−0.7
	Comp. Effect[b]	0.0	0.4	1.3***	0.2	0.7	−0.2	1.5***	0.0	−0.8	0.3	−0.5
	Comp. Effect[c]	−0.2	0.6	1.8***	0.1	0.7	−0.1	1.6***	−0.2	−0.6	0.3	−0.6
DE	Comp. Effect[a]	−0.6	1.0*	0.9	0.7	−0.1	−0.9	0.0	−0.6	0.3	0.2	0.5
	Comp. Effect[b]	0.1	1.2*	0.5	1.6***	−0.1	−1.9***	0.1	−1.0*	0.1	0.5	0.4
	Comp. Effect[c]	−0.6	1.0*	0.9*	0.7	0.0	−0.8	0.0	−0.6	0.2	0.2	0.5
EE	Comp. Effect[a]	0.4	0.9	−0.1	0.5	−0.2	0.2	0.7	−0.6	0.7	1.2**	0.2
	Comp. Effect[b]	−0.4	1.1	−0.1	0.8	−0.3	0.1	0.8	−0.6	0.5	1.3**	0.4
	Comp. Effect[c]	0.4	0.9	−0.2	0.5	−0.2	0.2	0.6	−0.6	0.7	1.2**	0.2
FI	Comp. Effect[a]	2.3***	1.0**	0.5	0.5	0.8*	−1.0**	−0.1	0.6	−0.4	0.6	0.0
	Comp. Effect[b]	12.2***	0.9	1.5**	−0.1	0.6	−1.2***	0.0	0.5	−0.3	0.7*	0.0
	Comp. Effect[c]	0.8*	0.9	1.2**	0.3	0.7*	−0.9***	0.0	0.6	−0.3	0.6	0.0
FR	Comp. Effect[a]	1.1***	1.1***	1.1***	0.8**	0.7**	0.3	0.7*	0.5	−0.3	0.5	0.2
	Comp. Effect[b]	−2.0	2.3***	1.0**	0.5	0.2	−0.7	0.7	0.5	1.2***	0.4	0.5
	Comp. Effect[c]	2.7***	1.1***	1.0***	0.2	1.3***	−0.4	0.8*	0.6*	0.1	0.5	0.2
LT	Comp. Effect[a]	−0.6	2.4***	1.7**	0.6	1.0	−1.6**	0.2	0.0	0.2	0.8	0.3
	Comp. Effect[b]	−0.7	2.4***	1.6*	0.6	0.9	−1.7**	0.1	−0.1	0.3	1.0	0.4
	Comp. Effect[c]	−0.5	2.3***	1.6**	0.6	0.8	−1.5**	0.2	0.1	0.2	0.7	0.3
LU	Comp. Effect[a]	2.7***	0.5	1.8*	0.6	1.7*	0.3	−4.6***	3.7***	0.7	2.7***	1.8**
	Comp. Effect[b]	3.0***	0.0	1.6*	0.8	2.5***	0.1	−5.2***	3.9***	0.2	2.5***	2.5**
	Comp. Effect[c]	2.3***	0.3	1.4*	0.4	1.2	0.4	−4.1***	3.3***	1.0	2.3***	1.7**
LV	Comp. Effect[a]	2.5***	1.8***	0.7	0.8	−0.6	1.1*	0.6	0.3	−0.2	0.3	1.4**
	Comp. Effect[b]	2.6***	1.7**	1.0	1.0	−0.8	1.0	0.3	0.4	−0.1	0.6	1.4*
	Comp. Effect[c]	2.3***	1.7***	0.6	0.8	−0.6	1.1*	0.6	0.3	−0.1	0.3	1.3**
MT	Comp. Effect[a]	1.6**	0.6	1.4**	1.0	1.1*	2.6***	0.4	0.9	0.9	−0.8	0.5
	Comp. Effect[b]	1.5**	1.2	0.5	0.3	0.9	2.7***	0.4	0.8	1.0	−0.9	0.4
	Comp. Effect[c]	1.4**	0.6	1.2*	0.9	1.1*	2.4***	0.4	0.9	0.8	−0.7	0.5
NL	Comp. Effect[a]	0.8	1.3**	0.7	0.9	1.5***	1.1*	1.5**	−1.5***	0.5	0.9	0.5
	Comp. Effect[b]	0.6	0.9	0.5	1.0	1.8***	1.3*	2.0***	−1.8***	0.4	0.6	0.5
	Comp. Effect[c]	0.6	1.1**	0.4	0.8	1.7***	1.1*	1.5**	−1.5***	0.4	0.7	0.7
SI	Comp. Effect[a]	−0.1	0.8	1.3*	1.9**	1.3*	1.6**	0.7	0.1	1.2*	−0.8	1.1*
	Comp. Effect[b]	−0.4	0.6	1.3	2.1***	1.4*	1.5*	0.7	0.4	1.1	−1.0	1.4*
	Comp. Effect[c]	−0.1	0.6	1.2	1.9***	1.2*	1.5*	0.8	0.2	1.3*	−0.8	1.3**
SK	Comp. Effect[a]	1.6***	0.3	−0.1	0.2	0.0	0.4	−0.2	−0.3	0.2	0.0	0.1
	Comp. Effect[b]	1.6***	0.2	−0.1	0.2	0.2	0.3	−0.3	−0.3	0.2	0.1	0.1
	Comp. Effect[c]	1.4***	0.3	−0.1	0.1	0.1	0.4	−0.1	−0.3	0.1	0.1	0.1

Note: The table reports the estimated compositional effect in percentage points. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Calculations are performed using the EU-SILC dataset.

[a]Estimates without industry effects.

[b]Estimates when industry effects are included in the compositional effects.

[c]Estimates when industry effects are not included in the compositional effects.

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