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Wage growth in Lithuania from 2008 to 2020: observed drivers and underlying shocks*

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ABSTRACT

This paper studies the drivers of wage growth in Lithuania over the period 2008–2020. Using administrative data as well as aggregate measures reflecting the state of the economy, we estimate an extended version of a wage Phillips curve. Our reduced-form estimates indicate that nominal wage growth was tightly linked to labor market fluctuation over this period. Labor productivity, changes in the minimum wage, and the composition of employment also contributed to wage dynamics. However, we find little evidence that past inflation has been a push factor. To understand the underlying economic primitives behind our findings, we estimate a structural Bayesian autoregressive model. Our structural analysis reveals a significant contribution from aggregate supply shocks, reflecting a stronger relationship between productivity and wages than implied by our reduced-form estimates. Moreover, a historical decomposition reveals that since 2013, wages grew over and above productivity due to rising aggregate demand and labor market disturbances.

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Wage growth; Phillips curve; structural BVAR; administrative data

1. Introduction

Since the Great Recession and up to the COVID-19 pandemic, weak wage growth has characterized the euro area labor market and has been a major concern for policymakers (Nickel et al., 2019). However, there was considerable heterogeneity between countries (see Figure 1). On the one hand, wage growth has been moderate in Southern and Western Europe, with annual growth rates below 3% in all these economies. On the other hand, wages in the Baltic States, Slovakia and Slovenia grew more than twice as fast as the euro area average.

In this article, we provide a detailed analysis of the factors underlying nominal wage growth observed in Lithuania between 2008–2020. We use rich administrative and aggregate data to highlight the factors behind this multi-faceted wage growth. We rely on microdata in order to account for the role of worker characteristics (e.g. age, gender), job characteristics (e.g. occupation, tenure), and firm profiles (e.g. location, sector) in wage growth, which is important in our setting given the changes that the Lithuanian

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*The views expressed in this article are those of the authors and do not necessarily reflect the position of the Bank of Lithuania or the Eurosystem. All errors are ours.

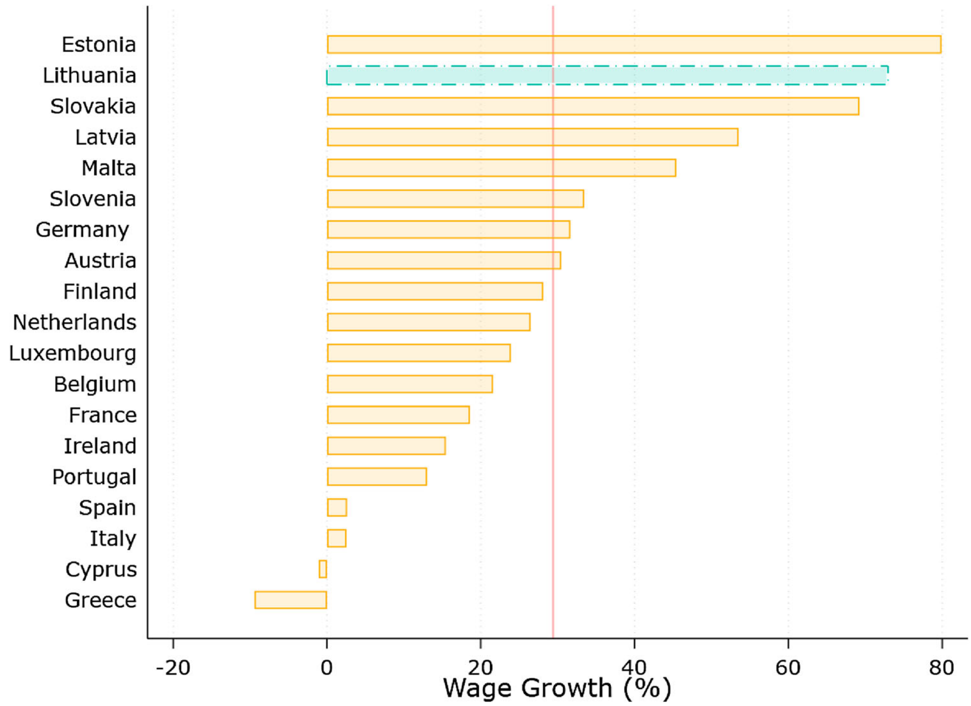

Figure 1. Nominal Wage Growth in the Euro Area, 2008–2020. Source: Authors' calculations based on Eurostat.

Notes: Wage growth refers to the (percent) change in average wages and salaries between 2008 and 2020. The vertical line represents the euro area average.

economy underwent after the Great Recession. Moreover, macroeconomic data combined with wages net of composition changes enable us to (i) measure the structural links between wage growth, price inflation and productivity growth as well as (ii) identify the primitives behind cyclical fluctuations of wage growth.

We explore these facets in three steps. First, we compare trends in the main aggregate indicators – productivity, inflation, labor market conditions, and minimum wages with nominal wage growth – in Lithuania and other euro area economies. This comparison highlights the outstanding dynamism of wage growth in Lithuania over the period. Second, we estimate an extended version of the canonical wage Phillips curve (Blanchard & Katz, 1999; Gali, 2011), to measure the correlation of key macroeconomic variables and workforce dynamics on observed wage growth. Third, we identify the underlying economic shocks that explain the cyclical dynamics of real wage growth. To do so, we estimate a structural Bayesian vector autoregressive model (BVAR) to quantify the role of aggregate supply and demand shocks, as well as labor market perturbations summarized in labor supply and wage bargaining shocks in the spirit of Conti and Nobili (2019) and Foroni et al. (2018).

By carrying out this in-depth analysis using state-of-the-art econometric methods, our article aims primarily at informing policymakers. In addition, our estimates can also be placed in the literature concerning estimates of price/wage Phillips curves after the Great Recession (Ball & Mazumder, 2021; Bańbura & Bobeica, 2023; Bulligan & Viviano, 2017).

Our findings are the following. First, compared to other euro area economies, Lithuania has experienced not only higher wage growth, but also higher increases in labor productivity as well as price and minimum wage levels and, at the same time, a faster reduction in labor market slack coupled with a larger decline in the working age population. Second, Lithuania has also exhibited changes in terms of the composition of employment, the most prominent being the aging of the population, as well as greater shares of employment in the service sector and in the two largest cities. Third, the decomposition of wage growth into observed factors using estimates from the wage Phillips curve reveals that wage growth seems to be extremely sensitive to changes in labor market slack (unemployment) throughout the period. Both labor productivity and the minimum wage also contributed to wage dynamics in specific periods, while the contribution of past inflation is nil. Fourth, our structural analysis in BVAR highlights that aggregate demand explains 20% of the variation in real wage growth in the short run and aggregate supply shocks 50%, and the rest being attributed to labor market disturbances. This suggests a closer relationship between productivity and wages than predicted by the reduced-form model, the latter being biased by the importance of wage bargaining disturbances in explaining the dynamics of the wage-unemployment relationship. Finally, the model reveals that the continuous increase in wage growth since 2013 has been driven primarily by aggregate demand and supply shocks or, loosely speaking, economic growth. In addition, labor market shocks positively contributed to wage growth above and beyond aggregate shocks. This suggests a stronger wage bargaining position for workers in recent years, probably driven by labor shortages and labor market policies.

The rest of the paper is organized as follows. Section 2 compares changes in aggregate variables, that are potentially linked to wage growth, between Lithuania and other euro area economies between 2008–2020. Section 3 describes the data we use in our analysis and provide an overview of the dynamics of the variables of interest. Section 4 presents the wage Phillips curve model and discusses the associated results, while Section 5 introduces the structural VAR approach and describes the historical decomposition of wage growth into its underlying economic fundamentals. Section 6 concludes.

2. The Lithuanian economy and the euro area

Since the enlargement of the European Union in 2004, the Baltic States in general, and Lithuania in particular, have been catching up with the most advanced economies (Randveer & Staehr, 2021). This process of convergence suggests that economic growth may be behind the observed trends in wage growth, especially given that Lithuania is still at the bottom part of the distribution of euro area countries in terms of wage levels (Figure 2). In this section, we compare Lithuania with other euro area economies by providing an overview of the evolution of economic indicators that are theoretically related to wage dynamics: labor productivity, inflation, labor market conditions, and minimum wage policy.

According to standard economic theory, if the labor supply is not perfectly elastic, the increase in labor productivity should induce wage growth at the macroeconomic level in the long run. Figure 3 shows labor productivity growth, measured as the growth rate in gross value added per employee, between 2008 and 2020. Looking at the average growth rate in the euro area, the evidence reveals that labor productivity has somewhat grown more than wages, in line with recent evidence on the decoupling of wages and

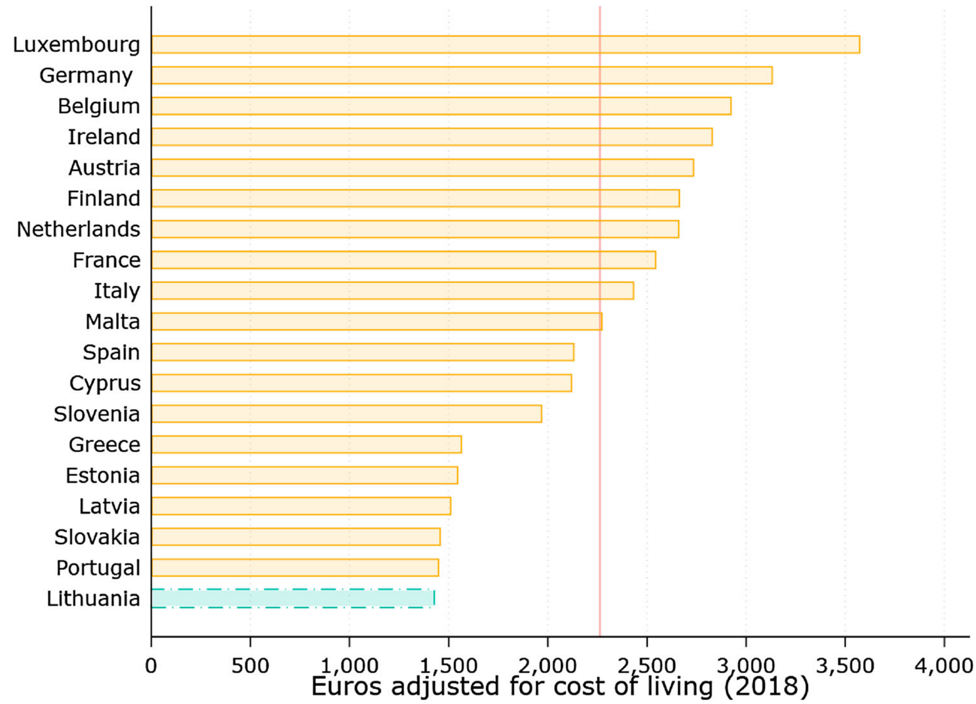

Figure 2. Monthly Earnings. Sources: Authors' calculations based on Eurostat.
Notes: Wages refer to gross monthly earnings adjusted for differences in the cost of living in 2018. Vertical line is the euro area average.

productivity in OECD countries (OECD, 2018a). However, despite being one of the countries with the highest productivity gains between 2008 and 2020, in Lithuania (as well as in Latvia, Estonia, Slovakia and Slovenia) wage growth has far outpaced productivity growth, highlighting that 'reverse' decoupling is a feature of some Central and Eastern European economies (Schröder, 2020). Therefore, the evidence suggests that labor productivity growth is a potential driver of the observed wage growth but, given the magnitude of the increase, it is unlikely to be the only one.

Another related dimension that can potentially affect wage growth is price pressure. A common reason why price growth may translate into wage growth is the existence of wage indexation, i.e. automatic wage increases linked to inflation. Importantly, a theoretical wage Phillips curve predicts a negative relationship between wage growth and the unemployment rate conditional on lagged price inflation (Gali, 2011). In this case, lagged inflation can be generally taken as an indicator of current expected inflation (Blanchard & Katz, 1999), and be used by workers to bargain over wages. Thus, even in the absence of wage indexation (as it is the case of Lithuania), past inflation could potentially affect wage growth. In Figure 4, we look at the the overall growth in harmonized consumer prices over 2008 and 2020. The figure echoes the well-documented episodes of missing inflation and disinflation in the euro area (Bobeica & Jarociński, 2019). Most relevant for our purposes is that the evidence reveals that, despite being above the euro area average, price inflation was still well

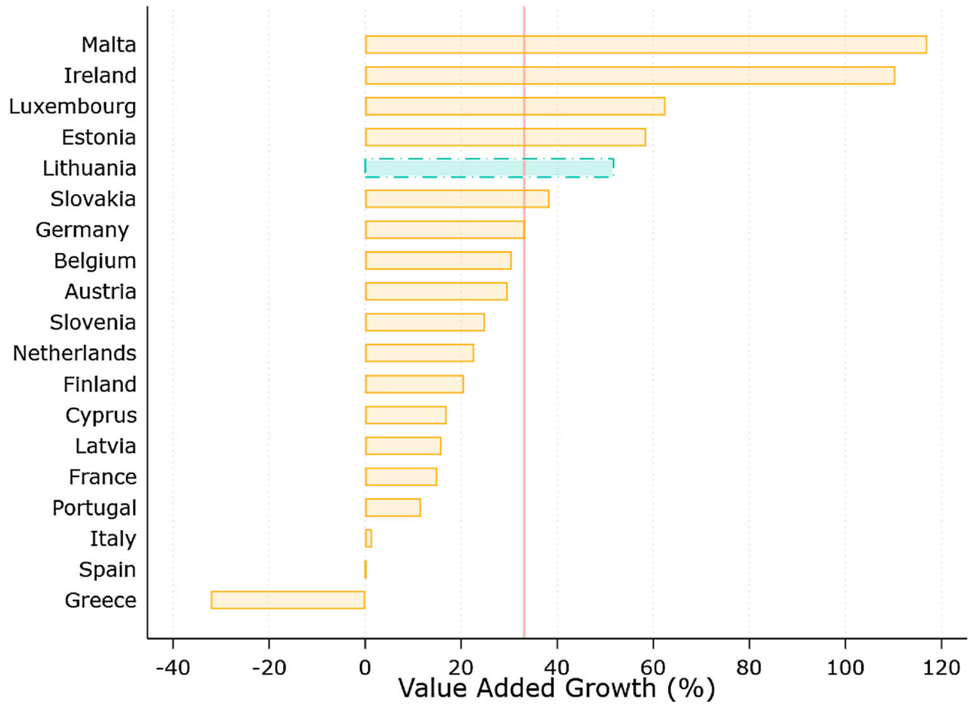

Figure 3. Labor Productivity. Source: Authors' calculations based on Eurostat.
Notes: Growth rates refer to the (percent) change in selected variables between 2008 and 2020. Labor productivity is measured as gross nominal value added per employee. The vertical line represents the euro area average.

below nominal wage growth, suggesting a weak link between price growth and wage growth over the period under analysis.

The state of labor market is arguably one of the main determinants of wages in modern economies. Standard search and matching theory predicts that tighter labor markets, i.e. when labor demand (job postings) exceeds labor supply (job seekers), are associated with higher wage growth, and vice versa. In other words, in tighter labor markets worker's bargaining position is stronger, allowing them to extract a larger surplus from the labor relationship with the firm (Mortensen & Pissarides, 1999).

Figure 5 compares labor market trends in the euro area, plotting the changes in working-age population (Panel A) and labor market slack (Panel B) between 2008 and 2020.[1] On the one hand, Panel A indicates that Lithuania has experienced a large contraction in its working-age population since 2008, which may imply a reduction in the effective labor supply. On the other hand, Panel B reveals that the country has shown a faster improvement in labor market conditions, as measured by labor market slack, relative to other euro area economies and comparable only to Latvia and Estonia. Taken together, a tighter labor market, fueled by economic growth, coupled with a fixed, or rather shrinking, labor supply, is consistent with labor market conditions playing an important role in the observed levels of wage growth in Lithuania between 2008 and 2020.

Figure 6 plots the change in the minimum wage level between 2008 and 2020. The figure indicates that the 5 countries with the largest cumulative increase in the

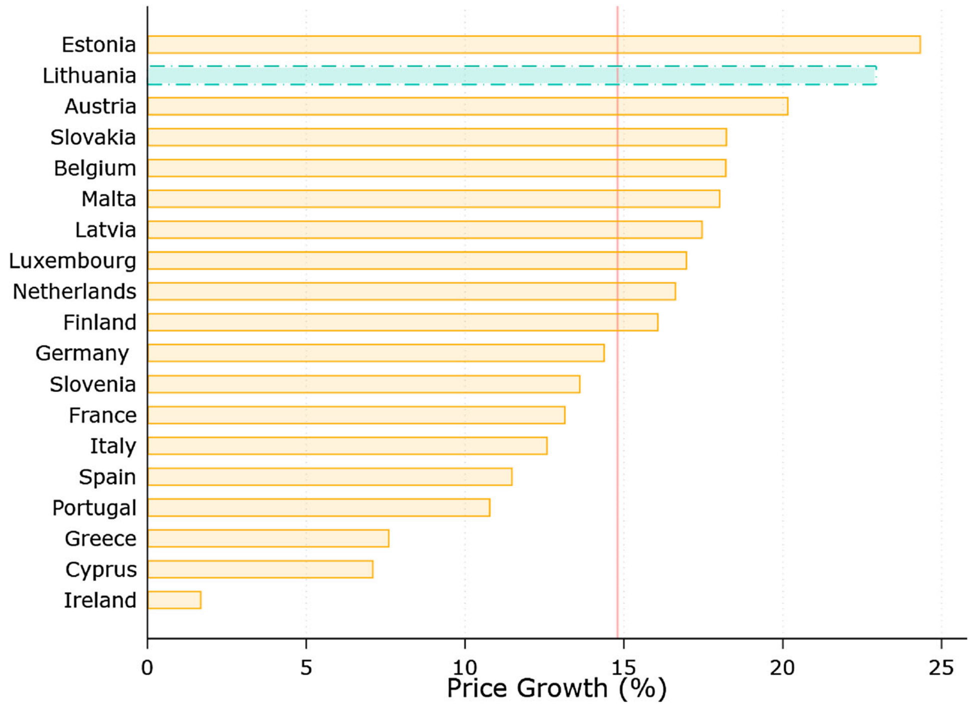

Figure 4. Consumer Prices. Source: Authors' calculations based on Eurostat.

Notes: Growth rates refer to the (percent) change in selected variables between 2008 and 2020. Consumer prices refer to the harmonized consumer price index. The vertical line represents the euro area average.

minimum wage are those that exhibit the highest wage growth over the period. This substantial increase in the minimum wage in these countries is explained by policy interventions to address the high degree of income inequality that characterizes several Central

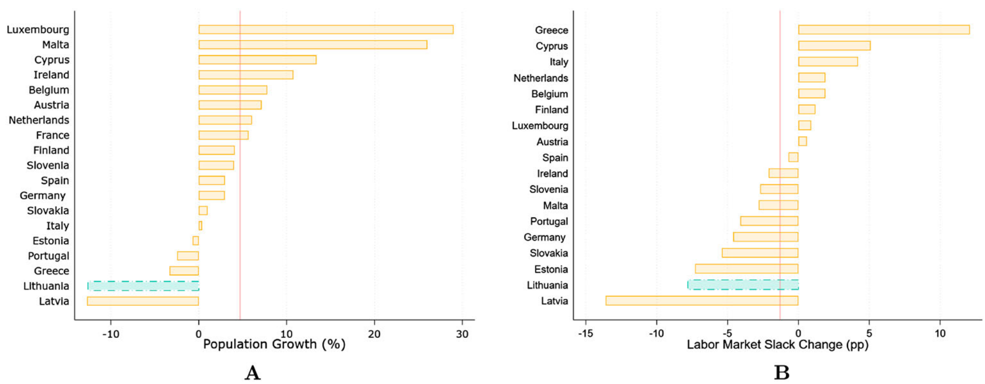

Figure 5. Labor Force and Labor Market Slack. (a) Working Age Population (b) Labor Market Slack. Source: Authors' calculations based on Eurostat.

Notes: Growth rates refer to the change in selected variables between 2008 and 2020. Labor market slack includes (i) the unemployed, (ii) underemployed part-time workers (i.e. part-time workers who want to work more), (iii) persons who are available for work but are not looking for a job, and (iv) persons who are looking for a job but are not available for a job. The change in labor market slack refers to the percentage point change between 2009 and 2020. France is excluded from the labor market slack evidence due to a lack of data. The vertical lines represent the euro area average.

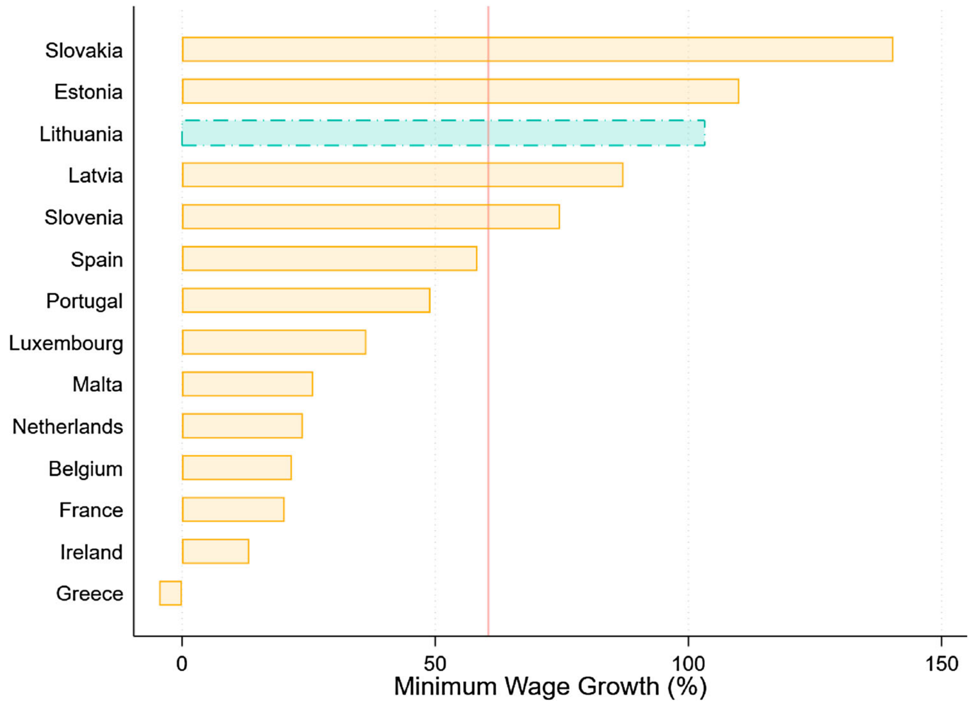

Figure 6. Minimum Wage Policy. Source: Authors' calculations based on Eurostat.

Notes: Growth rates refer to the (percent) change in selected variables between 2008 and 2020. Only countries with a national minimum wage in 2008 are included. The vertical line represents the euro area average.

and Eastern European economies relative to Western and Southern Europe (Brien et al., 2019; Bubbico & Freytag, 2018). Importantly, while minimum wage hikes mechanically push up wages at the bottom of the income distribution, whether they affect the wage growth of the average worker ultimately depends on (i) how deep the minimum wage increase in question bites in the distribution, and (ii) the magnitude of spillover effects (Fortin et al., 2021).

Existing studies on the effect of minimum wage hikes on wage growth in these economies suggest that, especially in the early part of our study period, minimum wage increases affected a non-negligible number of workers and the size of the spillover effects was substantial (see for instance Ferraro et al., 2018 for Estonia or Garcia-Louzao & Tarasonis, 2023 for Lithuania). Thus, although in theory there is no direct mapping of whether (and to what extent) minimum wage may affect average wage growth, the fact that Lithuania is among the countries with the highest wage growth *and* the highest total increase in minimum wage levels between 2008 and 2020 might be suggestive that minimum wage policy has played a role in wage dynamics in Lithuania.

The evidence in this section suggests that nationwide developments might have contributed to the wage dynamics observed in Lithuania. However, it could be argued that wage growth is not only determined by the variation in aggregate conditions, but also by micro-level changes affecting the composition of the labor force. To document the dynamics of worker, job, and firm characteristics, we use comprehensive administrative records covering a quarter of the Lithuanian population. In the following section, we provide a description of this microdata, which we will use in the econometric analysis, along with a discussion of some summary statistics derived from the data.

3. Data

3.1. Social security records

The main source of data comes from administrative records provided by the State Social Security Fund Board (SoDra).[2] The SoDra data is a longitudinal dataset composed of individuals born in an odd-numbered month of each even-numbered year who are enrolled in the Social Security system at any time between 2008 and 2020.[3] Prior to 2010, employers were required by law to report information on their employees only on a quarterly basis, while as of 2010 the frequency of data is monthly.

The dataset includes information on earnings and working days for every worker-firm pair in each period.[4] We use earnings and working days to compute wage rates referring to daily earnings.[5] In addition, the data provides identifiers for individuals and companies that allow tracking of matches between workers and companies over time, along with observed worker (e.g. gender, age), job (e.g. tenure, occupation), and firm (e.g. location, sector) characteristics. This is key for our purposes as it will allow us to account for changes in the composition of workforce that can affect the relationship between wage growth and the aggregate variables of interest.[6]

The SoDra dataset is supplemented with quarterly information on the unemployment rate, labor productivity, and inflation provided by Statistics Lithuania. Given the time-frequency with which these measures are observed, we construct a quarterly panel of workers employed between 2008 and 2020 who earned at least one monthly minimum wage.[7] The analysis sample contains about 250,000 individuals per quarter for a total of 11,043,371 worker-quarter observations.

3.2. Descriptive statistics

Before turning to the econometric analysis, we provide a brief description of the data available. In Figure 7, we plot our dependent variable, daily earnings growth, calculated from Social Security records and compare it to alternative measures of labor income obtained from national accounts or surveys. The graph reveals a strong correlation (0.83) between all the wage growth measures considered. However, compensation per employee or per hour shows more volatile behavior in certain periods relative to our daily earnings growth using insured earnings from the Social Security Administration. In addition, labor cost per hour exhibits an erratic behavior at the end of the period, potentially explained by the 2019 Lithuanian reform that shifted Social Security contributions from employers to employees, affecting the level of gross earnings as well as labor costs. However, despite the differences in nuance, regardless of the measure used, the same picture emerges: substantial wage growth after the Great Recession.

Figure 8 depicts wage growth along with the dynamics of the main aggregate indicators we consider in our analysis, namely labor productivity, unemployment, consumer prices,

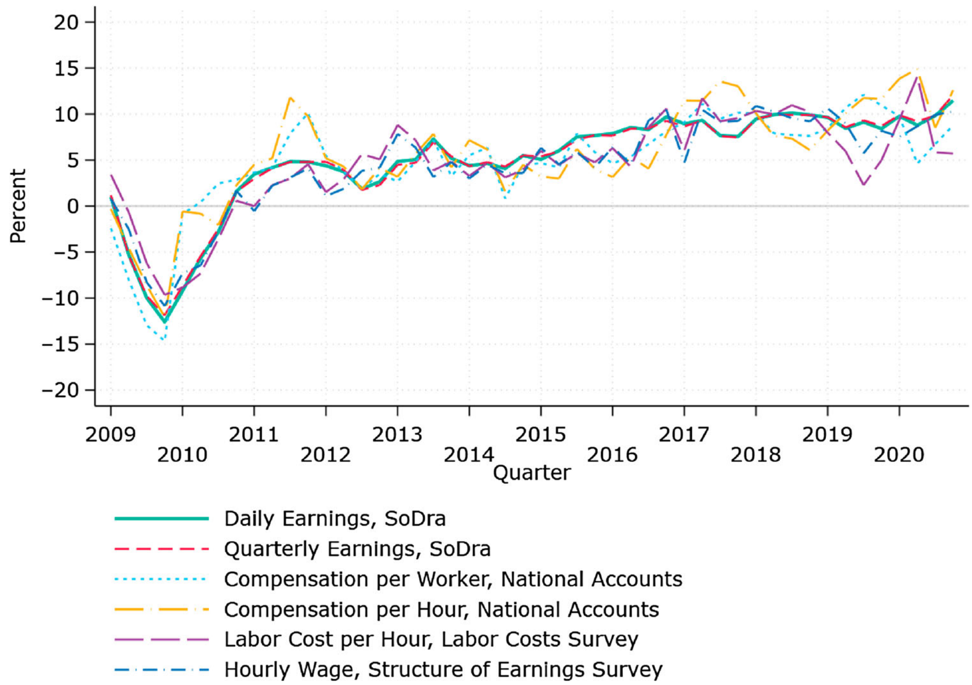

Figure 7. Alternative Measures of Nominal Wage Growth. Source: Authors' calculations based on SoDra and Statistics Lithuania.

Notes: Variables are expressed in growth rates computed as year-on-year changes of selected variables in nominal terms.

and the minimum wage. The evidence indicates that the evolution of aggregate indicators is linked to a greater or lesser extent to wage growth. On the one hand, the state of the labor market, as proxied by the unemployment rate, appears to mirror wage growth, especially during the Great Recession through 2019. This indicates that wages are closely linked to the performance of the labor market, which ultimately reflects conditions in the economy as a whole. On the other hand, labor productivity and, more dramatically, prices appear to show a somewhat looser link to wage growth. For example, labor productivity began to recover substantially faster after the Great Recession compared to wages, potentially driven by the sharp wage adjustment helping to preserve competitiveness. However, since around 2013 labor productivity growth has exhibited a more erratic behavior but it has ultimately lagged behind wage growth, which resonates with the evidence in Section 2. In the case of price growth, the graph displays a weak (or even negative sometimes) correlation between wage growth and inflation, in line with the fact that cumulative price growth was roughly 50 percentage points lower than cumulative wage growth between 2008 and 2020.

Wage growth may not only be driven by macroeconomic variables, but also by changes in the composition of the labor force, as well as by industry or location dynamics. Figure 9 shows changes in employment composition using information included in the microdata available. Panel A shows that the inverted sex ratio (more women than men) has remained barely unchanged since 2008. However, since 2015 when the euro was introduced in Lithuania, the share of foreigners (especially men) in the workforce has

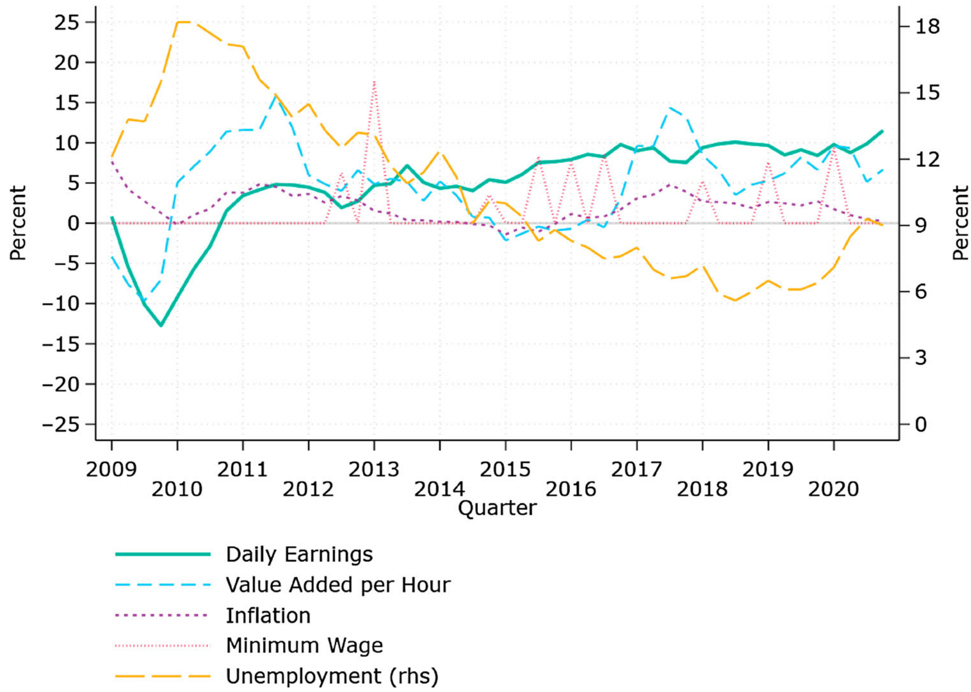

Figure 8. Wages, Productivity, Unemployment, and Prices. Source: Authors' calculations based on SoDra and Statistics Lithuania.

Notes: Daily earnings corresponds to the year-on-year change of quarterly nominal labor income divided by days worked in the quarter. Value added refers to the year-on-year change of nominal value added per hour. Inflation is computed using the year-on-year change of the quarterly consumer price index. The minimum wage measures the change in the national minimum wage with respect to its previous level.

increased. The effect of immigration flows on wages is ambiguous ex-ante, as the arrival of immigrants could put downward pressure on wages due to increased labor supply. However, if many of these immigrants are highly skilled individuals coming to fill the labor/skill shortages experienced by firms in Lithuania, this may push up wages due to scarcity-related higher bargaining power of these workers and upward slopping labor supply curves faced by firms. Panel B portrays a common picture in many advanced economies: the aging of the population, but such a phenomenon is particularly rapid in Lithuania (OECD, 2018b). The higher proportion of long-tenured workers in the labor force can affect wages through two margins. On the one hand, through seniority-based rules affecting wage growth within the firm, a mechanism consistent with an increase in long-term workers in the labor force. On the other hand, through fiercer competition among employers for their skills and experience in a context of shrinking labor supply as documented in Figure 5 Panel A and seemingly lack individuals to fill managerial positions (Panel D, Figure 9). Finally, panels E and F show that since 2008 services and the two largest cities (Vilnius and Kaunas) have increasingly accounted for a larger share of employment. Whether these trends have contributed or not to wage growth depends on the relative position of labor supply and demand in those markets. However, location shifts might mechanically increase average wages due to the well document big city premium and the dynamic benefits of working in big cities (see for instance de la Roca

Figure 9. Employment Composition. (a) Gender and Nationality (b) Age (c) Tenure (d) Occupation (e) Sector (f) Location. Source: Authors' calculations based on SoDra.

& Puga, 2017). Similarly, if the sectors that are booming are high-paying sectors, as the expansion of the fin-tech sector in recent years (Koronka, 2021), this may just directly contribute to higher wages.

So far, we have provided evidence of the evolution of possible factors underlying wage growth. However, we have documented the evolution of each of these factors in isolation. Still, it is possible that they interact in a non-negligible way, affecting their ultimate impact on the evolution of wages. Therefore, in the next section, we take them together in an econometric model to quantify their contribution to wage growth.

4. The observed drivers of wage growth

4.1. Econometric model

To document the contribution of observed nationwide economic developments that have potentially affected wage growth in Lithuania between 2008 and 2020, we estimate a wage Phillips curve specification in the spirit of Gali (2011).[8] Formally, our reduced-form model has the following specification

$$\Delta_h w_{ijt} = \beta_1 \theta_t + \beta_2 \theta_{t-h} + \beta_3 \Delta_h \psi_t + \beta_4 \pi_{t-1} + \beta_5 \Delta_1 \underline{w}_t + X_{ijt}\Omega + \eta_i + \phi_{j(i,t)} + \xi_{ijt} \quad (1)$$

where $\Delta_h w_{ijt}$ represents the change in the logarithm of (nominal) daily earnings of individual i working in firm j between quarter t and $t-h$, with h set to 4-quarters so that we investigate year-on-year (yoy) changes in daily wages, implicitly accounting for season effects. θ_t refers to the measure of labor market slack (i.e. the unemployment rate) in quarter t.[9] We include also the lag of θ_t, thereby accounting not only for the contemporaneous labor market situation but also its change.[10] Therefore, for a given state of the economy (level of slack, inflation, etc.), our wage Phillips curve specification accounts for the fact that wage growth may be different depending on whether the country is moving into or out of recession (Gali, 2011; Manning, 1993). $\Delta_h \psi_t$ represents productivity growth defined as the change in (log) value added per hour between period t and $t-h$. π_{t-1} corresponds to the lagged year-on-year inflation rate, which implies an assumption of backward-looking expectations.[11] $\Delta_1 \underline{w}_t$ is the change in the logarithm of the national daily minimum wage. To account for changes in workforce composition over time, our model includes both observed and unobserved characteristics. More precisely, X_{it} is a vector of observed (time-varying) characteristics corresponding to categorical variables for age, tenure, and occupation. η_i refers to worker permanent heterogeneity or 'ability', whereas $\phi_{j(i,t)}$ measures firm permanent heterogeneity or 'pay differentials' in the spirit of Abowd et al. (1999), and are meant to capture worker- and firm-specific components. ξ_{ijt} is a standard i.i.d error term.

Given the individual nature of our analysis and the inclusion of aggregate variables, the residuals in Equation (1) are both serially correlated within worker observations and cross-sectionally correlated for individuals in the same quarter. This implies that standard errors would be biased if common group errors are not accounted for (Moulton, 1990). To address this issue, we follow a common approach in the literature and estimate our reduced-form model in two steps (see Devereux, 2001; Solon et al., 1994; Verdugo, 2016, among others).[12] Therefore, in the first stage we estimate the following log-linear wage equation

$$w_{ijt} = \omega_t + X_{ijt}\Omega + \eta_i + \phi_{j(i,t)} + \xi_{ijt} \quad (2)$$

where ω_t represent quarter-year dummies. The point estimates of these calendar time effects thus measure the evolution of wages over time net of changes in workforce composition. In the second stage, we estimate the extended wage Phillips curve where the dependent variable are the net wages retrieve from the first stage[13]

$$\hat{\omega}_t = \alpha + \beta_1 \theta_t + \beta_2 \theta_{t-h} + \beta_3 \Delta_h \psi_t + \beta_4 \pi_{t-1} + \beta_5 \Delta_1 \underline{w}_t + \epsilon_t \quad (3)$$

where each of the β coefficients measure the effect of unit changes of each of the selected variables on nominal wage growth net of changes in the workforce.[14]

4.2. Wage phillips curve estimates

Table 1 reports the estimates of the wage Phillips curve. For comparison, we start showing the results using raw wages and including only the unemployment rate and inflation as regressors (as in Gali, 2011). Then, we extend the standard wage Phillips curve to include labour productivity growth and minimum wage changes. Column (4) presents our benchmark model where we use wages net of workforce composition as dependent variable in the extended wage Phillips curve.

The estimated effect of unemployment dynamics, θ_t and θ_{t-4}, on wage growth, have the sign predicted by theory (Gali, 2011). However, the point estimates are of larger magnitude relative to other developed countries, but consistent with evidence from other Central and Eastern European economies (Nickel et al., 2019). A common explanation is the lower downward nominal wage rigidity in Central and Eastern European countries, due to the low union density levels and coverage of collective agreements, which translates into a higher sensitivity of wages to labor market conditions (Bertola et al., 2012; Druant et al., 2012). The effect of past inflation, π_{t-1}, is small and economically insignificant.[15] The lack of responsiveness of wage growth to past inflation can be explained by both the lack of wage indexation in Lithuania (Druant et al., 2012), and the negative correlation between wages and prices during the Great Recessions together with low levels of inflation observed afterward, as described in Figure 8. With respect to labor productivity, ψ_t, the point estimates fall at the lower end of the existing studies across advanced economies (e.g. Greenspon et al., 2021; IMF, 2017; Nickel et al., 2019)), but again they are aligned with the evidence in other Central and Eastern European economics (Arpaia et al., 2016; Nickel et al., 2019). This illustrates the weak relationship between productivity growth and wages over the period analyzed, with productivity growing substantially less than wages between 2008 and 2020, as discussed in Section 2. Finally, the minimum wage, $\underline{w}_t$, has also an effect on average wage growth, with a point estimate similar to the existing findings in Central and Eastern European economies using a similar econometric model (Nickel et al., 2019).

Table 1. Wage Phillips Curve Estimates.

	(1)	(2)	(3)	(4)
θ_t	−1.7028***	−1.4728***	−1.3438***	−1.7839***
	(0.2110)	(0.1771)	(0.1736)	(0.2251)
θ_{t-4}	0.8159***	0.5339***	0.4793***	0.9009***
	(0.2047)	(0.1717)	(0.1642)	(0.1970)
π_{t-1}	0.0522	−0.2261	−0.1162	−0.0712
	(0.1764)	(0.2496)	(0.2387)	(0.2899)
$\Delta\psi_t$		0.2798***	0.3021***	0.3329***
		(0.0924)	(0.0867)	(0.1035)
$\Delta\underline{w}_t$			0.1412***	0.1368***
			(0.0363)	(0.0389)
Observations	48	48	48	48
R-squared	0.7757	0.8325	0.8529	0.8562

Source: Authors' calculations based on SoDra and Statistics Lithuania.

Notes: Columns (1) to (3) use as dependent variable the year-on-year (log) change of the *raw* average nominal wage. Column (4) instead relies on the year-on-year (log) change of the average nominal wage *net* of workforce composition. Regressions are weighted by the number of individual observations in each quarter. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3. Wage growth decomposition

To quantify the extent to which each of macroeconomic factors included in our econometric model are tied to the dynamics of wage growth in Lithuania between 2008 and 2020, we implement the decomposition proposed by Yellen (2015) using the estimates reported in Column (4) of Table 1.[16] Figure 10 unveils that the factors included in the wage Phillips curve seem to explain the bulk of the variation in nominal wage growth between 2008 and 2020, as indicated by the low contribution of residuals. The one remarkable exception is 2020 when the COVID-19 pandemic disrupted the economy, where the residuals seem to be the only driver of wage growth.

The results show that labor market slack was the main driver of wage growth dynamics. Between 2009 and 2011, it had a significant negative effect on its growth. Conversely, it contributed positively to its increase after 2014, as domestic demand strengthened.

On the other hand, labor productivity has also had a marked impact on wage growth. During the Great Recession (2009-2010), it depressed wages. On the contrary, during the recovery, it helped to offset the negative pressure on wages from labor market conditions. Subsequently, between 2013 and 2017, weak productivity growth dampened wage growth, mitigating the positive pressure on wages induced by falling unemployment.

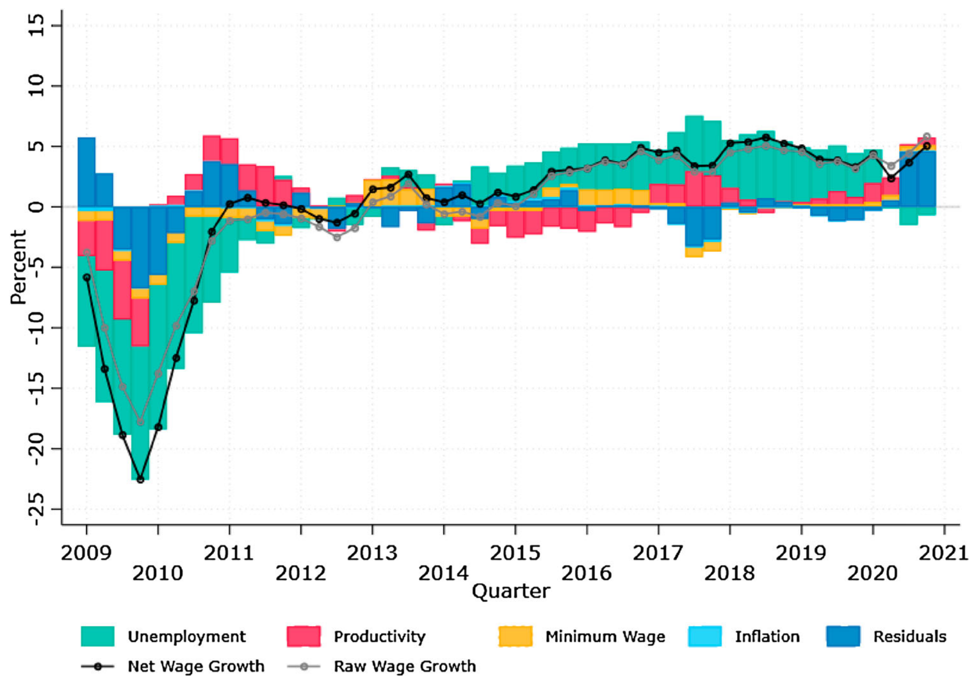

Figure 10. Reduced-form Wage Growth Decomposition. Source: Authors' calculations based on SoDra and Statistics Lithuania.

Notes: Decomposition based on the point estimates reported in Table 1 Column (5) from Equation (1) following Yellen (2015). The black (gray) lines are deviations of net (raw) daily earnings growth from its model-implied mean. Net wage growth refers to daily earnings net of workforce composition, i.e. age, tenure, and occupation along with worker and firm permanent heterogeneity. Contributions (including residuals) refer to deviations from their model-implied mean. Unemployment refers to the contribution of the contemporaneous plus the lagged unemployment rate. Productivity is the year-on-year change in (log) value added per hour. Inflation refers to a 4-quarter moving average of past inflation. Minimum wage is the change in the national monthly minimum wage.

Finally, starting in 2017, it has positively contributed to the wage growth, but to a lesser extent than labor market conditions.

The decomposition also highlights that minimum wage increases also played a role in wage growth. For instance, when the largest increase in the minimum wage in the history of Lithuania took place, a 17.7% hike that affected about 25% of the workforce (Garcia-Louzao & Tarasonis, 2023), the minimum wage emerged as the main contributor to nominal wage growth. Likewise, between October 2014 and July 2016, the minimum wage was raised 4 times with an average increase of 7%, and it was during this period that the minimum wage was as much responsible for wage growth as labor market slack.[17] Noteworthy, the decomposition reveals that the contribution of inflation to nominal wage growth was negligible between 2008 and 2020.

Finally, we plot the evolution of raw wages to assess the role of workforce composition. Consistent with the wage cyclicality literature, net wages are more sensitive to business cycle conditions. This higher sensitivity, which can also be seen by comparing the coefficient on the unemployment rate in Columns (3) and (4) in Table 1, is due to the counter-cyclical bias that arises from the fact that 'low-wage' jobs are underrepresented during economic booms. For example, the larger plunge in net wages between 2009-2010 compared to raw wages indicates that most of the jobs destroyed were low-productivity/low-wage jobs. Similarly, from 2012 onwards, although the differences are significantly smaller, we observe higher growth in net wages, again reflecting differences in the composition of the labor force over the economic cycle. Interestingly, at the end of the period, raw wages grew slightly more than net wages, suggesting an improvement in the workforce. However, the contribution of workforce composition to wage dynamics appears to be much less relevant than the macroeconomic factors considered.

While the wage Phillips curve approach is informative to identify the sensitivity of wage growth to inflation expectations, labor market slack, productivity growth, or other observed factors, the analysis has noteworthy limitations. Namely, the regression residuals may not be orthogonal to the explanatory variables. For example, the disturbance term might capture shocks to the natural wage markup, which in turn affects the rest of the macro variables.[18] Therefore, the wage Phillips curve does not allow us to distinguish between the underlying economic shocks driving the variables of interest (e.g, macroeconomic factors, labor supply changes, or structural reforms, among others). Unlike a reduced-form analysis, in a structural model, it is possible to disentangle these underlying economic shocks that drive wage growth. Importantly, a structural approach also helps to overcome potential simultaneity biases when, for example, correlated demand and supply shocks are hitting the economy. Thus, in the next section, we take a step forward and estimate a structural model to better understand the economic primitives underlying wage growth.

5. The underlying economic shocks

5.1. Structural BVAR

We estimate a structural BVAR to overcome the limitations of our reduced-form approach. Following Conti and Nobili (2019) and Foroni et al. (2018), we focus on four shocks that are arguably the main primitive sources of wage fluctuations: aggregate demand, aggregate supply, labor supply, and wage bargaining shocks. The latter are identified in the data inductively, i.e. by the effects that theory predicts they cause in the short run on economic variables.

The theoretical predictions are derived from DSGE models with labor market frictions, as in Galí et al. (2012). A positive aggregate demand shock, such as an unexpected increase in foreign demand, raises prices, output and lowers unemployment. This contributes to an increase in labor productivity. On the other hand, a positive aggregate supply shock leads to total productivity gains, boosting output, wages and labor productivity. This pulls down prices and unemployment. Such a shock may also reflect reforms aimed at strengthening the supply side of the economy, such as easing regulations or fostering competition among firms. Moreover, a negative labor supply shock leads to a decline in labor market participation. This loss of labor supply makes it more difficult for firms to fill job vacancies, leading to higher wages. At the same time, new entrants to the market are finding it easier to find a job. These combined effects cause output to fall and prices to rise. Finally, a wage bargaining shock that results in a gain in workers' bargaining power leads to higher wages and prices. As a result, firms run smaller surpluses with each hire, which then leads them to post fewer vacancies. In response, unemployment rises and output falls. These predictions provide us with a set of sign restrictions for identifying these structural shocks in the data. This set is summarized in the Table 2.

To identify the structural shocks, we rely on five quarterly time series between 2002Q1 and 2020Q4: real GDP, consumer price index (CPI), real wages (SoDra aggregated daily earnings deflated by the CPI), real labor productivity (value added per hour deflated by the CPI), and unemployment rate.[19] All variables are transformed into their natural logarithm, except for the unemployment rate which is used in levels. The model has 5 lags and the following econometric specification[20]

$$y_t' = c + \sum_{j=1}^{5} y_{t-j}' B_j + \varepsilon_t'. \tag{4}$$

where y_t is a vector of 5×1 endogenous variables (the data), c a vector of constants, B_j a 5×5 matrix of parameters, and ε_t a vector of exogenous innovations, $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$. Note that the innovations, ε_t, are not economically meaningful. The mapping to structural shocks is based on the identity: $\varepsilon_t' = \eta_t' \Phi$, where Φ is an orthogonal impact matrix of

Table 2. Sign Restrictions in the BVAR.

	Agg. Demand (+)	Agg. Supply (+)	Labor Supply (−)	Wage Bargaining (−)
Real GDP	+	+	−	−
Prices (CPI)	+	−	+	+
Real wages	+	+	+	+
Labor productivity	+	+		
Unemployment	−	−	−	+

Notes: Endogenous variables in rows, structural shocks in columns. Agg. stands for aggregate. The signs in parentheses in the headings indicate the nature of each shock. Sign restrictions are imposed on contemporaneous relationships between variables, i.e. in the impulse response impact matrix. A blank in the body of the table indicates that no sign restrictions are imposed.

impulse responses and $\eta_t \sim \mathcal{N}(0, I_5)$ are the structural shocks. This impact matrix must also respect the sign restrictions of the Table 2. For this purpose, we use the algorithm in Rubio-Ramirez et al. (2010).[21]

5.2. BVAR results

Figure 11 presents the variance decomposition of the model. The x-axis shows the horizons in quarters and the y-axis is the share of wage variance explained by each shock. The bulk of the short-term variations in real wages is due to macroeconomic shocks (around 70%). Demand shocks account for about 20% and aggregate supply shocks for roughly 50% over all horizons. The latter implies a close link between wages and total productivity, stronger than our reduced-form estimates capture. This is not surprising given that matching models with moderate wage rigidity predict large fluctuations in wages *after* aggregate supply (technology) shocks (see for instance Hall, 2005; Shimer, 2005). The strength of wage bargaining shocks is what confounds the results of the unconditional wage Phillips curve. This can be understood when looking at Figure 12, which shows these shocks capture about 30% of the short-term unemployment dynamics. In contrast, they are less important for real wages, accounting for about 10% of their variation. This suggests that the *structural* slope of the wage Phillips curve (the coefficient on the wage-unemployment relationship) may not be as large as our reduced-form estimates imply.

Figure 13 reports the historical (structural) decomposition of real wage growth implied by the structural model for the period of interest 2009–2020. Wage growth is expressed as the deviation of year-on-year changes from the unconditional model forecast.[22] This decomposition quantifies for each quarter the impact of the past and present accumulation of each type of shock in isolation. Therefore, it allows us to evaluate the relative contribution of each shock to wage growth.

The decomposition reveals that aggregate supply shocks (e.g. technology shocks) are the main driving force of wage growth over the entire period. This indicates that much of the wage evolution between 2009 and 2020 is linked to supply-side distortions, probably related to structural productivity dynamics, but also to technological absorption and

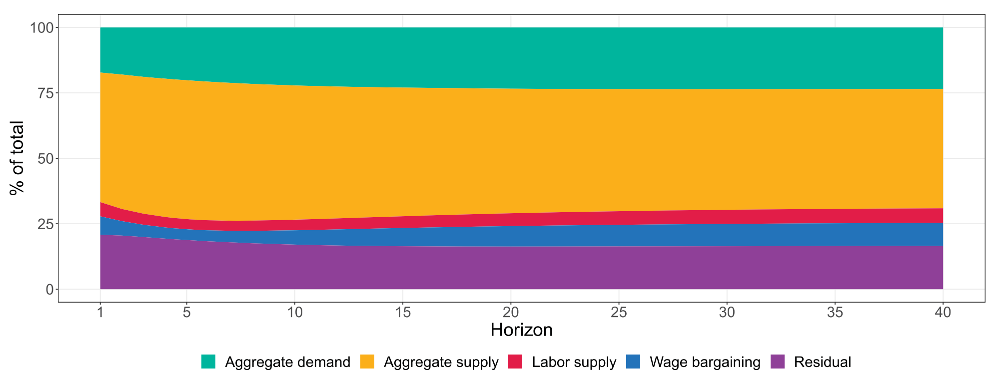

Figure 11. Variance Decomposition of the Real Wages.

Notes: The decomposition is based on the average draw satisfying the sign restrictions. The x-axis shows the horizons in quarters and the y-axis is the share of wage variance explained by each shock.

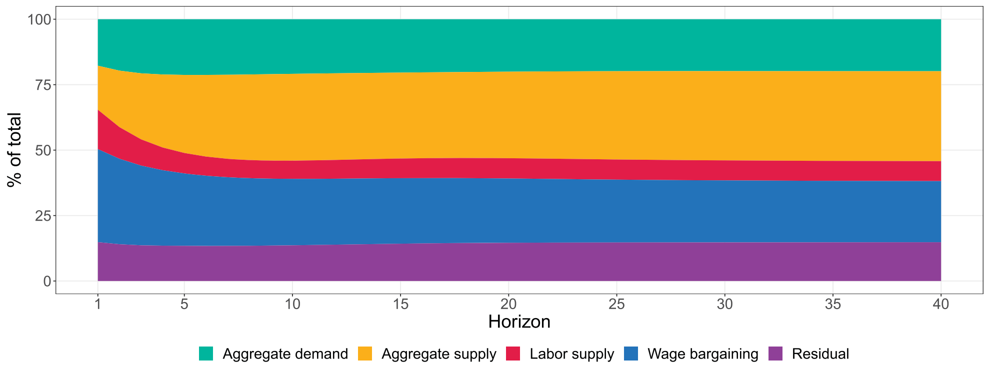

Figure 12. Variance Decomposition of the Unemployment Rate.

Notes: The decomposition is based on the average draw satisfying the sign restrictions. The x-axis shows the horizons in quarters and the y-axis is the share of unemployment variance explained by each shock.

increased competition between firms following the arrival of new businesses with the introduction of the euro in Lithuania in 2015.

Aggregate demand and wage bargaining shocks, in turn, appear as the shocks that contribute to *excess* wage growth. In other words, these shocks push wages above the fluctuations that would occur if wages only reacted to technology shocks. For instance, the figure points out that during and in the aftermath of the Great Recession, 2009–2011 in our analysis period, wages declined in excess of the supply shock as a consequence of the large contribution of the aggregate demand shock. This shock probably reflects the Government's reaction to cope with the global shock through austerity measures, such as job and wage cuts in the public sector, increases in corporate, value-added, and excise taxes, and the postponement of public investment. During this period, wage bargaining shocks also contributed to the decline in wages, probably revealing the increased labor market slack that could result from the austerity measures.

From 2013 onwards, wages increase almost steadily until the end of the period. Over and above the contribution of supply-side shocks, wage bargaining shocks started to

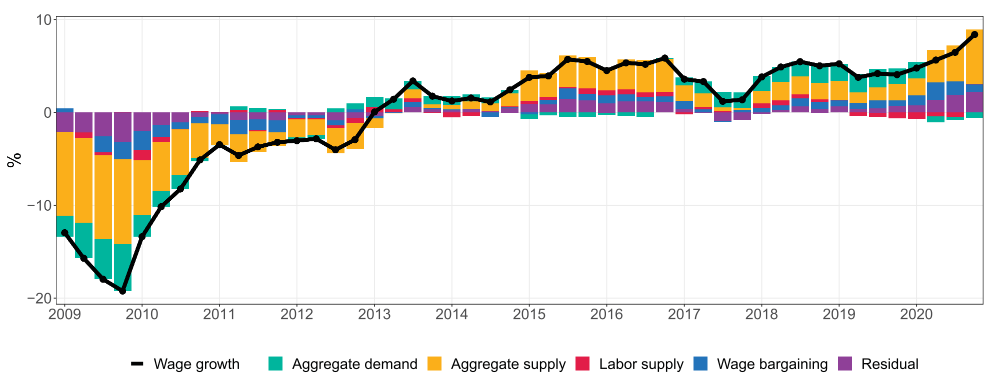

Figure 13. Structural Wage Growth Decomposition.

Notes: The black line shows year-on-year real wage growth expressed as its deviation from the unconditional model forecast. The stacked bars give the contribution of each shock to the evolution of the wage growth. The decomposition is based on the average draw satisfying the sign restrictions.

contribute positively and continuously to wage growth. Similarly, labor supply shocks also pushed wages up between 2013 and 2019, even if to a lesser extent. This is suggestive of negative labor supply shocks consistent with a shrinking labor force. In this regard, the positive contribution to wage growth of both shocks may reflect the labor shortages and the fixed (or shrinking) labor supply faced in the growing economy already discussed in Section 2. Importantly, they may also reflect the numerous minimum wage increases over the period, as well as the increased generosity of unemployment benefits in 2017.

Aggregate demand also played a role in wage dynamics over the period characterized by strong growth. For example, between 2015 and 2016, aggregate demand pushed wages down, plausibly due to the effects of the Russian ban on imports. From 2017, together with wage bargaining shocks, aggregate demand fueled wage growth in excess of structural technology dynamics, suggesting that strong economic growth (likely related to both internal and external demand forces) over this period is partly guilty of the observed wage dynamics.

6. Conclusions

This article investigates the main factors behind wage growth in Lithuania between 2008 and 2020. In a first step, we estimate a reduced-form wage Phillips curve and document a strong relationship between the nominal wage growth and labor market slack (unemployment), in line with what a standard new Keynesian wage Phillips curve would predict. We also find that labor productivity and minimum wage increases are linked to average wage growth, but to a lesser extent, while the sensitivity of nominal wage inflation to lagged price inflation was close to zero.

In a second step, we investigate the economic primitives underlying wage growth by means of a BVAR structural model. Our structural analysis reveals that about 15% of the short-run variation in real wages is explained by labor market shocks and 70% by aggregate demand and supply shocks. A historical decomposition reveals that since 2013, real wage growth has been mainly explained by aggregate supply shocks, probably reflecting productivity growth and strong technology absorption. Moreover, we find that since 2015 negative labor supply shocks and stronger bargaining power of workers coupled with aggregate demand shocks have pushed wages above the growth implied by supply shocks.

Overall, our results indicate that wage growth in Lithuania was largely driven by technology (productivity) shocks. However, both labor market and aggregate demand shocks contributed to wage growth above and beyond structural productivity dynamics. This contribution to wage growth reflects the result of labor shortages and policy changes that have strengthened the bargaining position of workers. Policymakers could therefore strive to reduce the upward pressure on wages resulting from labor shortages, but also promote investments to stimulate productivity growth, which has been rather sluggish since the Great Recession.

Notes

1. Labor market slack refers to (i) the unemployed, (ii) underemployed part-time workers (i.e. part-time workers who want to work more), (iii) persons who are available for work but are not looking for a job, and (iv) persons who are looking for a job but are not available for a job.
2. The dataset is confidential and provided under an exclusivity agreement by SoDra to the Bank of Lithuania.

3. Individuals registered with the Social Security administration include those making Social Security contributions (e.g. employees, self-employed) as well as people receiving any type of social benefits (e.g. unemployment insurance, child benefits, pension). However, due to legal reasons, individuals do not appear in our sample until they are 18, even if they were present in the Social Security system at younger ages.
4. The labor income variable refers to *all* work-related income that is subject to Social Security contributions, including the base salary, but also non-regular payments, such as bonuses, allowances, overtime pay, commissions or severance payments. However, we cannot compute gross monthly earnings net of additional remuneration not received each month, given the lack of more disaggregated information.
5. The dataset does not contain information on hours and, hence, hourly wages cannot be calculated. However, part-time employment is not common in Lithuania, accounting for roughly 6 percent of salaried employment.
6. Unfortunately, the dataset does not include information on educational attainment. In our reduced-form approach, we rely on permanent individual heterogeneity through worker-fixed effects to address this limitation under the assumption that education level loads on the fixed effects.
7. This restriction is imposed to consider workers with sufficient labor market attachment and to reduce the influence of part-time work that cannot be directly identified in the data.
8. The empirical model is also aligned with the one traditionally used in the literature on real wage cyclicality (see for instance Bils, 1985; Carneiro et al., 2012; Solon et al., 1994; Verdugo, 2016, among others), but it is extended to include productivity growth and changes in the minimum wage in order to document the contribution of these macro factors pushing wages (IMF, 2017; Nickel et al., 2019). As discussed in Blanchard and Katz (1999), our empirical nominal wage equation is closely related to a theoretical wage-curve derived from matching models.
9. It is important to note that in countries experiencing structural changes in the composition of the labor force, the unemployment rate may not be a perfect measure of slack. In Table A1 in the Appendix, we have experimented with alternative measures of slack and find no substantial changes in our estimates of the wage Phillips curve.
10. We adopt the benchmark formulation of Gali (2011), as the unemployment rate in Lithuania follows a similar autoregressive process to that in the United States, with the expected unemployment rate being a function of current and past unemployment rates. An empirically equivalent specification would be to use the change in the unemployment rate instead of its lagged value as in IMF (2017).
11. This assumption of backward-looking behavior is supported by data from the European Wage Dynamics Network survey, which reveals that Lithuanian companies are more likely to change wages based on past inflation than on actual or future inflation (Druant et al., 2012). A theoretical discussion can be found in Blanchard and Katz (1999).
12. An alternative approach would to estimate the worker-level regression and rely on two-way clustering to compute the standard errors (Cameron et al., 2011; Carneiro et al., 2012). Given the size of our dataset this alternative approach is more computationally demanding.
13. We weight the second stage regression to account for the number of observations observed at each calendar time.
14. In Table A2 in the Appendix, we estimate the same model by replacing residual wages with raw wages from the SoDra data or compensation per employee from the national accounts. Although the results are generally consistent, there are two important remarks. On the one hand, the use of raw wages results in a lower sensitivity of wages to labor market fluctuations, in line with the results of the literature on wage cyclicality. On the other hand, the use of compensation per employee reveals a stronger link between productivity and wage growth, but masks the contribution of changes in the minimum wage to average wage growth.
15. The strong relationship between unemployment and nominal wages, on the one hand, and the fact that price inflation has been rather low and stable, on the other, suggests a flattening of the price Phillips curve in Lithuania. Although this is an interesting angle to investigate, it is beyond the scope of this paper.

16. In practice, we run 5 separate regressions so that in each regression we set one explanatory variable (or a set of them in the case of unemployment and workforce characteristics) to zero and simulate the model. We then calculate the difference between the actual wage growth and the simulated value when a given regressor was set to zero. The resulting gap represents the historical contribution of that particular factor.
17. Note that, given the nature of our decomposition, the minimum wage mechanically has a negative contribution during the periods that remained unchanged.
18. See Erceg et al. (2000), Gali and Gambetti (2019), or McLeay and Tenreyro (2020) for detailed discussions on this issue.
19. We analyze real wages rather than nominal wages because BVAR sign restrictions are generally derived from theoretical predictions about the impulse responses of real wages. Our results hardly change with nominal wages. Furthermore, to be consistent with the reduced-form analysis, we rely on SoDra data to measure wages net of composition effects, but we show that the results are robust to the use of a more standard measure such as real compensation per employee (see Appendix, Figure A1).
20. We follow the common approach of using 5 lags in BVAR models of quarterly log-level variables (Foroni et al., 2018). Results barely change with 2, 3 or 4 lags. We assume Normal-diffuse priors as in Conti and Nobili (2019). The β coefficients (vectorized B) are sampled from a multivariate-Normal distribution with mean β_0 for which all entries are zero except the first lag of the dependent variable in its own equation. The variance-covariance of this distribution Ω_0 is diagonal with hyperparameters defined according to Canova (2007). The variance-covariance of the residuals Σ_ε is sampled in an inverse-Wishart distribution.
21. Under sign restrictions, the impact matrix Φ cannot be exactly identified. The identity $\varepsilon_t' = \eta_t'\Phi$ and the assumption $\eta_t \sim \mathcal{N}(0, I_5)$ require that $\Sigma_\varepsilon = \Phi\Phi'$ where Σ_ε is the variance-covariance matrix of the model. We ensure that this holds by means of a Cholesky factorization. The resulting impact matrix L can have different signs from those in Table 2. In short, the algorithm in Rubio-Ramirez et al. (2010) then consists in extracting N candidate impact matrices such that $\Psi_n = LQ_n$ for $n = 1, \ldots, N$ which will satisfy the sign restrictions. The Q_n matrices are random orthogonal matrices. We draw 10,000 candidates in our model.
22. Unconditional forecast corresponds to deterministic components of the model that is to the terms implying the initial conditions and the constant of the model.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333. https://doi.org/10.1111/ecta.1999.67.issue-2

Arpaia, A., Cardoso, P., Joseph, E., Kiss, Á., Pálvölgyi, B., Pierini, F., Vandeplas, A., & Van Herck, K. (2016). Labour market and wage developments in Europe, Annual review 2016. *Publications Office of the European Union; Luxembourg*.

Ball, L., & Mazumder, S. (2021). A phillips curve for the euro area. *International Finance*, *24*(1), 2–17. https://doi.org/10.1111/infi.v24.1

Bańbura, M., & Bobeica, E. (2023). Does the phillips curve help to forecast euro area inflation? *International Journal of Forecasting*, *39*(1), 364–390. https://doi.org/10.1016/j.ijforecast.2021.12.001

Bertola, G., Dabusinskas, A., Hoeberichts, M., Izquierdo, M., Kwapil, C., Montornès, J., & Radowski, D. (2012). Price, wage and employment response to shocks: evidence from the WDN survey. *Labour Economics*, *19*(5), 783–791. https://doi.org/10.1016/j.labeco.2012.03.008

Bils, M. J. (1985). Real wages over the business cycle: evidence from panel data. *Journal of Political Economy*, *93*(4), 666–689. https://doi.org/10.1086/261325

Blanchard, O., & L. F. Katz (1999). Wage dynamics: reconciling theory and evidence. *American Economic Review*, *89*(2), 69–74. https://doi.org/10.1257/aer.89.2.69

Bobeica, E., & Jarociński, M. (2019). Missing disinflation and missing inflation: a var perspective. In *57th issue (March 2019) of the international journal of central banking*.

Brien, S., Swalem, B., & MacDowal, A. (2019). *Central and Eastern Europe prosperity report: the lived experience* (Tech. Rep.). Legatum Institute.

Bubbico, R. L., & Freytag, L. (2018). *Inequality in Europe* (Tech. Rep.). European Investment Bank.

Bulligan, G., & Viviano, E. (2017). Has the wage phillips curve changed in the euro area? *IZA Journal of Labor Policy*, *6*, 1–22. https://doi.org/10.1186/s40173-017-0087-z

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, *29*(2), 238–249. https://doi.org/10.1198/jbes.2010.07136

Canova, F. (2007). *Methods for applied macroeconomic research* (Vol. 13). Princeton University Press.

Carneiro, A., Guimaraes, P., & Portugal, P. (2012). Real wages and the business cycle: accounting for worker, firm, and job title heterogeneity. *American Economic Journal: Macroeconomics*, *4*(2), 133–152.

Conti, A. M., & Nobili, A. (2019). *Wages and prices in the Euro area: exploring the nexus*. Banca d'Italia.

de la Roca, J., & Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, *84*(1), 106–142. https://doi.org/10.1093/restud/rdw031

Devereux, P. J. (2001). The clicality of real wages within employer-employee matches. *ILR Review*, *54*(4), 835–850. https://doi.org/10.1177/001979390105400405

Druant, M., Fabiani, S., Kezdi, G., Lamo, A., Martins, F., & Sabbatini, R. (2012). Firms' price and wage adjustment in Europe: survey evidence on nominal stickiness. *Labour Economics*, *19*(5), 772–782. https://doi.org/10.1016/j.labeco.2012.03.007

Erceg, C. J., Henderson, D. W., & Levin, A. T. (2000). Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics*, *46*(2), 281–313. https://doi.org/10.1016/S0304-3932(00)00028-3

Ferraro, S., Meriküll, J., & Staehr, K. (2018). Minimum wages and the wage distribution in Estonia. *Applied Economics*, *50*(49), 5253–5268. https://doi.org/10.1080/00036846.2018.1486017

Foroni, C., Furlanetto, F., & Lepetit, A. (2018). Labor supply factors and economic fluctuations. *International Economic Review*, *59*(3), 1491–1510. https://doi.org/10.1111/iere.2018.59.issue-3

Fortin, N. M., Lemieux, T., & Lloyd, N. (2021). Labor market institutions and the distribution of wages: the role of spillover effects. *Journal of Labor Economics*, *39*(S2), S369–S412. https://doi.org/10.1086/712923

Galí, J., Smets, F., & Wouters, R. (2012). Unemployment in an estimated new keynesian model. *NBER Macroeconomics Annual*, *26*(1), 329–360. https://doi.org/10.1086/663994

Gali, J. (2011). The return of the wage phillips curve. *Journal of the European Economic Association*, *9*(3), 436–461. https://doi.org/10.1111/jeea.2011.9.issue-3

Gali, J., & Gambetti, L. (2019). *Has the US wage Phillips curve flattened? A semi-structural exploration*. NBER Working Paper No. 25476.

Garcia-Louzao, J., & Tarasonis, L. (2023). Wage and employment impact of minimum wage: evidence from Lithuania. *Journal of Comparative Economics*, *51*(2), 592–609. https://doi.org/10.1016/j.jce.2022.12.002

Greenspon, J., Stansbury, A., & Summers, L. H. (2021). Productivity and pay in the United States and Canada. *International Productivity Monitor*, *41*, 3–30.

Hall, R. E. (2005). Employment fluctuations with equilibrium wage stickiness. *American Economic Review*, *95*(1), 50–65. https://doi.org/10.1257/0002828053828482

IMF (2017). Recent wage dynamics in advanced economies: drivers and implications. In *World Economic Outlook, October 2017: Seeking Sustainable Growth: Short-term Recovery, Long-term Challenges* (pp. 73–112).

Koronka, P. (2021). How did Lithuania become the EU's Hottest Fintech Hub? 6 insights from our expert panel. *Sifted: https://sifted.eu/articles/lithuania-eus-hottest-fintech-hub/*.

Manning, A. (1993). Wage bargaining and the phillips curve: the identification and specification of aggregate wage equations. *The Economic Journal*, *103*(416), 98–118. https://doi.org/10.2307/2234339

McLeay, M., & Tenreyro, S. (2020). Optimal inflation and the identification of the phillips curve. *NBER Macroeconomics Annual*, *34*(1), 199–255. https://doi.org/10.1086/707181

Mortensen, D. T., & Pissarides, C. A. (1999). New developments in models of search in the labor market. *Handbook of Labor Economics*, *3*, 2567–2627. https://doi.org/10.1016/S1573-4463(99)30025-0

Moulton, B. R. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *The Review of Economics and Statistics*, 334–338. https://doi.org/10.2307/2109724

Nickel, C., Bobeica, E., Koester, G., Lis, E., & Porqueddu, M. (2019). *Understanding low wage growth in the Euro area and European Countries*. ECB Occasional Paper No. 232.

OECD (2018a). Decoupling of wages from productivity. *What implications for public policies, OECD Economic Outlook* (pp. 51–65).

OECD (2018b). *OECD Economic Surveys: Lithuania*. OECD Publishing.

Randveer, M., & Staehr, K. (2021). Macroeconomic trends in the baltic states before and after accession to the EU. In *Does EU membership facilitate convergence? The experience of the EU's Eastern enlargement* (pp. 211–237). Springer.

Rubio-Ramirez, J. F., D. F. Waggoner, & Zha, T. (2010). Structural vector autoregressions: theory of identification and algorithms for inference. *The Review of Economic Studies*, *77*(2), 665–696. https://doi.org/10.1111/roes.2010.77.issue-2

Schröder, J. (2020). *Decoupling of labour productivity growth from median wage growth in central and Eastern Europe*. WIIW Research Report No. 448.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, *95*(1), 25–49. https://doi.org/10.1257/0002828053828572

Solon, G., Barsky, R., & Parker, J. A. (1994). Measuring the cyclicality of real wages: how important is composition bias? *Quarterly Journal of Economics*, *109*(1), 1–25. https://doi.org/10.2307/2118426

Verdugo, G. (2016). Real wage cyclicality in the eurozone before and during the great recession: evidence from micro data. *European Economic Review*, *82*, 46–69. https://doi.org/10.1016/j.euroecorev.2015.11.001

Yellen, J. L. (2015). Inflation dynamics and monetary policy: a speech at the Philip Gamble memorial lecture, University of Massachusetts, Amherst, Massachusetts, September 24, 2015.

Appendix. Additional Results

Table A1. Wage Phillips Curve Estimates: Sensitivity to Slack Measure.

	(1)	(2)	(3)	(4)	(5)
Unemployment rate	−1.7839***				
	(0.2251)				
Unemployment rate$_{t-4}$	0.9009***				
	(0.1970)				
Nonemployment rate		−2.5071***			
		(0.2922)			
Nonemployment rate$_{t-4}$		1.7184***			
		(0.2807)			
Unemployment gap			−1.4617***		
			(0.2367)		
Tightness				0.5214***	
				(0.1117)	
Tightness$_{t-4}$				−0.1170	
				(0.1068)	
Output gap					2.7941***
					(0.3950)
π_{t-1}	−0.0712	−0.0067	−0.5529**	−0.2159	−0.1787
	(0.2899)	(0.2837)	(0.2494)	(0.4913)	(0.2821)
$\Delta\psi_t$	0.3329***	0.2860***	0.6495***	0.3372*	0.3134***
	(0.1035)	(0.0875)	(0.1180)	(0.1975)	(0.1055)
$\Delta\underline{w}_t$	0.1368***	0.1442***	0.1884***	0.2931***	0.1668***
	(0.0389)	(0.0323)	(0.0547)	(0.0813)	(0.0531)
Observations	48	48	48	48	48
R-squared	0.8562	0.8801	0.7640	0.6332	0.7972

Source: Authors' calculations based on SoDra and Statistics Lithuania.Notes: Column (1) shows the wage Phillips curve based on the year-on-year (log) change of the average nominal wage *net* of workforce composition as explained in Equation (3). Column (2) to (5) uses alternative measures of economic/labor market slack. Nonemployment rate refers to all non-employed individuals. Unemployment gap is the deviation of current unemployment rate from NAIRU. Tightness stand for the job vacancy to unemployment ratio. Output gap corresponds to the deviation of current GDP from the potential GDP. Regressions are weighted by the number of individual observations in each quarter. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Wage Phillips Curve Estimates: Sensitivity to the Dependent Variable.

	(1) Residual wages	(2) Raw wages	(3) Compensation per employee
θ_t	−1.7839***	−1.3438***	−1.1015***
	(0.2251)	(0.1736)	(0.1556)
θ_{t-4}	0.9009***	0.4793***	0.4078***
	(0.1970)	(0.1642)	(0.1482)
π_{t-1}	−0.0712	−0.1162	−0.3872*
	(0.2899)	(0.2387)	(0.2135)
$\Delta\psi_t$	0.3329***	0.3021***	0.6127***
	(0.1035)	(0.0867)	(0.0891)
$\Delta\underline{w}_t$	0.1368***	0.1412***	0.0346
	(0.0389)	(0.0363)	(0.0500)
Observations	48	48	48
R-squared	0.8562	0.8529	0.8514

Source: Authors' calculations based on SoDra and Statistics Lithuania.
Notes: Column (1) shows the wage Phillips curve based on the year-on-year (log) change of the average nominal wage *net* of workforce composition as explained in Equation (3). Column (2) estimates the wage Phillips curve equation using *raw* wages, while Column (3) relies on compensation per employee obtained from national accounts. Regressions in Columns (1) and (2) are weighted by the number of individual observations in each quarter. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

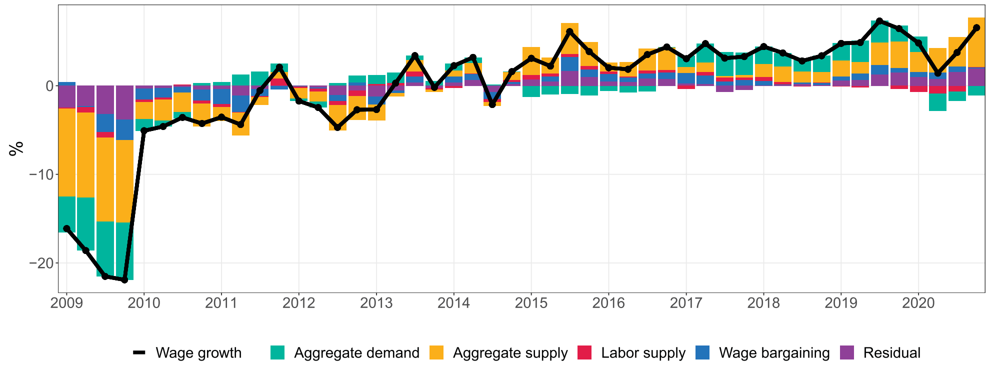

Figure A1. Structural Wage Growth Decomposition using Real Compensation per Employee.

Notes: The black line shows year-on-year real wage growth expressed as its deviation from the unconditional model forecast. The stacked bars give the contribution of each shock to the evolution of the wage growth. The decomposition is based on the average draw satisfying the sign restrictions.