

Explaining Deviations from Okun's Law*

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March 16, 2022

Abstract

Despite its stability over time, as for any statistical relationship, Okun's law is subject to deviations that can be large at times. In this paper, we provide a mapping between residuals in Okun's regressions and structural shocks identified with a SVAR model by inspecting how unemployment responds to the state of the economy. We show that deviations from Okun's law are a natural and expected outcome once one takes a multi-shock perspective, as long as shocks to automation, labor supply and structural factors in the labor market are taken into account. Our simple recipe for policy makers is that, if a positive deviation from Okun's law arises, it is likely to be generated by either positive labor supply or automation shocks or by negative structural factors shocks.

Keywords: Okun's law, Labor markets, Business cycle fluctuations, Bayesian VAR

JEL codes: E24, E32, C32

*This paper should not be reported as representing the views of the European Central Bank (ECB) and Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of the ECB and Norges Bank. We thank Laurence Ball, Ørjan Robstad, Francesco Zanetti and seminar participants at the ECB and Norges Bank for useful comments.

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1 Introduction

In 1962 Arthur Okun examined in a seminal paper ([Okun \(1962\)](#)) the empirical relation between changes in the unemployment rate and changes in real gross national output (GNP), or between the unemployment rate and a measure of the output gap. He found that a 1-percentage point decrease in real GNP growth was associated with a 0.3-percentage point increase in the unemployment rate. Since then, many studies have confirmed this finding and Okun’s law has become a classic ingredient in macroeconomic textbooks and a useful reference to calibrate forecasts (and forecasts revisions) produced by policy institutions ([An et al. \(2019\)](#)) and professional forecasters ([Ball et al. \(2015\)](#)). In an influential evaluation, [Ball et al. \(2017\)](#) examine data for 21 advanced countries and conclude that Okun’s law is a strong relationship in most countries and fairly stable over time. This evidence is seen as consistent with standard models in which fluctuations in unemployment are driven by aggregate demand shocks.

Despite its stability over time, as for any statistical relationship, Okun’s law is subject to deviations that are captured by the residuals in the regression. These deviations can be large at times. For example, unemployment was higher than expected in 2008 and 2009 at the outset of the Great Recession in the US (see, among others, [Owyang and Sekhposyan \(2012\)](#) and [Daly et al. \(2014b\)](#)). Subsequently, it has decreased to historically low levels while output growth has been modest both in the US and in the euro area. Deviations are more pronounced when using real-time data, as shown by [Daly et al. \(2014a\)](#), but remain sizeable even when using revised data.

One way to rationalize Okun’s law deviations is to invoke time variation in the Okun’s coefficient. [Owyang and Sekhposyan \(2012\)](#) and [Knotek II \(2007\)](#) find supportive evidence based on rolling regressions. In contrast, [Karlsson and Österholm \(2020\)](#) show that time variation is modest when estimating a hybrid time-varying parameter Bayesian Vectorautoregression model. In the literature, these possibly time-varying dynamics are usually associated to *non-linearities* in terms of asymmetries (i.e. unemployment responding more to the cycle during recessions than in booms as in [Cuaresma \(2003\)](#)),

threshold effects ([Christopoulos et al. \(2019\)](#)) or structural breaks ([Lee \(2000\)](#)).¹

In this paper, we provide an alternative explanation for deviations from Okun’s law based on the nature of the shocks hitting the economy in the context of a *linear* model. In particular, we show that deviations from Okun’s law are a natural and expected outcome once a multi-shock perspective is taken into account. The Okun’s law captures a simple correlation between two highly endogenous variables and this correlation is shaped by several shocks. The correlation may change over time just because the cocktail of shocks affecting the economy changes over time. We formalize our argument by building a bridge between Okun’s regressions and simple structural vectorautoregressive (SVAR) models used to compute shock-specific elasticities. In that sense, we adapt to Okun’s law the SVAR analysis on the slope of the Phillips curve proposed by [Bergholt et al. \(2022\)](#).

We make our argument in two steps. In a first experiment, we use a simple bivariate SVAR model identified with sign restrictions to identify a ”standard” shock moving unemployment and output in different directions, in keeping with Okun’s law, and an ”*unusual*” shock that moves unemployment and output in the same direction. Such a shock, which at this stage is left without economic interpretation, is a natural candidate to be an important driver of deviations from Okun’s law. In fact, we find that the ”unusual” shock plays a non minor role in explaining unemployment fluctuations in the U.S. and in the euro area and exhibits a strong positive correlation with Okun’s law residuals.

In a second step, we build a larger model to provide a structural interpretation to the unusual shock. In particular, we identify two shocks that according to standard macroeconomic theory are expected to generate a positive co-movement between output and unemployment. The first is an automation shock that increases productivity and output at the expense of human labor, thus moving output and unemployment in the same direction, at least on impact (cf. [Acemoglu and Restrepo \(2018\)](#) and [Bergholt et al. \(2021\)](#) among others). The second is a labor supply shock. Suppose an exogenous increase in participation. Many of the additional workers entering the labor force will quickly find

¹The literature studying non-linearities in Okun’s law is particularly voluminous. A recent broad overview of previous contributions, in addition to supporting evidence for a three-regime Okun’s relationship, is presented in [Donayre \(2021\)](#).

a job, thus increasing employment and production. However, as discussed originally in [Blanchard and Diamond \(1989\)](#), standard theory implies that at least some of these additional participants will experience an unemployment spell. Thus, unemployment and output are expected to co-move also in response to labor supply shocks which have been shown to be important drivers of economic fluctuations by [Shapiro and Watson \(1988\)](#), [Chang and Schorfheide \(2003\)](#) and [Faroni et al. \(2018\)](#). Our first result is that, once we recognize that automation shocks and labor supply shocks do play a role in economic fluctuations, deviations from Okun’s law are a natural outcome. We show that residuals in the Okun’s regression exhibit a strong positive correlation with the estimated series for automation and labor supply shocks.

In addition to labor supply and automation shocks, we identify three shocks that move unemployment and output in different directions: demand shocks, productivity shocks and a shock bundling together structural factors in the labor market like variations in the bargaining power of workers (also related to social and political distribution risk between labor and capital, as discussed in [Drautzburg et al. \(2021\)](#)), shocks to matching efficiency and shocks to unemployment benefits. Identifying many shocks that are consistent with the Okun’s law dynamics allows us to highlight our second result. One of these shocks, the structural factors shock, induce large effects on unemployment but relatively limited effects on output, thus generating a large negative conditional Okun’s correlation, much more negative than the coefficient obtained in a simple Okun’s regression. This implies that deviations from Okun’s law should be expected also in periods in which structural factors shocks are important, like the post Great Recession period in the euro area. In fact, we find that residuals in the Okun’s regression are negatively correlated with the structural factors shock series.

As far as we know, this is the first paper linking Okun’s law deviations to shocks originating in the labor market (labor supply shocks and structural factors shocks) and automation shocks. However, it is important to stress that other papers have highlighted the importance of shock heterogeneity in the context of Okun’s law. In their seminal paper, [Blanchard and Quah \(1989\)](#) describe the Okun’s coefficient as a mongrel coefficient

insofar as demand shocks generate a tight relation between output and unemployment while supply shocks do not. The supply shock estimated by [Blanchard and Quah \(1989\)](#) bundles together the four supply shocks that we disentangle in our system. In this spirit, [Daly et al. \(2013\)](#) estimate shock-specific Okun elasticities in response to shocks using instrumental variable local projections, with a special focus on the link between output components (like total hours and output per hour). Finally, [Ziegenbein \(2021\)](#) compute a shock-specific Okun elasticity in response to shocks using instrumental variables regressions. He finds that the Okun elasticity is largely stable across shocks. Notably, none of these papers consider shocks originating in the labor market and automation shocks which turns out to be crucial to explain deviations from Okun’s law in our set-up.

The remainder of paper is organised as follows. Section [2](#) provides updated estimates of Okun’s law for the U.S. and the euro area. Section [3](#) introduces a simple bivariate SVAR model to highlight the importance of taking a multi-shock perspective. Section [4](#) presents a larger SVAR model that we use to compute shock-specific Okun’s law elasticities and to explain deviations from the Okun’s regression. Section [5](#) provides some sensitivity analysis and an extension to analyze the case of Germany. Finally, Section [6](#) concludes.

2 Updated evidence on Okun’s law in the U.S. and euro area

In this Section, we present some basic facts about Okun’s law. In a first step, we re-estimate the Okun’s regression on a sample from 1949Q1 to 2019Q4 for the U.S. and from 1998Q1 to 2019Q4 for the euro area.² In particular, we run the following regression, both for the U.S. and euro area:

$$\Delta U_t = \alpha + \beta \Delta y_t + \epsilon_t, \tag{1}$$

²Given the exceptional reactions of macroeconomic variables to the COVID-19 pandemic, we prefer to stop the full sample evaluation in 2019, to avoid distortions in the results.

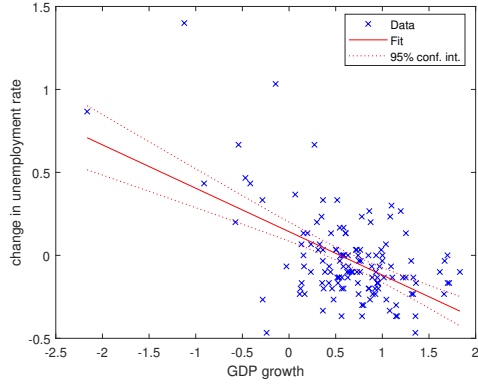
where U_t indicates unemployment rate and y_t refers to real GDP. Δ indicates quarter-on-quarter growth rates for GDP, and quarterly differences for unemployment rate.³ In first row of Figure 4, we present a scatterplot of the data and the estimated regression line with 95 percent confidence interval. The Okun's coefficient β is estimated at 0.28 for the U.S. and 0.29 for the euro area. Not surprisingly, the data exhibit a clear negative correlation between changes in unemployment and output growth and the estimated coefficients are totally in line with Okun's original estimates over the period 1947Q2 to 1960Q4. However, the fit of the regression is far from perfect and large deviations arise over the sample both in the U.S. and in the euro area. The residuals of the regression are plotted in the second line of Figure 4. In the U.S., unemployment was unusually high, given developments in GDP growth, during the last three recessions and in the early phase of recoveries but also in the second half of the 1990s. In contrast, unemployment was unusually low from 2011 to the end of the sample and also between 2003 and 2006 when growth decelerated with unemployment continuing to drift downward (cf. Knotek II (2007)). In the euro area, unemployment was unusually high, once again given developments in GDP growth, from 2002 to 2014 with the partial exception of the immediate pre-Great Recession period while it was particularly low from 2014 until the end of the sample. It is important to remark that these residuals do not capture statistical noise but large and persistent deviations from the estimated relationship. Our goal is to provide a structural interpretation to these persistent deviations that are particularly informative for our purposes.

One way to rationalize these deviations is to assume a time-varying relationship between changes in unemployment and GDP growth. In the third row of Figure 4 we present time-varying estimates of the Okun's coefficient (blue solid lines) based on a rolling estimation of the relation between unemployment and GDP with a window of 40 quarters, thus updating until 2019 the estimates provided by Owyang and Sekhposyan (2012). The results show that, despite the relations not dramatically changing, there are periods in which the estimated coefficient falls outside the confidence bands estimated on the full samples (dashed red lines). According to these estimates, the Okun's coeffi-

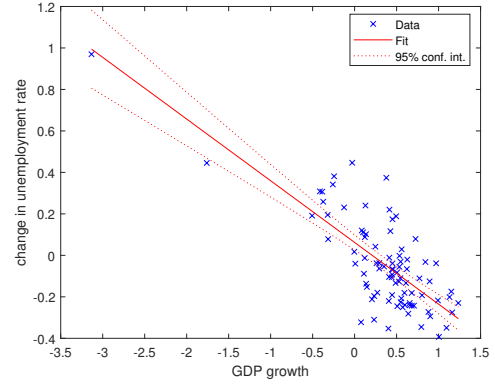
³Very similar results to the ones presented here are obtained if we run the regressions on year-on-year growth rates and four-quarter differences.

Figure 1: Okun's law in the U.S. and euro area: basic facts

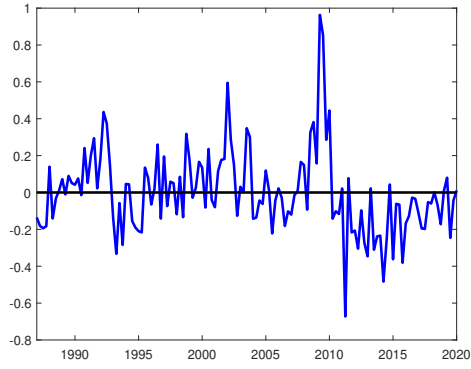
(a) Scatter plot - U.S.



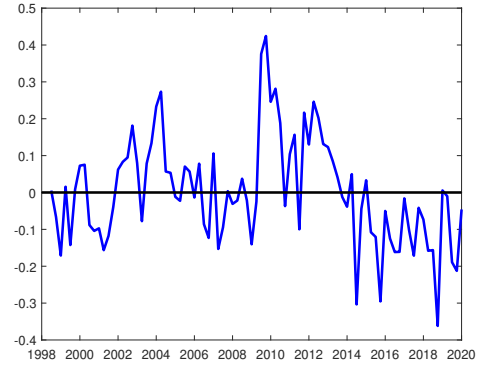
(b) Scatter plot - euro area



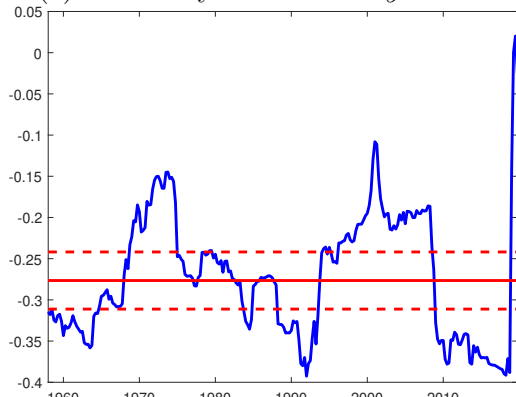
(c) OLS residuals - U.S.



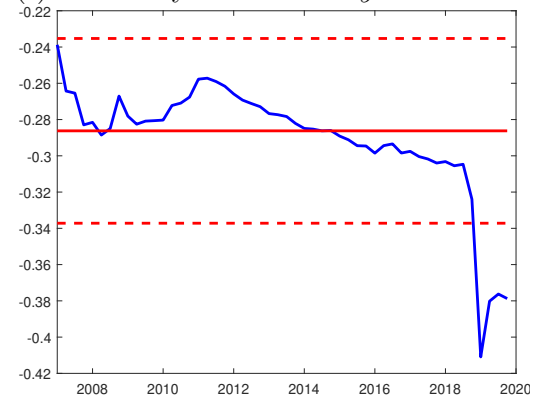
(d) OLS residuals - euro area



(e) Elasticity of ΔU to Δy - U.S.



(f) Elasticity of ΔU to Δy - euro area



Note: Panel (e) reports β of eq. (1), obtained with U.S. data on the sample 1948Q2-2019Q4 and its 95% confidence bands (in red), and the rolling estimates of β (in blue), computed with a window of 40 quarters. Panel (f) reports the same results for the euro area, obtained on the sample 1997Q2-2019Q4.

cient was particularly low around the 2000s in the U.S. and particularly high in recent years, both in the U.S. and in the euro area. As mentioned in the Introduction, these time-varying dynamics could capture non-linearities. In the remainder of this paper, we provide an alternative and possibly complementary explanation that stresses instead the role of shocks' heterogeneity.

3 A toy SVAR model

The Okun's regression suffers a clear endogeneity problem if both changes in unemployment and GDP growth respond to a battery of shocks driving economic fluctuations. However, the endogeneity problem is less severe if both variables are dominantly (although not exclusively) driven by aggregate demand shock which was Okun's underlying assumption. In this Section, our goal is to provide *prima facie* evidence that the endogeneity problem is relevant and shocks other than aggregate demand are at play. Imagine a shock (at the moment without any economic interpretation) moving changes in unemployment and GDP growth in the same direction. If such a shock plays a non minor role, deviations from Okun's law are the logic and expected consequence. We label the shock as *unusual* because changes in unemployment and GDP growth are negatively correlated unconditionally, thus implying that the unusual shock cannot be dominant. Nonetheless, it can rationalize deviations from Okun's law over history. Put differently, the unusual shock plays the same role of supply shocks when estimating Phillips curve regressions (cf. [Bergholt et al. \(2022\)](#)).

To check the importance of our unusual shock, we estimate a bivariate SVAR model which includes real GDP growth and changes in the unemployment rate:

$$y_t = C + \sum_{p=1}^P B_p y_{t-p} + u_t, \quad (2)$$

where y_t is a 2×1 vector including real GDP growth and changes in the unemployment rate, C is a 2×1 vector of constants, B_i for $i = 1, \dots, P$ are 2×2 parameters matrices, with P the numbers of lags of the endogenous variables included in the estimation, in

our specific case 4. u_t is the vector of residuals, with $u_t \sim N(0, \Sigma)$, where Σ is the 2×2 variance-covariance matrix. The OLS estimation of this system produces two reduced form residuals (an unemployment shock and a GDP growth shock) that at this stage have no structural interpretation. In order to obtain structural shocks, we use sign restrictions on the impact responses of shocks. Sign restrictions allow to obtain identification by drawing a number of orthonormal matrices, and consider only the ones which satisfy prior beliefs about the sign that certain shocks should have on certain endogenous variables.

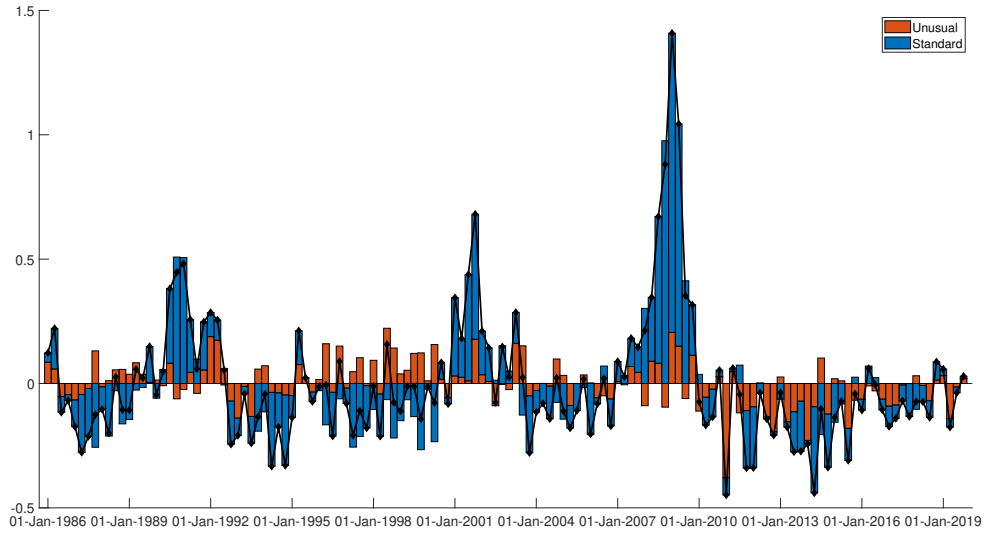
Our identification strategy relies on intuitive sign restrictions imposed on impact, as recommended by [Canova and Paustian \(2011\)](#). In addition to the unusual shock, we identify a standard shock that moves unemployment and output in different directions on impact, in keeping with Okun’s law. The model is estimated with Bayesian techniques and we use a standard Normal - Wishart prior, where the prior of the parameter matrices B_i follows a Normal distribution and the prior of the variance-covariance matrix Σ follows an inverse Wishart distribution. To obtain the identification with sign restrictions we implement the algorithm of [Arias et al. \(2018\)](#). The model is estimated using quarterly data, spanning 1985Q1-2019Q4 for the U.S., and 1997Q2-2019Q4 for the euro area.

In [Figure 2](#) we present historical decompositions for unemployment.⁴ As expected, the standard shock is the main driver of unemployment both in the U.S. and in the euro area. However, the unusual shock plays a non negligible role, especially at the end of the 90s and in the aftermath of the Great Recession in the U.S. Is such a non negligible (but still limited) role sufficient for explaining deviations from Okun’s law? We computed the pairwise correlation between Okun’s law residuals and the estimated series for the unusual shock. Interestingly, the two series exhibit a strong correlation, equal to 0.75 in the U.S. data and 0.73 in the euro area data. Thus, whenever unemployment is higher than what implied by Okun’s law, positive unusual shocks are hitting the economy. Notably, the

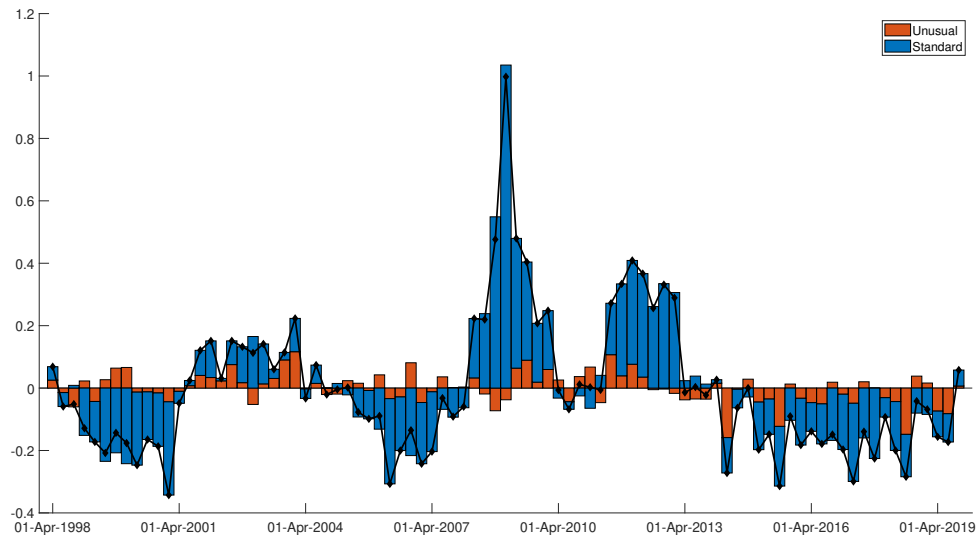
⁴More specifically, [Figure 2](#) reports historical decompositions of the quarterly change in the unemployment rate in deviation from its initial conditions (the deterministic component of the series, thus not explained by the shocks’ contributions). The figure plots the median of the shock contributions across the replications which satisfy the sign restrictions. We compute the ”median” contributions as follows: we estimate the model and save 10000 draws which satisfy the sign restrictions. For each draw, we compute the historical decomposition. We then compute the median contribution across the 10000 historical decompositions for each shock at each quarter.

Figure 2: Results for the bivariate toy model

(a) Historical decomposition: quarterly changes in the unemployment rate (U.S.)



(b) Historical decomposition: quarterly changes in the unemployment rate (euro area)



Note: The historical decompositions report the median shock contributions over 10000 replications. The series are reported in deviations from its initial conditions.

residuals are uncorrelated with the standard shocks, thus supporting the idea that the unusual shocks are important drivers of the residuals in the Okun’s regression. Having established that standard demand shocks are not the exclusive drivers of unemployment fluctuations, our next objective is to provide a structural interpretation to the unusual shock.

4 A larger SVAR model

In this Section, we estimate a larger SVAR model to obtain a more granular view of shock-specific Okun elasticities. We include five variables: real GDP growth, employment growth (measured as total hours growth), price inflation (computed as the growth of GDP deflator), real wage growth (computed as the growth in compensation per hour deflated by the GDP deflator)⁵ and changes in the unemployment rate. A detailed description of the series used is provided in Appendix A. The identification assumptions are summarized in the first panel of Table 1.⁶

Notably, we identify two shocks, an automation shock and a labor supply shock, that provide a structural interpretation to the unusual shock identified in the previous Section. Both shocks are assumed to generate a positive co-movement between output and unemployment. An automation shock captures technological progress that increases output and labor productivity at the expenses of employment, as discussed in [Acemoglu and Restrepo \(2018\)](#) and [Bergholt et al. \(2021\)](#) among many others. A labor supply shock captures exogenous variations in participation (driven, for example, by preferences, schooling decisions, demographics, pension reforms or immigration). As originally discussed in [Blanchard and Diamond \(1989\)](#) (and more recently by [Schiman \(2021\)](#)), a rise in participation leads to an increase of both employment (and thus production) and unemployment in the short run.

In addition, we identify three shocks consistent with the correlation implied by Okun’s

⁵We conducted the analysis also with nominal wage growth and all the results hold.

⁶As in the case of the toy model, we estimate our SVAR model with Bayesian techniques, Normal-Wishart prior, four lags and restrictions imposed on impact. We use quarterly data spanning 1985q1-2019q4 for the US, and 1997q2-2019q4 for the euro area. Details on the estimation are provided in Appendix B.1.

law: a demand shock (the only shock in the system moving output and prices in the same direction), a productivity shock (the only shock in the system moving employment and wages in the same direction) and a structural factors shock whose defining feature is to generate a positive co-movement between wages and unemployment. Wages and unemployment are negatively correlated in the data, in keeping with the wage Phillips curve. Therefore, structural factors shocks can be seen as shifters of the wage Phillips curve. One natural interpretation is that they capture variations in the bargaining power of workers. As shown by [Foroni et al. \(2018\)](#), a decrease in the bargaining power of workers increases GDP and employment while leading to a decrease in wages, prices and unemployment rate under a broad set of parameterizations. However, the same dynamics can be generated by a shock to the matching efficiency in the labor market, by a shock to the job destruction rate ([Zanetti \(2019\)](#)), by a shock to unemployment benefits or by variations in minimum wages, as shown recently by [Budrys et al. \(2021\)](#) for the case of Germany. Therefore, this shock is a catch-all shock for variations in structural factors in the labor market. The theoretical mechanisms supporting our restrictions are discussed in detail in Appendix [B.2](#).⁷

It is important to stress that all variables enter the model in first differences. Therefore, all shocks are allowed (without imposing) to have permanent effects. This seems a natural choice not only for the four supply shocks but also for the demand shock in light of the evidence of hysteresis mechanisms over our sample period, as documented by [Furlanetto et al. \(2021\)](#). On a similar note, supply shocks (and labor market shocks in particular) are allowed to drive the business cycle in keeping with [Drautzburg et al. \(2021\)](#) and [Shapiro and Watson \(1988\)](#) who show that wage bargaining power shocks and labor supply shocks play a role in the medium run but also at business cycle frequencies.

In a first exercise, we use our estimated SVAR as a filtering device. The model decomposes fluctuations in GDP growth and in unemployment growth into five components, each driven by one of the five shocks identified in our system. Therefore, it

⁷Strictly speaking, the restrictions on unemployment in response to demand, technology and automation shocks are not needed to achieve identification. We impose them to better characterize the different shocks. Note that all our results are confirmed also in a specification using the minimum set of restrictions.

Table 1: SVAR model: specification and results

Panel (a): Identification strategy						
	Demand shock	Technology shock	Structural Factors shock	Labour supply shock	Automation shock	
real GDP	+	+	+	+	+	
Employment	+	+	+	+	-	
Inflation	+	-	-	-		
Wage inflation		+	-	-		
Unemployment rate	-	-	-	+	+	
Panel (b): Conditional Okun's law elasticities						
	Demand shock	Technology shock	Structural Factors shock	Labour supply shock	Automation shock	β_{OLS}
U.S.	-0.27	-0.28	-0.80	0.13	0.29	-0.26
euro area	-0.32	-0.31	-0.50	0.28	0.27	-0.30
Panel (b) reports the results obtained running the regressions in eq. (1) on the component of the change in unemployment rate and output growth due to the shock indicated in the respective row.						
Panel (c): Pairwise correlations between OLS residuals and structural shocks						
	Demand shock	Technology shock	Structural Factors shock	Labour supply shock	Automation shock	
U.S.	0.07	0.05	-0.33	0.43	0.52	
euro area	0.15	0.06	-0.11	0.47	0.48	
Panel (c) shows the pairwise correlations of the OLS residuals obtained as in eq. (1), and the series of structural shocks obtained with the SVAR in Section (4).						
Panel (d): Robustness						
	Demand shock	Technology shock	Structural Factors shock	Labour supply shock	Automation shock	β_{OLS}
<u>Conditional Okun's law elasticities</u>						
R1: More GDP lags (US)	-0.43	-0.37	-0.93	-0.21	0.41	-0.45
R1: More GDP lags (EA)	-0.39	-0.39	-0.60	-0.03	0.34	-0.39
R2: Germany	-0.17	-0.17	-0.28	0.23	0.15	-0.10
R3: Barnichon and Mesters (2018)	-0.21	-0.24	-0.68	0.37	0.22	-0.29
<u>Pairwise correlations</u>						
R1: More GDP lags (US)	-0.04	-0.05	-0.51	0.40	0.46	
R1: More GDP lags (EA)	0.00	-0.18	-0.33	0.50	0.45	
R2: Germany	-0.06	-0.19	-0.26	0.55	0.45	
R3: Barnichon and Mesters (2018)	0.08	0.06	-0.19	0.29	0.50	
Panel (d) shows the results for the robustness check equivalent to what shown in Panels (b) and (c) respectively.						

is straightforward to run five regressions and obtain five conditional estimates for the Okun’s coefficient. The Okun’s coefficient estimated in equation (1) should be seen as a weighted average of the five conditional coefficients that are presented in the second panel of Table 1. Given our identification assumptions, it is not surprising that automation and labor supply shocks generate a positive conditional correlation between GDP growth and changes in unemployment both in the U.S. and in the euro area. What is less obvious is the fact that these shocks drive a sizeable share of unemployment fluctuations over history, as shown in Figure 3 where the two shocks are bundled together and represented by orange bars. We thus confirm that the two shocks provide a structural interpretation to the dynamics generated by the unusual shock in Figure 3. The two shocks are also natural drivers of the residuals in Okun’s regression. Whenever the residuals are positive, it means that unemployment is higher than what implied by GDP dynamics. Automation and labor supply shocks increase both GDP and unemployment. Therefore, we should observe a positive correlation between Okun’s residuals and the estimated series for labor supply shocks and automation shocks. We compute pairwise correlations in the third panel of Table 1 and we appreciate that this intuition is fully correct. Residuals in Okun’s regressions are positively correlated with the series for automation and labor supply shocks, both in the U.S. and in the euro area. All in all, we establish that the two shocks co-move with Okun’s law deviations.

Our second main result concerns the shocks that generate a negative correlation between output growth and changes in unemployment. While demand and productivity shocks generate a conditional Okun’s coefficient fully in line with the unconditional estimates and are bundled together in the blue bars in Figure 3), the structural factors shock generates a much more negative conditional correlation both in the U.S. and in the euro area.⁸ Such a strong negative correlation implies that structural factors shocks are also responsible for deviations from Okun’s law. In this case, however, the correlation between residuals and the shock series is expected to be negative: negative structural

⁸Interestingly, an important role of wage bargaining shocks for unemployment fluctuations is a common finding in the literature (cf. Budrys et al. (2021), Drautzburg et al. (2021) and Foroni et al. (2018)). In addition, Guisinger et al. (2018) show that the degree of unionization is one of the most important determinants of the differences in Okun’s coefficients across U.S. states.

factors shocks (that imply high unemployment and a contraction in GDP) are expected to generate positive residuals in the Okun’s regression. In fact, residuals are negatively correlated with structural factors shocks in the data, as shown in the third panel of Table 1. We estimate a correlation of -0.33 in the U.S. and -0.11 in the euro area. Note that we should not necessarily expect a strong correlation: Okun’s law residuals in a given period are driven also by the other shocks (and not only by structural factors shocks) and by shocks that originated in previous periods. Nonetheless, it is encouraging that our simple economic intuition finds support in the data. Interestingly, and in keeping with the similarity between conditional and unconditional Okun’s coefficients, demand shocks and productivity shocks are uncorrelated with the residuals. Not surprisingly given their high impact on unemployment, structural factors shocks explain a sizeable share of unemployment fluctuations over history (yellow bars in Figure 3). This is particularly evident for the euro area, after the onset of the financial crisis, where a significant number of countries implemented many labour markets reforms as part of the response to the crisis (see [Anderton and Di Lupidio \(2019\)](#)). This is reflected in a series of almost uninterrupted positive structural shocks identified by our model since 2013.

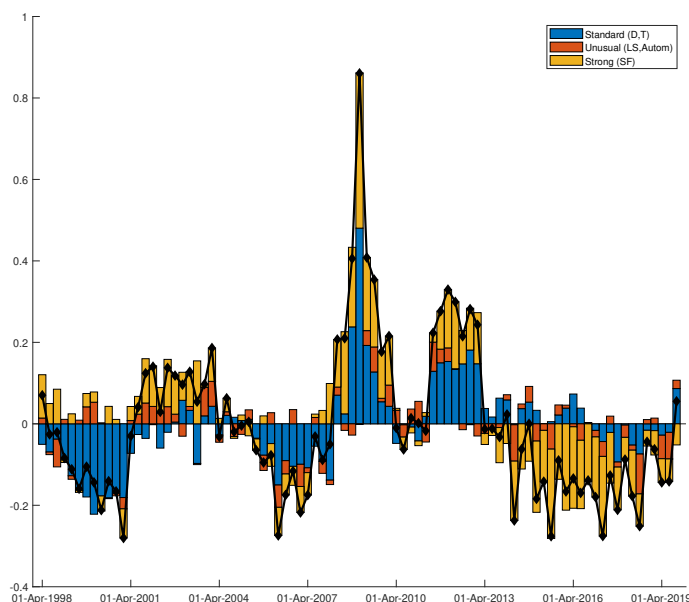
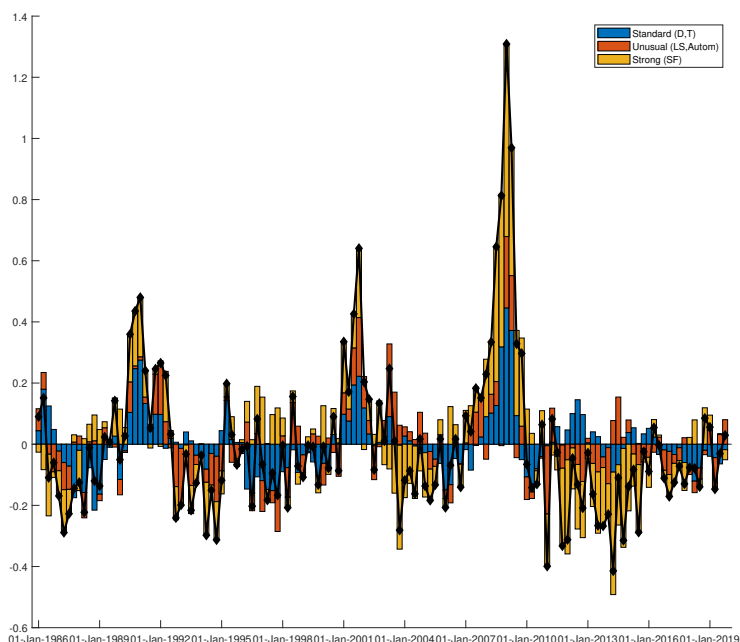
The third panel in Table 1 summarizes our simple recipe for policy makers: if a positive deviation from Okun’s law arises, it is likely to be generated by either positive labor supply or automation shocks or by negative structural factors shocks. Conversely, negative deviations are related to positive structural factors shocks or negative automation and labor supply shocks. As far as we know, this is the first paper providing a mapping between Okun’s law deviations and structural shocks. According to our results, it is possible that previous papers (see [Ziegenbein \(2021\)](#) and [Daly et al. \(2013\)](#)) found a limited role for shocks heterogeneity because they did not considered shocks originating in the labor market (labor supply and structural factors) and automation shocks. In fact, [Daly et al. \(2013\)](#) focus on shocks to interest rates, bond premiums, oil prices and TFP while [Ziegenbein \(2021\)](#) discusses the effects of tax, monetary policy, financial, technology and oil shocks.

Another way to look at conditional Okun’s law elasticities, complementary to what

Figure 3: Results for the more complex SVAR model

(a) Historical decomposition: quarterly changes in the unemployment rate (U.S.)

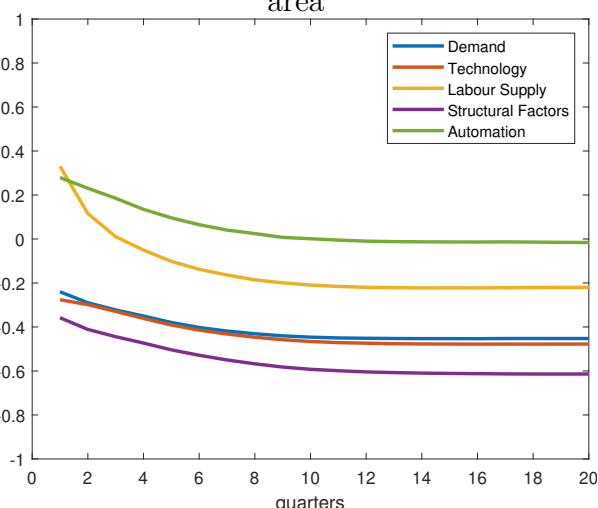
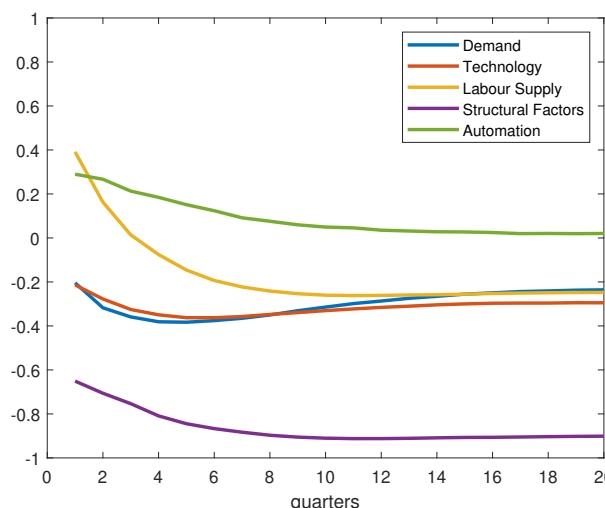
(b) Historical decomposition: quarterly changes in the unemployment rate (euro area)



Note: The historical decomposition reports the median shock contributions over 10000 replications. The series is reported in deviations from its initial conditions.

(c) Ratio of cumulative IRFs of unemployment rate and GDP growth - U.S.

(d) Ratio of cumulative IRFs of unemployment rate and GDP growth - euro area



Note: Panel (c) reports the ratios of the cumulative impulse response functions of unemployment rate relative to output to various shocks at different horizons for the US. Panel (d) reports the same results for euro area. The ratios are obtained as the median of the 10000 replications considered in the estimation.

shown in panel (b) of Table 1, is to consider the ratios between the cumulative change in the unemployment rate over the next h quarters and the cumulative change in real GDP growth over the same quarters. This corresponds to the ratio of the cumulative impulse response of the change in unemployment rate over the cumulative impulse response of the real GDP growth (for a similar way to analyse conditional elasticities, see [Forbes et al. \(2018\)](#) and [Ziegenbein \(2021\)](#)). Those ratios are reported in the second row of Figure 3. The panels show that in the U.S. and in the euro area unemployment responds differently relative to GDP growth depending on the nature of the shock. Differences are remarkable in the short run, but also at longer horizons. Those ratios can be interpreted as multipliers at different horizons, since they measure the cumulative relative change in the unemployment rate and output due to a specific shock. Once again, the ratio fluctuates between -0.2 and -0.3 in response to demand and technology shocks while it exhibits positive values in response to labor supply and automation shocks and more negative values in response to structural factors shocks (especially in the U.S.). Note that the differences are rather stables across different horizons with the exception of labor supply shocks in the U.S. where the Okun’s multiplier conditional on labor supply shocks tends to converge with the multiplier conditional on demand and technology shocks.

Finally, let us comment more on the endogeneity issue that motivates our analysis. So far, we stressed that output and unemployment are highly endogenous variables and thus the reader could easily conclude that the use of OLS to estimate Okun’s law should lead to highly biased estimates. Intriguingly, our results show that, if the object of interest is the response of unemployment to output conditional on demand shocks (i.e. Okun’s original assumption), using OLS delivers accurate results. In fact, the second panel of Table 1 shows that the unconditional estimate obtained with OLS and the estimate conditional on demand shocks are almost identical, both in the US (-0.26 vs -0.27) and in the euro area (-0.3 vs -0.32). This is the case because the unconditional estimate is subject to two compensating biases: labor supply and automation shocks imply an upward bias while structural factors shocks lead to a downward bias. The two biases roughly compensate each other, thus aligning the estimate conditional on demand shocks

with the unconditional estimate. Although slightly more involved, this argument reminds of a recent result by [Carvalho et al. \(2021\)](#) in the context of Taylor rules' estimation. These authors show that the bias in the OLS estimates of Taylor rule coefficients is small because monetary policy shocks explain a small share of fluctuations in inflation and measures of real economic activity. Okun's law residual (the equivalent of the monetary policy shock in the Taylor rule) is also relatively small (although not negligible at all) and, most importantly, is driven by two compensating factors (automation and labor supply shocks on one side and structural factors shocks on the opposite side). All in all, using OLS on the unconditional data provides accurate estimate of the Okun's coefficient in response to demand shocks (and, incidentally, the same result holds also for productivity shocks).

5 Robustness

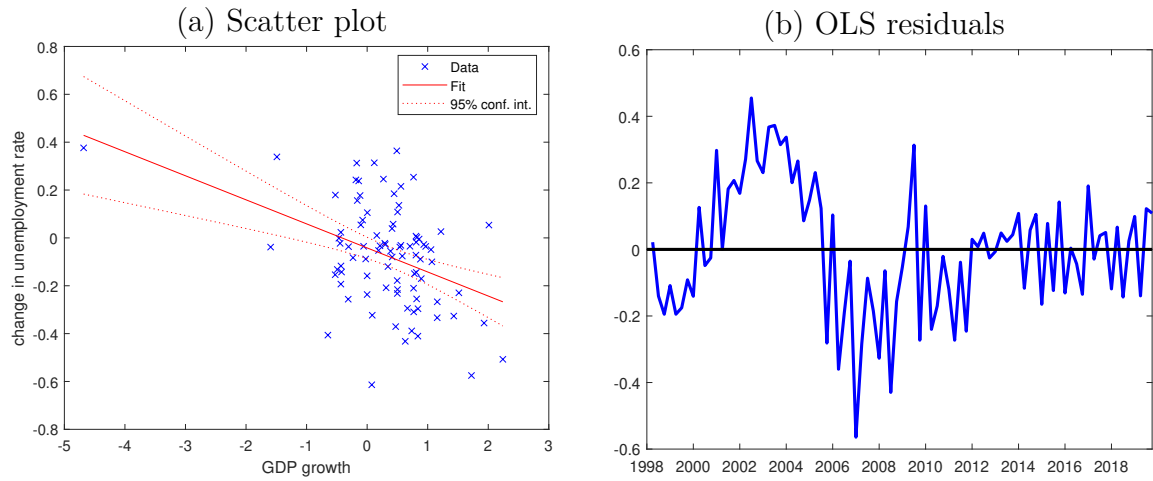
In a first exercise, we consider an alternative version of Okun's law proposed by [Ball et al. \(2017\)](#):

$$\Delta U_t = \alpha + \sum_{p=0}^P \beta_p \Delta y_{t-p} + \epsilon_t, \quad (3)$$

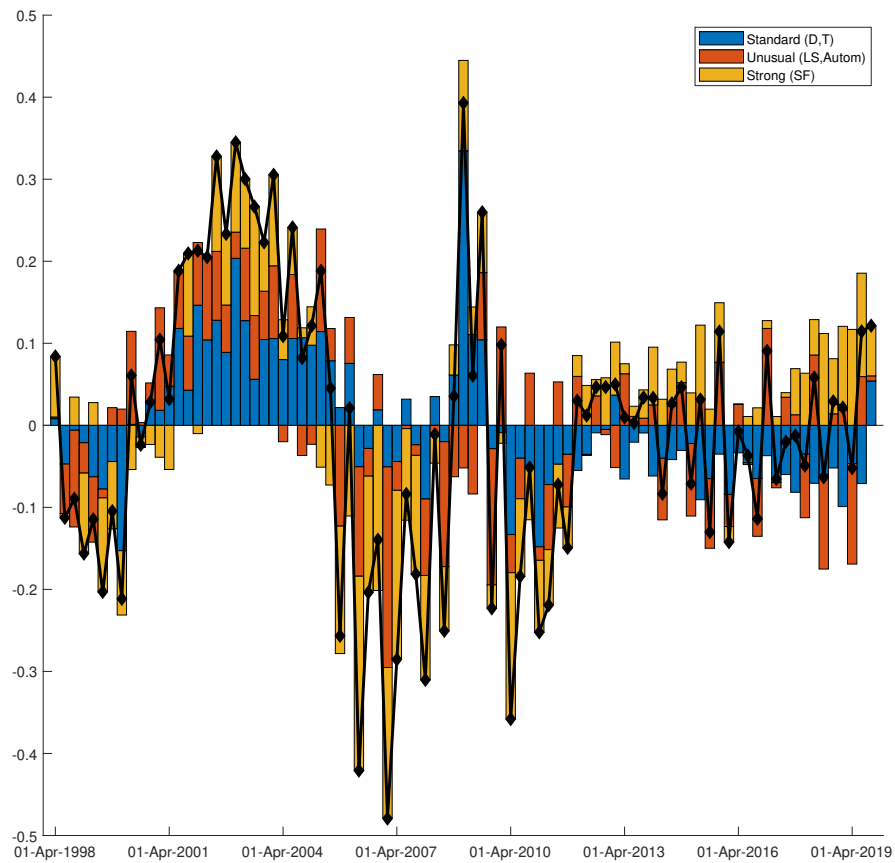
with $P = 2$ indicating the lags of output growth included in the equation, and the rest of the notation defined as in [Section 2](#).

[Ball et al. \(2017\)](#) argue that it is important to include lags of output growth because unemployment lags output movements in quarterly data. In a specification with two lags, the sum of coefficients on current and lagged output growth is about 0.5 (thus bigger than the standard estimate of 0.3 with no lags) when the equation is estimated on Okun's original sample. Therefore, we estimate this richer specification over our baseline samples on U.S. and euro area data and we correlate the residuals with the shocks recovered from our SVAR model presented in [Section 4](#). The results are summarized in the fourth panel of [Table 1](#). As in [Ball et al. \(2017\)](#), the Okun's coefficient (defined as the sum of coefficients on current and lagged output) is larger than in the standard

Figure 4: Results for Germany



(c) Historical decomposition: quarterly changes in the unemployment rate



Note: The historical decomposition reports the median shock contributions over 10000 replications. The series is reported in deviations from its initial conditions.

specification with no lags (-0.45 for the U.S. and -0.39 for the euro area). When we estimate the alternative specification with two lags on conditional data generated by the SVAR, we find familiar results with one exception. It is still the case that the Okun’s coefficients conditional on demand and on productivity shocks are almost identical to the unconditional estimate. In addition, it is still the case that the coefficient conditional on automation is positive while the coefficient on structural factors shock is large and negative. The new result is that the coefficient conditional on labor supply shocks is now slightly negative (although still much higher than the coefficient on demand, productivity and structural factors shocks). This is due to the fact that the unemployment response to a labor supply shock switches sign at horizon two. [Faroni et al. \(2018\)](#) show that a sign reversal in the unemployment response to labor supply shocks can be easily generated in the context of a New Keynesian model for a non negligible share of parameterizations. Finally, the pairwise correlation between regression’s residuals and structural shocks are quantitatively very similar to the case of baseline Okun’s law.

In a second exercise, we estimate our SVAR model for Germany over the sample 1997Q2-2019Q4. Being Germany the largest country in the European Union, this exercise is interesting *per se*. However, our main goal is to use Germany as a cross-check on the ability of our structural factors shocks to capture plausible dynamics. In the previous Section, we have shown that structural factors shocks have lowered the unemployment rate after 2013 in the euro area. A skeptical reader may think that the decline in unemployment should be driven more by the recovery in demand from the crisis in 2008 and 2011. To build confidence on our result for the euro area, we estimate our model for Germany where it is widely accepted that structural reforms had an impact on unemployment dynamics. In [Figure 4](#), we present the results. The Okun’s coefficient is estimated at -0.10 for Germany, thus very low when compared to the U.S. and the euro area. Residuals are once again persistent and especially large in the first part of the sample. The historical decomposition for unemployment shows that structural factors shocks favored high unemployment in the early 2000s while they had the opposite effect between 2004 and 2010, a period characterized by important structural reforms, as doc-

umented in [Fahr and Sunde \(2009\)](#) and [Burda and Hunt \(2011\)](#). After 2010, structural factors shocks increased unemployment. This last result is consistent with the emergence of bargaining power shocks in favor of workers, as documented by [Budrys et al. \(2021\)](#) who refer to a statutory minimum wage introduction in 2015, as well as a number of labor disputes led by the prominent union IG metall. These authors use narrative restrictions assuming the presence of a wage bargaining power shock in favor of workers precisely over the period 2014Q1-2015Q1. While our model is admittedly simple (and not suitable for any normative discussion), the patterns of structural factors shocks in Germany seem plausible, thus indirectly building some confidence also on the results for the euro area.⁹

Finally, in a third exercise, we investigate the role of demographic factors. In fact, we expect labor supply shocks (and to some extent also structural factors shocks) to capture, at least in part, these slow moving factors. One may wonder, however, whether demographic factors are the *exclusive* drivers of Okun’s law deviations. To check this conjecture, we re-estimate Okun’s law (equation (1)) using a measure of unemployment adjusted for demographic factors for the U.S., as computed by [Barnichon and Mesters \(2018\)](#). We estimate a Okun’s coefficient of -0.29. In the fourth panel of Table 1 we show the pairwise correlation between the residuals in the Okun’s regression and the structural shocks estimated in our baseline SVAR. The correlation between residuals and labor supply shocks decreases from 0.43 to 0.29, thus showing that demographic adjustment matters but only to some extent. The correlation is almost unchanged in response to demand, technology and automation shocks while the negative correlation between residuals and wage bargaining shock is somewhat reduced (from -0.33 to -0.19). We conclude that our baseline results are in part capturing demographic factors but are not driven *exclusively* by demographic factors.

⁹The conditional Okun’s coefficient estimated on the data generated by the SVAR model and the correlation between OLS residuals and structural shocks presented in the fourth panel of Table 1 are fully in line with our previous analysis for the U.S. and the euro area.

6 Conclusion

In this paper, we have provided a mapping between residuals in Okun’s law regressions and structural shocks. We have shown that deviations from Okun’s law are a natural and expected outcome once one takes a multi-shock perspective. While other papers have highlighted the importance of shock heterogeneity, no other paper has studied the peculiar role of automation, labor supply and structural factors shocks to explain deviation from Okun’s law. We show that, if a positive deviation from Okun’s law arises, it is likely to be generated by either positive labor supply or automation shocks or by negative structural factors shocks. Conversely, negative deviations are related to positive structural factors shocks or negative automation and labor supply shocks.

Notably, our paper should not be seen as a criticism to the use of Okun’s law for policy purposes. Our results are consistent with the influential evaluation by [Ball et al. \(2017\)](#). In fact, we show that a simple OLS estimation of Okun’s law provides an accurate estimate of the unemployment response to aggregate demand shocks. Our contribution consists in providing a structural interpretation for the deviations. In our view, such a structural interpretation with a quantitative flavor has been missing in the literature so far.

Note that we are not claiming that these shocks are the *exclusive* drivers of deviations from Okun’s law. Our explanation in the context of a simple linear model is *complementary* to explanation highlighting asymmetries, threshold effects and structural breaks in Okun’s law. In that sense, it is interesting to note how variables related to labor force participation, unionization, employment in the manufacturing sector (a sector heavily exposed to automation) have been associated with switches in regime ([Lee \(2000\)](#)) or as endogenous threshold ([Christopoulos et al. \(2019\)](#)) in papers stressing the importance of non-linearities. Further research is needed to disentangle the role of shock heterogeneity from genuine non-linearities in the transmission mechanism. Unfortunately, the literature has not reached a consensus on how to integrate sign restrictions into non-linear models.

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Online Appendix

A Data

We use quarterly data spanning 1985Q1-2019Q4 for the U.S., and 1997Q2-2019Q4 for euro area. When the original data is at a monthly frequency, we take quarterly averages of monthly data. Details on the series used and transformations are reported in Table 2. Data for the U.S. are downloaded from the FRED database, those for the euro area are downloaded from the ECB Statistical Data Warehouse. Nominal wages are deflated using the GDP deflator to obtain real wages.

B Structural VAR: estimation and identification

B.1 Bayesian estimation of the SVAR model

In this appendix we provide the details on the econometric procedure that we use for the estimation of the SVAR models in the paper.

We define our reduced form VAR as

$$y = \bar{X}\beta + \epsilon, \tag{4}$$

where $y = \text{vec}(Y)$, $\bar{X} = I_n \otimes X$, $\beta = \text{vec}(B)$, $\epsilon = \text{vec}(E)$, and $\epsilon \sim N(0, \bar{\Sigma})$, with $\bar{\Sigma} = I_n \otimes \Sigma$.

We choose the Normal-Wishart prior, and define the prior distribution for β , which follows a normal distribution:

$$\beta \sim N(\beta_0, \Sigma \otimes \phi_0), \tag{5}$$

with ϕ_0 a diagonal matrix.

The prior for Σ is an Inverse-Wishart:

$$\Sigma \sim IW(S_0, \alpha_0), \tag{6}$$

Table 2: Data description

U.S.			
Variable	FRED code	Description	Transf.
Real GDP	GDPC1	Real Gross Domestic Product, Billions of Chained 2012 Dollars, Quarterly, Seasonally Adjusted Annual Rate	q-o-q
Employment (total hours worked)	AWHNONAG	Average Weekly Hours of Production and Nonsupervisory Employees, Total Private, Hours, Monthly, Seasonally Adjusted	q-o-q
GDP deflator	GDPDEF	Gross Domestic Product: Implicit Price Deflator, Index 2012=100, Quarterly, Seasonally Adjusted	q-o-q
Nominal wages	AHETPI	Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private, Dollars per Hour, Monthly, Seasonally Adjusted	q-o-q
Unemployment rate	UNRATE	Unemployment Rate, Percent, Monthly, Seasonally Adjusted	changes
euro area (Euro area 19, fixed composition)			
Variable	SDW code	Description	Transf.
Real GDP	MNA.Q.Y.i8.W2.S1.S1.B.B1GQ. Z.Z.Z.XDC.LR.N	Gross domestic product at market prices, Chain linked volume, Calendar and seasonally adjusted data, Million euros	q-o-q
Employment (total hours worked)	ENA.Q.Y.i8.W2.S1.S1.Z.EMP. Z.T.Z.HW.Z.N	Total employment , All activities, Hours worked, Calendar and seasonally adjusted data	q-o-q
GDP deflator	MNA.Q.Y.i8.W2.S1.S1.B.B1GQ. Z.Z.Z.IX.D.N	Gross domestic product at market prices: Deflator (index), Calendar and seasonally adjusted data	q-o-q
Nominal ages	MNA.Q.Y.i8.W2.S1.S1.Z.COM HW.Z.T.Z.IX.V.N	Hourly compensation, All activities, Current prices, Calendar and seasonally adjusted data	q-o-q
Unemployment rate	LFSI.Q.i8.S.UNEHRT.TOTAL0. 15.74.T	Unemployment rate; Total; Age 15 to 74; Total; Seasonally adjusted, not working day adjusted	changes

where S_0 is a scale matrix and α_0 the degree of freedom of the prior.

The coefficients on the prior depends on hyperparameters. We run a grid search to determine the starting values: we define for every hyperparameter of the model a range of possible values and a step size of the increment within the range. For each combination of hyperparameters, we estimate the marginal likelihood for the model and we retain the combination that maximizes it. The ranges for the parameters cover the most common values in the literature.

In order to obtain the identification of structural shocks, we impose sign restrictions on the variance-covariance matrix we estimated, implementing the algorithm of [Arias et al. \(2018\)](#).

The practical implementation is conducted with the BEAR toolbox. For a full description of the steps of the Bayesian estimation we refer to the technical guide of the toolbox.

B.2 5-variables VAR: Identification of the shocks

We include 5 variables in our set up, and we make use of sign restrictions to identify the different shocks that affect the economy. All the restrictions are imposed on impact.

We identify five types of shocks, which represent different factors for movements in the labour market variables, whose signs are summarized in Table [3](#):

- A (expansionary) demand shock. This represents a shift in the demand curve, which pushes up output, employment and inflation, and lowers the unemployment rate. These dynamics are consistent with the effects induced by monetary policy, government spending, marginal efficiency of investment, discount factor and most financial shocks. However, at this stage, we are not interested in separating these shocks further, and they are all bundled together.
- A (positive) technology or productivity shock. An increase in productivity reduces the marginal costs for firms, and therefore pushes inflation down. However, it also creates a positive shift in the labour demand curve, which increases output,

employment and wage growth and, depending on the degree of nominal and real rigidities, may lower the unemployment rate.

- Two labour market shocks, i.e. shocks originating in the labour market itself (see [Foroni et al. \(2018\)](#)). Labour market shocks generate an inverse co-movement between output, employment and real wages. More in detail, we identify:
 - A (positive) labour supply shock. This shock represents an exogenous increase in labour supply, or a reduction in the disutility of working, which increases the number of participants in the labour market. This increase in the number of job seekers makes it easier for firms to fill vacancies and decreases hiring costs, therefore it leads to a decrease in wages and prices and to an increase in output and employment. Regarding the unemployment rate, it is reasonable to assume that at least on the first quarter some of the new participants will transit through unemployment (more than those already in the labour force since the previous period). The participation rate is by definition increasing in this type of shock.
 - A (positive) structural factors shock. This shock generates positive co-movement between wages and unemployment. One natural interpretation relates to the bargaining power of workers. A reduction in the bargaining power of workers has a direct negative effect on wages, thus contributing to lower marginal costs and prices. Since firms now capture a larger share of the surplus associated with employment relationships, it is a very good moment for them to hire and therefore they post more vacancies. This leads to an increase employment and a decrease in the unemployment rate. The same restrictions can be generated by a shock to the matching efficiency in the labor market or by a shock to unemployment benefits.
- A (positive) automation shock, which captures a negative co-movement between output growth and employment growth. This shock captures technological progress, in which output becomes more capital intensive at the expenses of labour. This

implies a decrease in employment and an increase in the unemployment rate, while output grows. For an analysis of this type of shock, see [Acemoglu and Restrepo \(2018\)](#) and [Bergholt et al. \(2021\)](#).

Table 3: Identification strategy

	Demand shock	Technology shock	Labour Supply shock	Structural factors shock	Automation shock
real GDP	+	+	+	+	+
Employment	+	+	+	+	-
Inflation	+	-	-	-	
Wage inflation		+	-	-	
Unemployment rate	-	-	+	-	+