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Robots and the Wedge between Wages and Productivity: A European Analysis[*]

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Abstract

We study the role of industrial robots in shaping the divergence between labor productivity and wages across European countries from 1995 to 2020. To this end, we develop a tractable theoretical model in which robots substitute for routine labor. The model predicts a widening wage-productivity gap with increasing robot adoption. Using harmonized country-sector-year data, we find a robust positive association between robot intensity and the wage–productivity gap, particularly in the manufacturing sector. The relationship remains stable when controlling for outsourcing and capital intensity. Instrumental variable estimates based on external robot trends from the United States, South Korea, and New Zealand support a causal link between robot adoption and the wage–productivity wedge.

JEL classification: E24, J11, J23, J24
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1 Introduction

In recent decades, labor productivity and GDP per capita have continued to rise, yet real wages for a large share of workers have stagnated. While real wages in advanced economies historically tracked aggregate productivity growth, this link has weakened since the late 1970s, leading to a growing gap between productivity and compensation. This divergence challenges standard economic models in which wage growth is tightly coupled with productivity gains. Acemoglu and Restrepo (2022) and Prettner (2023) have proposed models to explain the divergence between wages and productivity and showed their relevance for the United States (US).

Despite the previous focus on the US, similar wage-productivity patterns have emerged in many European countries, albeit with variation across regions and institutional settings. A large literature has explored job polarization and the impact of automation—particularly through industrial robots—on labor market outcomes (e.g., Autor et al., 2003; Acemoglu and Autor, 2011; Graetz and Michaels, 2018a; Acemoglu and Restrepo, 2020c).[1] The rise of new automation technologies such as AI has recently been examined by a growing body of literature. In terms of productivity, Acemoglu (2025) argues that the macroeconomic impact of AI has been modest, projecting gains of only 0.66% over the coming decade. By contrast, Venturini (2022) suggests that such technologies have contributed between 3% and 8% of total factor productivity gains since the 1990s and Minniti et al. (2025) show that, despite such productivity-enhancing effects, AI-innovation has reduced the labor income share in European regions by up to 0.31 percentage points between 2000 and 2017. While these studies highlight the potential of new technologies at the aggregate level for productivity and the labor income share, we focus on the role of industrial robots in shaping the differential evolution of wages versus productivity.

To this end, we study the effect of robot adoption on the gap between labor productivity and wages across European countries from 1995 to 2020. Motivated by an intuitive structural model, we focus on the role of automation in altering sectoral wage dynamics, where robots increase output more than they raise labor compensation. The model features a multi-country, multi-sector economy with imperfect substitutability between routine labor and industrial robots. This formulation leads to the testable prediction that robot adoption increases the wedge between value added per worker and wages.

We test this hypothesis using harmonized sector-level data on robot stocks from

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[1] The broader impact of automation technologies, including smart machines, has also been studied with Prettner and Bloom (2020) providing a comprehensive summary of the various effects of robots and other automation technologies on the labor market.

the International Federation of Robotics, matched to labor market outcomes from EU-KLEMS and the EU Labour Force Survey. The empirical strategy combines reduced-form panel regressions with an instrumental variables design. We first estimate models relating robot intensity to the wage–productivity wedge, controlling for international outsourcing and capital intensity. We then address potential endogeneity by instrumenting European sectoral robot intensity with external robot trends from the United States, South Korea, and New Zealand, following Acemoglu and Restrepo (2020a). The results support the theoretical prediction. Across specifications, robot adoption is positively associated with a widening wage–productivity wedge, particularly in the manufacturing sector. This relationship remains robust to controls for outsourcing and capital intensity and is reinforced by instrumental variable estimates.

We contribute to several strands of the literature. First, we extend the literature on automation and labor market outcomes (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020a; Graetz and Michaels, 2018b, e.g.,) by focusing not only on employment or wages, but on the wedge between labor productivity and wages—a more structural measure of decoupling. In this context, we provide novel empirical evidence from Europe, a setting that remains underexplored compared to the US. Second, we complement studies showing that real wages have diverged from productivity growth in recent decades, including work on the declining labor share and the rise of superstar firms (Karabarbounis and Neiman, 2014; Autor et al., 2020, e.g.,). We do so by offering a micro-founded, automation-based explanation for decoupling at the sector level, linking robot diffusion and substitution patterns to wage suppression relative to productivity.

The remainder of the paper is structured as follows. Section 2 contains the theoretical model, the main hypothesis, and an illustrative simulation of the effects of robot adoption on the wedge between wages and productivity. Section 3 is devoted to the description of the data, the empirical specification, and the identification strategy. Section 4 presents the main findings and Section 5 concludes.

2 Labor productivity, wages, and robots: theoretical considerations

In this section, we develop a simple theoretical model to formalize how robot adoption affects the wedge between labor productivity and wages. The framework captures key mechanisms of automation in a multi-country, multi-sector economy where robots and routine labor are imperfect substitutes, and it delivers the testable prediction that guides the empirical analysis.

Consider a multi-country and multi-sector setting, where final output in country i at time t is denoted by $Y_{i,t}$ and produced according to the production function

$$Y_{i,t} = {H_{i,t}}^{1-\alpha} \sum_{\omega=1}^{J} x_{\omega,i,t}^{\alpha}, \tag{1}$$

where $H_{i,t}$ refers to employment of workers who are still difficult (and sometimes impossible) to automate such as engineers, scientists, and managers, $x_{\omega,i,t}$ denotes the amount of intermediate ω used in the production of final output in country i, and α is the elasticity of final output with respect to intermediates (cf. Romer, 1990; Jones, 1995; Krenz et al., 2021; Prettner, 2023). The inverse demand function for intermediate inputs follows as

$$p_{\omega,i,t} = \alpha H_{i,t}^{1-\alpha} x_{\omega,i,t}^{\alpha-1}, \tag{2}$$

where $p_{\omega,i,t}$ is the price of intermediate ω. Equation (2) is a side constraint for the profit maximization problem of intermediate goods producers. Following Prettner (2023), intermediate goods producers have access to a production technology of the form

$$x_{\omega,i,t} = \left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} r_{\omega,i,t})^{\gamma_\omega}\right]^{\frac{\eta}{\gamma_\omega}}, \tag{3}$$

where $l_{\omega,i,t}$ is employment of workers who can be easily automated (such as assembly line workers) in sector ω in country i at time t, $a_{\omega,i,t}$ refers to the stock of labor augmenting technologies available to the workers in this sector, $r_{\omega,i,t}$ is robot adoption in sector ω, $b_{\omega,i,t}$ refers to the stock of robot augmenting technologies, γ_ω determines the elasticity of substitution between workers and robots that can differ across sectors, and η determines the elasticity of intermediate output with respect to effective labor input.

In such a setting, intermediate goods producers maximize their profits given by

$$\begin{aligned} \pi_{\omega,i,t} &= p_{\omega,i,t} x_{\omega,i,t} - w_{l,i,t} l_{\omega,i,t} - \kappa \cdot i_t \cdot r_{\omega,i,t} \\ &= \alpha H_{i,t}^{1-\alpha} \left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} r_{\omega,i,t})^{\gamma_\omega}\right]^{\frac{\alpha\eta}{\gamma_\omega}} - w_{\omega,l,i,t} l_{\omega,i,t} - \kappa \cdot i_t \cdot r_{\omega,i,t}, \end{aligned} \tag{4}$$

where $w_{\omega,l,i,t}$ is the wage rate of workers in sector ω in country i at time t, κ is the cost of one robot in terms of physical capital, and i is the interest rate paid on physical capital such that $\kappa \cdot i$ is the opportunity cost of one robot in terms of foregone capital income. We assume that the interest rate i_t is determined at the world market such that it does not depend on the saving behavior in the country under consideration. Profit maximization implies the following first-order conditions

$$\frac{\partial \pi_{\omega,i,t}}{\partial l_{\omega,i,t}} = \frac{\alpha^2 \eta H_{\omega,i,t}^{1-\alpha} (a_{\omega,i,t} l_{\omega,i,t})^{\gamma} \left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} r_{\omega,i,t})^{\gamma_\omega}\right]^{\frac{\alpha\eta}{\gamma_\omega}-1}}{l_{\omega,i,t}} - w_{\omega,\omega,l,i,t} \overset{!}{=} 0, \quad (5)$$

$$\frac{\partial \pi_{\omega,i,t}}{\partial r_{\omega,i,t}} = \frac{\alpha^2 \eta H_{\omega,i,t}^{1-\alpha} (b_{\omega,i,t} p_{\omega,i,t})^{\gamma_\omega} \left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} r_{\omega,i,t})^{\gamma_\omega}\right]^{\frac{\alpha\eta}{\gamma_\omega}-1}}{r_{\omega,i,t}} - \kappa \cdot i_t \overset{!}{=} 0. \quad (6)$$

From (5) and (6) it follows that profit-maximizing firms employ workers and robots up to the point at which the following relationships are fulfilled for factor employment and factor remuneration:

$$w_{\omega,l,i,t} = \frac{\alpha^2 \eta H_{\omega,i,t}^{1-\alpha} (a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} \left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} r_{t,\omega})^{\gamma_\omega}\right]^{\frac{\alpha\eta}{\gamma_\omega}-1}}{l_{\omega,i,t}}, \quad (7)$$

$$i_t = \frac{\alpha^2 \eta H_{\omega,i,t}^{1-\alpha} (b_{\omega,i,t} r_{\omega,i,t})^{\gamma_\omega} \left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} p_{\omega,i,t})^{\gamma_\omega}\right]^{\frac{\alpha\eta}{\gamma_\omega}-1}}{\kappa \cdot r_{\omega,i,t}}. \quad (8)$$

From now on, we focus exclusively on the wages given by (7) and how they are associated with labor productivity in the given sector. For this purpose, we assume a short-run perspective such that the skills of workers cannot yet adjust to automation (there is no retraining, etc.) and such that workers cannot move to a different sector. Labor productivity is measured by output per worker and given as

$$\frac{x_{\omega,i,t}}{l_{\omega,i,t}} = \frac{\left[(a_{\omega,i,t} l_{\omega,i,t})^{\gamma_\omega} + (b_{\omega,i,t} r_{\omega,i,t})^{\gamma_\omega}\right]^{\frac{\eta}{\gamma_\omega}}}{l_{\omega,i,t}}. \quad (9)$$

We immediately observe that labor productivity rises with the use of industrial robots for the reasonable parameter restriction of $\gamma_\omega \in (0, 1]$, implying that robots and workers are gross substitutes. Wages, by contrast, could decline with the use of industrial robots depending on the value of γ_ω. If robots and workers are perfect substitutes, i.e., if $\gamma_\omega = 1$, then wages will always fall with an increase in $r_{\omega,i,t}$. Overall, we would therefore expect the following result.

Hypothesis 1. *If a sector employs more robots ($r_{\omega,i,t}$ is higher for a given number of workers), the wedge between labor productivity and wages will be greater.*

We now illustrate the effects of the evolution of robots numerically. To this end, we consider a baseline value of $\alpha = 1/3$, set $\eta = 1$, and assume a substitutability parameter of $\gamma = 0.75$, implying that robots and workers are gross substitutes. Furthermore, to make sectors/countries comparable, we normalize the series to 100 in the initial year, which we set to 1995 to be consistent with the data available for the empirical implementation. To start the simulation, we assume that the use of robots is close to zero in 1995, which is a reasonable approximation for many countries and sectors. We let labor-augmenting technological progress (growth in a), robot-augmenting technological progress (growth in b), and increases in hours worked (growth in l) be 1% per year, while we leave the demand for intermediate goods constant by setting $H = 3$. Next, we simulate two scenarios. In the first, we let the stock of robots grow in line with a low value of 5% per year, whereas in the second, we let the stock of robots grow in line with a high value of 15% per year (see, for example, International Federation of Robotics, 2023). We display the result with respect to the evolution of the wedge between labor productivity and wages in Figure 1. The upper diagram refers to the case in which robot use grows at 5% per year and the lower diagram to the case in which robot use grows by 15% per year. We observe that the wedge between wages and labor productivity grows wider in the case of faster robot adoption, which is exactly the result reflected in Hypothesis 1.

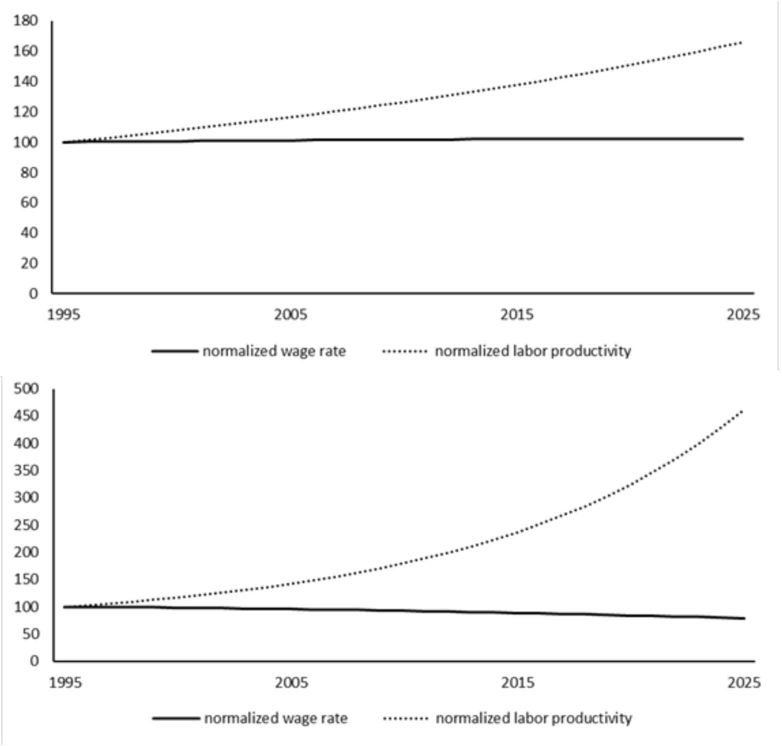

Figure 1: Normalized Wages and Normalized Labor Productivity; 1995=100.

3 Labor productivity, wages, and robots: empirical specification

To evaluate the hypothesis described in Section 2, we proceed in two stages. First, we document the reduced-form relationship between robot intensity and the wedge between labor productivity and wages by estimating a series of baseline regressions. Second, we address potential endogeneity concerns in robot adoption by implementing an instrumental variable strategy, using robot adoption in corresponding sectors of the US, South Korea, and New Zealand as an exogenous source of variation. This approach follows the identification strategy proposed by Acemoglu and Restrepo (2020a); Dauth et al. (2021), under the assumption that robot diffusion reflects global technological trends and is plausibly orthogonal to labor market conditions in European countries.

3.1 Reduced-form specifications

Our baseline specification to test Hypothesis 1 across sectors ω, countries i, and years t links the wedge between labor productivity and wages directly to robot intensity. Specifically, we estimate the regression

$$\log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right) = \beta_0 + \beta_1 \cdot \log\left(\frac{r_{\omega,i,t}}{l_{\omega,i,t}}\right) + \xi_\omega + \zeta_j + \varphi_t + u_{\omega,i,t}, \tag{10}$$

where the left-hand side represents the log of the *wage-productivity wedge*, defined as the ratio of value added per worker, $x_{\omega,i,t}/l_{\omega,i,t}$, to the real wage, $w_{\omega,l,i,t}$. This measure reflects the degree to which increases in labor productivity are translated into higher labor compensation. We compute this wedge using EU-KLEMS sector-level data from Bontadini et al. (2023) who provide information on value added, employment, labor compensation, and industry-level price indices.

The right-hand side regressor, $\log(r_{\omega,i,t}/l_{\omega,i,t})$, measures *robot intensity*—the density of robots per worker in a given sector and country-year—using robot stock data from the International Federation of Robotics (IFR) described in detail by Jurkat et al. (2021), aggregated to match EU-KLEMS sectors (see Table 4 in the Appendix). The IFR data distinguish between three types of robot sectoral assignments: (i) robots allocated to specific industry classifications, (ii) robots reported under an 'unspecified' category without sectoral detail, and (iii) a general total covering all industries. When robots are reported under the unspecified category, we redistribute them proportionally across the 14 sectors using fixed industry shares, conditional on the availability of partially classified data for the relevant country-year, following the procedure in Acemoglu and Restrepo (2020b). For country-years lacking sector-level data—particularly between 1995 and 2005—we impute missing values by applying the earliest observed sectoral distribution to year-specific aggregate robot stock levels, again as in Acemoglu and Restrepo (2020b). This procedure ensures consistency in sectoral assignment, while preserving aggregate robot counts. We exclude country-years with no reported robot activity (e.g., Cyprus, Malta). Table 5 summarizes the countries included in the final sample.

This specification allows us to examine whether sectors with higher robot adoption exhibit greater decoupling between wages and productivity, as predicted by the model in Section 2. The coefficient β_1 is of primary interest for testing Hypothesis 1, capturing the elasticity of the wage–productivity wedge with respect to robot intensity. In line with our theoretical framework, we expect $\beta_1 > 1$, implying that greater robot adoption is associated with a widening gap between value added per worker and labor compensation. The parameters ξ_ω, ζ_i, and φ_t denote sector, country, and time fixed effects, respectively, and $u_{\omega,i,t}$ is the error term.

We augment the baseline specification to account for potential confounders. First, outsourcing may affect the wage-productivity wedge in a similar manner to automation by shifting labor demand (Autor et al., 2016; Acemoglu and Restrepo, 2022). We control for this by including a measure of outsourcing, constructed as the cost share of imported intermediate inputs in total intermediate input use, following Feenstra and Hanson (1999), using data from the OECD ICIO tables. Second, we control for sector-level capital intensity, measured as the capital–labor (K/L) ratio, to account for broader capital deepening that could correlate with both robot adoption and labor market outcomes. The regression equation incorporating the j control variables in $X_{\omega,i,j,t}$ is given by

$$\log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right) = \beta_0 + \beta_1 \cdot \log\left(\frac{r_{\omega,i,t}}{l_{\omega,i,t}}\right) + \beta_j \sum_{j=2}^{J} X_{\omega,i,j,t} + \xi_\omega + \zeta_i + \varphi_t + u_{\omega,i,t}. \quad (11)$$

All other parts of the equation aside from the control variables correspond to those introduced in Equation (10).

We construct the outsourcing measure using data from the OECD ICIO tables. For each country-sector-year observation, we compute the ratio of imported intermediate inputs to total intermediate input use. Imported inputs are defined as off-diagonal entries in the input-output matrix (i.e., foreign-sourced inputs), while total inputs include both domestic and imported components, corresponding to the full column sum. The ICIO sectoral classification aligns exactly with our mapping between EU-KLEMS and IFR sectors, as summarized in Table 4.

The K/L ratio is calculated using EU-KLEMS data as the ratio of gross fixed capital formation (in chained linked volumes, 2015 prices) to the number of persons employed. For observations where disaggregated manufacturing sector capital data are missing, we impute values uniformly using the aggregate manufacturing sector for the same country and year, without incorporating additional information. This imputation is applied exclusively to manufacturing sectors. Figure 3 illustrates the extent and distribution of missing capital data over time, sectors, and countries.

As a robustness check, we control for routine task intensity (RTI) that varies across sectors to proxy the degree of substitutability between workers and robots. We construct sector-level RTI indicators using EU-LFS data merged with occupational RTI scores from Mihaylov and Tijdens (2019). RTI scores are assigned at the consolidated ISCO-08 3-digit level,[2] and aggregated to the sector level by computing a weighted mean within each country-sector-year:

$$\mathrm{RTI}_{w,i,t} = \frac{1}{N_{w,i,t}} \sum_{o=1}^{N_{w,i,t}} \mathrm{RTI}_{w,i,o,t},$$

where $N_{w,i,t}$ is the number of occupations in sector w in country i and year t. We then define $\bar{\gamma}_\omega = 1$ if a sector's average RTI is above the pooled median and 0 otherwise.

However, EU-LFS does not provide data on occupational structure for disaggregated manufacturing sectors listed in Table 4. For these cases, we impute the sectoral occupational structure uniformly using the aggregate manufacturing sector for the same country and year, without incorporating additional information. Table 6 presents descriptive statistics for the main variables used in the subsequent analysis.

We then add the $\mathrm{RTI}_{w,i,t}$ index as an additional control variable to Equation (11). As an alternative specification, we define indicator variable $\bar{\gamma}_\omega$ equal to 1 for sectors with above-median routine task intensity (RTI) and 0 otherwise. We then estimate the regression

$$\log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right) = \beta_0 + \beta_1 \cdot \log\left(\frac{r_{\omega,i,t}}{l_{\omega,l,i,t}}\right) + \beta_j \sum_{j=2}^{J} X_{\omega,i,j,t} + \beta_{J+1}\bar{\gamma}_\omega + \xi_\omega + \zeta_i + \varphi_t + u_{\omega,i,t}, \tag{12}$$

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[2] We retain only unambiguously corresponding occupations between ISCO-88 and ISCO-08.

where again all other parameters correspond to those introduced in Equation (11). We simply extend the specification by including the RTI-based indicator $\bar{\gamma}_\omega$.

We estimate Equations (10)-(12) using an unbalanced panel of European countries over the period 1995-2020, covering up to 14 manufacturing and service sectors per country-year (see Tables 4 and 5). For estimation, we employ the high-dimensional fixed effects estimator for linear models with multi-way fixed effects proposed by Correia et al. (2016).

Theoretical considerations suggest that causality runs from robot intensity to the wage-productivity wedge. The reverse channel is unlikely, yet possible: higher productivity at a given wage increases the competitiveness of labor relative to robots, making it less plausible that the wedge itself is driven by robot adoption. Empirically, identification strategies to address endogeneity include exploiting sector-level routine task intensity (Graetz and Michaels, 2018a) or instrumenting robot adoption using sectoral trends from other countries, as in Acemoglu and Restrepo (2020a). We employ the latter identification strategy in the following subsection.

3.2 Testing the causal relationship

To address the potential endogeneity of robot adoption in the baseline specifications (Equations (10)–(11)), we implement a two-stage least squares (2SLS) approach. The goal is to isolate variation in robot intensity driven by supply-side technological factors, rather than by endogenous demand-side responses such as changes in labor regulations, wage floors, or local labor market tightness, which may simultaneously affect robot adoption and wage dynamics.

Following Acemoglu and Restrepo (2020a) and Dauth et al. (2021), we instrument robot intensity at the country–sector–year level using robot adoption in the corresponding sectors of the US, South Korea, and New Zealand. The identifying assumption is that robot diffusion in these reference countries reflects global technological trends—driven primarily by supply-side innovations in robotics hardware and software and is orthogonal to labor market conditions in European countries. This cross-country variation serves as an exogenous source of sector-level robot adoption, making it a valid instrument for identifying the causal impact of automation on wages and productivity within Europe.

The first stage estimates predict robot intensity as

$$\log\left(\frac{r_{\omega,i,t}}{l_{\omega,i,t}}\right) = \gamma_0 + \gamma_1 \cdot \log\left(\frac{r_{\text{US;KR;NZ},\omega,t}}{l_{\text{US;KR;NZ},\omega,t}}\right) + \sum_{j=2}^{J} \delta_j X_{\omega,i,j,t} + \xi_\omega + \zeta_i + \varphi_t + \nu_{\omega,i,t}. \quad (13)$$

In the second stage, we replace the potentially endogenous term $\log\left(r_{\omega,i,t}/l_{\omega,i,t}\right)$ in each of the main regressions with its fitted value from Equation (13). This strategy is applied consistently across specifications, ensuring that all estimates reflect variation in robot adoption plausibly unrelated to domestic labor market shocks.

4 Results

In this section, we present estimates from a series of reduced-form specifications testing the theoretical prediction outlined in Section 2, following the econometric structure detailed in Section 3. We begin by reporting associational patterns between robot intensity and the wage-productivity wedge, then proceed to causal estimates using an instrumental variable strategy. Robustness checks are provided in the Appendix and described at the end of this section.

Figure 2 presents the evolution of the robot stock and the wedge between productivity and wages over time in the manufacturing sector (Left Panel) and the automotive industry (Right Panel) in European countries (weighted averages) since 1995. The figure shows that across all countries, robot stocks grew steadily from 1995 to 2020, with the robot stock in the automotive industry growing faster than in manufacturing overall. This reflects the automotive sector's historically high degree of robotization. The wage-productivity wedge displays a more volatile trajectory in both panels. In manufacturing, the wedge rose broadly over the sample period, peaking around 2009–2010, and remained high through 2019 before a sharp drop in 2020. In the automotive industry, it increased more sharply in the early period, reaching its peak around 2015–2016, and similarly fell steeply in 2019–2020. The pronounced decline at the end of the sample in both sectors is likely attributable to the disruptions of the COVID-19 pandemic rather than a reversal of the underlying trend. In general, robot adoption and the wage-productivity wedge show a broadly positive co-movement across both sectors, consistent with the theoretical prediction in Section 2.

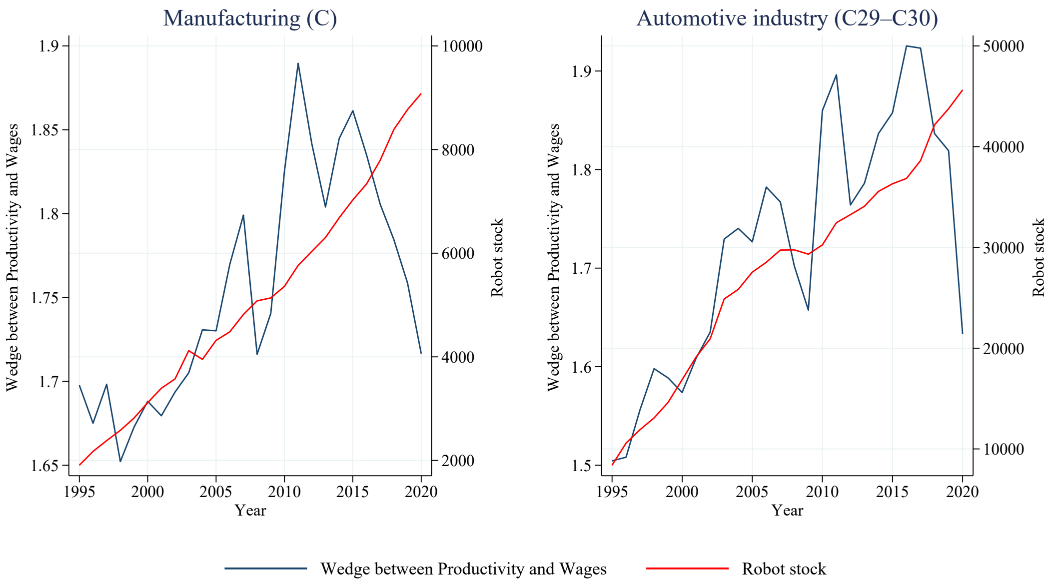

Figure 2: Evolution of the robot stock and the wage–productivity wedge across all countries weighted by employment in manufacturing (Left Panel) and in the automotive industry (Right Panel). The wedge is computed as the ratio of value added per worker to real compensation using EU-KLEMS data (Bontadini et al., 2023). Robot intensity is derived from IFR data (Jurkat et al., 2021), mapped to sectors and imputed where industry-level details are missing, following Acemoglu and Restrepo (2020b).

Table 1 reports OLS estimates of the relationship between robot intensity and the wage–productivity wedge, defined as the ratio of value added per worker to the real wage. Columns (1)–(2) cover all sectors, while Columns (3)–(4) restrict the sample to manufacturing sectors. Year fixed effects are included in Columns (2) and (4); all specifications include sector and country fixed effects.

Across all specifications, the estimated coefficient on robot intensity is positive and statistically significant. The coefficients are larger in the manufacturing subsample — ranging from 0.75 to 0.86 — compared to the full sample of sectors, where they range from 0.64 to 0.72, suggesting a stronger association between robot adoption and the wedge in manufacturing. The inclusion of year fixed effects slightly reduces the magnitude of the estimates in both samples, yet the positive and significant relationship persists, indicating that the association is not merely driven by common time trends. Despite indicating a positive association between robot adoption and the wage–productivity wedge, these estimates should be interpreted as descriptive correlations rather than causal effects.

	$100 \times \log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right)$			
	All sectors		Manufacturing sectors	
	(1)	(2)	(3)	(4)
log (Robot intensity$_{\omega,i,t}$)	0.72**	0.64**	0.86***	0.75**
	(0.33)	(0.27)	(0.28)	(0.28)
Constant	69.98***	69.66***	59.23***	58.99***
	(0.95)	(0.51)	(0.62)	(0.61)
Sector FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
N	8276	8276	5311	5311
Adj. R^2	0.56	0.56	0.44	0.45

Table 1: Baseline OLS: Robot Intensity and the Wage-Productivity Wedge

Notes: The table reports OLS estimates based on Equation (10). The sample includes all countries listed in Table 5. Standard errors in parentheses, clustered two-way by sector and country (all-sector models) and by country only (manufacturing models, 9 sub-sectors). Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To address potential confounding factors, we extend the baseline regression in Equation (11) to include additional sector-level controls. One concern is that outsourcing may affect the wage–productivity wedge through channels similar to automation, by altering the demand for domestic labor (Autor et al., 2016; Acemoglu and Restrepo, 2022). We account for this by controlling for outsourcing intensity, measured as the cost share of imported intermediate inputs in total intermediate input use, following Feenstra and Hanson (1999).

A second concern is that robot adoption, as a form of capital deepening, may be correlated with broader capital intensity trends. To avoid conflating general capital accumulation with automation-specific effects, we include the capital–labor (K/L) ratio as an additional control in all specifications.

Table 2 reports OLS estimates from extended specifications that include controls for outsourcing and capital intensity, as defined in Equation (11). Columns (1)–(4) cover all sectors and Columns (5)–(8) restrict the sample to manufacturing sectors. Within each group, year fixed effects are added in even-numbered columns, and the capital–labor ratio is introduced as an additional control in Columns (3)–(4) and (7)–(8).

The coefficient on robot intensity is positive and statistically significant across all eight specifications. Consistent with the baseline results in Table 1, the coefficients are larger in the manufacturing subsample, ranging from 0.80 to 0.96, compared to

0.64 to 0.85 in the full sample. The inclusion of year fixed effects moderately reduces the magnitude of the estimates but does not affect their significance, suggesting the association is not driven by common time trends. The outsourcing control enters with a negative sign in most specifications but is statistically significant only in Column (2), while the capital–labor ratio yields coefficients close to zero throughout. The inclusion of outsourcing and capital intensity controls has little impact on the main results, with these additional variables yielding generally imprecise and insignificant coefficients.

	$100 \times \log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right)$							
	All sectors				Manufacturing sectors			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (Robot intensity$_{\omega,i,t}$)	0.85**	0.64**	0.73*	0.74**	0.96**	0.84**	0.83**	0.80**
	(0.33)	(0.24)	(0.39)	(0.33)	(0.34)	(0.31)	(0.37)	(0.34)
log (Outsourcing$_{\omega,i,t}$)	-7.45	-10.06*	-7.99	-8.64	-3.87	-7.36	-9.16	-11.21
	(4.75)	(5.18)	(5.96)	(6.09)	(6.29)	(6.51)	(6.34)	(6.81)
log (K/L ratio$_{\omega,i,t}$)			0.00	0.00			0.00	0.00
			(0.00)	(0.00)			(0.00)	(0.00)
Constant	60.85***	56.55***	59.53***	58.70***	55.72***	51.41***	48.92***	46.54***
	(6.36)	(6.87)	(9.44)	(9.38)	(6.87)	(7.20)	(7.58)	(8.21)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	7912	7912	6484	6484	5077	5077	4159	4159
Adj. R^2	0.56	0.56	0.57	0.57	0.44	0.45	0.48	0.49

Table 2: Baseline OLS with controls: Robot Intensity and the Wage-Productivity Wedge Controlling for Outsourcing and Capital–Labor (K/L) Ratio

Notes: The table reports OLS estimates based on Equation (11). The sample includes all countries listed in Table 5. Standard errors two-way clustered by industry and country (all sectors) or country only (manufacturing, 9 sub-sectors). Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To examine whether the observed association between robot intensity and the productivity-wage wedge could be driven by the routine task content of sectors, rather than automation itself, we augment the baseline specification with RTI included as a level control in our robustness check. We consider two alternative measures: a binary indicator for above-median RTI and a continuous sector-level RTI mean derived from EU-LFS data. The results are reported in Table 7 in the Appendix.

Across both RTI measures and all specifications, the estimated coefficient on robot intensity remains positive and broadly stable relative to the baseline results, suggesting that sector routineness does not operate as an omitted variable in the main regressions. However, we must be especially cautious in interpreting these results, as they rely on imputed occupational structures for disaggregated manufacturing sectors—where detailed EU-LFS data are not available. All manufacturing sub-sectors share the same RTI within a country-year, the RTI control identifies cross-country-year variation in manufacturing routineness only.

The continuous RTI measure enters positively and is statistically significant in the all-sector specifications (Columns (5) and (6)), consistent with routine-intensive sectors exhibiting a wider productivity–wage wedge on average. In the manufacturing subsample, the RTI level control is imprecise and close to zero in all columns. These results reinforce the robustness of the main findings to the inclusion of routine task intensity as a control.

Although the inclusion of fixed effects and sector-level controls helps account for observable heterogeneity, endogeneity in robot adoption remains a concern. While our theoretical framework suggests that automation affects labor outcomes by altering the production structure, reverse causality cannot be fully ruled out. For instance, sectors with faster productivity growth at a given wage may be less likely to adopt robots if labor becomes more competitive. To address this concern, we turn to an instrumental variable strategy that isolates exogenous variation in robot adoption.

Following Acemoglu and Restrepo (2020a) and Dauth et al. (2021), we instrument robot intensity at the country–sector–year level using robot adoption in the corresponding sectors of the US, South Korea, and New Zealand. This instrument captures exogenous variation in robot diffusion driven by global technological trends, under the assumption that foreign sectoral robot use is uncorrelated with contemporaneous labor market conditions in European economies.

Table 3 presents 2SLS estimates of the relationship between robot intensity and the wage–productivity wedge using external robot trends as instruments. The upper panel reports second-stage coefficients; the lower panel reports the corresponding first-stage coefficients. The first-stage results confirm instrument relevance, with all three international series significantly predicting domestic robot adoption in most specifications. First-stage F-statistics exceed the conventional threshold of 10 in all eight columns, indicating strong instruments (Stock et al., 2002).

Columns (1)–(4) cover all sectors and Columns (5)–(8) restrict the sample to manufacturing. Within each group, even-numbered columns apply value-added weights, and Columns (3)–(4) and (7)–(8) additionally include controls for outsourcing and the capital–labor ratio.

	$100 \times \log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right)$							
	All sectors				Manufacturing sectors			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (Robot intensity$_{\omega,i,t}$)$^{\mathrm{IV}}$	0.69	0.69***	0.62	1.00***	0.92*	0.88**	0.89	-0.70
	(0.48)	(0.20)	(0.64)	(0.30)	(0.45)	(0.33)	(0.63)	(0.50)
log (Outsourcing$_{\omega,i,t}$)			-7.15	0.42			-9.28	4.71
			(6.05)	(6.41)			(7.53)	(3.91)
log (K/L ratio$_{\omega,i,t}$)			0.00	-0.00***			0.00	0.00***
			(0.00)	(0.00)			(0.00)	(0.00)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Weighted	No	Yes	No	Yes	No	Yes	No	Yes
N	7983	7983	6233	6233	5123	5123	3998	3998
First-stage F	30.80	14.55	30.22	14.53	42.18	150.70	41.53	53.74
	First-stage regression							
	log (Robot intensity$_{\omega,i,t}$)							
log (Robot intensity$_{\omega,US,t}$)	0.23**	0.29***	0.22**	0.28***	0.18**	0.11	0.13*	0.05
	(0.08)	(0.07)	(0.10)	(0.07)	(0.06)	(0.09)	(0.07)	(0.07)
log (Robot intensity$_{\omega,KR,t}$)	0.17	0.26**	0.17	0.19*	0.19***	0.25***	0.18***	0.11***
	(0.12)	(0.09)	(0.14)	(0.09)	(0.04)	(0.05)	(0.05)	(0.03)
log (Robot intensity$_{\omega,NZ,t}$)	0.28***	0.36***	0.20**	0.31***	0.31***	0.47***	0.20***	0.27***
	(0.07)	(0.11)	(0.07)	(0.09)	(0.06)	(0.08)	(0.05)	(0.08)
N	8008	7983	6258	6233	5148	5123	4023	3998
Adj. R^2	0.68	0.71	0.67	0.74	0.66	0.71	0.65	0.76

Table 3: IV Estimates: Robot Intensity Instrumented by Foreign Robot Stocks

Notes: The table reports 2SLS estimates based on Equation (10). The sample includes all countries listed in Table 5. Weights are based on real value added at the start of the period for each country. All models: sector and country FE, no year FE (year FE absorb cross-time instrument variation; KP $F < 0.1$ for all-sector TWFE specs). First-stage F: Kleibergen-Paap rk Wald statistic; Stock-Yogo (2005) 10% critical value = 13.91 (3 instruments). Standard errors clustered two-way by industry and country (all sectors) or by country only (manufacturing, 9 sub-sectors). Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In the unweighted specifications (Columns (1), (3), (5), and (7)), the IV estimates are positive but statistically imprecise for all sectors and statistically significant for manufacturing sector without year fixed effects. The weighted specifications controls yield more precisely estimated results: Columns (2) and (4) report significant effects of 0.69 and 1.00 for all sectors, and Column (6) reports significant effect of 0.88 in manufacturing. The inclusion of controls reduces precision in the manufacturing subsample, likely reflecting multicollinearity among controls in the smaller weighted sample. Controls for outsourcing and the capital–labor ratio have no consistent association with the wedge.

Overall, IV estimates are less precisely estimated, but broadly consistent with – and somewhat larger than – the corresponding OLS results, reinforcing a causal interpretation of the positive association between robot adoption and the wage–productivity wedge.

Controls for outsourcing and the capital–labor ratio have no consistent association with the wedge. Outsourcing is never statistically significant, while capital intensity is weakly negatively associated with the wedge in the weighted specifications.

All things considered, the reduced-form OLS and IV results indicate an economically meaningful link between robot adoption and the wedge between labor productivity and wages, particularly in manufacturing sub-sectors. This relationship persists when controlling for outsourcing, capital intensity and the RTI. The estimates of the instrumental variables reported in Table 3 reinforce this evidence, pointing to causal effects – even though less precisely estimated.

5 Conclusion

We examine whether robot adoption drove a growing wedge between labor productivity and wages in European countries from 1995 to 2020. Anchored in a simple theoretical model, we test whether automation increases the wage-productivity wedge, controlling for several potential confounding factors and providing the evidence for the causal link from robot intensity to the wage-productivity wedge.

Our empirical analysis produced two key findings. First, we documented a robust positive association between robot intensity and the wage–productivity wedge, especially in the manufacturing sector. This relationship remained stable across specifications controlling for outsourcing and capital intensity, aligning with the theoretical prediction that automation can contribute to decoupling between wages and productivity even in the presence of traditional production factors. These results are broadly robust controlling for routine intensity by country-year-sectors.

Instrumental variable estimates using external robot adoption trends in the US, South Korea, and New Zealand reinforce the main correlational patterns, even though the coefficients are less precisely estimated. These results strengthened the case for a causal interpretation of the robot–wedge link, but should be taken with caution.

Overall, our findings offer qualified support for the presented model and the hypothesis that robot adoption contributes to wage–productivity decoupling. At the same time, they underscore the importance of cautious interpretation and the need for future research into the institutional, structural, and macroeconomic forces mediating the effects of automation on labor income.

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A Appendix

klems23_code	**klems23_lab**	**ifr_code**	**ifr_ sector**
A	Agriculture, forestry and fishing	A-B	Agriculture, forestry, fishing
B	Mining and quarrying	C	Mining and quarrying
C10_C12	Manufacture of food products; beverages and tobacco products	10-12	Food and beverages
C13_C15	Manufacture of textiles, wearing apparel, leather and related products	13-15	Textiles
C16_C18	Manufacture of wood, paper, printing and reproduction	16, 17-18	Wood and furniture + Paper
C20_C21	Chemicals; basic pharmaceutical products	19, 20-21	Pharmaceuticals, cosmetics + other chemical products n.e.c.
C22_C23	Manufacture of rubber and plastic products and other non-metallic mineral products	22, 23	Rubber and plastic products (non-automotive) + Glass, ceramics, stone, mineral products (non-auto)
C24_C25	Manufacture of basic metals and fabricated metal products, except machinery and equipment	24-28	Metal
C26_C27	Computer, electronic, optical products; electrical equipment	26-27	Electrical/electronics
C28	Manufacture of machinery and equipment n.e.c.	28	Industrial machinery
C29_C30	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment	29, 30	Automotive + Other vehicles
D_E	Electricity, gas, steam; water supply, sewerage, waste management	E	Electricity, gas, water supply
F	Construction	F	Construction
P	Education	P	Education/research/development
TOT	Total - all NACE activities	0	All Industries

Table 4: Sectoral correspondence between EU-KLEMS and IFR industry classifications

EU Countries in the sample	
Austria	Bulgaria
Belgium	Croatia
Denmark	Czech Republic
Finland	Estonia
France	Hungary
Germany	Latvia
Italy	Lithuania
Netherlands	Poland
Portugal	Romania
Spain	Slovakia
Sweden	Slovenia
United Kingdom	

Table 5: List of countries included in the sample

Figure 3: Heatmaps of K/L ratios by sector, before and after imputation. The top panel displays observed K/L ratios across sectors and years based on available EU-KLEMS data. The bottom panel shows the same metric after imputing missing values using country-year averages within broader sector aggregates.

	mean	sd	p25	median	p75	min	max	N
log(Productivity-wage wedge)	67.25	41.66	40.75	58.23	83.64	-113.00	335.89	8346
log(Robot intensity)	-3.85	5.64	-10.18	-1.89	0.96	-15.41	4.97	8302
log(Robot stock)$^{\mathrm{US}}$	3.72	6.79	-6.91	5.91	9.14	-6.91	11.95	8372
log(Robot stock)$^{\mathrm{KR}}$	3.29	5.91	1.87	4.45	8.03	-6.91	12.24	8372
log(Robot stock)$^{\mathrm{NZ}}$	-3.67	4.78	-6.91	-6.91	2.12	-6.91	6.25	8050
log(Outsourcing)	-1.32	0.49	-1.65	-1.28	-0.96	-4.01	-0.22	9152
K/L ratio	1846.07	6760.37	68.11	139.53	611.64	4.35	89618.42	6930
RTI	-0.29	0.25	-0.42	-0.25	-0.14	-0.98	0.22	6298

Table 6: Descriptive statistics for the main variables of interest.

	$100 \times \log\left(\frac{x_{\omega,i,t}/l_{\omega,i,t}}{w_{\omega,l,i,t}}\right)$							
	Binary RTI, All sectors		Binary RTI, Manufacturing		Continuous RTI, All sectors		Continuous RTI, Manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (Robot intensity$_{\omega,i,t}$)	0.52	0.70*	0.63**	0.69**	0.39	0.62	0.62**	0.68**
	(0.47)	(0.34)	(0.30)	(0.29)	(0.47)	(0.38)	(0.28)	(0.29)
$\bar{\gamma}_{\omega}^{RTI}$	3.09	4.20	1.77	1.59				
	(3.38)	(4.43)	(1.75)	(2.22)				
RTI$_{\omega,i,t}$ (mean)					16.68*	25.97**	4.27	-0.19
					(7.69)	(11.79)	(7.18)	(13.57)
log (Outsourcing$_{\omega,i,t}$)	-7.92	-7.33	-9.20	-10.48	-8.66	-7.44	-9.14	-10.45
	(7.31)	(8.39)	(6.83)	(7.26)	(7.80)	(8.81)	(6.95)	(7.16)
log (K/L ratio$_{\omega,i,t}$)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	5292	5292	3802	3802	5292	5292	3802	3802
Adj. R^2	0.573	0.575	0.496	0.504	0.575	0.577	0.496	0.504

Table 7: OLS with RTI Level Control

Notes: RTI added as a level control. Binary RTI: indicator for above-median RTI (global pooled median). Continuous RTI: sector-level mean from EU-LFS based on Mihaylov and Tijdens (2019). All specifications include outsourcing and K/L ratio controls. Columns (1)–(2) and (5)–(6): all sectors, two-way clustering by sector and country. Columns (3)–(4) and (7)–(8): manufacturing (9 sub-sectors), country-only clustering. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.