JULY 2025

Working Paper 267

Robots, shoring patterns, and employment:

What are the linkages?

Hylke Dijkstra and Konstantin M. Wacker

The Vienna Institute for International Economic Studies
Wiener Institut für Internationale Wirtschaftsvergleiche

Robots, shoring patterns, and employment:

What are the linkages?

HYLKE DIJKSTRA
KONSTANTIN M. WACKER

Hylke Dijkstra is PhD Candidate University of Groningen, The Netherlands. Konstantin M. Wacker is Associate Professor at the University of Groningen, The Netherlands and Research Associate at The Vienna Institute for International Economic Studies (wiiw).

K.M. Wacker acknowledges funding from European Union's Horizon 2.2 and 2.2.3 programmes under grant agreement No. 101056793 ('Twin Seeds').

The authors would like to thank Gaaitzen de Vries, Hagen Kruse and Tim de Leeuw for providing and processing data, participants at CORA Frankfurt, the GGDC conference in Groningen, and workshops in Milan and Parma for valuable comments and discussions, and Bart Los and Erik Dietzenbacher for fruitful conceptual discussions.

Abstract

In this paper, we analyse how robotisation is associated with industry output and its production inputs. We therefore link data on employment, robotisation and input-output relations for 15 manufacturing industries across 35 countries. Analysing the decade prior to 2018, we show that robotising industries experience increases in output and approximately equiproportional increases in value added, employment, domestic intermediate inputs and foreign intermediate inputs. Owing to this equiproportionality, robotising industries do not see a significant change in their domestic input ratios (value added plus domestic intermediates relative to total inputs).

Our empirical results document that robotising industries are thriving in terms of output generation, that those thriving industries are internationally well integrated, and that their output expansion is associated with employment generation. Industries that use an increasing share of domestic production inputs generally experience less favourable output and employment developments, although this association is imprecisely estimated.

Keywords: Robots, reshoring, employment, labour, production location, global value chains, GVCs

JEL classification: E23; J23; O30

CONTENTS

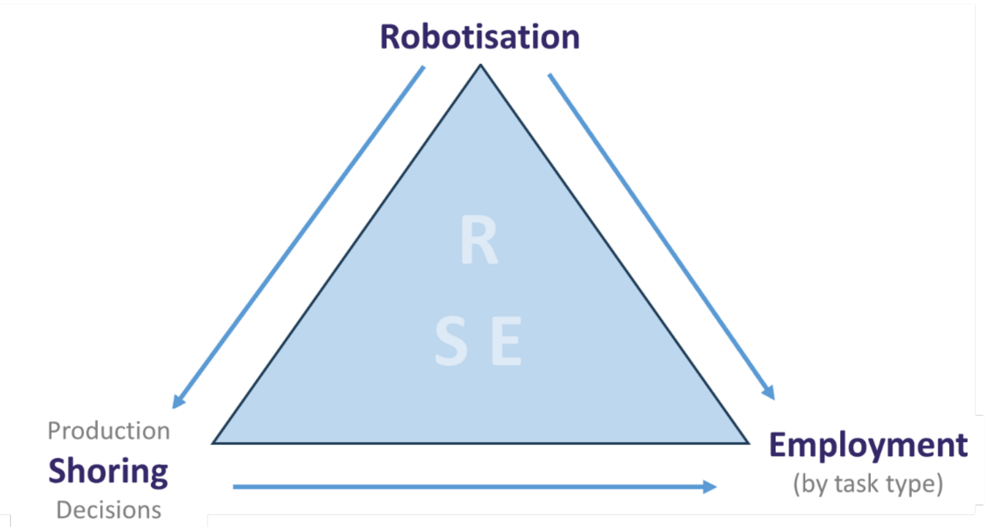
TABLES AND FIGURES

1. Introduction

How does robotisation influence the production inputs that an economy uses? Does employment decline in the face of robotisation? Can robots bring back previously offshored production steps? Those questions are intensively discussed by researchers, policy actors and the general public, and they become increasingly important in the context of strategies aimed at 'bringing back' production with the objective of employment creation, 'making countries great again', and achieving 'strategic autonomy' (European Union, 2020).

To highlight the interrelation between robots, shoring decisions and employment, we propose to consider their connection in an RSE triangle, as depicted in Figure 1. Its robotisation-employment angle is widely analysed, with conflicting evidence.[1] For example, Acemoglu and Restrepo (2020) find negative consequences of robot exposure on regional labour markets in the US. Conversely, Dauth et al. (2021) find no such aggregate employment effect for Germany when using a similar approach. Studies that rely on cross-country industry level data, as we do in our paper, usually find insignificant or heterogeneous employment effects (e.g. Graetz and Michaels, 2018; de Vries et al., 2020; Reljic et al., 2023; Muris and Wacker, 2025).[2] In a meta-analysis of 33 studies with 644 estimates, Guarascio et al. (2024) document a small average negative near-zero relationship between robotisation and employment, with quite a variation across studies and estimates. As the authors highlight, this heterogeneity in results may be driven by effects that operate through global value chains (GVCs).

Figure 1 / The RSE triangle



[1] Mondolo (2022), Restrepo (2023) and Jurkat et al. (2023) survey this literature.

[2] Chen and Frey (2024) confirm such cross-country heterogeneity when analysing variation across regions.

The robot-shoring angle is less researched and empirically similarly equivocal. Several studies suggest that workers in lower-wage countries compete with robots in higher-income trading partners (e.g. Stemmler, 2023; Kugler et al., 2020; Carbonero et al., 2020; Gravina and Pappalardo, 2022). For example, Faber (2020) estimates that 5% of US robots primarily compete with workers in Mexico, a traditional US offshoring location. If this is the case, one would expect that robotisation, through lower domestic production costs in high-income countries, creates an incentive to relocate production towards the robotising home economy. But whether a relationship between robotisation in high-income countries and employment declines in low-wage countries actually brings back employment to high-income countries is questionable. For example, De Backer et al. (2018) find evidence that robots in high-income countries reduced the rate of offshoring in recent years, but do not find that robots motivate firms to reshore jobs back home. Chen and Frey (2024) find mixed evidence across countries, which is also echoed in other studies. For example, Cilekoglu et al. (2024) show that robot adoption did not affect domestic sourcing of Spanish firms in 2006-2016 and increased foreign sourcing activities. Conversely, cross-country and industry-level results from Krenz et al. (2021) suggest that robotisation is associated with reshoring intensity, which, in turn, seems positively associated with employment increases of professionals, but negatively (and statistically imprecisely) associated with employment of workers in elementary routine occupations. A key challenge to investigate this R-S angle, and for the RSE relationship more broadly, is how to measure and conceptualise (re-)shoring.

Broadly speaking, the conflicting findings in the literature reflect two schools of thought about the RSE relationship. The first is perhaps best summarised by Gunter Erfurt from the solar module producer Meyer Burger, who highlighted that ‘without subsidies, production costs of a solar module would be more or less equal everywhere. Labour costs in modern manufacturing are so low, you can produce everywhere you want, due to automation.’[3] In this view, robotisation is associated with production (re-)location, but hardly has a shoring-related impact on employment.

A second school of thought, however, highlights that robotisation always needs some complementary labour – for installation, process optimisation or maintenance, for example. Although there may be a domestic labour-replacing RE effect, robot-induced reshoring may hence create a positive indirect RSE effect. An example is the children’s bike producer Woom, which planned to bring back production to Europe that had been previously offshored to Bangladesh: although the novel production factory in Świebodzin (Poland) was planned to be almost entirely automated, this turned out to be infeasible in practice. High-skilled labour was required for process restructuring, and blue-collar workers are still working in the new plant. But how representative this particular case is remains questionable.

Contribution In this paper, we systematically investigate the relationships between robotisation, shoring patterns and employment in 15 manufacturing industries across 35 countries over the decade up to 2018.[4] Our key innovation in this context is to analyse the interrelationships between changes in key RSE variables through a simple internationally fragmented production structure that can be linked to inter-country input-output tables (ICIOTs). This allows us to separately investigate the relationship

[3] Gunter Erfurt, Handelsblatt Today podcast, 15 June 2023.

[4] Data constraints limit us to those industries and years. This limitation avoids inclusion of the COVID-19 pandemic years, with possibly peculiar effects in the RSE relationship (e.g. Abeliansky et al., 2023), and the focus on manufacturing reduces cross-sector heterogeneities (see Bekhtiar et al., 2024).

between robotisation, on the one hand, and total output, value added, employment, and domestic and foreign intermediate input use, on the other.

Our approach of investigating the relationship between robots and production inputs leads us to a simple measure of domestic production input intensity, the domestic input ratio (DIR). We define this DIR as value added plus domestic intermediate inputs relative to overall gross output of an industry, formally: DIR= (VA+DII)/x, where the latter, because output is the sum of inputs, includes the former two inputs plus foreign intermediate inputs (x = VA + DII + FII). This approach has several attractive features to capture changing shoring patterns and production relocations in the context of robotisation. For example, it can be related to firms' decision of input choice in the presence of robotization (see Krenz et al., 2021, who provide a theoretical model for this mechanism). Moreover, although the DIR is not a measure for reshoring, it allows assessment of whether different types of reshoring, as classified by Gray et al. (2013), are consistent with macroeconomic data, namely in-house reshoring and insourcing, both of which operate through value added, and outsourcing-related reshoring, which operates through domestic intermediate inputs.

Our econometric methodology facilitates a reduced-form separation of scale vs. substitution effects of robotisation. In a first step, we analyse the partial correlation of robots with each of the input factors value added, labour, domestic and foreign intermediate inputs. This jointly captures scale and substitution effects, which can be compared to a raw scale effect that we derive from the partial correlation between robots and industry output. In a second step, we then include industry output into our regression equations. This enables the partial correlations between robots and production input factors to be interpreted as reduced-form substitution effects, conditional on the scale of an industry's gross output.

Key findings Our key empirical finding is that industries that robotise increase their scale of production. This scale effect lifts the demand for all production input factors. Beyond that, robotisation is not systematically biased in favour of or against any broad input factor. Value added, foreign inputs and domestic inputs all increase in the presence of robots, in slightly declining magnitude and mostly as a consequence of the scale effect. Holding an industry's gross output constant, we observe the same ranking, with small (and insignificant) increases in value added, and minor decreases in foreign and, particularly, domestic intermediate inputs. If anything, therefore, our results indicate that value added substitutes for domestic inputs in the presence of robotisation. Putting those pieces together, it follows that our domestic input ratio (DIR = [VA+DII]/x) shows a flat-zero correlation with robotisation because the opposing movements in VA and DII in the numerator largely offset each other. In other words, robotisation is not associated with a relevant relocation of production towards the robotising economy.

Policy implications from our paper should be inferred with a degree of caution. We provide descriptive correlations limited to the manufacturing sector (and do not account for foreign vs. domestic value added in intermediate inputs through GVCs). What is clear from our results, however, is that robot-induced reshoring and associated employment increases are a myth at the macro level. Broadly speaking, and not surprisingly, industries that generate employment are industries that thrive (in the sense of increasing output). We show that those thriving industries robotise. And they remain internationally well integrated: an industry's domestic input ratio is negatively correlated with its overall output. Although the latter relationship is statistically indistinguishable from 0, the RSE patterns documented in our paper suggest that an industrial strategy that focuses on industries that 'bring back production' will not create additional employment. We would go one step further and argue that it is a strategy that bets on losers.

Despite the aggregate zero-substitution between robotisation and employment that our results suggest for manufacturing industries, this does not mean that individual employees will not lose their jobs. In particular, manual workers performing routine tasks are likely to be replaced, and hence there is a need for social and training programmes. The importance of the latter is further emphasised by our finding that some industries thrive more than others. Education and training programmes should be designed to facilitate such structural changes.

Relation to the literature. Our paper relates to a broader literature on how technology affects production input choices. Key studies on the robot-employment angle are referenced above; Schwark and Tryphonides (2025) focus on digitalisation but, similarly to our study, take a broader perspective on production inputs, notably intermediate inputs. Key literature on the robots-shoring angle is also referenced above.

Krenz et al. (2021) provide a theoretical model that suggests that robotisation leads to a relocation of previously offshored production but without creating jobs for routine-task workers in the reshoring economy and find some descriptive support for this mechanism in cross-country industry-level data. This differs from our empirical results for reasons on which we elaborate below. Aside from a different approach on what to measure and how, the key difference to our results stems from the fact that Krenz et al. (2021) restrict variation in their empirical reshoring measure to industries that do reshore (in their definition). Their empirical results hence suggest a positive relationship between reshoring *intensity* and robotisation conditional on reshoring taking place, and not a relationship between reshoring activity and robotisation. We, conversely, document that no relationship between robotisation and domestic production input intensity exists, unless we focus on the approximately 25% of industries in our sample that do possibly reshore. We show that those 25% of industries experience rather mediocre output dynamics, and hence consider that they should not be the focus of employment analysis. In fact, it could well be that the association between ‘reshoring’ intensity and robotisation in those industries actually reflects foreign supply uncertainty and hence ‘decoupling’ rather than ‘reshoring’ (see Burkhart et al., 2023; Firooz et al., in press): when firms or industries can no longer reliably source foreign inputs, they substitute them with domestic value added, notably robots. This, however, is a completely different mechanism from robot-induced reshoring.

Our cross-country industry-level results are broadly consistent with more disaggregated findings by Stapleton and Webb (2020) and Cilekoglu et al. (2024) about Spanish manufacturing firms, which suggest that robots primarily have a scale effect and that robotising, thriving firms are generally internationally well integrated. Broadly similar patterns are documented at the industry level in Artuc et al. (2023).

Structure of the paper. In Section 2, we highlight how an accounting identity for gross industry output can be used to trace changes in an industry’s location and structure of production, notably patterns such as outsourcing, offshoring and reshoring. We then define the domestic input ratio, DIR, based on those considerations and explain why it is the right measure, and conceptually appealing, to analyse what happens to industry inputs in the presence of robotisation. Section 3 presents our econometric specification and how we estimate it. Section 4 describes the data, while Section 5 presents the results and Section 6 sets out our conclusions.

2. Conceptual framework

We are interested in an economy's aggregate production structure for output *x*. Specifically, we want to investigate if the increased use of robots in production is associated with absolute and relative changes in other production inputs. Our empirical analysis will investigate this relationship at the industry level across countries.

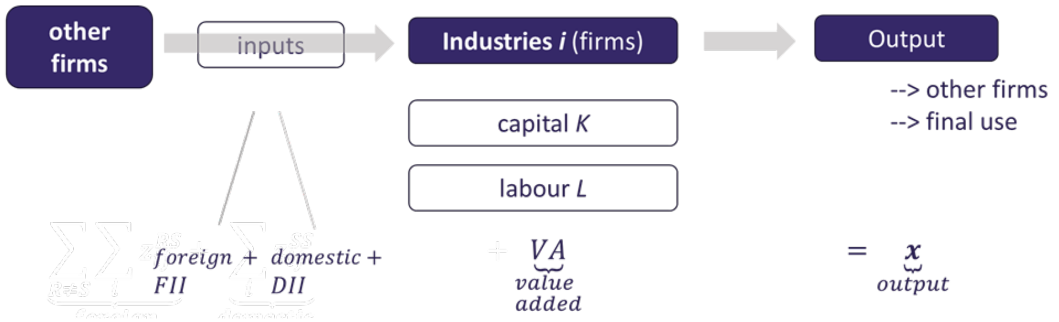
2.1. PRODUCTION WITH DOMESTIC AND FOREIGN INPUTS

A firm that produces output *x* uses labour *L*, capital *K* and intermediate inputs, which may stem from home (domestic intermediate inputs, *DII*) or abroad (foreign intermediate inputs, *FII*). Capital and labour add value, defined as value added *VA=VA(K,L)*. Assuming that an industry *i* consists of a representative firm, we can hence write its gross industry output as:

$$x_i = VA_i + DII_i + FII_i, \tag{1}$$

which is a simple accounting identity for gross industry output x_i. Figure 2 illustrates this production structure. It is worth noting that DII and FII may both contain domestic and foreign value added.[5]

Figure 2 / Schematic production structure with (international) fragmentation



2.2. THE ROLE OF ROBOTS IN PRODUCTION WITH DOMESTIC AND FOREIGN INPUTS

What would happen in the context of the production identity in equation (1) if robots come into play? By definition, robots are capital *K*, and they may additionally increase productivity. As long as robots do not merely substitute domestic labour, they will hence increase value added *VA*. This robot-employment

5 This is most easily seen by highlighting that output x_i may either be final output (that is consumed or goes into capital formation) or an intermediate input for another firm in the same industry *i*, or another industry *j≠i*, which is either domestic or foreign. In other words, DII and FII in equation (1) are interim points of a value chain (e.g. Johnson and Noguera, 2012; Koopman et al., 2014; Los et al., 2015).

angle has been discussed at length in the literature referenced above and it appears implausible from this literature that robots replace labour on a one-to-one basis in value added because not all tasks (especially analytical non-routine ones) can simply be replaced by robots. One would hence expect that robots are positively associated with value added.[6]

What about the relationship between robotisation and intermediate inputs *FII* and *DII*? Those intermediate inputs are themselves aggregates of *VA* at earlier production stages. If they contain a high degree of manual routine inputs, it is reasonable to assume that robots substitute those upstream inputs. This is the idea of 'robot-induced reshoring' (the R-S angle of the RSE triangle): high-income countries have previously offshored manual routine production steps to low-income countries, where wages are lower. With the availability of robots at reasonable prices in high-income countries, the cost advantages of low-wage countries for those tasks diminish and so they are increasingly reshored. If this is the case, ceteris paribus, we would observe an increase in the ratio *VA/FII*. However, this is not obvious: modern production requires a lot of imported intermediate inputs from other high-income countries, which are not necessarily easy to replace by robots.

If *FII* or *DII* mainly contain tasks that can technically be replaced by robots, and whether such a replacement is economically profitable, thus remains an empirical question. It follows that, even though robots should be positively correlated with an industry's value added, the relationship with the VA/x ratio depends on the substitution between robots and other production inputs, *DII* and *FII*.

2.3. SHORING PATTERNS: OUT-, OFF-, RE-; AND THE DOMESTIC INPUT RATIO

It is instructive to discuss how the schematic production structure in Figure 2 relates to key concepts that aim to describe changing locations of production in a globalised economy, such as 'sourcing' and 'shoring'.[7] For example, for a firm or industry that *outsources*, it is reasonable to assume that its (DII+FII)/VA ratio increases and also, accordingly, its (DII+FII)/x ratio. This firm or industry produces less 'in-house' and hence adds less value per unit of output (*VA/x*↓). The lower in-house value added is substituted by intermediate inputs from other firms.

A firm or industry that *offshores* particularly increases its *foreign* intermediate inputs *FII*. *Offshore intensity* could hence meaningfully be defined by the ratio *FII/x*. Movements in this ratio would isolate changes in *FII* from a mere change in the scale of production: $\Delta(FII/x)>0$ captures that an industry more intensively uses foreign inputs for a given unit of output and is thus offshoring. Even if overall output *x* declines, and *FII* remains constant, this appears meaningful.

It is tempting to then define *reshoring* inversely as $\Delta(FII/x)<0$, which is, however, not convincing because output *x* may go up, such that $\Delta(FII/x)<0$, without a specific production step having been reshored (in the sense of 'brought back').[8] Imposing constraints such as requiring $\Delta FII<0$ are neither conceptually

[6] Note that this is true even if robots replace labour. A positive relation between robots and value added implies that in the context of robotisation, returns to labour decrease less than returns to robotisation capital increase.

[7] In this paper, we define a 'domestic input ratio' (DIR) and discuss what it means in terms of 'location of production'. We do not claim to measure 'sourcing' or 'shoring'. In our context, 'shoring' simply refers to changes in the DIR.

[8] This is most readily apparent in the case of an industry or firm *i* that produces two products, a and b, where a is fully produced in-house (through VA) and b consists of VA+DII+FII. If output of a rises but b remains unaffected, x rises and $\Delta(FII/x)<0$ without any reshoring: nothing has happened to production of b.

convincing nor empirically appealing because to do so would limit any assessment to a small and unrepresentative selection of industries. In short, we think reshoring cannot be meaningfully measured at the macro level. At best, we may observe patterns that are consistent with reshoring taking place, such as Δ(FII/x)<0.

To trace broad changes in the location of production, with a focus on foreign vs. domestic inputs, we hence propose another concept, the *domestic input ratio* (DIR), which we define for industry *i* as the inverse of the FII/x offshore intensity:

$$DIR_i \equiv (VA_i + DII_i)/x_i. \qquad (2)$$

The DIR is intuitively appealing: at a given production step, it measures what share of direct production inputs is sourced domestically, and what share originates from abroad. Robot-induced changes in the DIR are most likely to stem from an increase in *VA* resulting from robotisation, but robotisation could, in principle, also lead to an increase in *DII* (for example, when domestic industries provide intermediate inputs that complement automation, such as installation and maintenance services).

Note that by 'direct' production input, we disregard that *DII* may contain foreign value added from earlier production stages and that *FII* may contain domestic value added from earlier production stages. Such a global value chain (GVC) decomposition is in principle feasible (and is compared to the DIR in our companion paper: Dijkstra and Wacker, 2025), but misleading for the purpose of our analysis: a firm or industry that robotises decides on in-house value added (robots vs. labour) vs. intermediate inputs that are available domestically (DII) and from abroad (FII). What matters to a firm is the relative price of those intermediate inputs and their substitutability with robots at a given production stage, not the production history of those intermediate inputs. Whether robotisation changes the structure of a GVC is an interesting, but entirely different question. In other words, at the particular production step of our empirical analysis, a representative firm (or industry) considers the value chain of any *FII* and *DII* as given (as long as we abstract from intra-firm trade).[9]

In case one wants to relate our DIR measure to reshoring, the reshoring typology of Gray et al. (2013) is instructive to see the merits of DIR. The authors distinguish four types of reshoring: *in-house reshoring* (shifting from offshore wholly owned facilities to home-based ones), *reshoring for insourcing* (relocating from offshore suppliers to home-based wholly owned facilities), *reshoring for outsourcing* (moving from offshore wholly owned facilities to home-based suppliers), and *outsourced reshoring* (transferring from offshore suppliers to home-based suppliers). *FII* would decrease in all four cases, while *VA* would increase in the first two cases and *DII* would increase in the last two. Our DIR hence principally captures all those aspects in different sub-components. Notably, it explicitly includes the *VA* component, which is an important mechanism for (in-house and insourcing) reshoring and a key difference to the measure for reshoring intensity proposed by Krenz and Strulik (2021).

---

9 Further note that we can additionally decompose all terms in equation (2). In particular, we can investigate what happens to employment (and different types of labour) in the VA term, and whether DII and FII stem from the same industry *i*, or another industry *j≠i*.

3. Empirical methodology and econometric estimation

We are first interested in estimating the relationship between an industry's robot intensity *RI* and its production input sourcing strategy (the R-S angle in Figure 1). In particular, we analyse how many inputs an industry sources from domestic suppliers (*DII*) and produces in-house (*VA*) relative to its sourcing from foreign suppliers (*FII*) in the presence of robotisation. Subsequently, we will investigate how such sourcing patterns link to employment (the S-E angle in Figure 1).

3.1. SEPARATION OF AGGREGATE EFFECTS INTO SCALE AND SUBSTITUTION

To empirically estimate the relationship between robotisation and production input sourcing, it is important to understand that robots will have two effects. First, robots are expected to improve productivity, and robotising industries are hence expected to produce more output *x*. We refer to this as a ***scale*** effect. Second, we hypothesise that robots change industries' sourcing pattern: they may rely less on intermediate inputs from domestic and/or foreign suppliers. We refer to this as a ***substitution*** effect.

Analytically separating the scale effect from the substitution effect is important in empirical analysis. Using ratios of production inputs as the dependent variable in a regression, such as our DIR, tells us something about substitution patterns between inputs. Although economically informative, this provides a limited picture of how production input factors are affected by robotisation: aggregate effects will also reflect changes in the scale of production.[10]

This distinction is particularly important from a policy perspective. On the one hand, this is because aggregate effects are most important for an economy. Suppose we find a substitution effect such that the ratio of domestic inputs (DII or VA) relative to foreign intermediate inputs (FII) declines. Employment of domestic labour may still rise in this case if FII simply rises more strongly. On the other hand, substitution effects are still relevant because they could indicate that particular groups of workers are temporarily replaced, which requires the design of adequate labour market policies.

Regressing changes of a production input *y* (such as VA, DII, FII, or sub-categories thereof) on changes in robotisation intensity for industry *i* in country *c* provides us with an *aggregate* relationship $\beta_{y,a}$ between robotisation and production inputs:

$$\Delta y_{ci} = \beta_{y,a} \Delta RI_{ci} + \delta_c + \varepsilon_{ci}, \qquad \text{aggregate regression} \qquad (3)$$

10 Studies should be careful to distinguish both aspects. For example, if a study finds that robotisation is associated with more FII sourcing or GVC backward integration, is that conditional on production scale or not? Not all empirical studies are clear and consistent in this regard.

As mentioned, production input *y* may change in the presence of robotisation as a consequence of robots replacing that production input (substitution) or robots changing the scale of overall production, with associated changes in all production inputs.

To gauge the *scale* effect of robotisation, we estimate the relationship between changes in output *x* and changes in robot intensity *RI*:

$$\Delta x_{ci} = \beta_1 \Delta RI_{ci} + \delta_c + \varepsilon_{ci}, \qquad \text{scale regression} \qquad (4)$$

with the clear expectation $\beta_1 > 0$: robotisation is expected to be associated with gross output increases. Moreover, $\beta_1 > \beta_{y,a}$ suggests that robotisation is less (or under-proportionally) correlated with an increase of production input *y* than with output *x*, suggesting negative substitution between *RI* and *y*.

To better understand *substitution* effects, we report results for two specifications. The first looks at the partial correlation between robot intensity and production input *y* (more precisely, its natural logarithm), holding the scale of production *x* constant:

$$\Delta y_{ci} = \beta_{y,b1} \Delta RI_{ci} + \theta_y \Delta x_{ci} + \delta_c + \varepsilon_{ci}, \qquad \text{substitution regression} \qquad (5)$$

This provides a direct estimate of the relationship between robot intensity and production inputs, conditional on output *x*, which is correlated with robotisation according to equation (4). A negative $\beta_{y,b1}$ indicates that, conditional on output *x*, less of input *y* is required as robotisation increases – consistent with the idea that robots substitute input *y* in the production of *x*.

Another way to gauge the substitution effect is to regress production inputs *y* relative to output *x* on robot intensity:

$$\Delta \left(\frac{y}{x}\right)_{ci} = \beta_{y,b2} \Delta RI_{ci} + \delta_c + \varepsilon_{ci}, \qquad \text{alternative substitution regression} \qquad (6)$$

Again, a negative $\beta_{y,b2}$ is indicative of a substitution effect: less of input *y* is required per output unit *x* as robotisation increases. Equation (6) directly motivates a specification where our DIR is regressed on robotisation to test if robots substitute for foreign production inputs (in which case we could expect DIR to increase and hence $\beta_{DIR,c}$ to be positive).

3.2. DIR AND (RE-)SHORING

Changes in the domestic input ratio, as defined in equation (2), can result from the numerator or denominator. An increase in the DIR, for example, could reflect lower output *x* with given domestic inputs or domestic input use increasing faster than output. If the goal is to measure ‘reshoring’, it is tempting to put all sorts of constraints on the developments of *DII* and *x*; this is essentially what Krenz et al. (2021) and Krenz and Strulik (2021) do for their measure of reshoring intensity.

We will instead focus on a separation of cases in which ΔDIR>0 and ΔDIR≤0, where the former is broadly consistent with reshoring taking place, because it will be sufficient to make our case. This leads us to an interaction-type regression equation such as:

$$\Delta y_{ci} = b_{2y,a}\Delta RI_{ci} \times \Delta DIR \leq 0_{ci} + b_{3y,a}\Delta RI_{ci} \times (\Delta DIR > 0)_{ci} + \delta_c + \varepsilon_{ci}. \quad (7)$$

3.3. SCALE AND SUBSTITUTION IN THE SHORING-EMPLOYMENT ANGLE

To additionally separate if changes in employment (EMPN) are plausibly driven by substitution of foreign through domestic production inputs (ΔDIR>0 for given x) or reflect additional scale effects (e.g. ΔDIR>0 owing to *x* rising faster than domestic inputs), we will additionally estimate regressions such as:

$$\Delta\ln(EMPN)_{ci} = \gamma_{EMPN,a}\Delta DIR_{ci} + \delta_c + \varepsilon_{ci}. \quad (8)$$

And

$$\Delta\ln(EMPN)_{ci} = \gamma_{EMPN,b1}\Delta DIR_{ci} + \theta_{EMPN}\Delta x_{ci} + \delta_c + \varepsilon_{ci}. \quad (9)$$

where we again separate the cases ΔDIR>0 from ΔDIR≤0.

3.4. ECONOMETRIC CONSIDERATIONS AND ESTIMATION

We estimate the above equations using a weighted least squares (WLS) first-difference estimator using differences over 10-year periods, with the 2004-2008 average as the starting point and the 2014-2018 average as the end point.

This first-difference specification controls for unobserved heterogeneity within countries and within industries, which are differenced away. Furthermore, the country fixed effect δ_c controls for systematic country-level time trends in the regression variables. The ultimate reason for this specification is its consistency with the previous empirical industry-level literature on the robot-employment angle. Consider the case where *y* is (the log of) employment. In this case, we obtain for equation (3):

$$\Delta\ln(EMPN)_{ci} = \beta_{EMPN,a}\Delta RI_{ci} + \delta_c + \varepsilon_{ci}. \quad (10)$$

which is consistent with specifications in Graetz and Michaels (2018), de Vries et al. (2020), and Bekhtiar et al. (2024). Following this literature and given our ultimate interest in understanding country-level employment trends, we use a WLS approach, weighting industries by their initial employment shares within each country. Note that this approach still gives equal weight to all countries in the analysis. We also follow those studies by using heteroscedasticity-robust standard errors that are two-way clustered by country and industry, which is facilitated by the *ivreg2* command in STATA 18.

4. Data and descriptives

We combine the widely used robot dataset from the International Federation of Robotics (IFR) with OECD employment data, which can be further broken down by occupations (Kruse et al., 2023), and data from the OECD Inter-Country Input-Output (ICIO) tables on an industry-year level for 15 manufacturing industries. Those industries essentially match the ISIC Rev. 4 classification, but because IFR aggregates industries 20-21 (chemical products) and 26-27 (electronics), we perform the same aggregation for our other data. A breakdown of employment data into occupations is possible only until 2018 and is less reliable before 2000. We hence construct five-year averages for the periods 2014-2018 and 2004-2008 for all our series, which are the basis for the long-run differences we are interested in.[11]

A complete list of countries and industries included in our final sample (509 observations) is available in the Appendix.

4.1. DATA ON OUTPUT, INPUTS, AND THE DOMESTIC INPUT RATIO

We use the OECD ICIO tables (OECD, 2023) for data on output x, foreign and domestic intermediate inputs FII and DII and for calculating the DIR. The ICIO tables (ICIOTs) contain information on the flows of goods and services from different industries in certain countries to other industries and final users in other countries. The latest edition of ICIOTs has 45 unique industries at the 2-digit level based on ISIC Rev. 4. The tables are provided for 76 countries (and the 'rest of the world') from 1995 to 2020. Because the rest of the world is included as an additional country, the ICIOTs cover the entire world economy.

Figure 3 illustrates a highly simplified example of such an ICIO table for two countries (A and B) and two industries (1 and 2). Output *x* of industry 1 in country A, x_1^A, is produced by using inputs supplied by A2, B1, B2, by (other firms within) the same industry A1, and by using the own industry's capital and labour, which add value w_1^A to gross output x_1^A. The grey areas highlight intermediate input transactions that take place domestically (DII). This simple example helps to illustrate that in the much larger OECD ICIOTs, we obtain the components of an industry *i*'s total inputs (equal to output x_i^c) in country *c* as:

$$DII_i^c \equiv \sum_j z_{ji}^{cc}. \qquad (11.a)$$

$$FII_i^c \equiv \sum_{r \neq c} \sum_j z_{ji}^{rc}. \qquad (11.b)$$

[11] We slightly deviate from the robot-employment literature referenced earlier, which usually compares long-run changes between two specific years (e.g., 2015 vs. 2005). Instead, comparing changes over five-year averages has the advantage that idiosyncratic shocks in individual years are averaged out.

where *j* and *i* index industries and *r* indexes other countries than *c*. Note that we chose indices that are consistent with our regression equations (see Section 3), but that deviate from most input-output conventions. Data for value added can be observed directly in the ICIOTs for each country-industry. Based on this information, the domestic input ratio is then calculated as:

$$DIR_i^c \equiv \frac{\left(w_i^c + \sum_j z_{ji}^{cc}\right)}{x_i^c}. \tag{12}$$

Figure 3 / Simplified ICIO table

Inputs used by …

Inputs supplied by …

	A1	A2	B1	B2
A1	z_{11}^{AA}	z	z	z
A2	z_{21}^{AA}	z	z	z
B1	z	z	z	z
B2	z	z	z	z
Value added	w_1^A	w	w	w
Output	x_1^A	x	x	x

.

4.2. DATA ON ROBOTS

Data on robots originate from IFR. In line with Graetz and Michaels (2018) and de Vries et al. (2020), we use the perpetual inventory method to construct robot stocks from reported deliveries, assuming a depreciation rate of 10%. This robot stock is divided by thousands of employees in the respective industry (from OECD TiM, see below) to construct 'robot density'. Using raw or log changes in this robot density is not recommended, because of very low (or zero) starting values in the mid-2000s. We hence follow the above-cited studies and construct percentiles of (employment-weighted) changes. Details can be inferred from the STATA code, which will be made available on GitHub.

4.3. EMPLOYMENT DATA

For absolute employment numbers, we rely on the 2023 edition of OECD's Trade in employment (TiM) database (variable EMPN). Additionally, we provide some plausibility checks with occupational employment shares, drawing on Kruse et al. (2023), and follow the rationale of Reijnders and de Vries (2018).[12]

[12] The data is constructed using detailed survey and census data from statistical offices and provides employment shares for 13 occupational groupings by country-industry pairs. Following the previous literature (notably de Vries et al., 2020), we group and aggregate those occupational employment shares by country-industry-year into task categories of routine vs. non-routine and manual vs. analytical. Details are available upon request.

4.4. DATA DESCRIPTIVES

Table 1 provides summary statistics of key variables as they enter the regression equation (in first differences over 10 years, see Section 3 above). A complete list of countries and industries included in our final sample (509 observations) is available in the Appendix.

An aspect worth noting in Table 1 is that output, value added and intermediate input use (domestic and foreign) have, on average, increased in our sample, while employment (EMPN) has declined. Foreign intermediate inputs (FII) have increased faster than domestic intermediate inputs (DII), in proportionate terms, and faster than overall output and value added. It is further worth noting that beneath aggregate employment developments, there is a remarkable shift towards higher shares of non-routine and analytical workers across industries and countries, on average (not reported in Table 1).

Table 1 / Summary statistics of key variables

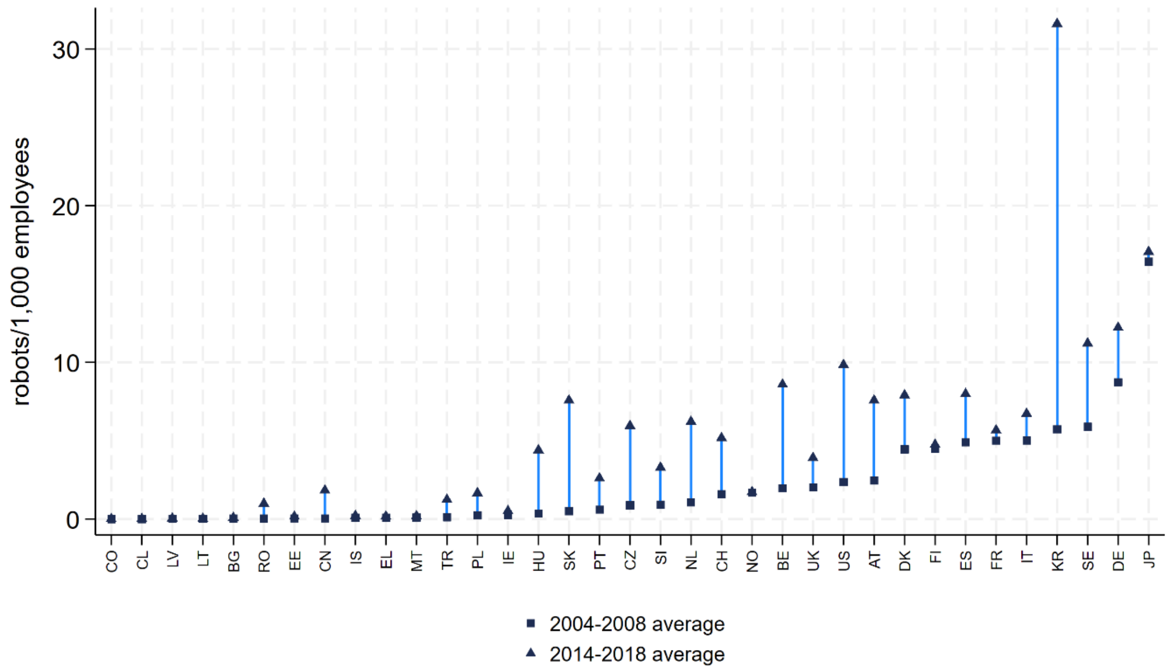
	N	mean	SD	min	max
Δ ln (EMPN)		-0.113	0.288	-1.39	0.92
Δ RI (percentile)		0.500	0.290	0.00	1.00
Δ ln (x)		0.100	0.430	-1.70	1.42
Δ ln (value added)		0.113	0.462	-2.37	2.01
Δ ln (DII)		0.034	0.471	-2.24	1.66
Δ ln (FII)		0.184	0.440	-1.56	1.81
Δ DIR		-0.021	0.049	-0.22	0.23
Observations	509				

Source: own calculations based on data from OECD and IFR

Changes in robot intensity (Δ RI) are constructed in percentiles and hence range from 0 to 1, with a mean of 0.5. Figure 4 shows trends in the underlying data on the manufacturing sector's robot adoption across countries in our sample. Those numbers (robots per thousand employees) are the basis for the percentile changes we calculate for our regression analysis. Perhaps the most striking feature is the considerable heterogeneity in robot adoption across countries. This reflects, in general, that ageing societies are more open to robot adoption and that robot adoption is more widespread in the automotive industry. What stands out in terms of trends is the enormous increase in automation in South Korea.

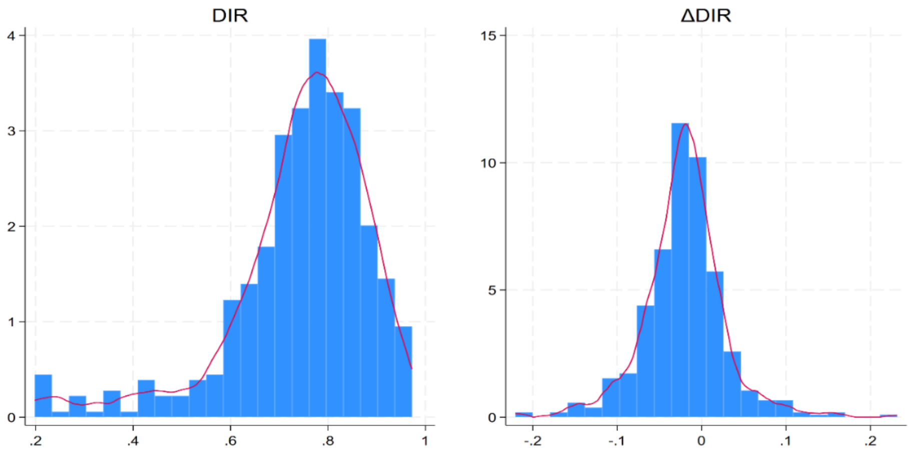
About 75% of production inputs are domestic (value added + DII; see left panel of Figure 5), with a considerable degree of heterogeneity across countries and industries. Overall, the distribution of our DIR is relatively smooth. This is also the case for changes in the DIR, which enter our regression framework, reported in the right panel of Figure 5, and in our view is a practical advantage over the reshoring intensity measure of Krenz et al. (2021) and Krenz and Strulik (2021). On average, the domestic input ratio has declined by 2.1 percentage points over the sample decade. In total, 135 country-industry observations show a positive ΔDIR (26.5%), which one could principally consider consistent with reshoring patterns.

Figure 4 / Trends in robot adoption



Source: own calculations based on data from OECD and IFR

Figure 5 / Sample distribution of the domestic input ratio



Source: own calculations based on data from OECD

4.5. PLAUSIBILITY CHECK: REPLICATING DE VRIES ET AL. (2020)

To ensure plausibility of our data and its comparability with earlier results, we start with a replication of the main results in de Vries et al. (2020). This entails running regression equation (5) above, or variants thereof with different employment shares as the dependent variable.

Appendix Table A1 reports the results of this exercise. The table is consistent with the upper panels of Tables 3 and 4 in de Vries et al. (2020) and principally shows similar results:[13] the overall relationship between robot adoption and employment is statistically indistinguishable from 0 (column (1)). However, this masks considerable heterogeneities across occupational groups. As column (2) indicates, the employment share of occupations performing routine tasks declines in industries that experience higher robot adoption. The estimated magnitude is smaller than in de Vries et al. (2020; Table 3A(2)) but overall is comparable. Similar to de Vries et al. (2020: Table 4A), and in line with the economic reasoning that robots replace manual routine labour, we find this relationship to be driven by routine manual employment (column (4)), not routine analytical employment shares (column (5)).

[13] There are three key differences from de Vries et al. (2020): the time period covered, the industry classification and coverage (which is limited to manufacturing in our case), and the fact that de Vries et al. include two additional control variables (investment and value added) that are not available to us.

5. Empirical results

5.1. MAIN RESULTS

Column (1) of Table 2 reports our main benchmark result for scale effects, as specified in regression equation (4): a one-unit increase in robot intensity *RI* (from the lowest to the highest percentile) of an industry is associated with a 18.4% increase of this industry's gross output. This coefficient estimate for β_1 provides our benchmark, against which we compare the estimates for $\beta_{y,a}$ to see if an input factor over- or under-proportionately increases in the presence of robotisation (compare Section 3.1).

Column (2) of Table 2 reports the result for *y=VA* (value added from capital and labour). We observe that a one-unit increase in robot intensity is associated with a 20.1% increase in value added. As one may expect, an industry's value added hence slightly over-proportionately increases in the presence of robotisation, plausibly reflecting that robotising industries (and firms) do more 'in-house'. $\hat{\beta}_{VA,a} > \hat{\beta}_1$ further suggests that the intensity of VA in gross output *x* increases with robotisation, which is principally in line with column (3) of Table 2: conditional on the scale of output *x*, robot intensity is positively associated with value added (although small and statistically insignificant, reflecting that the difference between the estimates in columns (1) and (2) is small). Column (4), which uses the intensity of *VA* in output *x* as the dependent variable confirms a small positive (insignificant) relationship.

The same rationale can then be applied to the other input factors *y*. Column (5) of Table 2 shows that employment increases by 14.3% in the presence of a one-unit increase in robot intensity. Although smaller than $\hat{\beta}_1$=0.184, it leads to a $\hat{\beta}_{EMPN,b1}$ that is slightly positive (but statistically indistinguishable from 0; see column (6) of Table 2). Together with the clearly below-unitary elasticity between output and employment (0.631), this could capture complementarities between robots and labour in production but would require a more sophisticated analysis in the context of a proper production function (such as provided by DeCanio, 2016; Koch and Manuylov, 2023; Saam, 2024). Column (7) of Table 2 confirms this overall picture. The coefficient estimate of 1.95 may appear high compared to other columns but also reflects the relatively high employment/output ratio (8.6 on average, with a SD of 11.0).

Table 2 / Robotisation, output, value added and employment

	(1) Δ ln(x)	(2) Δ ln(VA)	(3) Δ ln(VA)	(4) Δ (VA/x)	(5) Δ ln (EMPN)	(6) Δ ln (EMPN)	(7) Δ (EMPN/x)
Δ RI (percentile)	0.184**	0.201***	0.034	0.010	0.143	0.027	1.948
	(0.09)	(0.06)	(0.03)	(0.01)	(0.09)	(0.04)	(1.24)
Δ ln(x)			0.908***			0.631***	
			(0.07)			(0.07)	
r2	0.035	0.035	0.689	0.003	0.029	0.552	0.009
N	509	509	509	509	509	509	509
#Countries	35	35	35	35	35	35	35

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. Country fixed effects are included in all regressions and partialled out in the reported r2.

Appendix Table A1 highlights that considerable heterogeneities across worker groups are masked below this aggregate relationship between employment and robotisation (see Section 4.5). In particular, the share of routine manual workers declines in the context of robotisation; a finding that mimics de Vries et al. (2020) and is consistent with recent analysis of regional Italian data performed by Caselli et al. (2025).

Table 3 contains our results for intermediate inputs. *DII* and *FII* under-proportionately increase in the presence of robotisation, in the sense that their estimated partial correlation coefficients in columns (1) and (4) are smaller than $\hat{\beta}_1$ (column (1) of Table 2). Holding an industry's output level constant, we hence find negative estimates in columns (2) and (5) of Table 3, which is significant in the former case for *DII*. This indicates that industries that robotise rely significantly less on domestic intermediate inputs for the production of a unit of output. This effect appears insignificant for foreign intermediate inputs (column (5)). Both aspects are confirmed when intermediate inputs are measured as a ratio of overall output: in the presence of robotisation, the DII/x ratio declines (column (3)), while the correlation between robotisation and the FII/x ratio is estimated to be a flat zero (column (6)). It is finally worth highlighting that in absolute terms, industries that robotise rely more, not less, on foreign intermediate inputs to meet the increased scale of gross production (column (4)) – FII and x increase in the same proportion (column (6)).

Table 3 / Results per intermediate input component

	(1) Δ ln(DII)	(2) Δ ln(DII)	(3) Δ (DII/x)	(4) Δ ln(FII)	(5) Δ ln(FII)	(6) Δ (FII/x)
Δ RI (percentile)	0.129	-0.064***	-0.016**	0.157	-0.036	0.006
	(0.10)	(0.02)	(0.01)	(0.11)	(0.04)	(0.01)
Δ ln(x)		1.051***			1.047***	
		(0.06)			(0.06)	
r2	0.014	0.845	0.009	0.017	0.711	0.002
N	509	509	509	509	509	509
#Countries	35	35	35	35	35	35

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. Country fixed effects are included in all regressions and partialled out in the reported r2.

The overall result from our exercise so far is that robotising industries increase output and that all other input factors increase under-proportionately with robotisation, although by small and mostly statistically insignificant margins. Notably, we find that robotising industries use DII relatively less intensively (columns (2) and (3) of Table 3) but add slightly more value added 'in-house' (columns (3) and (4) of Table 2). Note that both aspects work in opposite directions in the numerator of the domestic input ratio defined in equations (2), thereby offsetting each other.

Column (1) of Table 4 illustrates what the findings for production inputs that we have uncovered so far imply for the domestic input ratio (DIR), a measure that gauges the location of production in a given production step. The result is a flat zero: robotisation on an aggregate level is virtually uncorrelated with the DIR and hence with a relocation of production inputs towards the robotising economy. As the previous analysis has shown, this largely reflects a zero correlation of robotisation with FII (beyond scale effects) and a slight substitution of domestic value added for DII in the presence of robotisation.

Table 4 / Results for the domestic input ratio

	(1) Δ DIR	(2) Δ DIR	(3) Δ (FII/x)
Δ RI (percentile)	-0.006 (0.01)		
Δ RI x ΔDIR<0		-0.029*** (0.01)	0.029*** (0.01)
Δ RI x ΔDIR>0		0.072*** (0.02)	-0.072*** (0.02)
r2	0.002	0.355	0.355
N	509	509	509
#Countries	35	35	35

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry.Country fixed effects are included in all regressions and partialled out in the reported r2.

5.2. SYSTEMATIC HETEROGENEITY ACROSS INDUSTRIES

One may wonder how our flat-zero results for the domestic input ratio relate to the findings of Krenz et al. (2021) that suggest a positive relationship between robotisation and reshoring. Aside from their approach to measure 'reshoring intensity', a key difference is that Krenz et al. (2021) limit variation in reshoring to industries that *do* reshore (in their definition; most consistent with 'outsourced reshoring' in the sense of Gray et al., 2013). In the context of our framework, this would be most consistent with country-industry observations for which ΔDIR>0.[14]

We illustrate what this difference implies in the context of our dataset. Among our 509 country-industry observations, only 135 do 'reshore' in the sense that ΔDIR>0. If we allow the coefficient $\beta_{DIR,a}$ to vary between those 135 country-industries and the remaining ones, we find strong heterogeneities across both parts of the sample (see column (2) of Table 4): in 'reshoring' industries (ΔDIR>0), robotisation is associated with a higher domestic input ratio. But in all other industries, the partial correlation is opposite and negative. This result explains where the empirical findings in Krenz et al. (2021) stem from: their study is limited to industries that do reshore. In our view, this provides an inaccurate representation of what is going on in the whole economy.

Given the systematic heterogeneity across industries, it is of further interest how 'reshoring' industries (ΔDIR>0) differ from those with ΔDIR<0, especially with respect to robotisation. It follows from column (2) of Table 4 that robotisation is negatively correlated with FII intensity in 'reshoring' industries (see also column (3) of Table 4). Whether robotisation leads to less foreign input use in a causal sense is up for debate – the documented pattern could as well reflect that industries that face difficulties to maintain FII supply defensively respond with robotisation. Firooz et al. (in press) suggest the latter pattern for the US: rising trade uncertainty results in less foreign input use and reshoring, which could be achieved by robotisation, with unclear employment effects. We hence move towards analysing the relationship between shoring patterns and employment.

14 We do not think that ΔDIR>0, or any other industry-level measure, is a good indicator of reshoring but given that several studies hold other opinions, we still consider it illustrative to follow their rationale.

5.3. THE S-E ANGLE: WHAT HAPPENS IN INDUSTRIES WITH INCREASING DOMESTIC INPUT RATIOS?

Can we say that industries that 'bring back production' (in the sense that ΔDIR>0) observe employment increases? To address this issue, it is again useful to first gauge a possible scale effect of shoring. We therefore regress log changes in gross output *x* on changes in the DIR. Results are reported in column (1) of Table 5 and show a statistically insignificant negative correlation. Industries that moved towards a more domestic input mix were not generating more gross output – if anything, rather the opposite.[15] The inclusion of robotisation does not change much in this context (see column (2) of Table 5).

Column (3) of Table 5 shows that industries that 'bring back production' (in the sense that ΔDIR>0) do not observe employment increases. If anything, the opposite happens due to the above-mentioned scale effect (ΔDIR>0 is associated with less overall production). Even if we control for possible overall output declines in 'reshoring' industries, the domestic input ratio is not significantly correlated with employment increases: the estimated coefficient in column (4) of Table 5 is statistically indistinguishable from 0 and, when taken at face value, economically small: a one-standard-deviation increase in an industry's ΔDIR is associated with a 0.6% employment increase in that industry.

Table 5 / Shoring and employment

	(1) Δ ln(x)	(2) Δ ln(x)	(3) Δ ln (EMPN)	(4) Δ ln (EMPN)	(5) Δ ln (EMPN)	(6) Δ ln (EMPN)	(7) Δ ln (EMPN)
Δ DIR	-0.636 (0.55)	-0.590 (0.57)	-0.276 (0.49)	0.131 (0.25)	-0.240 (0.50)		
Δ RI (percentile)		0.181** (0.08)			0.142* (0.09)		
Δ RI x ΔDIR<0						0.147* (0.08)	0.027 (0.04)
Δ RI x ΔDIR>0						0.130 (0.11)	0.026 (0.05)
Δ ln(x)				0.639*** (0.07)			0.631*** (0.07)
r2	0.010	0.044	0.003	0.552	0.031	0.030	0.552
N	509	509	509	509	509	509	509
#Countries	35	35	35	35	35	35	35

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. Country fixed effects are included in all regressions and partialled out in the reported r2.

What role does robotisation play in this context? Controlling for shoring patterns, we find a positive correlation between robotisation and employment (column (5) of Table 5). The magnitude is almost identical to column (5) of Table 2, where the DIR was not controlled for, but the parameter is now more precisely estimated and hence statistically significant on the 10% level. Column (6) of Table 5 highlights that this positive correlation shows only negligible differences across industries with ΔDIR<0 and ΔDIR>0 and column (7) reiterates that this is mostly because of a scale effect: robotising industries are those that increase the scale of production *x*, with largely proportionate increases in demand for all production input factors.

[15] Although imprecisely estimated, the point estimate is not economically negligible at face value: the sample standard deviation of ΔDIR is 0.05, translating to a gross output decrease of 3.1%.

6. Conclusion

This paper contributes to the ongoing debate concerning robotisation, reshoring and employment. We have taken the issue of what shoring patterns can and cannot be measured on the macro (cross-country industry) level more seriously than previous papers in this literature. For this purpose, we built on a production structure with fragmented production steps, a corresponding descriptive regression framework and corresponding data from inter-country input-output tables. In particular, we defined a domestic input ratio (DIR) and analysed how its components (value added, and domestic and foreign intermediate inputs) behave in the presence of robotisation.

Our key empirical finding is that industries that robotise observe increases in their gross output and that the mix of production inputs to generate this output remains, perhaps surprisingly, largely unaffected. In other words, robots plausibly have a scale effect but do not seem to induce relevant factor substitution, at least in our aggregate dataset and descriptive analysis.

Our results call into question the narratives of robot-induced reshoring and that reshoring could 'bring back jobs'. First, we highlighted that robotising industries do not 'reshore' more. The presented evidence is rather in favour of robotisation being a defensive response by firms that face problems or concerns with global supply chains. Consistent with this interpretation, industries with a higher domestic input ratio overall produce less output. In other words: 'reshoring' industries produce less, but with higher domestic input content.

Second, this casts doubt on the employment potential of 'bringing back production'. Our paper has documented that industries that experience output growth, and associated rises in employment, are generally robotising and increase their scale of production through proportionate increases in foreign intermediate inputs. In other words: successful industries embrace technology, are internationally integrated and generate jobs.

Three areas for future research emerge from our findings. First, our results are largely descriptive and do not claim to capture causal effects. Nevertheless, they question the above-mentioned narratives of robot-induced reshoring and 'bringing back jobs', which themselves are based on less convincing evidence. Estimates that are based on more plausible causal identification strategies will certainly enrich the debate and policy choices. In this context, cross-fertilisation between micro (firm-level) and macro (cross-country industry-level) studies is particularly promising, as each has different merits.

A second line of future research concerns the further breakdown of employment into task categories and intermediate inputs into within-industry and cross-industry inputs. In this paper, we have focused on the conceptual question of how robots, shoring and employment can be consistently related on a cross-country industry level, but we will further disaggregate our findings in future contributions. Particularly, our key finding that robotisation increases output without much factor bias does not imply that no shifts occur within broad employment. We will therefore take a more detailed look at different employment tasks.

Finally, our paper has focused on what happens at a certain production stage of a highly fragmented global production process. In other words, we have assumed that all ultimate inputs to domestic intermediate inputs are domestic (and vice versa for foreign intermediate inputs). This makes sense for our analysis of what industries do at a given production step, but paints an incomplete picture of how robotisation restructures the complete value chain. Current work in progress (Dijkstra and Wacker, 2025) will allow us to analyse this issue more thoroughly.

References

Abeliansky, A.L., Prettner, K. & Stöllinger, R. (2023). Infection risk at work, automatability, and employment. WU Vienna University of Economics and Business, Department of Economics Working Paper No. 352.

Acemoglu, D., LeLarge, C. & Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. National Bureau of Economic Research (NBER) Working Paper No. 26738.

Acemoglu, D. & Restrepo, P. (2018). Modeling automation. American Economic Association, *AEA Papers and Proceedings*, 108, 48-53.

Acemoglu, D. & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *The Journal of Economic Perspectives*, 33(2), 3-30.

Acemoglu, D. & Restrepo, P. (2020). Robots and jobs: Evidence from US local labor markets. *Journal of Political Economy*, 128(6), 2188-2244.

Artuc, E., Bastos, P. & Rijkers, B. (2023). Robots, tasks, and trade. *Journal of International Economics*, 145: 103828. https://doi.org/10.1016/j.jinteco.2023.103828.

Artuc, E., Christiaensen, L. & Winkler, H. (2019). Does automation in rich countries hurt developing ones? Evidence from the U.S. and Mexico. World Bank Jobs Working Paper No. 25.

Bekhtiar, K., Bittschi, B. & Sellner, R. (2024). Robots at work? Pitfalls of industry-level data. *Journal of Applied Econometrics,* 39(6), 1180-1189.

Buckley, P.J., Strange, R., Timmer, M.P. & de Vries, G.J. (2020). Catching-up in the global factory: Analysis and policy implications. *Journal of International Business Policy*, 3(2), 79-106.

Burkhart, D.V., Bode, C. & Peters, K. (2023). Decoupling of global supply chains: Drivers, constraints, and alternatives, in: Bode, C., Bogaschewsky, R., Eßig, M. & Lasch, R. (eds). *Supply management research*. Springer Nature, 151-168.

Carbonero, F., Ernst, E. & Weber, E. (2020). Robots worldwide: The impact of automation on employment and trade. IAB Discussion Paper No. 7/2020, Institute for Employment Research.

Caselli, M., Fracasso, A., Scicchitano, S., Traverso, S. & Tundis, E. (2025). What workers and robots do: An activity-based analysis of the impact of robotization on changes in local employment. *Research Policy,* 54(1): 105135. https://doi.org/10.1016/j.respol.2024.105135

Chen, C. & Frey, C.B. (2024). Robots and reshoring: A comparative study of automation, trade, and employment in Europe. *Industrial and Corporate Change*, 33(6), 1331-1377. https://doi.org/10.1093/icc/dtae012

Cheng, H., Jia, R., Li, D. & Li, H. (2019). The rise of robots in China. *The Journal of Economic Perspectives*, 33(2), 71-88.

Cilekoglu, A.A., Moreno, R. & Ramos, R. (2024). The impact of robot adoption on global sourcing. *Research Policy*, 53(3): 104953. https://doi.org/10.1016/j.respol.2024.104953

Cortes, G.M., Jaimovich, N., Nekarda, C.J. & Siu, H.E. (2020). The dynamics of disappearing routine jobs: A flows approach. *Labour Economics*, 65.

Dauth, W., Findeisen, S., Suedekum, J. & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6), 3104-3153.

De Backer, K., DeStefano, T., Menon, C. & Suh, J.R. (2018). Industrial robotics and the global organisation of production. OECD Science, Technology and Industry Working Paper 2018/03.

De La Rica, S., Gortazar, L. & Lewandowski, P. (2020). Job tasks and wages in developed countries: Evidence from PIAAC. *Labour Economics*, 65.

de Vries, G., Gentile, E., Miroudot, S. & Wacker, K.M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66. DOI: 10.1016/j.labeco.2020.101885.

DeCanio, S.J. (2016). Robots and humans – complements or substitutes? *Journal of Macroeconomics*, 49, 280-291.

Dijkstra, H. & Wacker, K.M. (2025). Offshoring, reshoring, and the location of production – a cross-country industry-level dataset. Mimeo: University of Groningen.

El-Sahli, Z. & Gullstrand, J. (2023). Why reshore? Evidence from Swedish firms. *Economics Letters*, 227: 111116.

European Union (2020). A new industrial strategy for Europe. Document 52020DC0102.

Faber, M. (2020). Robots and reshoring: Evidence from Mexican local labor markets. *Journal of International Economics,* 127: 103384. https://doi.org/10.1016/j.jinteco.2020.103384

Feenstra, R.C. (2008). Offshoring in the global economy. The Ohlin Lectures.

Fierro, L.E., Caiani, A. & Russo, A. (2022). Automation, job polarisation, and structural change. *Journal of Economic Behavior & Organization* 200, 499-535.

Firooz, H., Leduc, S. & Liu, Z. (in press). Reshoring, automation, and labor markets under trade uncertainty. *Journal of International Economics*: 104091.

Frey, C. & Osborne, M.A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254-280.

Gao, X., Hewings, G.J.D. & Yang, C. (2022). Offshore, re-shore, re-offshore: what happened to global manufacturing location between 2007 and 2014? *Cambridge Journal of Regions, Economy and Society*, 15(2), 183-206.

Ghodsi, M., Reiter, O., Stehrer, S. & Stöllinger, R. (2020). Robotisation, employment and industrial growth intertwined across global value chains. wiiw Working Paper No. 177, April, wiiw, Vienna.

Goos, M., Manning, A. & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *The American Economic Review*, 104(8), 2509-2526.

Graetz, G. & Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, 100(5), 753-768.

Gravina, A.F. & Pappalardo, M.R. (2022). Are robots in rich countries a threat for employment in emerging economies? *Economics Letters*, 221: 110888.

Gray, J.V., Skowronski, K., Esenduran, G. & Rungtusanatham, M.J. (2013). The reshoring phenomenon: What supply chain academics ought to know and should do. *Journal of Supply Chain Management*, 49 (2), 27-33.

Guarascio, D., Piccirillo, A. & Reljic, J. (2024). Will robot replace workers? Assessing the impact of robots on employment and wages with meta-analysis. LEM Working Paper 2024/03.

Harrigan, J., Reshef, A. &. Toubal, F. (2016). The march of the techies: Technology, trade, and job polarization in France, 1994-2007. National Bureau of Economic Research (NBER) Working Paper No. 22110.

International Federation of Robotics (2016). World Robotics Industrial Robots 2016.

International Federation of Robotics (2012). World Robotics Industrial Robots 2012.

Johnson, R.C. & Noguera, G. (2012). Accounting for intermediates: Production sharing and trade in value added. *Journal of International Economics*, 86(2), 224-236.

Jurkat, A., Klump, R. & Schneider, F. (2023). Robots and wages: A meta-analysis. ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg.

Kim, J. & Park, C-Y. (2020). Education, skill training, and lifelong learning in the era of technological revolution. ADB Economics Working Paper No. 606.

Koch, M. & Manuylov, I. (2023). Measuring the technological bias of robot adoption and its implications for the aggregate labor share. *Research Policy*, 52(9): 104848. https://doi.org/10.1016/j.respol.2023.104848

Koopman, R., Wang, Z. & Wei, S-J. (2014). Tracing value-added and double counting in gross exports. *The American Economic Review*, 104(2), 459-494.

Krenz, A., Prettner, K. & Strulik, H. (2021). Robots, reshoring, and the lot of low-skilled workers. *European Economic Review*, 136(C): 103744.

Krenz, A. & Strulik, H. (2021). Quantifying reshoring at the macro-level – Measurement and applications. *Growth and Change*, 52(3), 1200-1229.

Kruse, H., Timmer, M.P., de Vries, G.J. & Ye, X. (2023). Export diversification from an activity perspective: An exploration using occupation data. World Bank Policy Research Working Paper No. 10463, World Bank Group, Washington, D.C.

Kugler, A.D., Kugler, M., Ripani, L. & Rodrigo, R. (2020). U.S. robots and their impacts in the tropics: evidence from Colombian labor markets. National Bureau of Economic Research (NBER) Working Paper No. 28034.

Lábaj, M. & Majzlíková, E. (2023). How nearshoring reshapes global deindustrialization. *Economics Letters*, 230: 111239.

Li, D., Jin, Y. & Cheng, M. (2024). Unleashing the power of industrial robotics on firm productivity: Evidence from China. *Journal of Economic Behavior & Organization*, 224: 500-520.

Los, B., Timmer, M.P. & de Vries, G.J. (2015). How global are global value chains? A new approach to measure international fragmentation. *Journal of Regional Science*, 55(1), 66-92.

Marcolin, L., Miroudot, S. & Squicciarini, M. (2019). To be (routine) or not to be (routine), that is the question: a cross-country task-based answer. *Industrial and Corporate Change*, 28(3), 477-501.

Martens, B. & Tolan, S. (2018). Will this time be different? A review of the literature on the impact of artificial intelligence on employment, incomes and growth. JRC Digital Economy Working Paper 2018-08.

Michaels, G., Natraj, A. & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over 25 years. *The Review of Economics and Statistics*, 96(1), 60-77.

Mondolo, J. (2022). The composite link between technological change and employment: A survey of the literature. *Journal of Economic Surveys*, 36(4), 1027-1068.

Muris, C. & Wacker, K.M. (2025). Estimating interaction effects with panel data. GLO Discussion Paper No. 1583; revised & resubmitted: *Journal of Applied Econometrics*.

Nguyen, T.T. (2023). Does automation adoption drive reshoring? A cross-country investigation. Mimeo.

OECD (2023). OECD Inter-Country Input-Output Database. http://oe.cd/icio.

Reijnders, L.S.M. & de Vries, G.J. (2018). Technology, offshoring and the rise of non-routine jobs. *Journal of Development Economics*, 135, 412-432.

Reljic, J., Cirillo, V. & Guarascio, D. (2023). Regimes of robotization in Europe. *Economics Letters*, 232: 111320.

Restrepo, P. (2023). Automation: Theory, evidence, and outlook. National Bureau of Economic Research (NBER) Working Paper No. 31910.

Ross, M.B. (2017). Routine-biased technical change: Panel evidence of task orientation and wage effects. *Labour Economics*, 48, 198-214.

Saam, M. (2024). Estimating the elasticity of substitution between robots and labor. Paper presented at CORA 2024 – Conference on Robots and Automation; Frankfurt, 24 September.

Schwark, F. & Tryphonides, A. (2025). The effects of digitalization on production. *European Economic Review* 171: 104896. https://doi.org/10.1016/j.euroecorev.2024.104896

Stapleton, K. & Webb, M. (2020). Automation, trade and multinational activity: Micro evidence from Spain. CSAE Working Paper Series 2020-16, Centre for the Study of African Economies, University of Oxford.

Stemmler, H. (2023). Automated deindustrialization: How global robotization affects emerging economies – Evidence from Brazil. *World Development* 171: 106349.

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R. & de Vries, G.J. (2015). An illustrated user guide to the world input-output database: The case of global automotive production. *Review of International Economics*, 23(3), 575-605.

Van Reenen, J. (2011). Wage inequality, technology and trade: 21st century evidence. *Labour Economics*, 18(6), 730-741.

Yang, Z. (2017). Who will satisfy China’s thirst for industrial robots? The Diplomat, 19 May.

Appendix

COUNTRIES AND INDUSTRIES IN THE FINAL SAMPLE

Countries (each 15 observations, unless indicated differently): Austria, Belgium, Bulgaria, Chile (14), China, Colombia, Czechia, Denmark (14), Estonia (13), Finland, France, Germany, Greece, Hungary, Iceland (13), Ireland, Italy, Japan, Latvia (12), Lithuania (14), Malta (11), Netherlands, Norway (14), Poland, Portugal, Romania, Slovakia, Slovenia (14), South Korea, Spain, Sweden, Switzerland, Turkey, UK, US.

Industries:

10-12	Food, beverages, tobacco
13-15	Textiles
16	Wood and furniture
17-18	Paper and paper products
19	Pharmaceuticals, cosmetics
20-21	Other chemical products
22	Rubber and plastic products (non-automotive)
23	Glass
24	Basic metals
25	Metal products (non-automotive)
26-27	Electrical-electronics
28	Industrial machinery
29	Automotive
30	Other vehicles
91	All other manufacturing branches

Table A1 / Robots and employment (WLS regression results)

	(1) ΔIn (EMPN)	(2) ΔRoutine EMP share	(3) ΔNon-routine EMP share	(4) ΔRoutine manual EMP share	(5) ΔRoutine analytic EMP share
ΔRI (percentile)	0.143	-0.011***	0.011***	-0.013*	0.001
	(0.09)	(0.00)	(0.00)	(0.01)	(0.01)
r2	0.029	0.003	0.003	0.003	0.000
Observations	509	509	509	509	509
#Countries	35	35	35	35	35

Notes: Robust standard errors in parentheses. Multi-way clustering by country and industry. Country fixed effects are included in all regressions and partialled out in the reported r2.

IMPRESSUM

Herausgeber, Verleger, Eigentümer und Hersteller:
Verein „Wiener Institut für Internationale Wirtschaftsvergleiche“ (wiiw),
Wien 6, Rahlgasse 3

ZVR-Zahl: 329995655

Postanschrift: A 1060 Wien, Rahlgasse 3, Tel: [+431] 533 66 10, Telefax: [+431] 533 66 10 50
Internet Homepage: www.wiiw.ac.at

Offenlegung nach § 25 Mediengesetz: Medieninhaber (Verleger): Verein "Wiener Institut für Internationale Wirtschaftsvergleiche", A 1060 Wien, Rahlgasse 3. Vereinszweck: Analyse der wirtschaftlichen Entwicklung der zentral- und osteuropäischen Länder sowie anderer Transformationswirtschaften sowohl mittels empirischer als auch theoretischer Studien und ihre Veröffentlichung; Erbringung von Beratungsleistungen für Regierungs- und Verwaltungsstellen, Firmen und Institutionen.

wiiw

wiiw.ac.at

https://wiiw.ac.at/p-7383.html