Heterogeneous Wage Phillips Curves: A Matter of Skills?
Evidence From Euro Area Sectors

Preliminary version

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Abstract

This paper studies the slope of the wage Phillips curve in the euro area since 2000 using sectoral disaggregated data. We first construct sectoral unemployment rates using individual-level data from the EU Labour Survey. This measure reveals that unemployment varies considerably between sectors and exhibits common dynamics across euro area countries. We then estimate the slope of the wage Phillips curve using country-sector level data. Our empirical approach relies on a shift-share instrument that exploits sectoral labour markets' exposure to age-specific unemployment rates. The estimates show that the average slope is relatively steep: a one percentage point decrease in unemployment leads to a 0.7 percent increase in wage growth. In addition, the large cross-section of the data suggests that the slope is convex and very steep for unemployment rates lower than 7%. We then estimate wage Phillips curves for each individual industry. Our results document significant sectoral heterogeneity in the sensitivity of wage growth to unemployment, with slope estimates ranging from -0.3 to -2, and suggest an important role for the level of skills. In particular, the slope of the wage Phillips curve is flat in the low-skilled sectors and steep in the high-skilled sectors.

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1 Introduction

Originally proposed by Phillips (1958), the dynamic relation between wage inflation and unemployment has since been incorporated in standard New Keynesian models (Galí, 2011). An extensive number of studies have adopted this framework to estimate the slope of Phillips curve using aggregate macroeconomic data (Ciccarelli and Osbat, 2017; Coibion and Gorodnichenko, 2015; Del Negro et al., 2020; Galí and Gambetti, 2019). This approach is however subject to important limitations.

First, these models traditionally ignore heterogeneity among households, firms or sectors. A new class of theoretical models, known as Heterogeneous Agents New Keynesian (HANK) models, has since emerged by combining heterogeneous agent models with New Keynesian models. Although central banks should focus primarily on aggregate variables, HANK models provide valuable insights into the implications of heterogeneity for the conduct of monetary policy, notably through redistribution (Ampudia et al., 2018; Auclert, 2019; Kaplan et al., 2018).[1] Heterogeneity has also been introduced across workers in New Keynesian models with search-and-matching frictions to study labour market dynamism.[2]

Second, there are practical difficulties in using aggregate data and time-series estimation techniques to identify the slope of the Phillips curve, notably due to the presence of cost-push shocks. To address these issues and better estimate Phillips curves, a new strand of research has used subnational data and applied panel data estimation methods (Fitzgerald et al., 2020; Hazell et al., 2022; McLeay and Tenreyro, 2020).[3] These studies point to a stronger role of unemployment (or marginal costs) as determinant of inflation, in particular when unemployment is at very low levels (Babb and Detmeister, 2017; Kumar and M. Orrenius, 2016). Additionally, the use of sectoral-level data has unveiled considerable heterogeneity in the slope of the price Phillips curve across industries (Byrne et al., 2013; Imbs et al., 2011).

While studies have mostly illustrated sectoral heterogeneity in prices, this paper is the first, to the best of our knowledge, to look at sectoral heterogeneity in the wage Phillips curve. More specifically, we exploit industry-level data for labour markets to estimate wage Phillips curves in the euro area. Our sample covers 17 euro area countries and up to 18 sectors, as classified by the NACE Rev. 2 nomenclature of Eurostat, for the 2000-2020 period.

[1]Households are for example different in terms of wealth, income or propensity to consume.

[2]The benchmark New Keynesian model with search-and-matching frictions and with a representative agent has been developed in Blanchard and Galí (2010).

[3]Other studies have for example relied on instrumental variable methods to estimate the slope of the Phillips curve. For instance, Barnichon and Mesters (2021) have used monetary policy shocks, identified using high-frequency data, as instruments for the output gap.

We first construct a new indicator on unemployment at the sectoral level by using individual-level data from the EU Labour Force Survey. Using this metric, we document new stylized facts about sectoral labour markets. This measure demonstrates that unemployment varies widely across sectors and tends to exhibit similar dynamics across euro area countries. In addition, a variance decomposition shows that sector-specific characteristics alone explain a fifth of unemployment's variability.

We estimate the slope of the wage Phillips curve using our country-sector level panel dataset. To identify the causal effect of a change in sectoral unemployment on sectoral wage growth, we adopt an instrumental variable approach by relying on a shift-share (Bartik-like) instrument that exploits sectoral labour markets' exposure to age-specific unemployment rates. Our results provide evidence of a relatively steep wage Phillips curve in the euro area: a point percentage decrease in unemployment leads to a 0.7 percent increase in wage growth. However, the slope estimate masks strong nonlinearities. The large cross-section of the data suggests that the slope is convex and very steep for unemployment rates lower than 7%. By contrast, the slope is nearly flat when unemployment exceeds that threshold.

We then estimate the slopes of the wage Phillips curve for each individual sector, using the euro area countries as the cross-sectional units. We find large sectoral differences in the sensitivity of wage growth to unemployment. The estimates of the slope range from -0.3 to -2. What can explain the sectoral discrepancy in the relationship between wage growth and the unemployment rate? We find an important role for the level of skills in shaping the wage Phillips curve. In particular, wage growth in the high-skilled sectors, such as the finance and insurance sector, reacts strongly to changes in unemployment whereas the wage responsiveness to labour market tightness is subdued in the low-skilled sectors, such as construction. By contrast, we do not find a role for the occupation composition of employment in shaping the wage Phillips curve.

Related literature. This paper contributes to the vast literature on Phillips curve estimation (Coibion and Gorodnichenko, 2015; Del Negro et al., 2020; Galí, 2011; Galí and Gambetti, 2019; Stock and Watson, 2019). By relying on cross-sectional variation in disaggregated sectoral data, this paper contributes more specifically to the emerging literature that uses subnational data to handle the identification challenges of the estimation of the Phillips curve. These papers notably document steeper Phillips curves with regional-level data than with aggregate data, both for the United States and the euro area (Fitzgerald et al., 2020; Hooper et al., 2020; Levy, 2019; McLeay and Tenreyro, 2020). In a prominent paper, Hazell et al. (2022)

estimate the slope of the Phillips curve using cross-sectional data for US states. They find a modest decline in the slope of the Phillips curve since the 1980s. Applying their regional estimates in an aggregate framework, they document essentially no missing disinflation or missing reinflation over the past few business cycles. As a complement to regional data, Imbs et al. (2011) find evidence of strong sectoral heterogeneity in the price Phillips curve using French data, notably through the backward looking component of inflation and the duration of nominal rigidities. Byrne et al. (2013) also document significant sectoral heterogeneity for a panel of advanced countries. Additionally, evidence for the United States suggests large variation in price stickiness across industries (Leith and Malley, 2007; Nakamura and Steinsson, 2008).

Furthermore, this paper connects to the studies that explore nonlinearities in the wage-unemployment relationship. For instance, Babb and Detmeister (2017) and Kumar and M. Orrenius (2016) use state-level data to demonstrate that the wage Phillips curve exhibits convex and nonlinear behavior in the United States when unemployment is at low levels. These empirical findings have been supported by recent theoretical works that model nonlinearities of the Phillips curve in New Keynesian models (Benigno and Eggertsson, 2023; Harding et al., 2022).

Our study also makes a contribution to the growing literature that incorporates heterogeneity among workers into New Keynesian models (Alves et al., 2020; Auclert, 2019; Debortoli and Galí, 2021; Kaplan et al., 2018). Specifically, our empirical findings offer supporting evidence to existing theoretical research that explores skill heterogeneity among workers. For instance, Dolado et al. (2021) develop a New Keynesian model with capital-skill complementarity and heterogeneity in search-and-matching frictions of high-skilled versus low- skilled workers. Within their framework, capital serves as a substitute for low-skilled labour and high-skilled workers face lower separation rates, higher bargaining power, and better matching efficiency. Their model predicts that an expansionary monetary policy leads to increased labor income inequality by raising the relative labor share for high-skilled workers. Moreover, Chaudhuri (2020) introduces skill heterogeneity into the standard New Keynesian model with price and wage rigidities of the wage Phillips curve proposed by Galí (2011). In this model, low-skilled workers exhibit higher elasticity of labor supply and labor demand, resulting in a flatter wage Phillips curve for this group of workers.

Finally, our analysis is also related to empirical studies that rely on shift-shares instruments as part of their identification strategy. Originally developed by Bartik (1991), the formal conditions of application of Bartik instruments have been recently discussed in Adão et al. (2019), Borusyak et al. (2022) and Goldsmith-

Pinkham et al. (2020). These instruments have been employed across many fields in economics, ranging from immigration to international trade (Autor et al., 2013; Blanchard and Katz, 1992; Card, 2001). In macroeconomic studies, Chodorow-Reich and Wieland (2020) for example exploit variation in local labor markets' exposure to industry reallocation, using the areas' initial industry composition and national industry employment trends, to construct their shift-share instrument. Their results point to uneven effects of reallocation over the business cycle. Furthermore, as part of their empirical approach to estimate a Phillips curve in the United States, Hazell et al. (2022) use a shift-share instrument similar to Bartik (1991) that leverages on unemployment shares of individual industries at the state level.

This paper is organized as follows. Section 2 describes the data collection and the methodology to calculate sectoral unemployment rates. It also lays out summary statistics and presents salient facts regarding sectoral labour markets. Section 3 discusses our empirical approach and reports the estimate of the slope of the wage Phillips curve. Section 4 presents the sectoral wage Phillips curves and studies the importance of skills in shaping the wage Phillips curve. Section 5 documents a range of robustness checks and Section 6 concludes.

2 Data and stylized facts

2.1 Data collection

We rely on disaggregated economic data at the industry-level, provided from Eurostat or constructed on our own using the EU Labour Force Survey. Sectors are defined according to the NACE Rev. 2 nomenclature, which designates the statistical classification of economic activities in the European Union (Eurostat, 2008).[4] A revision of this classification (from NACE Rev. 1.1 to NACE Rev. 2) took place in 2008 to better reflect changes in economic structures and organisations, as well as technological developments. We use the Eurostat's correspondence between NACE Rev. 2 and NACE Rev. 1.1 to construct harmonized country-sector time series over the 2000-2020 period (see Table A1 in Annex A.1). However, the transition between NACE Rev. 1.1 and NACE Rev. 2 was not fully coordinated as some NACE 1.1 sectors were divided into multiple NACE 2 sectors.[5] As a result, data are

[4]NACE is the French acronym for "Nomenclature statistique des activités économiques dans la Communauté européenne".

[5]For example, the NACE 1.1 "Real estate, renting and business activities" was separated into three NACE 2 sectors: "Real estate activities", "Professional, scientific and technical activities" and "Administrative and support service activities".

only available from 2000 for a limited number of industries. Table 1 presents our sector coverage, which includes four industrial sectors (B-E), the construction sector (F), eight sectors in private services (G-N), three sectors in public services (O-Q) as well as the entertainment sector (R) and other sectors (S).[6] Our final dataset includes 18 (9) sectors for 17 euro area countries from 2008 (2000) to 2020 at annual frequency.[7]

Table 1: Sectoral coverage

Code	Name	Short name	Time coverage
B	Mining and quarrying	Mining	2000-2020
C	Manufacturing	Manuf.	2000-2020
D	Electricity, gas, steam and air conditioning supply	Elec.	2008-2020
E	Water supply, sewerage, waste management and remediation activities	Water	2008-2020
F	Construction	Const.	2000-2020
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	Retail	2000-2020
H	Transportation and storage	Transp.	2008-2020
I	Accommodation and food service activities	Acc./Food	2000-2020
J	Information and communication	IT	2008-2020
K	Financial and insurance activities	Fin./Ins.	2000-2020
L	Real estate activities	Real Est.	2008-2020
M	Professional, scientific and technical activities	Scien./Techn.	2008-2020
N	Administrative and support service activities	Support	2008-2020
O	Public administration and defence; compulsory social security	Publ. Admin	2000-2020
P	Education	Educ.	2000-2020
Q	Human health and social work activities	Health	2000-2020
R	Arts, entertainment and recreation	Arts	2008-2020
S	Other service activities	Other	2008-2020

Note: This table describes the 18 sectors according to the NACE Rev. 2 classification, and their time coverage.

We exploit the EU Labour Force Survey (EU-LFS) to calculate a new measure of unemployment at the sector-level for euro area countries. The EU-LFS is a large household sample survey conducted by all EU countries since 1983. Every year, interviews are conducted by national statistical authorities for millions of individuals with various characteristics (gender, age, education, etc.) and employment status in member countries. All respondents receive a weighting coefficient, which is used to make the survey as representative of the population as possible. This data is then compiled by Eurostat to produce official statistics on national-level employment and unemployment in member countries. For our purposes, the EU-LFS also provides information on the sector in which individuals are employed. In addition, for each unemployed person, information on the sector in which they were previously employed is also available.[8] We use this information to calculate

[6] We exclude for data purposes the agricultural sector as well as the activities of households as employers and the activities of extraterritorial organizations.

[7] The euro area countries are Austria, Belgium, Estonia, Finland, France, Germany, Greece, Italy, Ireland, Spain, Latvia, Lithuania, Luxembourg, the Netherlands, Portugal, Slovakia and Slovenia.

[8] This information is available in the annual EU-LFS but not in the quarterly EU-LFS for the workers unemployed for more than a year, which represents a significant proportion of unemployment in euro area countries.

our industry-level measure of unemployment rate for euro area countries, which is defined as the following:[9]

$$u_{i,t} = \frac{\sum \text{Unemployed persons at time } t \text{ whose previous job was in sector } i}{\text{Labour force in sector } i \text{ at time } t} \tag{1}$$

where the labour force in sector i represents the sum of the number of employed persons in sector i and the number of unemployed persons whose previous job was in sector i.[10] Section 2.2 will present the stylized facts about sectoral unemployment rate in the euro area.

The EU Labour Force Survey also reports the highest level of education attained by each individual following the International Standard Classification of Education (ISCED). Three levels of education are available: low (corresponding to a lower secondary education level, see Table A2 in Annex A.3), medium (upper secondary) and high (third level). We calculate our industry-specific education measure as the percentage of the workforce with low, medium or high levels of education in each sector.

We rely on Eurostat for the other main variables of interest, namely nominal wage growth and labour productivity growth. For each industry, nominal wage growth is proxied by the log change of the "wages and salaries" component of the hourly labour cost index (LCI).[11] Labour productivity growth is calculated as the log change of the gross value added (GVA) in real terms per hour worked for each sector.[12]

Finally, we also obtain from Eurostat at the country-level the unemployment rate, nominal wage growth and labour productivity growth, calculated as the percentage change of GDP per hour worked (in real terms). In addition, Eurostat provides indicators at the national level on the unemployment rate by age group, which we will use for our instrumental variable approach (see Section 3.1). This indicator is available for ten age groups, subdividing the working population into

[9] The U.S. Bureau of Labor Statistics and the Office for National Statistics employ the same definition to calculate their estimates of sector-level unemployment rate using the U.S. Current Population Survey and the UK Labour Force Survey, respectively.

[10] We consider the experienced labor force and therefore exclude the unemployed individuals with no previous working experience.

[11] Wage and salary costs include direct remuneration, bonuses, and allowances paid by an employer in cash or in kind to an employee in return for work done, payments to employees saving schemes, payments for days not worked and remuneration in kind such as food, drink, fuel, company cars, etc.

[12] We collect information about GVA and hours worked separately for the public sector and for the real estate sector as GVA per hour worked is not directly provided by Eurostat for these sectors. We do not differentiate labour productivity growth between public sectors for data purposes. Data for labour productivity growth are winzorized at the 1% and 99% levels.

equal 5-year age brackets.[13] We also get national unemployment by education attainment, which is available for three education levels (low, medium or high). As household inflation expectations do not exist for individual euro area countries, we will use previous year's inflation as a proxy for inflation expectations. We therefore complement our dataset with national inflation, measured as the log change of the HICP index.

2.2 Five facts about sectoral unemployment in the euro area

We exploit our new sectoral unemployment measure and present five stylized facts about labour market dynamics across countries, sectors and education levels in euro area countries, which motivates the empirical analysis that follows.

Fact #1: Unemployment varies widely across sectors. It is no longer a matter of doubt that economic performance varies substantially across euro area countries. It is becoming increasingly clear, however, that these disparities also occur within countries. Recent empirical studies have for example highlighted strong dispersion of unemployment rates across regions (e.g. Levy (2019) for the euro area, Hooper et al. (2020) for the United States). Our data reveal that national unemployment rates also conceal considerable heterogeneity between sectors (Table 2). While national unemployment stood at 10.5% over the 2008-2020 period, the interquartile range of sectoral unemployment averaged 4.1 percentage points. Unemployment was around 4% in the public service sectors (public administration, education and health). By contrast, it reached more than 10% in construction, in accommodation and food services and in administrative and support service activities.[14] In the retail and manufacturing sectors, which together account for 29% of employment in euro area countries, the unemployment rate averaged around 8%. The sectoral heterogeneity can also be observed in the volatility of unemployment rates, which were particularly elevated in the cyclically-sensitive industries, such as construction or real estate. Conversely, the standard deviations of unemployment was relatively low in some private industries, as for instance in the financial and insurance activities or in the professional, scientific and technical activities, as well in public services.

[13] The age groups are distributed according to the following 10 brackets: [15-19], [20-24], [25-29], [30-34], [35-39], [40-44], [45-49], [50-54], [55-59] and [60-64].

[14] The administrative and support service sector includes the activities of temporary employment agencies, which contributes to the high level of unemployment in this sector.

Table 2: Summary statistics for sectoral unemployment

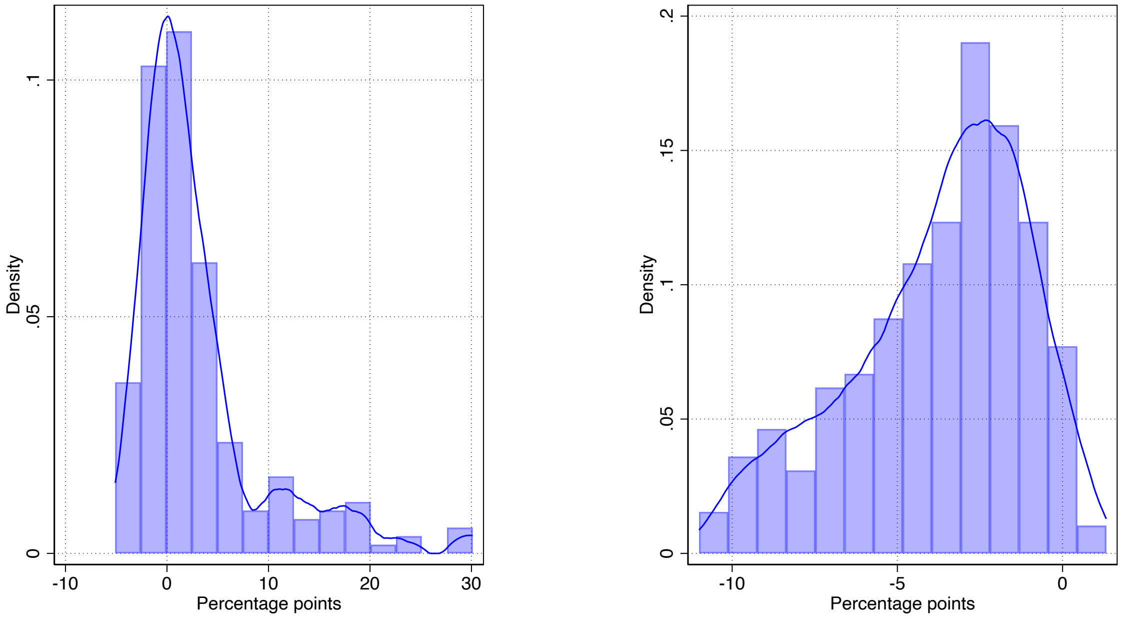
	Mean	Median	Std. Dev.	10th pct	90th pct
National unemp. rate	10.52	9.00	5.23	5.40	17.80
Mining	9.07	6.97	6.57	2.18	18.07
Manuf.	8.00	6.59	5.15	2.96	15.86
Elec.	4.76	3.34	4.08	1.21	10.05
Water.	7.80	6.16	6.57	2.12	14.59
Const.	12.68	9.07	10.77	3.70	30.04
Retail	8.16	7.31	4.33	3.36	14.53
Transp.	6.27	5.34	3.66	2.39	10.91
Acc./Food	12.35	11.29	6.28	5.63	21.22
IT	5.83	4.67	4.22	2.14	11.26
Fin./Ins.	4.02	3.30	2.50	1.55	7.11
Real Est.	6.69	5.25	5.92	1.72	14.20
Scien./Techn.	4.79	3.80	3.40	1.82	9.23
Support	10.72	10.03	5.71	4.65	18.91
Publ. Admin	4.50	3.06	4.28	1.08	11.62
Educ.	3.82	3.00	2.56	1.42	7.17
Health	4.09	3.51	2.47	1.62	7.17
Arts	8.73	8.05	5.96	2.97	15.87
Other	7.26	6.35	4.62	2.45	13.17

Note: This table reports descriptive statistics at the sectoral level for average unemployment rate (in %) across euro area countries over the 2008-2020 period. Sectors follow the NACE Rev. 2 classification (see Section 2.1).

Fact #2: Sectoral labour markets dynamics are common across countries. Euro area sectors also vary significantly in the structural state of their labour market slack, which tends to be common across countries and over time. For example, Figure 1 reports, for each country-sector unit and for each year, the deviation of the unemployment rate vis-à-vis the national unemployment rate for the construction and the IT sectors. The positive deviation depicted in Figure 1a shows that unemployment in the construction sector tends to be structurally higher, across euro area countries and over time, than unemployment in the rest of the economy. By contrast, the negative deviations of the IT sector highlights that unemployment is structurally lower in this industry (Figure 1b). Figure B.1 in Annex B shows that this is typically valid for all sectors. For instance, unemployment in the finance and insurance industry as well as in science and technology were systematically lower than the national unemployment rate, while the opposite is true for the manufacturing and the retail sectors.

Fact #3: Sector-specific characteristics account for a large share of unemployment's variation. We further explore the dimensions of unemployment's variation across the country-sector observations in our sample. Specifically, we project

Figure 1: Sectoral unemployment in deviation from national unemployment



(a) Construction

(b) IT

Note: This chart depicts the histograms of the deviation of sectoral unemployment rate from the national unemployment rate for the construction and IT sectors over the 2008-2020 period.

our measure of sectoral unemployment on various subsets of fixed effects and report the adjusted R^2 in Table 3. While country fixed effects alone explain a sizeable share of unemployment variation (36%), sector fixed effects alone explain 20% of sectoral unemployment patterns. This further suggests a central role of sectoral characteristics in explaining disparities in unemployment rates. The combined two sets of fixed effects explain almost 60% of the variability in sectoral unemployment rates. By contrast, variation over time accounts for only a small share (6%) of unemployment variation.

Table 3: Variance decomposition of sectoral unemployment

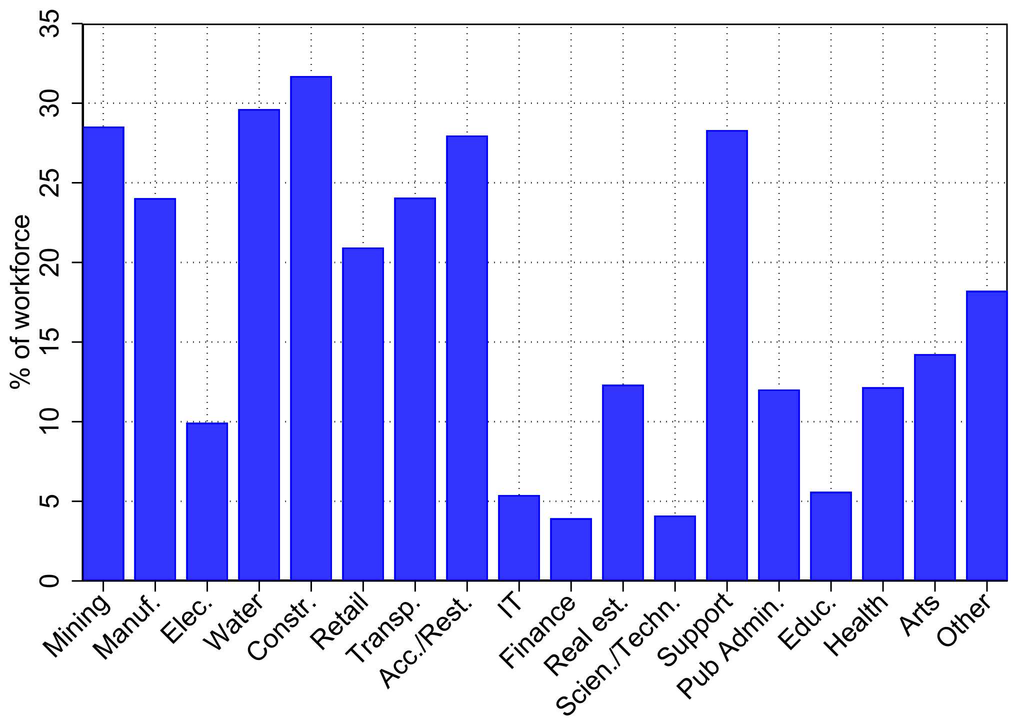
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Adjusted R^2	0.36	0.20	0.057	0.57	0.42	0.26	0.63
Country FE	✓	-	-	✓	✓	-	✓
Sector FE	-	✓	-	✓	-	✓	✓
Time FE	-	-	✓	-	✓	✓	✓
N	3908	3908	3908	3908	3908	3908	3908

Note: This table reports the projection of the sectoral unemployment rate on different sets of fixed effects. The sample includes 18 NACE 2 sectors for 17 euro area countries over the 2008-2020 period.

Fact #4: The wage-unemployment relation differs significantly across sectors. Additional summary statistics reported in Table C1 in Annex C reveal that the cross-sector variation for nominal wage growth was less pronounced than for unemployment, ranging from 2.43% to 3.42% over the 2008-2020 period. As a result, the contemporaneous correlation between nominal wage growth and unemployment rates varies considerably across industries, which motivates the ensuing analysis. In some sectors, the correlation was close to zero (for instance in the mining sector), whereas it was relatively elevated in other sectors such as in the IT sector (correlation coefficient of -0.43).

Fact #5: Low-educated workers are concentrated in certain sectors. One key aspect that varies substantially across sectors is the average education level of workers, captured by the widespread distribution of low education levels across sectors shown in Figure 2. According to the EU Labor Force Survey data, while the share of low-skilled workers was on average close 30% in the construction sector and in the catering sector, it averaged less than 5% in the financial and scientific sectors. As Table C1 in Annex C reports, the share of medium-skilled and high-skilled are also strongly heterogeneous across sectors.

Figure 2: Share of low-educated workers by sector



Note: This chart shows the percentage of low-educated workers in the workforce by sector on average across euro area countries over the 2008-2020 period.

3 Baseline estimation

3.1 Empirical approach

Taking advantage of our country-sector level data, we seek to estimate a reduced form of the New Keynesian wage Phillips curve with adaptive inflation expectations à la Galí (2011). We study this relationship for three distinct samples due to the 2008 revision of the NACE sector classification (see Table 1 in Section 2.1). The first sample considers 9 sectors and 17 euro area countries for the period 2000 through 2020, while the second sample includes 18 sectors from 2008 to 2020 for the same countries.[15] For consistency, we also estimate the wage Phillips curve over the 2008-2020 period using the 9 sectors of the first sample. In the following specification, we assume that the parameters to be estimated are the same for all sectors:

$$\pi^w_{c,i,t} = \alpha + \psi u_{c,i,t} + \delta \pi_{c,t-1} + \zeta \mathbf{X}_{c,i,t} + \varepsilon_{c,i,t} \tag{2}$$

where the dependent variable, $\pi^w_{c,i,t}$, denotes nominal wage growth in country c, industry i and year t. Our main variable of interest is the current level of sectoral unemployment $u_{c,i,t}$, whose parameter ψ corresponds to the slope of the wage Phillips curve. We assume adaptive inflation expectations where $\pi_{i,t-1}$ captures national inflation in year $t-1$. We add a vector of control variables $\mathbf{X}_{c,s,t}$ that includes labour productivity growth and a rich set of country-sector and sector-time fixed effects. Standard errors are clustered at the country-sector level.

Our panel data approach relies on the large cross-country and cross-sector variation, stressed in Section 2.2, to identify the slope of the wage Phillips curve. The use of disaggregated data and the presence of a rich set of fixed effects allow for a better identification of the slope (Fitzgerald et al., 2020; Hazell et al., 2022; McLeay and Tenreyro, 2020). The presence of sector-time fixed effects can for instance control for monetary policy reactions, for long-run inflation expectations or for any time-varying difference in sectoral economic performances (e.g. productivity) that are common to all euro area countries. Similarly, the use of country-sector fixed effects can control for any potential time-invariant unobserved factors specific to each country-sector pair. However, the residuals in equation 2 still contain all sectoral labour supply shocks that are not systematically related to the control variables, such as for instance labour market reallocation between sectors or migration

[15] The 9 sectors of the first sample are "Mining and quarrying", "Manufacturing", "Construction", "Wholesale and retail trade", "Accommodation and food services activities", "Financial and insurance activities", "Public administration", "Education" and "Health" (see Table 1 in Section 2).

changes. As a result, the OLS estimate of ψ is likely to be biased. To identify the causal effect of a change in sectoral unemployment on sectoral wage growth, our baseline framework therefore requires an instrument that captures variation in sectoral labour demand.

We introduce a shift-share (Bartik-like) instrument, exploiting the sectoral workforce composition by age group. Originally popularized by Bartik (1991) and Blanchard and Katz (1992) to investigate the effects of local employment growth on local wage growth in the United States, shift-share designs have since then been employed in many economic studies (e.g. Autor et al., 2013; Card, 2001; Chodorow-Reich and Wieland, 2020; Hazell et al., 2022). Bartik instruments typically rely on an accounting identity, which decomposes the variable of interest as the product between a set of shocks, the *shifts*, and a set of weights, the *shares*. For our purpose, we decompose unemployment in a given country, sector and year as the inner product between age-group shares and age-group unemployment rates. The Bartik instrument can be written as

$$z_{c,i,t} = \sum_{k} \omega_{c,i,k,\tau} u_{c,k,t} \tag{3}$$

where $\omega_{c,i,k,\tau}$ corresponds to the *shares* and is calculated as the percentage of workers in age group k, country c and sector i in a pre-period τ.[16] The set of *shifts* $u_{c,k,t}$ represent the national and age-specific k unemployment rates in country c at time t. We consider 10 age groups, which subdivide the working population into 5-year age brackets (from 15 to 64, see Section 2).

The statistical properties of Bartik-like instruments and the conditions sufficient for the consistency of the estimator have been recently discussed in Adão et al. (2019), Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020). Formally, and as stated by Goldsmith-Pinkham et al. (2020), consistency of $\hat{\psi}$ can be established either in terms of the *shares* or the *shifts*. We summarize in Table 4 the exposure shares and the shifts of the Bartik instruments over the three samples. First, our shift-share instrument relies on a very large set of "shocks", varying at the country level (17 euro area countries), age-group level (10 age brackets) and time level (13 or 21 time periods depending on the samples). In addition, there is a widespread distribution of shocks across age groups, with an average unemployment of 11.3% and 12.1%, a within-country standard deviation of 7.2 and 7.8 and a within-country interquartile range of around 5 percentage points. This suggests that our identifying assumption is plausible as *national* unemployment rates for a narrowly limited

[16]We calculate the *shares* using individual-level information from the EU Labour Force Survey (see Annex A).

Table 4: Summary statistics for the shares and shifts

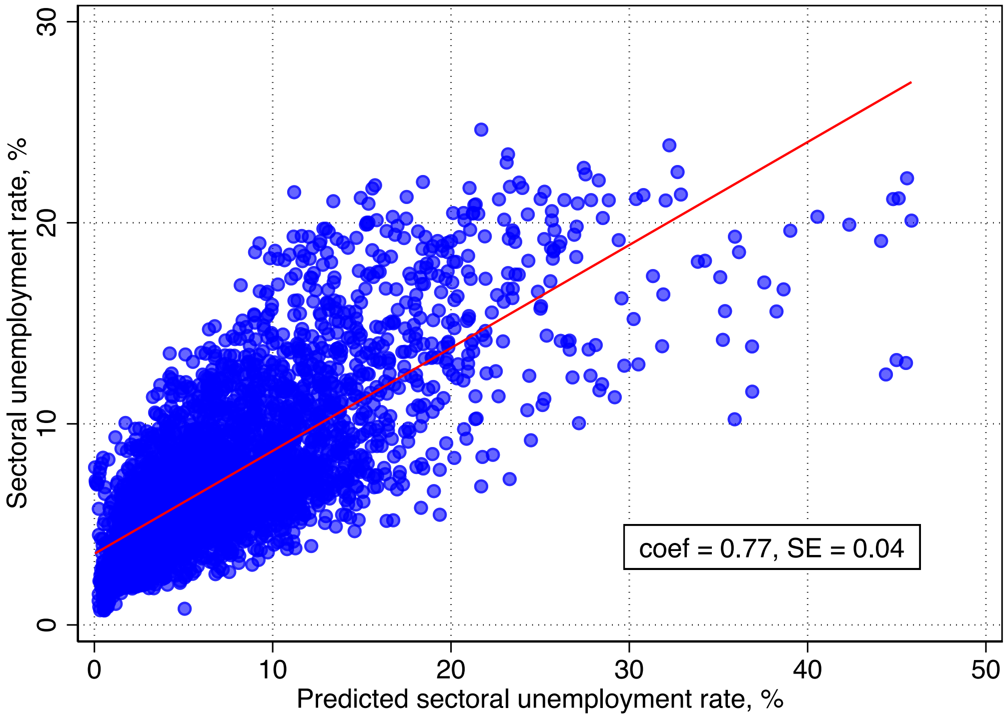
	2000-2020	2008-2020	2008-2020
		Shares	
Number of sectors	9	9	18
Exposure share (average)	0.10	0.10	0.10
Herfindahl index	0.13	0.13	0.13
		Shifts	
Age-specific unemployment (average)	11.3	12.1	12.1
Standard deviation	7.2	7.8	7.8
Interquartile range	5.0	5.4	5.4
Number of shocks (total)	3415	2171	2171
By country	201	128	128

Note: This table reports the summary statistics of the exposure shares and the shocks used in the shift-share instrument. The figures for the exposure shares correspond to their average across sectors within a given country for $\tau = 2000$ (Column 1) or $\tau = 2008$ (Columns 2 and 3). The Herfindahl index is defined as $\sum_k \omega^2_{c,i,k,\tau}$ and is reported on average across countries, sectors and years. The figure for the national unemployment by age group correspond to the average across countries and sectors over the different time samples. The standard deviations and the interquartile ranges are averages within countries.

age group are a priori sufficiently random not to be affected by unobserved *sectoral* labour supply shocks. Second, we follow Goldsmith-Pinkham et al. (2020) and fix the weights at the start-of-period ($\tau = 2000$ or 2008). The exposure shares average 10% and are little concentrated over the age groups, as the Herfindahl index shows. Therefore, the consistency of the estimator $\hat{\psi}$ can follow from the large number of shifts and from the sufficiently dispersed exposures shares (Borusyak et al., 2022).

3.2 2SLS estimates

Figure 3: First-stage regression, 2008-2020



Note: This figure shows the relation between the sectoral unemployment rate and its predicted values from the first stage regression of equation 2. Data for 18 sectors and 17 countries over the 2008-2020 period.

We now turn to our empirical results. We first present the results of the first-stage regressions of our IV estimates for the three different samples described in the previous section. Figure 3 plots the values of the predicted sectoral unemployment rate implied by the first-stage regression in relation to the actual data for the sample with 18 sectors over the 2008-2020 period. The strong and positive correlation reveals the high predictive power of our shift-share instrument. Table 5 confirms the relevance of our instrument for the other two samples (Columns 1 and 2). All coefficients associated with $z_{c,i,t}$ are positive, statistically significant at a 1% level and range between 0.77 and 0.82. In addition, the F-statistics are well above the conventional threshold.

Table 6 presents our baseline estimates of the slope of the wage Phillips curve. The first three columns show the 2SLS estimates of equation 2 separately for the 2000-2020 and 2008-2020 periods and with 9 or 18 sectors. For comparison, the last two columns provide the OLS estimates of the wage Phillips curve with country-

Table 5: 2SLS first-stage regression

Dependent variable: sectoral unemployment rate

	2SLS first-stage estimates		
	2000-2020	2008-2020	2008-2020
	(1)	(2)	(3)
Bartik instrument	0.80***	0.82***	0.77***
	[0.066]	[0.073]	[0.042]
F-stat > 10	✓	✓	✓
Number of sectors	9	9	18
Country-Sector FE	✓	✓	✓
Sector-Time FE	✓	✓	✓
N	2317	1700	3409
R^2	0.86	0.90	0.89

Note: This table reports the first stage estimates of equation 2. All regressions include past inflation and labour productivity growth as control variables. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

level data.[17] Starting with the 2SLS estimates, our estimated slope of the wage Phillips curve is negative and statistically significant at a 1% level. The large cross-section variation of the data yields precise estimates of ψ, as shown by the relatively low standard deviations. The coefficient of -0.55 in Column 1 indicates that a decrease by 1 percentage point in the unemployment rate leads to an increase in wage growth by 0.55 percentage points over the 2000-2020 period. Our results over the more recent period (2008-2020) are consistent for both sectoral coverages. The coefficients are only slightly larger in absolute terms compared with the pre-crisis period (-0.68 and -0.69). We test whether the slope has changed after the Great Financial Crisis. Formally, we augment our baseline regression (for the sample with 9 sectors over the 2000-2020 period) with an interaction term between the unemployment rate and a dummy variable that takes 1 for the post-2008 period. The results do not provide any strong evidence of a change in the slope in the most recent period (see Table C2 in Annex), in line with Ciccarelli and Osbat (2017).[18] If anything, the estimates point to a flattening of the curve after 2008.

One key finding of the recent empirical literature is that the estimates of the

[17] The estimated equation is similar to equation 2, with the exception that labour productivity is measured by GDP per hour worked.

[18] By contrast, Levy (2019) and Oinonen and Paloviita (2014) find evidence of a steepening of the wage and price Phillips curves, respectively, in recent years in the euro area.

Table 6: 2SLS second-stage regression

Dependent variable: nominal sectoral wage growth

	I. Country-sector panel (2SLS)			II. Country panel (OLS)	
	2000-2020	2008-2020	2008-2020	2000-2020	2008-2020
	(1)	(2)	(3)	(4)	(5)
Unemployment	-0.55***	-0.68***	-0.69***	-0.45**	-0.60***
	[0.075]	[0.091]	[0.067]	[0.17]	[0.17]
Past inflation	0.00	-0.32**	-0.19*	0.25*	-0.33
	[0.10]	[0.13]	[0.10]	[0.13]	[0.22]
Labour productivity	0.041*	0.015	0.032*	0.22*	0.036
	[0.021]	[0.021]	[0.016]	[0.10]	[0.10]
Number of sectors	9	9	18	-	-
Sector-Time FE	✓	✓	✓	-	-
Country-Sector FE	✓	✓	✓	-	-
Country FE	-	-	-	✓	✓
Time FE	-	-	-	✓	✓
N	2233	1660	3369	327	218

Note: This table reports the second-stage estimates of equation 2. Standard errors (in brackets) are clustered at the country-sector level in Columns 1 to 3 and at the country level in Columns 4 and 5. * / ** / *** indicate 10% / 5% / 1% significance level.

slope of the Phillips curve with regional-level data tends to be steeper than when estimated with aggregate data (Babb and Detmeister, 2017; Fitzgerald et al., 2020; Hooper et al., 2020; McLeay and Tenreyro, 2020). We find consistent results with our country-sector panel data. As Columns 4 and 5 show, our OLS estimates of equation 2 with country-level data yield coefficients lower in size than our estimates with country-sector level data. Nevertheless, the presence of country and time fixed effects already allows for a better identification of the curve and attenuates the lowering effects of potential confounding factors that are unobserved, such as monetary policy (McLeay and Tenreyro, 2020). In addition, the more limited cross-sectional variability of the data leads to a lower precision of the estimates: the standard deviations are 2 to 3 times higher compared with the standard deviations of Columns 1 to 3.

Looking at the other covariates, the coefficient associated with past inflation is positive, though not statistically significant, for the period 2000-2020 with data at the country-sector level (Column 1). By contrast, the coefficient is negative and statistically significant when we focus on the period following the Great Financial

Crisis, highlighting the period of low inflation in the euro area during these years (Columns 2 and 3). The sign of the coefficients is similar for the OLS estimates in Columns 4 and 5. Finally, an increase in labor productivity growth has a positive effect on wage growth, but the coefficients are at most statistically significant at a 10% level.

How do 2SLS estimates compare with OLS estimates? The OLS estimations of equation 2 yield significantly lower coefficients for ψ, ranging from -0.30 to -0.38 (see Table C3 in Annex). The sources of the bias in ψ thus appear to attenuate the sensitivity of wage growth to unemployment towards zero. One potential explanation lies in the fact that lower wage growth in one sector can lead to labor supply shifts to other industries, thus reducing labor supply in that sector.

3.3 Nonlinearity

Both theoretical and empirical research has recently suggested that changes in unemployment may have an asymmetric effect on wages and prices, and that the Phillips curve may be nonlinear (Babb and Detmeister, 2017; Benigno and Eggertsson, 2023; Harding et al., 2022; Kumar and M. Orrenius, 2016; Wright, 2023). The large cross-section of our data allows the exploration of nonlinearities in the wage-unemployment relation. We follow Kumar and M. Orrenius (2016) and augment our baseline model with a linear spline term with one knot at $\bar{u}$, corresponding to the long-term average unemployment rate for all sectors and for all countries. $\bar{u}$ takes the values of 6.7% and 7.2% for the 2000-2020 and 2008-2020 periods, respectively. We estimate the following equation by 2SLS[19]

$$\pi^{w}_{c,i,t} = \alpha + \psi_1 u_{c,i,t} + \psi_2 \max(u_{c,i,t} - \bar{u}, 0) + \delta\pi_{c,t-1} + \zeta\mathbf{X}_{c,i,t} + \varepsilon_{c,i,t} \quad (4)$$

The parameter ψ_2 in equation 4 captures the nonlinearity of the wage Phillips curve. The wage Phillips curve is downward sloping and convex if $\psi_1 < 0$ and $\psi_2 > 0$. Specifically, ψ_1 represents the slope before the kink, whereas $\psi_1 + \psi_2$ captures the slope when the unemployment rate is above its long-term average. The other variables are specified as in equation 2. Alternatively, as in Kumar and M. Orrenius (2016), we test the nonlinearity by including a restricted cubic spline term with 3 knots at the 25$^{\text{th}}$, 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the distribution.[20] In this specification, the wage Phillips curve is modelled as a continuous smooth function

[19] We estimate equation 4 by 2SLS and we instrument $u_{c,i,t}$ and $\max(u_{c,i,t} - \bar{u}, 0)$ by $z_{c,i,t}$ and $\max(z_{c,i,t} - \bar{z}, 0)$, where $\bar{z}$ is the long-term average of the shift-share instrument.

[20] For the 2000-2020 (2008-2020) period, $\bar{u}$ takes the values of 2.8% (3.2%) for the 25$^{\text{th}}$ percentile, 5.1% (5.5%) for the median and 8.9% (9.3%) for the 75$^{\text{th}}$ percentile.

Table 7: 2SLS second-stage regression with nonlinear terms

Dependent variable: nominal sectoral wage growth

	2000-2020			2008-2020		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment	-1.59***	-1.65***	-0.53***	-1.63***	-1.63***	-0.66***
	[0.27]	[0.29]	[0.078]	[0.22]	[0.24]	[0.093]
Linear spline term	1.23***			1.12***		
	[0.30]			[0.24]		
Cubic restricted spline term		0.64***			0.56***	
		[0.16]			[0.13]	
1 / Unemployment			2.52**			2.74
			[1.19]			[2.15]
Past inflation	-0.034	-0.032	-0.019	-0.19*	-0.19*	-0.33**
	[0.099]	[0.100]	[0.11]	[0.100]	[0.10]	[0.13]
Labour productivity	0.029	0.031	0.044**	0.024	0.026	0.017
	[0.019]	[0.019]	[0.021]	[0.017]	[0.017]	[0.022]
Number of sectors	9	9	9	18	18	18
Sector-Time FE	✓	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓	✓
N	2233	2233	2233	3369	3369	1660

Note: This table reports the second-stage estimates of equation 4. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

that is linear before the first knot, a piecewise cubic polynomial between adjacent knots, and linear again after the last knot.[21] Finally, as a third test, we include a convex term corresponding to the inverse of the unemployment rate.

Table 7 reports the results. The linear spline term is positive and statistically significant at a 1% level for both time periods, suggesting that the wage Phillips curve is strongly nonlinear (Columns 1 and 4). In particular, the wage-unemployment relation is very steep when the unemployment is below its long-term average (coefficient of -1.6) but becomes flat when the unemployment rises above 7%. From this level, a percentage point decline in the unemployment rate is associated with a 0.36 (Column 1) or 0.51 (Column 2) increase in wage growth. The results for the second specification also indicate nonlinearity in the wage Phillips curve (Columns 2 and

[21] See Dupont (2002) for a description.

4): the cubic spline term is positive and statistically different from 0. Finally, the coefficient associated with the inverse of the unemployment rate is positive for both time periods (Columns 3 and 6), showing convexity in the relation, but is statistically insignificant for the 2008-2020 period. Overall, these results provide evidence of nonlinearity in the wage Phillips curve in euro area countries with sectoral data, which echoes similar findings from the empirical literature using state-level data for the United States (Babb and Detmeister, 2017; Bishop and Greenland, 2021; Kumar and M. Orrenius, 2016).

4 Sectoral wage Phillips curves

4.1 Sectoral estimates

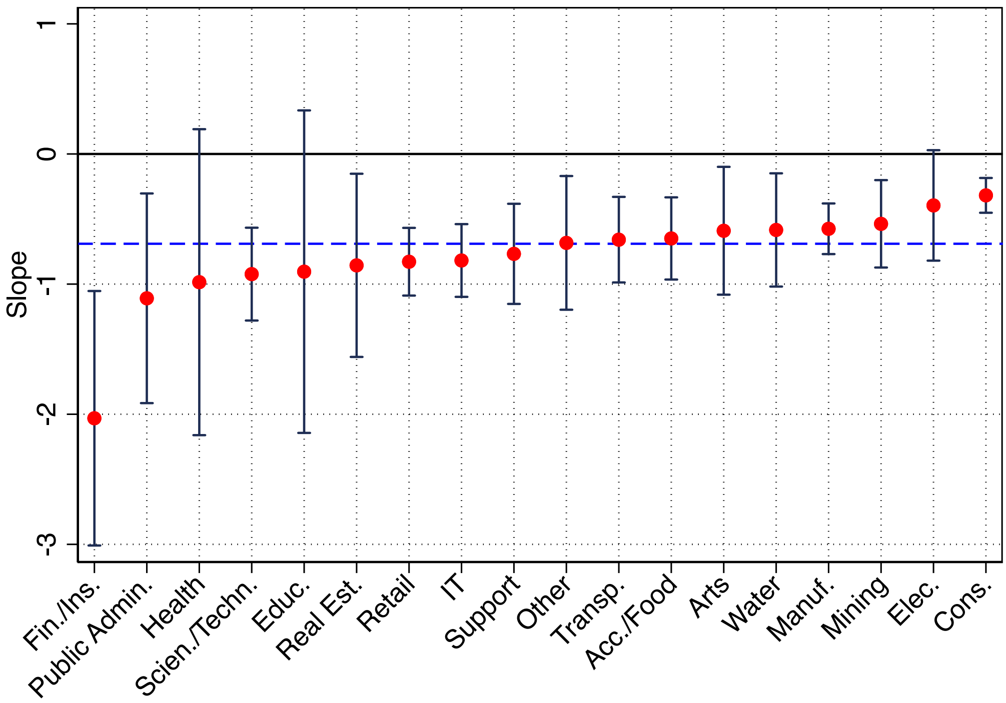
Thus far, we have assumed that data can be pooled across sectors and reported results restricting the estimates on the wage Phillips curve specifications to be the same across sectors. However, evidence for the price Phillips curve shows that there is considerable sectoral heterogeneity in the response of prices to changes in marginal costs, hence suggesting the existence of sector-specific Phillips curves (Byrne et al., 2013; Imbs et al., 2011; Leith and Malley, 2007). We now explore the heterogeneity of the slope of the wage Phillips curve across industries. We follow Byrne et al. (2013) in using the countries as the cross-sectional units to estimate a wage Phillips curve for each individual sector. Specifically, we estimate for a given sector i the following equation with a panel of 17 euro area countries and 13 or 21 time periods:

$$\pi^w_{c,i,t} = \alpha_i + \psi_i u_{c,i,t} + \delta_i \pi_{c,t-1} + \zeta_i \mathbf{X}_{c,i,t} + \varepsilon_{c,i,t} \quad i \in \{1 \dots 18\} \tag{5}$$

where the variables $u_{c,i,t}$ and $\pi_{c,t-1}$ for country c, sector i and time t are as in equation 2. The vector $\mathbf{X}_{c,i,t}$ includes labour productivity growth and a set of country and time fixed effects. Importantly, in this specification, the parameters to be estimated (ψ, δ and ζ) vary across industries i. We cluster the standard errors at the country level.[22]

[22] In their analysis using sector-level data on prices and marginal costs for France, Imbs et al. (2011) apply a SURE correction to account for cross-sector interdependencies. Similarly, Byrne et al. (2013) estimate a heterogeneous coefficient model using common correlated effects to account for the potential unobserved common factors reflecting cross-sectional linkages. Our instrumental variable approach already deals with endogeneity concerns, and prevents the estimates of ψ_i to be biased by, for instance, unobserved labour supply shocks (see Section 3.1).

Figure 4: 2SLS estimates of sectoral wage Phillips curves



Note: This figure reports the sector-specific 2SLS estimates of the wage Phillips curve. 90 percent confidence intervals are reported around point estimates. The dotted line represents the 2SLS estimate of ψ in equation 2. Sample with 18 sectors and 17 euro area countries over the 2008-2020 period.

Figure 4 reports graphically the sector-by-sector estimates of the coefficients ψ and their 90% confidence intervals for the 18 sectors over the 2008-2020 period. First, the results provide empirical support for the relevance of wage Phillips curve at the sectoral level. Nearly all ψ-coefficients are negative and statistically different from 0 at a 10% level, as shown by the confidence bands (see Tables C4-C6 in Annex). Two public sectors are exceptions: healthcare and education, which can be explained by the fact that wage growth in public services is likely to not be dependent on current macroeconomic conditions.[23] However, the sector-by-sector estimates are on average less precise, as the standard deviations reported in Tables C4-C6 show, than the estimates obtained using the panel for all sectors (equation 2). This can be related to the smaller number of observations for each panel estimated.

Second, the point estimates conceal substantial heterogeneity in the wage Phillips

[23]Tables C4-C6 in Annex C also report the first-stage estimation results of equation 2. It is worth noting that, although F-statistics are above the conventional threshold, the shift-share instrument is less relevant for the public sectors (”Public administration”, ”Education” and ”Health”) as well as for ”Electricity” compared with the other private service sectors.

curve across sectors. Once we allow for sectoral heterogeneity, the coefficients for ψ range from -0.3 in the construction sector to -2 in finance and insurance. This corresponds respectively to around half and more than the double of the slope coefficient estimated in equation 2, represented by the horizontal dotted line in Figure 4. Focusing on private sectors, outside the financial sector, the slope is also relatively steeper for the science and technology sector (coefficient of -0.92) as well as for the retail (-0.83) and IT (-0.82) sectors. On the other hand, the response of wages to unemployment is less pronounced in catering (coefficient of -0.65), manufacturing (-0.57) and mining (-0.54). As we described in Section 2.2, these industries, along with construction, tend to have the highest proportion of low-skilled workers (see Figure 2). The sectoral heterogeneity in wage Phillips curve is also largely present when we extent the time period to 2000 for 9 sectors (see Figure B.2 in Annex). Although confidence bands are somewhat wider, the point estimates for the ψ-coefficients vary for that period between -1.2 and -0.3. Again, the slopes are visually steeper in the sectors with few low-educated workers and relatively flat in the low-skilled industries. The estimates for the other coefficients are consistent with our previous findings. In particular, past inflation and labour productivity growth do not seem to be strong drivers of wage growth after 2008.

Overall, our results provide evidence of considerable sectoral heterogeneity in the wage Phillips curve, echoing evidence for its price counterpart (Byrne et al., 2013; Imbs et al., 2011; Leith and Malley, 2007). The wide variation in the coefficients may not only reflect the nonlinearities observed in Section 3.3, but also point to a role for skills that we study in the next section.

4.2 Skills heterogeneity and the wage Phillips curve

What could contribute to the sectoral heterogeneity in the slope of the wage Phillips curve? As we documented in Section 2.2, an important factor differentiating the sectors is the level of educational attainment, for which the sector-by-sector analysis of Section 4.1 suggested a role in shaping the wage Phillips curve. In particular, the slopes were visually flatter in the sectors with relatively higher shares of low-skilled workers. To formally test this assumption, we augment our baseline framework (equation 2) with an interaction term between the unemployment rate and the share of low-skilled workers, $s^{low}_{c,i,t}$, in country c, sector i and time t. We estimate by 2SLS the following equation using the panel with 18 sectors over the

2008-2020 period[24]

$$\pi^w_{c,i,t} = \alpha + \beta_1 u_{c,i,t} + \beta_2 u_{c,i,t} \times s^{low}_{c,i,t} + \delta \pi_{c,t-1} + \zeta \mathbf{X}_{c,i,t} + \varepsilon_{c,i,t} \tag{6}$$

where β_1 and β_2 capture the slope of the wage Phillips curve for different shares of low-skilled workers. In particular, the slope is downward sloping if $\beta_1 < 0$, and becomes flatter when $\beta_2 > 0$. As an alternative specification, we interact the unemployment rate with the share of high-skilled workers. In that model, a $\beta_2 < 0$ would indicate a steeper wage Phillips curve in the high-skilled sectors.[25] To guard from omitted variables, we include a rich set of control variables in vector $\mathbf{X}_{c,i,t}$ in addition to country-sector and sector-time fixed effects. Specifically, we include at the country-sector and time levels labour productivity growth, the share of low-skilled workers, the share of high-skilled workers, the share of part-time workers and the share of female workers. Additionally, we include at the country level the share of workers that are trade union members from the OECD/AIAS ICTWSS database. Standard errors are clustered at the country-sector level.

However, the variation of the slope across sectors could also reflect the type of jobs workers occupy. In recent work, Daniele and Riccardo (2021) find that the occupation composition of the labour market in favour of non-routine jobs flattens the price Phillips curve.[26] The occupation composition strongly differs across sectors but is not necessarily related to the level of skills. For instance, the simple correlation between the share of low-skilled workers and the share of workers with occupations qualified as "elementary" by the ISCO classification is only 0.3.[27] This suggests that a significant proportion of workers with relatively high education levels occupy jobs demanding lower skills.[28] To study whether the heterogeneity of the slope can be explained by the type of occupations rather than by the education level, we interact the unemployment rate with the share of workers with elementary occupations. Alternatively, we consider a specification where the un-

[24] We instrument $u_{c,i,t}$ and $u_{c,i,t} \times s^{low}_{c,i,t}$ by $z_{c,i,t}$ and $z_{c,i,t} \times s^{low}_{c,i,t}$.

[25] The two tests are different as in one case, we test the effect of a higher share of low-skilled workers with respect to the shares of medium-skilled workers and high-skilled workers whereas in the second case, we test with respect to the shares of low-skilled workers and medium-skilled workers.

[26] However, they find little evidence for an effect on the wage Phillips curve.

[27] ISCO is the acronym for "International Standard Classification of Occupations" and is one of the main international classifications for which ILO is responsible, see https://www.ilo.org/public/english/bureau/stat/isco/ for a complete description of the occupations. Elementary occupations are for instance cleaners and helpers, food preparation assistants, or labourers in mining, construction, manufacturing and transport.

[28] In fact, the over-qualification rate, defined as the persons with a tertiary level of educational attainment working in low- or medium-skilled occupations, was 21% on average in euro area countries in 2020.

Table 8: 2SLS second-stage regression with skills and occupations

Dependent variable: nominal sectoral wage growth

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment	-0.70***	-0.74***	-1.42***	-0.44***	-0.72***	-0.54***
	[0.084]	[0.081]	[0.15]	[0.13]	[0.11]	[0.089]
Unemployment × ShareLowSkills			0.027***			
			[0.0043]			
Unemployment × ShareHighSkills				-0.0092**		
				[0.0045]		
Unemployment × ShareElementary					-0.0017	
					[0.0070]	
Unemployment × ShareProfessionals						-0.013*
						[0.0067]
ShareLowSkills		0.082	-0.23***	0.079	0.083	0.083
		[0.064]	[0.070]	[0.060]	[0.064]	[0.060]
ShareHighSkills		0.068	0.052	0.13	0.068	0.070
		[0.078]	[0.074]	[0.085]	[0.078]	[0.078]
ShareElementary		0.058	0.11*	0.059	0.073	0.056
		[0.065]	[0.064]	[0.063]	[0.096]	[0.063]
ShareProfessionals		-0.0079	-0.021	-0.017	-0.0078	0.047
		[0.065]	[0.062]	[0.065]	[0.065]	[0.075]
Number of sectors	18	18	18	18	18	18
Controls	–	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓	✓
Sector-Time FE	✓	✓	✓	✓	✓	✓
N	1835	1835	1835	1835	1835	1835

Note: This table reports the second-stage estimates of equation 6. Control variables are past inflation, labour productivity growth, the share of part-time workers, the share of female workers, and the share of trade union members. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

employment rate is interacted with the share of workers occupying jobs qualified as "professionals", which by contrast require the highest level of skills.[29]

Table 8 reports the results. We first re-estimate equation 2 as the sample with the new control variables differs from our baseline framework. Column 1 shows

[29]Occupations qualified as professionals include for example the science and engineering professionals, the health professionals, or the information and communications technology professionals.

the estimates for this sample but without the control variables. The estimated coefficient of the slope is negative, statistically different from 0 at a 1% level and very close to our benchmark result (coefficient of 0.70), so as the slope estimate when we include the control variables (Column 2). The third column reports the second-stage regression results of equation 6. The coefficient β_1 is negative and statistically significant (at a 1% level) and suggests that the slope of the wage Phillips curve is -1.42 when the share of low-skilled workers is null. The coefficient of the interaction term β_2 is positive and statistically significant at a 1% level. This indicates that the slope is flatter when the share of low-skilled workers is elevated, hence supporting our initial assumption. Similarly, the coefficient β_2 associated with the share of high-skilled workers is negative and statistically significant from 0 at a 5% level (Column 3). Quantitatively, the β_2-coefficient in this specification is three times lower compared with the baseline estimates of Column 2.

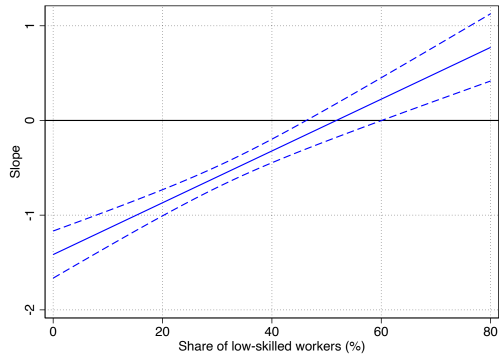
To further gauge the economic relevance of these findings, Figures 5a and 5b represent the slope of the wage Phillips curve conditional on the shares of low-skilled and high-skilled workers, respectively. For both variables, the sensitivity of wages to unemployment exhibits strong heterogeneity across education levels. Specifically, the slope of the wage Phillips curve is -1.31 when the share of low-skilled workers is at the lowest decile of our sample distribution (3.8%). This is significantly steeper than when the share of low-educated workers is at the upper decile of the distribution (42%), for which the coefficient is -0.3. The results give a similar picture when we interact with the share of high-skilled workers, although the differences in slope across the distribution of high-skilled shares are less pronounced than for the low-skilled shares. In particular, the estimated slopes are -0.55 and -1.05 when the share of high-skilled workers is at the 10^{th} and 90^{th} percentiles of the distribution, respectively.

Finally, the last two columns of Table 8 report the results when we interact the unemployment rate with the share of workers by occupation. The estimates of β_2 are not statistically significant for the elementary positions (Column 5) and statistically significant, but at a 10% level, for the professionals (Column 6). Similarly, Figures 5c and 5d depict the conditional slope of the wage Phillips curve, showing visually that the slope does not depend on the occupation composition of the sectoral workforce.

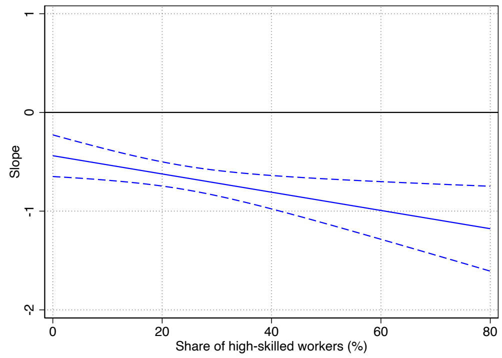
5 Robustness checks

In this section, we perform a number of robustness checks of our baseline estimates. First, we re-estimate equation 2 using alternative sectoral wage measures.

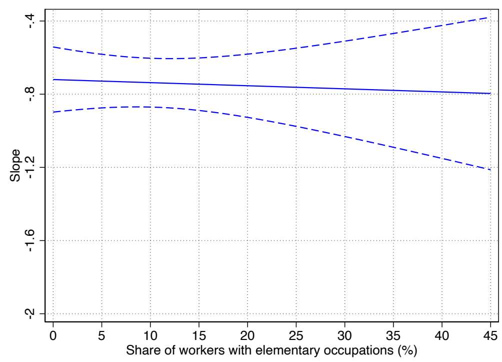
Figure 5: 2SLS estimates conditional on the share of workers by skills and by occupations



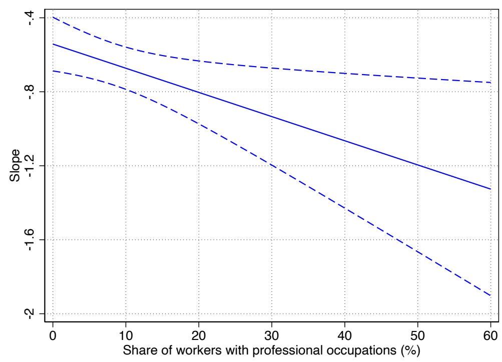
(a) Low-skilled



(b) High-skilled



(c) Elementary occupations



(d) Professionals

Note: This figure reports the second-stage estimates of equation 6. Panel 5a shows the slope of the wage Phillips curve for different shares of low-skilled workers, Panel 5b for different shares of high-skilled workers, Panel 5c for different shares of workers occupying elementary jobs, and Panel 5d for different shares of workers with professional occupations. The x-axis is bounded by the 90^{th} percentile of the conditional variables. The dotted lines correspond to the 90% confidence intervals.

In particular, we use the compensation of employees per hour worked and the unit labour cost. These wage measures are also available at the industry level but not for all sectors.[30] Table D1 in Annex reports the estimation of equation 2 using different wage measures with consistent samples over the 2008-2020 period. The estimates of the slope remain overall very close of our baseline results.

Second, we test the robustness of our results by considering alternative inflation measures. In our baseline framework, we measure inflation expectations by realized inflation in the previous year. Headline inflation includes changes in food, tobacco and energy prices, which are the most volatile items of the HICP index. We exclude these components and use instead the core inflation rate, which better reflects underlying macroeconomic conditions. Again, our results are robust to this alternative option (see Table D2 in Annex): the inflation rate did not seem to be relevant indicator to explain nominal wage growth in the past 20 years. [I also plan to use Consensus Forecasts and inflation expectations of professional forecasters]

As noticed in Section 4.1, the shift-share instrument was a less relevant instrument for the sector-by-sector estimates of the slope in public services. We check the consistency of our results by estimating our baseline equation excluding the public sector (public administration, education and health) from our sample. Our samples therefore include 6 sectors for the 2000-2020 period and 15 sectors for the 2008-2020 period. Table D3 presents the results. The coefficient of the slope is slightly lower for the 2000-2020 period compared with our baseline results (-0.47 versus -0.55), although the two point estimates are not statistically different from each other. On the other hand, the slope estimate remains consistent for the 2008-2020 period (-0.66 versus 0.69).

Third, we use an alternative decomposition of the unemployment rate to construct our shift-share instrument. Specifically, we decompose unemployment as the inner product between skill-group shares and and skill-group unemployment rates. The Bartik instrument is the following

$$z^*_{c,i,t} = \sum_s \omega_{c,i,s,\tau} u_{c,s,t} \tag{7}$$

where s denotes the subscript for three skill groups: low, medium and high. $\omega_{c,i,s,\tau}$ is the percentage of workers in skill group s, country c and sector i in a pre-period τ. The set of shifts $u_{c,s,t}$ represent the national skill-specific s unemployment rates

[30] Wage growth measured either by the compensation of employees per hour worked or by the unit labour cost are not available for the real estate sector as well as for public services (public administration, education and health). We do not control for labour productivity growth when using the unit labour cost as this is defined as the ratio of labour costs to labour productivity, and is therefore already adjusted for productivity.

in country c at time t. This Bartik instrument presents disadvantages compared with our original shift-share instrument. First, we have a less important number of shifts (3 skill groups as opposed to 10 age groups), which undermines the consistency of our instrumental approach (Borusyak et al., 2022). Second, the shocks are not as-good-as-randomly-assigned, as employment in some sectors might depend disproportionately more on labour market developments of certain skills (e.g. low-skilled for the construction sector). Nevertheless, the results presented in Table D4 provide robust estimates of the slope of the wage Phillips curve.

Additionally, we verify the robustness of our slope estimates conditional on the share of workers by education levels or by occupations to an alternative measure of labour market tightness. Specifically, we re-estimate equation 6 replacing the unemployment rate with the job vacancy rate, available at the sectoral level in Eurostat. The job vacancy rate measures the proportion of total positions that are vacant and is defined as number of job vacancies over the number of occupied posts plus the number of job vacancies. Since the job vacancy rate is a demand-side indicator of labour market tightness, it is not subject to labour supply shifts and we can estimate equation 6 by OLS. Table D5 in Annex reports the results. At first glance, the job vacancy rate is not a relevant indicator to explain sectoral wage growth (Column 1). However, the variable becomes statistically significant different from 0 at a 1% level when adding an interaction term between this indicator and the share of low-skilled workers (Column 2). An increase in the job vacancy rate, indicating a tighter labour market, is positively associated with nominal wage growth. Consistent with our initial findings, the relation between wage growth and labour market tightness is less sensitive when the share of low-skilled workers is high, as shown by the negative and statistically significant (at a 1% level) interaction term. In addition, the interaction term between the job vacancy rate and the share of high-skilled workers is positive and statistically significant but only at the 10% level (Column 4). However, the occupation levels do not seem to be relevant to explain wage growth (Columns 4 and 6), hence supporting our baseline results.

Finally, to mitigate endogeneity concerns coming from the shares of workers by education levels or by occupations, we take these indicators as fixed at the beginning of the sample in 2008 and re-estimate equation 6. The interaction term between the unemployment rate and the share of low-skilled workers remains positive and statistically significant at a 1% level and lies in the same range of our baseline estimates (see Table D6 in Annex). By contrast, the interaction term with the share of high-skilled workers continues to be negative but is no longer statistically significant from 0.

6 Conclusion

Exploiting sector-level data and using an instrumental variable approach, this paper finds a relatively steep slope of the wage Phillips curve in euro area countries, and documents large discrepancies across sectors. We first describe large variation in labour market dynamics across industries by constructing a new measure of sectoral unemployment using individual-level data from the EU Labour Force Survey. Using a shift-share instrument that exploits sectoral labour markets' exposure to age-specific unemployment rates, our estimates first show that the slope of the wage Phillips curve is relatively steep. More specifically, we find that a decrease in the unemployment rate leads to an increase in wage growth by 0.7%. Our estimates show that the slope becomes very steep for unemployment rates below 7%. Above that threshold, the slope is nearly flat. We then estimate a wage Phillips curve slope for each individual industry. Our results highlight considerable sectoral heterogeneity across sectors. To explain this heterogeneity, we study the importance of skills. Our results indicate that the slope is flatter in the low-skilled sectors compared with the high-skilled sectors.

Policymakers could read interesting implications at several levels. First, the relationship between wage growth and unemployment may have been more important when using disaggregated data at the sectoral level than previously thought with aggregated data, in particular when labour markets are tight. Second, this analysis highlights that skills heterogeneity matters for the conduct of monetary policy. In particular, the unemployment-inflation trade-off is weaker in the economic activities with a large presence of low-skilled workers. This for example means that expansionary monetary policy tends to exacerbate inequality between high-skilled and low-skilled sectors, through larger wage growth differentials. Finally, our results suggest that policymakers should focus on improving the skills of individuals rather than the occupations themselves.

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A The EU Labour Force Survey

A.1 Correspondence between NACE Rev. 2 and NACE Rev. 1.1

NACE is the acronym (*Nomenclature générale des Activités économiques dans les Communautés Européennes*) used by Eurostat to designate the various statistical classifications of economic activities developed since 1970 in the European Union. A revision of this classification, from NACE Rev. 1.1 to NACE Rev. 2, took place in 2008 to better reflect changes in economic structures and organisations, as well as technological developments (Eurostat, 2008). Table A1 presents the correspondence between the economic sectors of NACE Rev. 1.1 and NACE Rev. 2.

Table A1: Correspondence table between NACE Rev. 2 and NACE Rev. 1.1

NACE Rev. 2		**NACE Rev. 1.1**	
Sector	**Description**	**Sector**	**Description**
B	Mining and quarrying	C	Mining and quarrying
C	Manufacturing	D	Manufacturing
D E	Electricity, gas, steam and air conditioning supply Water supply, sewerage, waste management and remediation activities	E	Electricity, gas and water supply
F	Construction	F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	G	Wholesale and retail trade: repair of motor vehicles, motorcycles and personal and household goods
I	Accommodation and food service activities	H	Hotels and restaurants
H J	Transportation and storage Information and communication	I	Transport, storage and communications
K	Financial and insurance activities	J	Financial intermediation
L M N	Real estate activities Professional, scientific and technical activities Administrative and support service activities	K	Real estate, renting and business activities
O	Public administration and defence; compulsory social security	L	Public Administration and defence; compulsory social security
P	Education	M	Education
Q	Human health and social work activities	N	Health and social work
R S	Arts, entertainment and recreation Other service activities	O	Other community, social and personal services activities

Note: This table describes the correspondence between the NACE Rev. 1.1 classification, valid until 2008, and its the revision, the NACE Rev. 2 classification.

A.2 Sectoral unemployment rate

Description to come.

A.3 International Standard Classification of Education (ISCED)

ISCED is the reference international classification for organising education programmes and related qualifications by levels and fields. The last revision (ISCED 2011) has nine education levels, from level 0 to level 8. The EU Labour Force Survey classifies as ″low″ the levels 1 to 3, as ″medium″ the levels 3 and 4 and as ″high″ the levels 5 to 8.

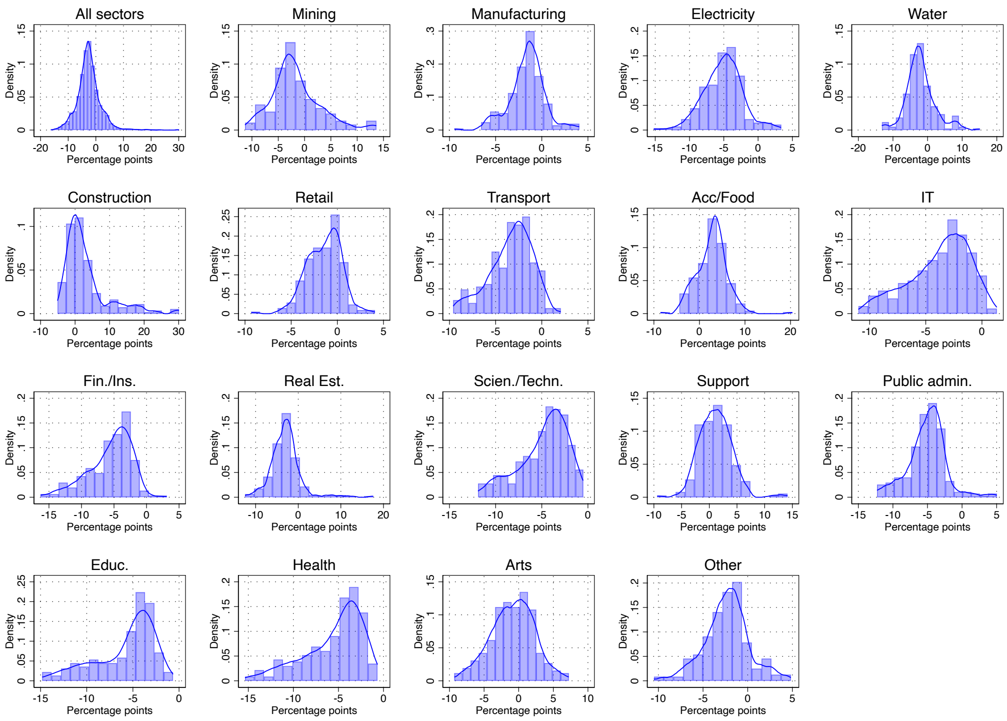
Table A2: Education levels according to Eurostat following the ISCED classification

Eurostat classification	Level	ISCED-11
Low	0	Early childhood education
	1	Primary education
	2	Lower secondary education
Medium	3	Upper secondary education
	4	Post-secondary non-tertiary education
High	5	Short-cycle tertiary education
	6	Bachelor's or equivalent level
	7	Master's or equivalent level
	8	Doctoral or equivalent level

Note: This table describes the education levels of the ISCED-11 classification and their classification by Eurostat.

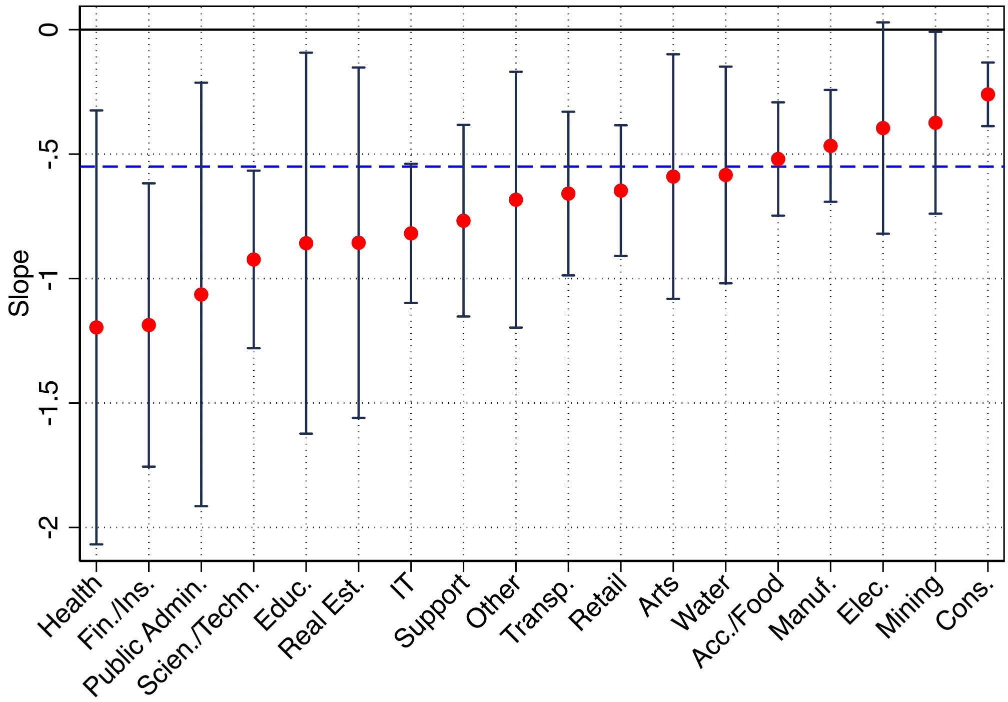
B Additional figures

Figure B.1: Deviation of sectoral unemployment from national unemployment



Note: This chart depicts the histograms of the deviation of sectoral unemployment rate from the national unemployment rate for all individual sectors over the 2008-2020 period.

Figure B.2: 2SLS estimates of sectoral wage Phillips curves (2000-2020)



Note: This figure reports the sector-specific 2SLS estimates of the wage Phillips curve. 90 percent confidence intervals are reported around point estimates. The dotted line represents the 2SLS estimate of ψ in equation 2. Sample with 9 sectors and 17 euro area countries over the 2000-2020 period.

C Additional tables

Table C1: Additional summary statistics

Sector	LCI	Labour prod.	Corr(π^w, u)	Emp. share	Share low-skilled	Share medium-skilled	Share high-skilled
Mining	2.94	1.83	-0.09	0.3	28.5	51.4	20.1
Manuf.	3.19	2.23	-0.25	15.2	24.0	52.4	23.5
Elec.	2.53	1.09	-0.19	0.8	9.9	48.4	41.7
Water	2.43	-0.60	-0.34	0.7	29.6	50.4	20.0
Const.	2.64	0.81	-0.37	7.2	31.7	53.5	14.7
Retail	3.04	1.75	-0.33	14.0	20.9	56.3	22.7
Transp.	2.80	0.10	-0.33	5.6	24.1	57.7	18.2
Acc./Food	3.42	-1.25	-0.26	4.8	28.0	57.2	14.8
IT	2.96	1.16	-0.43	3.1	5.4	34.2	60.4
Fin./Ins.	2.52	0.67	-0.16	3.2	3.9	36.2	59.9
Real Est.	3.06	0.87	-0.25	0.8	12.3	48.1	39.6
Scien./Techn.	2.79	0.33	-0.37	5.2	4.1	27.6	68.3
Support	3.29	0.86	-0.35	3.7	28.3	49.3	22.4
Publ. Admin	2.84	0.27	-0.09	7.1	12.0	42.1	45.9
Educ.	2.72	0.27	-0.29	7.8	5.6	23.0	71.4
Health	3.19	0.27	-0.35	9.9	12.2	42.6	45.2
Arts	3.41	-0.47	-0.24	1.8	14.2	43.8	42.0
Other	3.33	-0.01	-0.32	2.2	18.2	54.2	27.6

Note: This table reports the mean of listed variables by NACE 2 sector across euro area countries over the 2008-2020 period. The first and second columns present the average nominal wage growth (in %) and the average labour productivity productivity growth (in %). The third column shows the simple correlation between nominal wage growth and unemployment. The fourth column shows the employment share (as a % of total employment) and the following columns describe the average share of low/medium/high-skilled workers by sector (in % of the workforce).

Table C2: Post-2008 change in the slope of the wage Phillips curve

Dependent variable: nominal sectoral wage growth

	I. Country-sector panel (2SLS)	II. Country panel (OLS)
	2000-2020	2000-2020
	(1)	(2)
Unemployment	-0.79***	-0.42
	[0.17]	[0.25]
Unemployment × Post-2008	0.25*	-0.038
	[0.15]	[0.23]
Past inflation	-0.0059	0.24**
	[0.10]	[0.11]
Labour productivity	0.041*	0.21*
	[0.021]	[0.11]
Number of sectors	9	-
Sector-Time FE	✓	-
Country-Sector FE	✓	-
Country FE	–	✓
Time FE	–	✓
N	2233	327

Note: This table reports the second-stage estimates of equation 2 augmented with a interaction term between the unemployment rate and a dummy variable that takes 1 after 2008. Standard errors (in brackets) are clustered at the country-sector level in Column 1 and at the country level in Column 2.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table C3: OLS estimation

Dependent variable: nominal sectoral wage growth

	Country-sector panel (OLS)		
	2000-2020	2000-2020	2008-2020
	(1)	(2)	(3)
Unemployment	-0.30***	-0.36***	-0.38***
	[0.052]	[0.056]	[0.040]
Past inflation	0.23***	-0.40***	-0.28***
	[0.066]	[0.12]	[0.093]
Labour productivity	0.043**	0.014	0.029**
	[0.019]	[0.018]	[0.014]
Number of sectors	9	9	18
Sector-Time FE	✓	✓	✓
Country-Sector FE	✓	✓	✓
N	3007	1909	3858

Note: This table reports the OLS estimates of equation 2. Standard errors (in brackets) are clustered at the country-sector level in Column 1 and at the country level in Column 2.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table C4: 2SLS estimates of sectoral wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Mining	Manuf.	Elec.	Water.	Cons.	Retail
Unemployment	-0.54**	-0.57***	-0.40	-0.58**	-0.32***	-0.83***
	[0.20]	[0.12]	[0.26]	[0.27]	[0.082]	[0.16]
Past inflation	-0.33	-0.044	-0.40	-0.13	-0.17	-0.0026
	[0.44]	[0.22]	[0.36]	[0.25]	[0.34]	[0.19]
Labour productivity	-0.0088	-0.0098	0.067	0.082*	0.0029	0.19**
	[0.038]	[0.033]	[0.053]	[0.044]	[0.030]	[0.073]
2SLS first stage estimates						
Bartik instrument	0.89***	0.93***	0.55***	0.93***	2.09***	0.79***
	[0.139]	[0.061]	[0.047]	[0.190]	[0.196]	[0.034]
F-stat > 10	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	172	191	187	188	190	191

Note: This table reports the 2SLS first stage and the 2SLS second stage of equation 5 for the ”Mining”, ”Manufacturing”, ”Electricity”, ”Water”, ”Construction” and ”Retail” sectors. Standard errors (in brackets) are clustered at the country level.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table C5: 2SLS estimates of sectoral wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Transp.	Acc./Food	IT	Fin./Ins.	Real Est.	Scien./Techn.
Unemployment	-0.66***	-0.65***	-0.82***	-2.03***	-0.86*	-0.92***
	[0.20]	[0.19]	[0.17]	[0.60]	[0.43]	[0.22]
Past inflation	0.15	-0.011	0.21	-0.29	-0.45	0.37*
	[0.52]	[0.33]	[0.45]	[0.23]	[0.29]	[0.20]
Labour productivity	0.077	-0.051	0.040	0.016	0.013	0.098
	[0.046]	[0.085]	[0.068]	[0.046]	[0.10]	[0.065]
2SLS first stage estimates						
Bartik instrument	0.71***	0.88***	0.67***	0.35***	0.68***	0.61***
	[0.033]	[0.067]	[0.100]	[0.070]	[0.129]	[0.057]
F-stat $>$ 10	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	191	191	191	191	188	191

Note: This table reports the 2SLS first stage and the 2SLS second stage of equation 5 for the "Transport", "Accommodation and food services", "IT", "Finance and Insurance", "Real Estate" and "Science and Technology" sectors. Standard errors (in brackets) are clustered at the country level.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table C6: 2SLS estimates of sectoral wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Support	Public Admin.	Educ.	Health	Arts	Other
Unemployment	-0.77***	-1.11**	-0.90	-0.99	-0.59*	-0.68**
	[0.23]	[0.49]	[0.76]	[0.72]	[0.30]	[0.31]
Past inflation	-0.64**	-1.26***	-0.33**	-0.55***	-0.46**	0.56
	[0.24]	[0.14]	[0.15]	[0.12]	[0.18]	[0.38]
Labour productivity	0.057	0.15	0.29*	0.15	0.036	-0.12*
	[0.068]	[0.16]	[0.15]	[0.15]	[0.064]	[0.071]
2SLS first stage estimates						
Bartik instrument	0.78***	0.48***	0.42***	0.38***	0.72***	0.77***
	[0.087]	[0.086]	[0.054]	[0.039]	[0.078]	[0.053]
F-stat > 10	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	191	178	178	178	191	191

Note: This table reports the 2SLS first stage and the 2SLS second stage of equation 5 for the "Support services", "Public administration", "Education", "Health", "Arts and entertainment" and "Other" sectors. Standard errors (in brackets) are clustered at the country level.
* / ** / *** indicate 10% / 5% / 1% significance level.

D Robustness checks

Table D1: 2SLS estimates of the wage Phillips curve with alternative wage measures

Dependent variable: nominal sectoral wage growth

Wage growth measure:	Labour cost index	Comp. per hour worked	ULC
Unemployment	-0.651***	-0.575***	-0.689***
	[0.0663]	[0.0852]	[0.0967]
Past inflation	-0.0721	-0.360***	-0.184
	[0.109]	[0.120]	[0.176]
Labour productivity	0.0288*	0.408***	
	[0.0162]	[0.0602]	
Number of sectors	14	14	14
Sector-Year FE	✓	✓	✓
Country-Sector FE	✓	✓	✓
N	2647	2648	2648

Note: This table reports the 2SLS second stage of equation 2 with alternative wage measures. Column 1 reports the slope estimate using the labour cost index, Column 2 with compensation per hour worked and Column 3 with the unit labour cost. We do not control for labour productivity growth when using the unit labour cost as it this measure is adjusted for productivity. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table D2: 2SLS estimates of the wage Phillips curve using core inflation

Dependent variable: nominal sectoral wage growth

	2000-2020	2008-2020	2008-2020
	(1)	(2)	(3)
Unemployment	-0.59***	-0.73***	-0.72***
	[0.077]	[0.093]	[0.069]
Core inflation	-0.030	-0.38**	-0.21
	[0.13]	[0.17]	[0.13]
Labour productivity	0.039*	0.014	0.032**
	[0.021]	[0.022]	[0.016]
Number of sectors	9	9	18
Sector-Time FE	✓	✓	✓
Country-Sector FE	✓	✓	✓
N	2154	1660	3369

Note: This table reports the 2SLS second stage of equation 2 using core inflation in previous year. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table D3: 2SLS estimates of the wage Phillips curve excluding public services

Dependent variable: nominal sectoral wage growth

	2000-2020	2008-2020	2008-2020
	(1)	(2)	(3)
Unemployment	-0.47***	-0.61***	-0.66***
	[0.071]	[0.085]	[0.066]
Past inflation	0.14	-0.14	-0.096
	[0.12]	[0.14]	[0.11]
Labour productivity	0.032	0.0019	0.027*
	[0.020]	[0.021]	[0.016]
Number of sectors	6	6	15
Sector-Time FE	✓	✓	✓
Country-Sector FE	✓	✓	✓
N	1528	1126	2835

Note: This table reports the 2SLS second stage of equation 2 excluding public services. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table D4: 2SLS estimates of the wage Phillips curve using Bartik instrument based on skill groups

Dependent variable: nominal sectoral wage growth

	2000-2020	2008-2020	2008-2020
	(1)	(2)	(3)
Unemployment	-0.50***	-0.70***	-0.72***
	[0.072]	[0.087]	[0.065]
Past inflation	0.21***	-0.37***	-0.27***
	[0.079]	[0.13]	[0.10]
Labour productivity	0.048**	0.022	0.034**
	[0.021]	[0.021]	[0.015]
Number of sectors	9	9	18
Sector-Time FE	✓	✓	✓
Country-Sector FE	✓	✓	✓
N	2988	1909	3858

Note: This table reports the 2SLS second stage of equation 2 instrumenting the unemployment rate by the Bartik instrument based on a skill-group decomposition. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

Table D5: Estimates of the wage Phillips curve using the job vacancy rate

Dependent variable: nominal sectoral wage growth

	(1)	(2)	(3)	(4)	(5)
JVR	0.046	1.52***	-0.86	0.13	-0.20
	[0.35]	[0.52]	[0.61]	[0.45]	[0.45]
JVR × ShareLowSkills		-0.078***			
		[0.021]			
JVR × ShareHighSkills			0.026*		
			[0.014]		
JVR × ShareElementary				-0.0073	
				[0.020]	
JVR × ShareProfessionals					0.014
					[0.015]
ShareLowSkills	-0.020	0.054	-0.021	-0.019	-0.019
	[0.056]	[0.065]	[0.056]	[0.057]	[0.057]
ShareHighSkills	0.050	0.030	-0.000059	0.049	0.048
	[0.061]	[0.060]	[0.063]	[0.061]	[0.060]
ShareElementary	0.19**	0.20*	0.18*	0.20*	0.19*
	[0.095]	[0.10]	[0.095]	[0.11]	[0.095]
ShareProfessionals	-0.060	-0.059	-0.060	-0.060	-0.081
	[0.076]	[0.077]	[0.076]	[0.076]	[0.082]
Number of sectors	18	18	18	18	18
Controls	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓
Sector-Time FE	✓	✓	✓	✓	✓
N	1701	1701	1701	1701	1701

Note: This table reports the estimation of equation 6 using the job vacancy rate (JVR) as the measure of labour market tightness. Standard errors (in brackets) are clustered at the country-sector level. * / ** / *** indicate 10% / 5% / 1% significance level.

Table D6: 2SLS estimates of the wage Phillips curve fixing the shares in 2008

Dependent variable: nominal sectoral wage growth

	(1)	(2)	(3)	(4)	(5)
Unemployment	-0.70***	-1.53***	-0.53***	-0.75***	-0.48***
	[0.084]	[0.16]	[0.12]	[0.12]	[0.099]
Unemployment × $\text{ShareLowSkills}^{2008}$		0.029***			
		[0.0044]			
Unemployment × $\text{ShareHighSkills}^{2008}$			-0.0079		
			[0.0049]		
Unemployment × $\text{ShareElementary}^{2008}$				-0.00031	
				[0.0066]	
Unemployment × $\text{ShareProfessionals}^{2008}$					-0.017**
					[0.0072]
Number of sectors	18	18	18	18	18
Controls	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓
Sector-Time FE	✓	✓	✓	✓	✓
N	1835	1835	1835	1835	1835

Note: This table reports the estimation of equation 6 using the shares fixed in 2008. Standard errors (in brackets) are clustered at the country-sector level.
* / ** / *** indicate 10% / 5% / 1% significance level.

E Country-specific slopes

E.1 Time sample: 2008-2000, Number of sectors = 18

Table E1: 2SLS estimates of country wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Austria	Belgium	Estonia	Finland	France	Germany
Unemployment	1.70*	-0.24***	-1.11***	-1.02**	-0.85***	-0.31***
	[0.89]	[0.056]	[0.26]	[0.35]	[0.24]	[0.092]
Past inflation	2.20*	0.44***	-0.071	0.56**	-0.090	0.60***
	[1.13]	[0.027]	[0.13]	[0.26]	[0.10]	[0.12]
Labour productivity	0.087	-0.012	0.100**	-0.11**	0.0049	-0.0072
	[0.18]	[0.012]	[0.042]	[0.046]	[0.036]	[0.037]
2SLS first stage estimates						
Bartik instrument	1.78***	0.76***	0.72***	0.80***	0.72***	0.87***
	[0.456]	[0.094]	[0.097]	[0.108]	[0.177]	[0.133]
F-stat > 10	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	108	233	215	231	195	232

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E2: 2SLS estimates of country wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Greece	Ireland	Italy	Latvia	Lithuania	Netherlands
Unemployment	-1.11***	-0.38***	-0.78***	-1.57***	-2.79***	-1.04***
	[0.26]	[0.11]	[0.16]	[0.25]	[0.46]	[0.19]
Past inflation	-0.071	0.41**	0.14	0.25	1.73***	0.43**
	[0.13]	[0.19]	[0.14]	[0.16]	[0.31]	[0.16]
Labour productivity	0.100**	0.024	-0.054	-0.010	0.29**	-0.43**
	[0.042]	[0.041]	[0.048]	[0.053]	[0.13]	[0.20]
2SLS first stage estimates						
Bartik instrument	0.72***	0.83***	0.54***	0.80***	0.69***	0.47***
	[0.097]	[0.208]	[0.091]	[0.112]	[0.108]	[0.047]
F-stat > 10	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	215	234	234	198	179	225

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E3: 2SLS estimates of country wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Portugal	Slovakia	Slovenia
Unemployment	-0.80***	-1.52***	-1.79***
	[0.14]	[0.31]	[0.36]
Past inflation	-0.54**	0.096	1.10***
	[0.22]	[0.26]	[0.22]
Labour productivity	-0.054	-0.013	0.084
	[0.11]	[0.052]	[0.081]
2SLS first stage estimates			
Bartik instrument	0.79***	0.50***	0.53***
	[0.107]	[0.066]	[0.098]
F-stat > 10	✓	✓	✓
Sector FE	✓	✓	✓
N	234	195	188

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E.2 Time sample: 2000-2000, Number of sectors = 9

Table E4: 2SLS estimates of country wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Austria	Belgium	Estonia	Finland	France	Germany
Unemployment	2.43*	-0.12	-1.11**	-0.098	-0.55***	-0.27***
	[1.16]	[0.073]	[0.34]	[0.22]	[0.099]	[0.078]
Past inflation	3.72*	0.51***	0.094	0.46**	-0.091	0.36*
	[1.82]	[0.034]	[0.11]	[0.18]	[0.13]	[0.17]
Labour productivity	-0.15*	0.013	0.14**	-0.084**	0.12	-0.012
	[0.066]	[0.0075]	[0.061]	[0.028]	[0.066]	[0.050]
2SLS first stage estimates						
Bartik instrument	1.62***	0.72***	0.75***	0.95***	0.91***	0.83***
	[0.478]	[0.131]	[0.180]	[0.170]	[0.188]	[0.199]
F-stat > 10	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	54	144	108	184	102	179

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E5: 2SLS estimates of country wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Greece	Ireland	Italy	Latvia	Lithuania	Netherlands
Unemployment	-1.11**	-0.32*	-0.54*	-2.56***	-2.22***	-1.58***
	[0.34]	[0.15]	[0.24]	[0.62]	[0.54]	[0.34]
Past inflation	0.094	0.45*	0.31	0.51**	1.35***	0.38
	[0.11]	[0.21]	[0.19]	[0.22]	[0.16]	[0.20]
Labour productivity	0.14**	0.015	-0.024	-0.10	0.17	-0.25
	[0.061]	[0.023]	[0.034]	[0.11]	[0.25]	[0.26]
2SLS first stage estimates						
Bartik instrument	0.75***	0.98**	0.57***	0.79***	0.80***	0.43***
	[0.180]	[0.389]	[0.172]	[0.187]	[0.159]	[0.066]
F-stat > 10	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N	108	117	186	131	107	179

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E6: 2SLS estimates of country wage Phillips curves

Dependent variable: nominal sectoral wage growth

	Portugal	Slovakia	Slovenia
Unemployment	-0.66***	-1.18**	-1.65**
	[0.18]	[0.41]	[0.51]
Past inflation	-0.63**	0.54**	0.66*
	[0.21]	[0.17]	[0.31]
Labour productivity	0.048	0.12**	0.074
	[0.19]	[0.044]	[0.11]
2SLS first stage estimates			
Bartik instrument	0.79***	0.55***	0.54***
	[0.173]	[0.094]	[0.188]
F-stat > 10	✓	✓	✓
Sector FE	✓	✓	✓
N	159	124	93

Standard errors in brackets

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$