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Exploring the impact of automation on employment during expansions and contractions: An examination of Okun's Law

Michał Brzozowski, University of Warsaw, Faculty of Economic Sciences, brzozowski@wne.uw.edu.pl (corresponding author)
Joanna Siwińska-Gorzelak, University of Warsaw, Faculty of Economic Sciences, siwinska@wne.uw.edu.pl

Abstract. *This article examines the impact of robotization on the short-term correlation between employment and output. We estimate the Okun's Law relationship utilizing panel data from 35 OECD countries for the period from 1996 to 2020. Our empirical evidence, backed up by a battery of robustness tests, consistently shows that automation contributes to job-preserving recessions by mitigating increases in unemployment during economic contractions. This challenges common assumptions regarding the detrimental impact of automation on employment. Additionally, we do not find support for the notion that automation causes jobless recoveries.*

Keywords: *Okun's Law, job-preserving contractions, jobless growth, automation, robotization, unemployment, economic growth.*

1. Introduction

Okun's Law – the short-run, negative correlation between output and unemployment – holds a prominent place within macroeconomic theory, teaching and policy analysis. A large body of empirical literature has examined the practical relevance of Okun's Law – including, for example, the recent studies by Ball et al. (2019), Ball, Leigh and Loungani (2017), An et al. (2019), Aguiar-Conraria, Martins and Soares (2020), Grant (2018) and Farole, Ferro and Gutierrez (2017). While these investigations generally affirm the empirical validity of Okun's Law, the authors also note significant cross-country variations in the magnitude of the Okun coefficient, which remain largely unexplained (Ball et al. 2019). These variations manifest themselves across countries, sectors, periods and demographic groups of workers.

Automation emerges as a key factor influencing the magnitude of the Okun coefficient, since it has strong effects on labour demand, employment structure and firms' productivity (Graetz and Michaels 2018; Acemoglu and Autor 2011; Goos, Manning and Salomons 2009; Autor, Levy and Murnane 2003; Acemoglu, Koster and Ozgen 2023; Chung and Lee 2023). Despite the confirmed impact of modern, digital technologies on labour markets, the specific link between robotization and the short-term correlation between unemployment and output has not been systematically examined in the existing literature. This article seeks to fill that gap.

Our study aimed to conduct an empirical assessment of the impact of robotization on the short-run correlation between output and (un)employment.[1] Its primary contribution lies in providing consistent empirical evidence, supported by a battery of robustness tests, indicating the substantial impact of robotization on the Okun coefficient in developed countries. We show that robots contribute to reducing the Okun coefficient, particularly during economic downturns. To mitigate concerns about the endogeneity of automation and labour market dynamics, this research adopts an instrumental variable estimation approach. A diverse set of instruments and various estimators are employed to ensure the robustness of the findings.

Our findings have important policy implications. They indicate that fiscal and monetary policies aimed at stabilizing output will have different effects on employment stability, depending on the country's degree of robotization. They also show that, contrary to common assumptions about the detrimental effects of robotization on employment, robotization contributes to job-preserving recessions. To the best of our knowledge, this is the first article to provide this kind of evidence.

The structure of the article is as follows. In section 2, we discuss the relevant literature and formulate our hypothesis. In section 3, we present our empirical work: our data, methodology and results. Section 4 summarizes our findings and provides some conclusions.

2. Literature review and hypothesis

Okun's Law holds a prominent place in macroeconomic literature and policy analysis. Empirical studies confirm a significant, negative correlation between unemployment and output over the short run. Yet, controversies relate to the size and stability of the Okun coefficient across time, countries and industries (An et al. 2019; Ball et al. 2019; Ball, Leigh and Loungani 2017; Grant 2018). Recent studies point to a wide range of factors that may change the short-run correlation between output and unemployment, including mean unemployment, GDP per capita, share of services in GDP, demographics and employment protection legislation (Ball et al. 2019; An, Bluedorn and Ciminelli 2021; Aguiar-Conraria, Martins and Soares 2020). Moreover, the Okun coefficient has been shown to change over time and stages of the business cycle (Berger, Everaert and Vierke 2016; Grant 2018; Aguiar-

[1] Okun's Law describes an inverse relationship between output and unemployment. However, changes in the rate of unemployment are negatively correlated with change in employment, and Okun's Law can be rephrased as a positive relationship between output and employment.

Conraria, Martins and Soares 2020), highlighting the fact that it is susceptible to change and its magnitude responds to changes in structural and cyclical variations.

Nevertheless, a crucial element absent from discussions surrounding Okun's Law is the impact of automation on the size of the Okun coefficient. Modern technologies, including robotization, exert a profound influence on labour markets and on firms' productivity, likely altering the short-run correlation between output and (un)employment. Although the initial pessimistic forecasts of massive job losses due to automation (Brynjolfsson and McAfee 2014; Frey and Osborne 2017) now appear overstated, there is no doubt that labour markets are undergoing significant transformation, caused by information technologies, automation and digitalization. The alteration of the structure of labour demand is one of the more prominent consequences of modern technologies for labour markets. These technologies substitute for some tasks traditionally performed by humans, simultaneously provoking a cascade of additional adjustments. This results in an alteration of labour demand, particularly for workers equipped with specific skills. In this context, a prominent strand of literature has elaborated on the phenomenon of routine-biased technological change (RBTC). This implies that modern technologies, including robotization, substitute for human tasks that are routine and easy to codify, yet not necessarily simple. Therefore, modern technologies contribute to the observed decline in the number of routine repetitive jobs (not only manual but also cognitive), and a simultaneous increase in demand for non-routine jobs that are skill-based, as well as simple and manual (Autor, Levy and Murnane 2003; Autor and Dorn 2013; Dao et al. 2017; Autor and Salomons 2018; Vivarelli 2014; Acemoglu and Restrepo 2019). The routine jobs susceptible to automation tend to be located in the middle of the earnings ladder and non-routine jobs are often performed by workers with high skill levels, in the case of cognitive tasks, and by workers with low skill levels and low wages, in case of manual non-routine jobs. Accordingly, one of the consequences of RBTC is labour market polarization, a process that has been observed over the last 40 years in the United States and in other developed countries (Autor and Dorn 2013; Cortes et al. 2020; Goos, Manning and Salomons 2009; de Vries et al. 2020; Acemoglu and Restrepo 2019). These changes have consequences for the responsiveness of labour markets to various shocks (Ebeke and Eklou 2023; Lin and Weise 2019). Nevertheless, as we have already stated, the impact of robotization on the responsiveness of (un)employment to deviations of output from its potential has not yet been examined in the literature.

In this article, we posit that countries' progress in adopting modern technologies and the resulting process of RBTC, as well as the impact of robotization on firms' production processes and productivity, are likely to change and attenuate the cyclical response of unemployment to short-run output fluctuations. We identify at least four reasons for this shift.

First, the diminishing share of middle-skilled routine jobs induced by RBTC may have repercussions on the cyclical reaction of employment to output changes, particularly during recessions. In line with the Schumpeterian perspective on the cleansing effect of recessions (Aghion and Howitt 1992; Aghion and Saint-Paul 1998; Caballero and Hammour 1994), these are seen to accelerate RBTC (Hershbein and Kahn 2018). Empirical investigations have consistently revealed that the most substantial employment declines during recessions in the United States and other developed countries have affected routine jobs (Jaimovich and Siu 2020; Foote and Ryan 2014; Anghel, de la Rica and Lacuesta 2013; Verdugo and Allègre 2020). Given that higher rates of robotization in developed countries are linked to a reduced proportion of cyclically sensitive routine jobs (de Vries et al. 2020), we postulate that increased robotization, all else being equal, is associated with a diminished cyclical responsiveness of employment to output fluctuations. This effect is plausibly more pronounced during recessions.

Second, the view that RBTC implies a weakening of cyclical fluctuations of employment is further validated by the correlation between RBTC and increased demand for skilled workers capable of performing non-routine tasks that complement automation technologies (Acemoglu and Autor 2011; Tang, Huang and Liu 2021; Vivarelli 2014; Acemoglu, Koster and

Ozgen 2023). As highlighted in the literature, the skills and qualifications of the workforce have emerged as pivotal factors in the success of modern, innovative factories, with skill shortages identified as a prominent impediment to the successful implementation of modern technologies (Kamble, Gunasekaran and Sharma 2018; Raj et al. 2020; Gal et al. 2019; Ballestar et al. 2022). Consequently, trained and skilled workers are deemed to be the principal assets of modern enterprise (Riley, Michael and Mahoney 2017), potentially making firms reluctant to fire these workers during recessions and enhancing their employment stability.[2] Thus, not only does the reduction in middle-skilled routine work contribute to greater employment stability under higher robot exposure, but an increase in the number and importance of skilled non-routine workers further enhances this stability.

Interesting evidence corroborating but also nuancing this proposition is provided by Damiani, Pompei and Kleinknecht (2023). Their research reveals that, within industries characterized by sophisticated organizational structures and production processes reliant on internal knowledge, the implementation of robotics reduces the use of temporary contracts, particularly among highly skilled workers. Longer job tenures are valuable to employers, as innovative competencies depend on the firm's internal knowledge, encompassing worker-embodied, often tacit, knowledge. Conversely, this pattern is not observed in industries where production processes are significantly less complex and rely more on external knowledge sources. In these industries, the adoption of robots is associated with an increase in the number of temporary positions. Hence, the effect of robot intensity is not uniform and depends on the complexity of the organizational structure and production process. Nevertheless, Damiani, Pompei and Kleinknecht (2023) emphasize that the intensity of robot exposure is significantly higher among industries with more complex structures and production processes, and that the stabilizing effect dominates. Higher job stability for robot-exposed workers in manufacturing is also confirmed by Dauth et al. (2017) in the case of Germany.

Third, stabilizing employment during recessions is more attainable for companies in a good financial situation, as demonstrated, for example, by Bäurle, Lein and Steiner (2021). Substantial evidence suggests that robot-adopting firms are characterized by higher value added, productivity, sales per worker and employment when compared with non-adopters (Acemoglu, Lelarge and Restrepo 2020; Acemoglu, Koster and Ozgen 2023; Koch, Manuylov and Smolka 2021; Bonfiglioli et al. 2022). Furthermore, studies indicate that firms that use digital information and communication technologies (ICTs) demonstrate greater resilience to economic downturns. Copestake, Estefania-Flores and Furceri (2022) and Crivelli, Furceri and Toujas-Bernaté (2012), drawing on data from over 20,000 firms in 74 countries, reveal that firms that are more digitalized experience a lower fall in revenue during recessions, compared with their less digitalized counterparts. In a similar vein, Ballestar et al. (2021), drawing on data from over 4,000 Spanish companies, demonstrate that firms that use robots are more resilient to unfavourable events. Additionally, Bertschek, Polder and Schulte (2019), based on aggregated firm-level data from 12 countries, indicate that ICT-intensive firms exhibit heightened resilience to economic downturns. While ICT intensity is not the same as robot intensity, there is a clear positive relationship between the two (Presidente 2023; OECD 2017, 37).

On a national level, Papaioannou (2023) finds that countries with higher ICT intensity exhibited greater resilience to the recession caused by the COVID-19 pandemic and experienced lower output losses. Thus, compared to non-adopting counterparts, the heightened resilience to recessions observed in ICT-intensive and robotized firms, coupled with their generally superior performance, may contribute to the stabilizing effect of exposure to robotization on employment throughout economic cycles.

[2] According to Grant (2018), firms that heavily invest in training their staff are reluctant to lay off in recessions. Yet, in upswings, these firms hire more employees, as training takes time.

Fourth, robots have been changing the production function, implying that, in concurrence with the rising trend in robotization, shocks in robot prices may take on an increasingly prominent role in the volatility of GDP. As theoretically posited by Lin and Weise (2019), these shocks affect the stock of robots and, therefore, output. Yet, owing to the countervailing effects of fluctuations in robot numbers on employment, they diminish the sensitivity of employment to output fluctuations. While our analysis investigates the responsiveness of (un)employment to short-run changes in GDP originating from various sources, this mechanism may also contribute to the reduction of the Okun coefficient.

In summary, greater exposure to robots is linked to a diminished share of routine jobs, which are typically more susceptible to fluctuations in the business cycle, particularly during economic downturns. Concurrently, there is an increase in the proportion of skilled workers with valuable expertise and this group is anticipated to enjoy higher employment stability. Firms adopting robots also demonstrate increased resilience to recessions. In addition, as robots become an important factor of production, shocks to robot prices cause output to change, but owing to offsetting effects on employment, the unemployment response to these shocks is muted. Taken together, these factors suggest that adopting robots can attenuate the sensitivity of employment to output fluctuations. However, this effect may not be uniform throughout the business cycle. As the evidence suggests, by changing the skill and task structure of the workforce (reducing the share of routine jobs and increasing the share of high-skilled workers), robotization may diminish the Schumpeterian "cleansing effect" of recessions on employment, as firms become more reluctant to fire highly skilled workforce during downswings (Grant 2018). Moreover, robots have been shown to increase firms' resilience to recessions. Consequently, the decrease in the Okun coefficient may be more significant during output contractions, compared to expansions, resulting mostly in job-preserving recessions.

The findings of Ballestar et al. (2021), focusing on Spanish manufacturing companies, support this proposition by revealing that firms adopting robots exhibit greater stability in employment at the firm level. Additional empirical evidence at the country level, linking the Okun coefficient to robotization, is provided in the works of Burger and Schwartz (2018) and Jaimovich and Siu (2020). Contrary to the proposition formulated above, these authors posit that labour market polarization underlies the observed phenomenon of "jobless recoveries", implying a decrease in the Okun coefficient during economic upturns. However, Graetz and Michaels (2018), analysing data from 17 industrialized countries, demonstrate that labour market polarization and susceptibility to automation are not significantly associated with jobless recoveries. Hence, the country-level evidence is inconclusive and limited to economic upturns only.

Building on this evidence, we formulate a hypothesis, which we subsequently test in the following section. Our hypothesis posits that *increased robotization mitigates the responsiveness of (un)employment to cyclical output fluctuations* and that *this effect is particularly pronounced during economic downturns*.

3. Empirical evidence

3.1. Data and estimation methods

The sample covers 35 countries in the Organisation for Economic Co-operation and Development (OECD)[3] and the period from 1996 to 2020; the panel is unbalanced and observations are annual at the country level. Data on unemployment rates, employment (including a breakdown by occupation) and sectoral share of value added are drawn

[3] Australia, Austria, Belgium, Canada, Chile, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Latvia, Lithuania, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Republic of Korea, Slovakia, Slovenia, Spain, Sweden, Switzerland, Türkiye, United Kingdom and United States.

from the OECD.Stat database. Data on the operational stock of robots were retrieved from the database of the International Federation of Robotics (IFR). The IFR records the global count of industrial robots and distinguishes them from service robots. This is why installations of robots documented by the IFR are concentrated in industry in general (manufacturing, construction, mining and quarrying, and electricity, gas and water supply) and in manufacturing in particular.

The value of robot intensity in the sample varies greatly, as table SA1 in the supplementary online appendix illustrates. The average number of robots installed per 1,000 employees is approximately 1.17, but the standard deviation is much higher, at nearly 1.7. Colombia has the lowest average robot intensity (0.005), whereas the Republic of Korea has the highest mean level of robotization, surpassing 6.77.[4] Notwithstanding these differences, the findings presented in this work remain insensitive to the removal of any country from the sample.

The main conjecture that we make in this article is that automation moderates the relationship between unemployment and output. To quantify automation, we used the robot intensity, *robot*, calculated as the ratio of the current operational stock of robots in a country divided by the number of employed persons in 1995. We normalized the number of robots by employment in the pre-sample year to avoid a mechanical negative correlation of robot densification with the regressand, which is the unemployment rate or, in the robustness check, the level of employment.

We relied on the interaction variable to test the moderating effect of robotization on the relationship between output and unemployment. Using *i* to denote countries and *t* as a time index, Okun's Law can be written as equation (1):

$$cyclical\ unemployment_{it} = \alpha_i + \beta_1 output\ gap + \beta_2 robot + \beta_3 (robot \times output\ gap) + u_{it} \qquad (1)$$

Cyclical unemployment is defined as the difference between the actual unemployment rate and its long-run level, commonly referred to as the natural unemployment rate. Similarly, the output gap is the difference between the log of the actual level of real GDP and the log of long-run output, known as the potential output. To obtain long-run levels, the output and unemployment series were smoothed using the Hodrick–Prescott filter with the smoothing parameter set to 400 or to 6.25 (to ensure the robustness of the results). We used the fixed effects method in the analysis, whereby the parameter α_i is intended to capture the impact of time-invariant omitted variables that are assumed to be correlated with the included regressors.

Estimation of equations "in levels" – that is, equation (1) – must be preceded by an estimation – by means of the Hodrick–Prescott filter – of potential output and the natural rate of unemployment, which are unobservable. Regardless of the method used, these estimates are uncertain. To overcome this difficulty, the "changes" version of Okun's Law (equation (2)) has been proposed as an alternative specification of the relationship between output and unemployment:

$$\Delta unemployment_{it} = \alpha_i + \beta_1 output\ growth + \beta_2 robot + \beta_3 (robot \times output\ growth) + u_{it} \qquad (2)$$

Equation (2) can be derived from equation (1) but the estimates of coefficient β_2 are biased if the natural rate of unemployment or the rate of growth of potential output vary over time because, in this case, the error term would be correlated with unemployment change and output growth. Consequently, equation (1), in levels, is our preferred specification and we use equation (2) as a robustness check.

Technically, Okun's Law can be decomposed into the effect of output on employment and the effect of employment on the rate of unemployment (see Ball, Leigh and Loungani

[4] Mean values calculated over the entire sample period based on IFR and OECD data – not shown in table SA1.

2017; An, Bluedorn and Ciminelli 2021); the impact of employment and output underlies the relationship between output changes and the rate of unemployment expressed in equations (1) and (2). Therefore, the following specifications – alternatives to equations (1) and (2) – have been formulated as equation (3) for the equation estimated in levels and equation (4) for the equation in first differences:

$$cyclical\ employment_{it} = \alpha_i + \beta_1 output\ gap + \beta_2 robot + \beta_3 (robot \times output\ gap) + u_{it} \tag{3}$$

$$\Delta employment_{it} = \alpha_i + \beta_1 output\ growth + \beta_2 robot + \beta_3 (robot \times output\ growth) + u_{it} \tag{4}$$

Cyclical employment – that is, the deviation of the observed logarithm of employment from its long-run level – was obtained with the aid of the Hodrick–Prescott filter with the smoothing parameter set to 400; Δ*employment* is the first difference of the logarithm of employment, indicating the rate of change of employment.

The specifications of Okun's Law in which employment replaces unemployment, equation (4) in particular, make it possible to analyse the employment intensity of growth. Although this issue has received less attention in the literature than other labour market indicators, it has been shown that the elasticity of employment with respect to output is a key factor explaining heterogeneous responses of unemployment rates to contractions and expansions (see Crivelli, Furceri and Toujas-Bernaté 2012). In addition, equations (3) and (4) can be estimated to find out the effect of output changes on employment by sector (industry and services). Gelfer (2020) documented a stronger response of employment to declines in GDP in more capital-intensive sectors (manufacturing and construction sectors) than in services.

The main hypothesis in this article is that the estimated coefficient $\hat{\beta}_3$ in equations (1) to (4) is different from zero. However, the values of $\hat{\beta}_1$ and $\hat{\beta}_3$ are likely to depend on the business cycle. Many authors point to the non-linearity of Okun's Law, meaning that the value of the Okun coefficient may be different in different phases of the business cycle. It should be noted that most of the evidence comes from the United States (see Owyang and Sekhposyan 2012; Berger, Everaert and Vierke 2016; Grant 2018; Aguiar-Conraria, Martins and Soares 2020; Donayre 2022), but thresholds in the Okun's Law relationship have also been detected in Europe (Nebot, Beyaert and García-Solanes 2019).

Building on this evidence, we estimated equations (1) to (4) on two subsamples restricted to periods of either economic downturns or upturns. We rely on the sign of the output gap to distinguish expansions from contractions, as deviations of observed output from its long-term potential are a common measure of fluctuations in economic activity. Moreover, using the output gap to discriminate between stages of the economic cycle allowed us to obtain subsamples of similar sizes, enabling the comparison of estimation results.

The endogeneity of robot adoption is the major challenge of research on the relationship between automation and labour market performance. Robotization is likely to be a response of firms to labour market tightness, leading to the problem of reverse causality in the Okun's Law equation estimated in this article. To cope with this concern, we adopted the instrumental variable estimation strategy. The key factor in the successful implementation of this method is the use of appropriate instruments. Our choice of instrumental variables was guided by the fact that robot adoption depends on the sectoral structure of the economy, demographic structure and the proportion of workers performing routine and non-routine jobs (see Fernández-Macías, Klenert and Antón 2021; Acemoglu and Restrepo 2022; Reijnders and de Vries 2018).

Consequently, the set of instruments includes the country's old-age dependency ratio calculated as the share of people aged 50 and over in the total population. It also incorporates the country's share of GDP of the two sectors characterized by relatively high robot density in all OECD countries, namely the sectors producing transport equipment and motor vehicles, trailers and semi-trailers. It includes the share of GDP of sectors with a low degree of robotization across OECD countries, specifically the textiles, clothing, leather and footwear sector. In addition, robot density was instrumented by the share of employment of the two most non-routine occupations (managers and skilled agricultural, forestry and fishery workers) and the share of employment of the following routine occupations, susceptible to automation: plant and machine operators, clerical support workers, elementary occupations and technicians (see Goos, Manning and Salomons 2014). The structure of employment by occupation (one-digit ISCO-08 categories)[5] and sectoral contributions to GDP (two-digit NACE sections)[6] in 1995 – that is, in the pre-sample period – were employed to strengthen the exogeneity of these metrics. Only a subset of the instruments listed above was used in each regression equation (see the notes below each table) and the choice was guided by the results of the instrument validity tests described below. It is important to stress that, given that robot intensity is interacted with the output gap or the output growth rate, the instrumental variables described above were also interacted with the corresponding measure of the state of the business cycle.

The baseline results were obtained using the standard instrumental variables estimator: a two-stage least squares (2SLS) estimator, which produces consistent estimates of the coefficients even in the presence of heteroskedasticity. However, heteroskedasticity leads to inefficient instrumental variables estimates of the coefficients and inconsistent standard errors. Our second approach is the two-step generalized method of moments (GMM) estimator, which allows for efficient estimation in the presence of heteroskedasticity.

The standard GMM estimator is obtained by minimizing the GMM objective function in the second step, treating the weighting matrix as a constant matrix. Hansen, Heaton and Yaron (1996) show that continuous updating of the weighting matrix performs better for annual data (which we use) than other ways of weighting the moment conditions. In addition, the continuous updating estimator was found to have a lower median bias than the other estimators. Hence, our third estimator is the GMM continuously updated estimator (CUE) developed by Hansen, Heaton and Yaron (1996).

The fourth estimator applied in this article is the limited information maximum likelihood (LIML) estimator. It improves upon the 2SLS estimator, which is known to have large biases when many instruments are used. Hahn, Hausman and Kuersteiner (2004) provide evidence that the CUE and LIML estimator perform better than the 2SLS and standard GMM estimators in the presence of weak instruments. It should be noted, however, that the LIML estimator is efficient only under homoskedasticity. The results reported in the next section were obtained using these four estimators.

The standard errors found in each table were obtained from the Eicker–Huber–White "sandwich" estimator of variance and are robust to the presence of arbitrary heteroskedasticity. We did not assume the existence of an intra-cluster, within-panel or cross-panel correlation (clustering on time) because we assumed heteroskedasticity to be of unknown form. Since econometric theory and existing simulation evidence are unclear about the reliability of cluster-robust inferences from the models estimated by instrumental variables (MacKinnon, Ørregaard Nielsen and Webb 2023), we did not compute cluster-robust standard errors.

To overcome possible autocorrelation in the error terms, we used the extension of the Eicker–Huber–White sandwich estimator proposed by Newey and West (1987). This estimator uses the Bartlett kernel, which, according to Kolokotrones, Stock and Walker (2024), is optimal among first-order kernels. Our estimates are thus consistent when there is autocorrelation in addition to heteroskedasticity.

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[5] ISCO-08 is the fourth iteration of the International Standard Classification of Occupations, adopted by the ILO in 2008.

[6] NACE, from the French title *Nomenclature statistique des activités économiques dans la Communauté européenne*, is the classification of economic activities in the European Union.

The validity of instruments is of great importance when the instrumental variables method is used. We relied on tests of under-identification, weak identification and over-identifying restrictions to ensure that our estimators perform well. The under-identification test is a Lagrange multiplier (*LM*) test of whether the excluded instruments are correlated with the endogenous regressors. The null hypothesis is that the equation is under-identified, while a rejection of the null, when the Kleibergen–Paap *LM* statistic exceeds the critical value, indicates that the model is identified.

Weak identification arises when the excluded instruments are only weakly correlated with the endogenous regressors. Although LIML estimators are quite robust to weak instruments, other estimators can perform poorly. We report a Cragg–Donald Wald *F* statistic, following the suggestion made by Staiger and Stock (1997) that the instruments are not weak if the *F* statistic is greater than 10.

The joint null hypothesis of the Sargan–Hansen (*J*) test of over-identifying restrictions is that instruments are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. A rejection of the null hypothesis casts doubt on the validity of the instruments.

3.2. Okun's Law in contractions

This section reports the results of the estimation of equations (1) to (4), using the four instrumental variable estimators described above and restricting the sample to include periods when the output gap is negative. As was mentioned before, the instruments for robot intensity were selected based on the results of their validity tests and they are listed in the notes below each table.

The results of the estimation of equation (1) for periods of contraction are presented in table 1. The heading of each column specifies the estimator used to obtain the results.

Table 1. Okun's Law in contractions: Equation in levels with the cyclical rate of unemployment as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output gap	–55.675***	–59.480***	–57.055***	–68.895***
	(9.442)	(8.940)	(9.913)	(8.367)
robot	0.112	0.116	0.128	0.205
	(0.162)	(0.161)	(0.179)	(0.173)
robot × output gap	20.620***	20.799***	22.110***	25.024***
	(6.360)	(6.305)	(7.103)	(6.229)
Number of observations	364	364	364	364
R^2	0.240	0.237	0.225	0.185
Cragg–Donald Wald *F* statistic	28.916	28.917	28.918	28.919
Sargan–Hansen *J* statistic	5.334	5.334	5.272	4.291
(*p*-value)	(0.149)	(0.149)	(0.153)	(0.232)
Kleibergen–Paap *LM* statistic	15.509	15.509	15.509	15.509
(*p*-value)	(0.004)	(0.004)	(0.004)	(0.004)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot × output gap* are the following: (*output gap × share of GDP of the textiles sector in 1995*), (*output gap × share of GDP of the vehicles sector in 1995*), (*output gap × share of employment of clerical workers in 1995*), (*output gap × share of employment of managers in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

We find that the key variable in Okun's Law – that is, the value of the output gap – is significant and has, as expected, a negative relationship with the cyclical rate of unemployment. The interaction term between output gap and robot intensity, which is the focus of our study, is positive, indicating that unemployment becomes less responsive to output slowdowns when automation becomes more widespread. The effect of robotization itself on the deviation of unemployment from its long-run trend is not statistically significant. It should be noted that the results of the instrument validity tests show that the identification issue is not of concern.

Although the equation in levels is our preferred specification, we checked whether the estimates are sensitive to the use of first differences in unemployment and the log of output instead of the gaps between these variables and their long-term values. The results of the estimation of the equation in differences are presented in table 2.

Table 2. Okun's Law in contractions: Equation in differences with the change in the rate of unemployment as the dependent variable.

Estimator	2SLS	GMM	LIML	CUE
output growth	–43.866***	–47.079***	–43.997***	–47.891***
	(4.087)	(3.755)	(4.119)	(3.420)
robot	–0.659***	–0.704***	–0.670***	–0.738***
	(0.165)	(0.163)	(0.170)	(0.181)
robot × output growth	8.579***	10.528***	8.647***	11.291***
	(2.774)	(2.554)	(2.838)	(2.505)
Number of observations	339	339	339	339
R^2	0.504	0.477	0.500	0.458
Cragg–Donald Wald *F* statistic	42.105	42.106	42.107	42.108
Sargan–Hansen *J* statistic	4.098	4.098	4.079	3.630
(*p*-value)	(0.251)	(0.251)	(0.253)	(0.304)
Kleibergen–Paap *LM* statistic	18.156	18.156	18.156	18.156
(*p*-value)	(0.001)	(0.001)	(0.001)	(0.001)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot × output growth* are the following: (*output growth × share of GDP of the textiles sector in 1995*), (*output growth × share of GDP of the vehicles sector in 1995*), (*output growth × share of employment of clerical workers in 1995*), (*output growth × share of employment of managers in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

Regression of changes in the rate of unemployment on output growth produced results similar to those obtained from estimating equation (1). The main conclusion is reinforced since the interaction term is positive and significant, pointing to the fact that the change in unemployment in response to declines in output is subdued by automation. Interestingly, the coefficient of robot intensity itself is negative and significant, which suggests that automation stabilizes unemployment.

Using four estimators and two versions of conventional Okun's Law, we find that automation attenuates the influence of recessions on unemployment. Now we look at the elasticity of employment with respect to declines in output. The results of the estimation of equation (3) are presented in table 3. Since the gap between the observed rate of unemployment and its long-run level was replaced with the deviation of employment from its long-run level, the expected sign of the coefficient of the output gap is positive.

Table 3. Okun's Law in contractions: Equation in levels with the level of cyclical employment (difference between observed and long-term employment in logs) as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output gap	0.831***	0.809***	0.837***	0.809***
	(0.107)	(0.104)	(0.108)	(0.104)
robot	−0.006**	−0.005*	−0.006**	−0.005*
	(0.003)	(0.003)	(0.003)	(0.002)
robot × output gap	−0.265***	−0.229***	−0.271***	−0.232***
	(0.088)	(0.079)	(0.091)	(0.076)
Number of observations	413	413	413	413
R^2	0.281	0.299	0.278	0.297
Cragg–Donald Wald *F* statistic	35.752	35.753	35.754	35.755
Sargan–Hansen *J* statistic	2.461	2.461	2.451	2.496
(*p*-value)	(0.482)	(0.482)	(0.484)	(0.476)
Kleibergen–Paap *LM* statistic	15.805	15.805	15.805	15.805
(*p*-value)	(0.003)	(0.003)	(0.003)	(0.003)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot × output gap* are the following: (*output gap × share of GDP of the textiles sector in 1995*), (*output gap × share of GDP of the transport equipment sector in 1995*), (*output gap × share of employment of clerical workers in 1995*), (*output gap × share of employment of elementary occupations in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

As can be seen in table 3, when the actual output of the economy falls below its capacity, employment is below its natural level. However, the positive relationship between employment and output is weakened by the adoption of robots, as indicated by the negative sign of the interaction term between robot intensity and output gap. This result suggests that the costs of labour mobility, which encourage firms to respond to (adverse) business cycle fluctuations by adjusting the labour utilization rate rather than the level of employment, increase in more automated economies. It should also be noted that the coefficient of robot intensity itself is negative, as it was in table 2. This contradictory evidence of the effect of robotization on employment and unemployment implies that we cannot draw robust conclusions in this regard.

To confirm the abating effect of robotization on the employment intensity of growth, we estimate equation (4) and report the results in table 4. Although the significance level of the interaction term decreases (the chance to reject the null hypothesis increased to 5 per cent), the claim that automation makes employment less responsive to output in recessions seems to be justified.

Lastly, we check whether our estimations of the preferred specification in equation (1) are robust to the method of extraction of cyclical components. We had previously used the Hodrick–Prescott filter with the smoothing parameter set to 400 in order to decompose the output and unemployment series into the trend and cyclical components. Ravn and Uhlig (2002) study optimal values of the smoothing parameter for different frequencies of observations and recommend setting the smoothing parameter to 6.25 for annual data. We followed their suggestions in our calculation of the cyclical unemployment and output gap. The results presented in table SA3 in the supplementary online appendix reveal that our findings are not sensitive to the way in which the cyclical components of unemployment and output are obtained. The coefficient of the output gap remains negative and the coefficient of the interaction term is positive.

Table 4. Okun's Law in contractions: Equation in differences with the rate of change of employment (variation of the log of employment) as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output growth	0.628***	0.593***	0.640***	0.582***
	(0.074)	(0.067)	(0.078)	(0.068)
robot	0.007***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
robot × output growth	−0.113**	−0.106**	−0.121**	−0.103**
	(0.048)	(0.046)	(0.053)	(0.047)
Number of observations	385	385	385	385
R^2	0.472	0.465	0.458	0.460
Cragg–Donald Wald *F* statistic	46.937	46.938	46.939	46.940
Sargan–Hansen *J* statistic	5.663	5.663	5.575	5.182
(*p*-value)	(0.129)	(0.129)	(0.134)	(0.159)
Kleibergen–Paap *LM* statistic	21.392	21.392	21.392	21.392
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot × output growth* are the following: (*output growth × share of GDP of the transport equipment sector in 1995*), (*output growth × share of employment of technicians in 1995*), (*output growth × share of employment of elementary occupations in 1995*), (*output growth × share of employment of machine operators in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

Ample evidence on the impact of robotization on the Okun coefficient in contractions has been provided in this section. We find that increases in the rate of unemployment and reductions in the level of employment during the contraction phase of the business cycle are less pronounced in countries with high robot intensity. This result is not sensitive to the choice of the estimation method, the specification of Okun's Law and the extraction method of cyclical fluctuations. It follows that a high level of robotization does not encourage firms to lay off workers in recessions. Additionally, we do not find a robust relationship between the size of cyclical movements of (un)employment and automation.

3.3. Okun's Law in expansions

In this section, we focus on Okun's Law during expansion phases of the business cycle. The sample has been restricted to include periods when the output gap is positive or zero. We estimated all specifications of Okun's Law expressed by equations (1) to (4). The estimates of the equation in levels using the difference between the observed and long-run level of unemployment are presented in table 5.

Only the coefficients of the output gap are significant in table 5, meaning that unemployment falls below its long-term level during economic upturns. This effect is not moderated by robot intensity because the coefficient of the interaction term is not significant. It seems that during expansions robotization does not prompt firms to substitute capital services for labour, in which case the sign of the interaction term would be positive. To strengthen this conclusion, we estimate equation (2) and report the results in table 6.

The estimates of the equation in differences, displayed in table 6 do not undermine the main conclusion. When the economy expands, the robot intensity does not alter the relationship between the change in the rate of unemployment and the rate of GDP growth. Next, we turn to the robustness check, which consists in replacing the rate of unemployment with employment as the dependent variable (see tables 7 and 8).

Table 5. Okun's Law in expansions: Equation in levels with the cyclical rate of unemployment as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output gap	−24.820***	−26.138***	−24.858***	−26.371***
	(2.611)	(2.474)	(2.631)	(2.509)
robot	−0.027	−0.055	−0.028	−0.062
	(0.084)	(0.080)	(0.086)	(0.082)
robot × *output gap*	−5.006	−1.741	−4.913	−0.806
	(5.244)	(4.644)	(5.344)	(4.719)
Number of observations	423	423	423	423
R^2	0.368	0.355	0.367	0.350
Cragg–Donald Wald *F* statistic	44.152	44.153	44.154	44.155
Sargan–Hansen *J* statistic	2.735	2.735	2.730	2.519
(*p*-value)	(0.434)	(0.434)	(0.435)	(0.472)
Kleibergen–Paap *LM* statistic	27.196	27.196	27.196	27.196
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot* × *output gap* are the following: (*output gap* × *share of GDP of the textiles sector in 1995*), (*output gap* × *share of GDP of the vehicles sector in 1995*), (*output gap* × *share of employment of clerical workers in 1995*), (*output gap* × *share of employment of managers in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

Table 6. Okun's Law in expansions: Equation in differences with the change in the rate of unemployment as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output growth	−21.268***	−23.209***	−21.196***	−23.271***
	(3.327)	(2.962)	(3.366)	(2.876)
robot	−0.002	−0.072	−0.001	−0.069
	(0.146)	(0.136)	(0.149)	(0.136)
robot × *output growth*	−8.445	−5.801	−8.616	−5.935
	(5.434)	(4.892)	(5.550)	(4.864)
Number of observations	413	413	413	413
R^2	0.369	0.375	0.367	0.375
Cragg–Donald Wald *F* statistic	45.437	45.438	45.439	45.440
Sargan–Hansen *J* statistic	1.868	1.868	1.868	1.771
(*p*-value)	(0.600)	(0.600)	(0.600)	(0.621)
Kleibergen–Paap *LM* statistic	26.658	26.658	26.658	26.658
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot* × *output growth* are the following: (*output growth* × *share of GDP of the textiles sector in 1995*), (*output growth* × *share of GDP of the vehicles sector in 1995*), (*output growth* × *share of employment of clerical workers in 1995*), (*output growth* × *share of employment of managers in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

Table 7. Okun's Law in expansions: Equation in levels with the level of cyclical employment (difference between observed and long-term employment in logs) as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output gap	0.438***	0.436***	0.440***	0.428***
	(0.045)	(0.042)	(0.046)	(0.043)
robot	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
robot × output gap	0.025	0.012	0.022	0.023
	(0.084)	(0.078)	(0.088)	(0.079)
Number of observations	449	449	449	449
R^2	0.262	0.260	0.262	0.261
Cragg–Donald Wald *F* statistic	61.553	61.554	61.555	61.556
Sargan–Hansen *J* statistic	5.214	5.214	5.227	5.216
(*p*-value)	(0.157)	(0.157)	(0.156)	(0.157)
Kleibergen–Paap *LM* statistic	31.174	31.174	31.174	31.174
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot × output gap* are the following: (*output gap × share of GDP of the textiles sector in 1995*), (*output gap × share of GDP of the transport equipment sector in 1995*), (*output gap × share of employment of clerical workers in 1995*), (*output gap × share of employment of agricultural workers in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

Table 8. Okun's Law in expansions: Equation in differences with the rate of change of employment (variation of the log of employment) as the dependent variable

Estimator	2SLS	GMM	LIML	CUE
output growth	0.265***	0.263***	0.262***	0.308***
	(0.084)	(0.059)	(0.085)	(0.062)
robot	−0.002	−0.001	−0.002	−0.002
	(0.003)	(0.002)	(0.003)	(0.002)
robot × output growth	0.127	0.078	0.132	0.137*
	(0.090)	(0.067)	(0.095)	(0.073)
Number of observations	431	431	431	431
R^2	0.215	0.221	0.214	0.205
Cragg–Donald Wald *F* statistic	37.902	37.903	37.904	37.905
Sargan–Hansen *J* statistic	5.304	5.304	5.251	6.079
(*p*-value)	(0.151)	(0.151)	(0.154)	(0.108)
Kleibergen–Paap *LM* statistic	27.914	27.914	27.914	27.914
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: Standard errors shown in brackets are robust to heteroskedasticity and autocorrelation. The instrumental variables used for *robot* and *robot × output growth* are the following: (*output growth × share of GDP of the transport equipment sector in 1995*), (*output growth × share of employment of technicians in 1995*), (*output growth × share of employment of elementary occupations in 1995*), (*output growth × share of employment of machine operators in 1995*) and old-age dependency ratio.

Source: Our own calculations based on OECD and IFR data.

The evidence presented in table 7 provides support for the point made earlier concerning the zero effect of robotization on the Okun coefficient during economic upturns. The willingness of firms to create jobs – or, more precisely, to increase employment above its long-run level – when the economy enters an expansion phase is not affected by the degree of automation. Similarly, in table 8, the estimation of equation (4) in periods of increased economic activity shows that the elasticity of employment to output is not influenced by robot intensity.

So far, our analysis leads to the conclusion that the impact of robotization on the value of the Okun coefficient is asymmetric in that it depends on the state of the business cycle. Automation helps contain dramatic increases in unemployment (reductions in the level of employment) during the contraction phases of the business cycle. This job-preserving effect in economic downturns is unfortunately not accompanied by a weakening of the jobless recovery phenomenon: the Okun coefficient is not affected by robotization during economic upswings. The first result is novel in the literature, while the second casts doubt on the universality of the conclusion reached by Burger and Schwartz (2018) for the United States, that the adoption of routine-replacing technology makes jobless recoveries more likely.

3.4. Robustness tests: Employment protection legislation and intersectoral relationships

Empirical evidence shows that labour market institutions can both encourage automation and change the value of the Okun coefficient (e.g. see Presidente 2023). Countries with more labour-friendly institutions are likely to experience a more subdued adjustment of employment to output volatility. Additionally, the cost-saving decrease in worker turnover that robots bring about may make investments in robotics particularly appealing to businesses in those countries. Therefore, it is crucial to verify that robot intensity continues to be a substantial moderating factor in the link between unemployment and output, after controlling for employment protection legislation.

To achieve this, we extended the set of regressors in equations (1) and (2) to include a variable capable of capturing the effect of strong employment protection on the responsiveness of unemployment to output. Okun's equation estimated in levels is now expressed as equation (5) in its revised specification:

$$\begin{aligned} cyclical\ unemployment_{it} = \alpha_i + \beta_1 output\ gap + \beta_2 robot + \beta_3(robot \times output\ gap) \\ + \beta_4(strong\_ep \times output\ gap) + u_{it} \end{aligned} \quad (5)$$

and the equation in first differences takes the form of equation (6):

$$\begin{aligned} \Delta unemployment_{it} = \alpha_i + \beta_1 output\ growth + \beta_2 robot + \beta_3(robot \times output\ growth) \\ + \beta_4(strong\_ep \times output\ growth) + u_{it} \end{aligned} \quad (6)$$

The newly constructed variables are the interaction terms *strong_ep* × *output gap* and *strong_ep* × *output growth*, where *output gap* and *output growth* have been defined as in the baseline regression equations. The dummy variable *strong_ep* takes the value of 1 for strict regulation on dismissal for workers on regular contracts.

The degree of employment protection was categorized according to version 2 (1998–2019) of the indicator of strictness of employment protection compiled by the OECD.[7] We consider employment protection to be strong (and give *strong_ep* a value of 1) when the value of the indicator is in the fifth quintile of its distribution in the sample. We examined the results' sensitivity to using the third tertile of the indicator's distribution in the sample in order to ensure the validity of our findings.

[7] OECD, "Strictness of Employment Protection", OECD Indicators of Employment Protection database, https://www.oecd.org/en/data/datasets/oecd-indicators-of-employment-protection.html (accessed 24 June 2025).

The aim of this section is to confirm that the coefficient $\hat{\beta}_3$ in equations (5) and (6) remains statistically significant despite including labour market institutions as a possibly important determinant of the Okun coefficient. Stated otherwise, this is an omitted-variable test. The results of the estimation of equations (5) and (6) are shown in supplementary online appendix tables SA4 and SA5, respectively. The main results remain unaltered and provide further support for the conjecture that unemployment is less responsive to recessions in countries where work automation is more advanced. Consistent with earlier results, the impact of robotization on the Okun coefficient is not statistically significant in expansions. It should be noted that strict employment legislation does not appear to have an impact on the Okun coefficient, regardless of how "strict" is defined. It is also noteworthy that the results reported in table SA5 point to a mitigating influence of employment protection legislation on unemployment surges in contractions.

The analysis of the results of tests of under-identification, weak identification and over-identifying restrictions does not raise doubts about the validity of instruments. Thus, we can confidently draw the conclusion that, even in countries where employment protection legislation is strict, robots weaken the response of unemployment to output contractions.

Robots are predominantly used in manufacturing sectors. However, owing to the intersectoral relationships between manufacturing and services, robotization (concentrated in the former sector) can also affect employment and, consequently, the Okun coefficient in services. Employment and wage shifts in manufacturing affect labour demand in services through two main channels. Services are intermediate inputs in the production of goods, and growth in manufacturing creates jobs in (mainly business) services. Second, changes in labour demand in manufacturing have an effect on wages and income, which in turn influences the demand for services – mostly personal ones. In addition to these general intersectoral relationships, automation opens new ways through which employment in manufacturing and employment in services are related. We provide a brief discussion of these automation-induced spillover effects in employment in supplementary online Appendix 3, where tables SA6 to SA9 report the results of our estimation of Okun's equation in services and industry. The key finding of this robustness test is that, during contractions, both in industry and in services, the value of the Okun coefficient depends negatively on robot intensity.

In summary, we have analysed the impact of robotization on the relationship between employment and output over the business cycle. We find compelling evidence that robot intensity exerts a non-linear influence on the value of the Okun coefficient: automation reduces job losses during contractions but its effect during expansions is zero. We do not find support for attributing "jobless recoveries" or "jobless growth" to robot adoption. On the contrary, we find that machines controlled by computers cushion the negative effects of economic contractions on employment and unemployment throughout the whole economy, in the industrial sectors, and to a slightly lesser extent in services. These results are robust to endogeneity, the choice of estimator, the Okun's Law specification, inclusion of labour market regulation as another moderating variable, and the method of decomposing the employment and unemployment series into trend and cycle.

4. Summary and conclusions

The ongoing transformation of labour markets through robotization has attracted substantial scholarly attention. Although existing literature has extensively addressed the impact of robots on employment levels, occupational structures and wages, unexplored connections between robotization and labour market outcomes still remain. An area that has received inadequate attention is the impact of robotization on the value of the Okun coefficient.

In addressing this research gap, the main proposition of this article is that the adoption of modern technologies, referring to RBTC in general – and robotization in particular – is likely to moderate the cyclical responsiveness of employment to short-term output fluctuations, thereby changing the Okun coefficient. However, since there is evidence of an asymmetric reaction of employment to economic expansions and recession, the effect might not be uniform across the stages of the business cycle.

Our econometric research was based on panel data covering 35 OECD countries and the period from 1996 to 2020. To ensure robustness, we employed four distinct panel data estimation methods suitable for instrumental variables estimation and estimated two versions of Okun's Law. We also employed four different estimators: the standard instrumental variables estimator (2SLS), the standard GMM estimator, the limited information maximum likelihood estimator (LIML) and the GMM continuously updated estimator (CUE).

Irrespective of the method employed, our results consistently indicate three key findings. First, the influence of robotization on the Okun coefficient is asymmetric, contingent upon the business cycle stage. Second, automation mitigates increases in unemployment (and reductions in employment) during contraction phases of the business cycle, contributing to job-preserving recessions. This result is novel and is an important addition to the ongoing discussion about the impact of new technologies on employment levels. Third, this job-preserving effect during economic downturns is not accompanied by a mitigation of the jobless recovery phenomenon, as robotization does not impact the Okun coefficient in economic upswings. This result raises doubts regarding the universality of the conclusion that automation and a resulting polarization of labour markets underlie the observed phenomenon of "jobless recoveries".[8]

Our results not only add to the scholarly literature, they are also important from the policy perspective. Among others, they indicate that fiscal and monetary policies targeting output stabilization will have different effects on employment stability depending on the degree of robotization.

Competing interests

The authors declare that they have no competing interests.

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