RESEARCH REPORT
STUDY PAPER 286
APRIL 2026

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THE ROCKWOOL FOUNDATION
RESEARCH

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Published by:

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April 2026

Where Production Meets Automation: Robots and the International Geography of Production*

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7 April 2026

Abstract

This paper investigates the relationship between industrial robot adoption and offshoring decisions at the firm level. Using comprehensive matched employer–employee and customs data from Denmark for the period 1995–2022, we construct a direct measure of robot adoption based on firms' imports of industrial robots, as well as a narrow definition of offshoring derived from firm-level trade flows. We find that robot adoption is positively associated with increases in both the extensive and intensive margins of offshoring, even after accounting for prior offshoring experience. Our findings are consistent with automation complementing rather than substituting for global sourcing. The results are robust to dynamic event study estimations, instrumental variable specifications, and alternative measures of adoption. We further document that robot adoption coincides with increases in firms' scale and productivity, as well as a broader range of offshored products and destinations. These patterns suggest that automation goes hand in hand with firm expansion and diversification, deepening integration into global production networks.

JEL Classifications: F14, F61, O33, D22, L60.

Keywords: Robot adoption, offshoring, global value chains.

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*We would like to thank the Rockwool Foundation for financial support of the data collection and the research conducted for this paper. We thank Pierpaolo Parrotta for his helpful comments.

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1 Introduction

Over recent decades, many firms based in advanced economies have increasingly fragmented their production processes, shifting labor-intensive tasks to lower-wage countries. This strategy has been a defining feature of global value chains and has largely been motivated by cost advantages (Grossman and Rossi-Hansberg, 2006; Kim et al., 2025). The accelerating development and adoption of automation technologies, especially industrial robotics, may now be altering the advantages behind these global production arrangements. Robots have been shown to displace workers at repetitive tasks (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). In theory, automation can substitute for offshoring by allowing firms in high-wage countries to replace low-skilled labor abroad with machines at home (often termed reshoring), thereby reducing the relative benefit of relocating production (Krenz et al., 2021). Conversely, automation may also complement offshoring if it raises productivity, lowers coordination costs, and enables firms to scale operations across borders (Acemoglu and Restrepo, 2018). Theoretical models suggest that automation and offshoring can be mutually reinforcing: automation facilitates better task–skill matching at home, while offshoring allows firms to exploit global labor markets (e.g., Faia et al., 2020).

Whether robot adoption enhances or reduces offshoring is therefore ultimately an empirical question.[1] Several recent papers studying this question (Faber, 2020; Stapleton and Webb, 2023; Artuc et al., 2023; Cilekoglu et al., 2024; Faber et al., 2025; Firooz et al., 2025; Baur et al., 2025) have provided contradictory answers, reflecting not only differences in institutional settings and periods studied, but also substantial heterogeneity in definitions of automation and offshoring, as well as in empirical strategies. A key limitation of much of this literature is its reliance on industry, region, or commuting zone level measures of robot ex-

[1] Recent business commentary illustrates these divergent possibilities. For example, *Reuters* reports that UK retailer Currys is simultaneously increasing automation and expanding offshoring to India, using automation to enhance rather than replace global production networks. *UK's Currys targets more automation and offshoring to mitigate cost hikes, Reuters, January 15th 2025.* In contrast, an *Economist* article on Adidas's "Speedfactory" in Germany describes how advanced robotics enabled the firm to reshore certain production stages from Asia to Europe, highlighting the potential for automation to support localized manufacturing. *Adidas's high-tech factory brings production back to Germany, The Economist, January 14th 2017.*

posure, which implicitly assume that firms within narrowly defined industries or geographical areas face similar incentives and constraints to adopt automation. As emphasized by Koch et al. (2019), this aggregation obscures potentially important firm-level selection and adjustment mechanisms. Firms tend to differ in their technological capabilities, organizational structures, and access to complementary skills, all of which shape both the likelihood of adopting robots and the way automation interacts with global sourcing decisions. Industry- or regional-level measures therefore conflate adopters and non-adopters and cannot capture the within-firm adjustments. Our paper contributes by directly addressing these limitations. We provide comprehensive firm-level evidence based on Danish register data and objective measures of actual robot adoption, combined with granular trade data that allow us to identify offshoring at the product–firm level.

We provide several new findings: First, robot adoption is positively associated with increases in offshoring. This result survives different regression designs, including staggered treatment and instrumental-variable specifications, and alternative definitions of key variables. Second, robot-adopting firms not only deepen existing global supply chains, but also expand their international activities to cover more destination countries and a larger number of offshored products. The evidence is consistent with automation and offshoring being complements rather than substitutes. Instead of triggering reshoring or retreat from global value chains, robot adoption goes hand in hand with greater firm integration into international production networks, potentially attributable to scale expansion and productivity improvements.

We leverage a comprehensive matched employer–employee dataset for Denmark, covering all private industries in the economy. We use an objective and direct measure of actual robot adoption at the firm level, based on detailed product-level trade records, following Mann and Pozzoli (2024). Similarly, for offshoring, we adopt a narrow and rigorous measure based on firm-level matched trade data, identifying offshoring as the simultaneous import and export of the same HS8 product category, a method consistent with the literature (Olney and

Pozzoli, 2021).

We use mainly two difference-in-differences regression designs. First, we estimate the association between robot adoption and offshoring using linear two-way fixed effects models that account for a rich set of covariates. To attenuate selection into treatment, we construct a matched sample using cross-validated Lasso logit propensity scores and restrict the control group to firms above the year-specific 75th percentile of the propensity score distribution for adopting industrial robots. Second, we implement dynamic event study models using the Sun and Abraham (2021) estimator, which accommodates staggered adoption and uses never-treated firms as the control group.[2]

We find evidence that robot adoption is positively associated with both the extensive and intensive margins of offshoring. In our most complete specification, we find that robot-adopting firms feature an 8 percentage point higher probability of offshoring and a 18 percent higher value of offshored goods, conditional on offshoring. The positive association with the extensive margin also holds after controlling for prior offshoring and re-estimating the coefficient on a sample of firms that had already offshored at least once before adoption, suggesting that automation reinforces rather than replaces global sourcing, even among experienced offshoring firms. Using the dynamic regression set-up, we find that the positive association of robot adoption with offshoring persists over time. We further show that robot adoption goes hand in hand with increases in firm sales, size, and labor productivity, as well as a shift in workforce composition toward non-routine tasks. These patterns are consistent with the hypothesis that automation is part of a broader firm upgrading process that expands scale and operational scope, which, in turn, leads to more offshoring.

To further characterize these relationships, we extend the analysis by unpacking offshoring outcomes along additional dimensions. Specifically, we show that robot adoption is not only linked to the probability and value of offshoring, but also to the number of offshored

[2] Koch et al. (2019) provide firm-level evidence that robot adoption is characterized by positive selection: ex ante more productive and larger firms are significantly more likely to adopt robots. This non-random adoption highlights the importance of addressing selection into treatment in terms of observable characteristics, such as firm size, when estimating the effects of automation.

products and sourcing destinations, indicating broader and more geographically diversified global sourcing. We also find that robot adoption is associated with a disproportionate expansion of offshoring through the introduction of new products rather than increases in existing ones, consistent with firms widening the scope of their global sourcing. Moreover, this product-level pattern is stronger for high- and medium-technology goods than for low-technology ones, suggesting that automation particularly facilitates the offshoring of more technologically sophisticated inputs, potentially because productivity gains from automation expand firm scale and increase demand for advanced intermediate inputs. Disaggregating by destination, we find that automation is associated with increased offshoring to both advanced and developing economies, with a slightly stronger correlation for the former. These results relate to the aggregate trade patterns recently documented by Baur et al. (2025), who show that automation in high-income countries can reduce imports from developing countries in the same industry but increase demand for inputs in related upstream or downstream sectors.[3]

We supplement the main analysis with additional refinements to strengthen identification, validate our measure of adoption and investigate firms' heterogeneity. First, we implement an instrumental variable strategy to attenuate potential endogeneity in robot adoption. Using the historical density of robot installers and mechanical repair technicians in each municipality in 1995, we isolate exogenous variation in firms' access to automation capabilities. The IV estimates are larger than the baseline OLS results. Under the validity of the exclusion restriction, this pattern is consistent with OLS providing a lower bound estimate. However, the IV estimates should be interpreted as local average treatment effects (LATE) for firms more exposed to municipalities with a high share of installers. Second, we show that the positive relationship between robot adoption and offshoring persists when using two alternative data sources to measure robot adoption: firm-level survey data and online job posting

[3]While our findings differ in sign at the firm level, this contrast may partly reflect differences in data coverage and aggregation: our Danish microdata capture firms' direct sourcing decisions across all partner countries, whereas Baur et al. (2025) study trade between Latin American exporters and automated industries in advanced economies.

data. Further analysis shows that the positive association of automation with offshoring holds across firm size, sector, and location, and is not driven by the way we construct the sample.

We contribute to a nascent empirical literature studying the interaction between robot adoption and offshoring. Most of the papers in the literature rely on industry-level measures of robot adoption and come to different conclusions regarding the effect of automation on offshoring and international trade. Faber (2020) and Bonfiglioli (2023) construct shift-share measures of robot adoption at the commuting-zone level and provide evidence that robot imports reduce offshoring in US local labor markets. In studies at the industry-country level, Faber et al. (2025) and Firooz et al. (2025) find that political, economic, and trade uncertainty lead to reshoring of production from developing to developed countries. Both papers draw a connection to automation. Faber et al. (2025) find that only industries with a high automation potential reshore. In Firooz et al. (2025), reshoring increases the scale of domestic production, which in turn makes it profitable to invest in automation. In contrast to these negative results, Artuc et al. (2023) find positive effects of domestic robot adoption on offshoring. They show that greater robot intensity in Northern industries is associated with higher imports from and exports to less developed countries. In a Ricardian model, they show that a fall in robot prices reduces production costs in the North, increasing competitiveness and exports while expanding demand for imported goods from the South. Baur et al. (2025) use firm-level export data from four Latin American countries to examine how robot adoption in high-income destination markets affects North–South trade. They find that automation in a Northern industry reduces imports from Southern firms in the same industry but raises demand for inputs from other industries along the value chain. These heterogeneous effects may help reconcile their findings with ours: while their results capture substitution at the industry level, our analysis identifies within-firm complementarities between automation and offshoring across multiple sourcing destinations and products.

To date, only a few studies use firm-level data to examine the interaction between automation and offshoring, and these are relatively limited in scope. Stapleton and Webb (2023) and Cilekoglu et al. (2024) rely on surveys of manufacturing firms in Spain. Stapleton and Webb (2023) show that automation can, under certain conditions, promote offshoring to lower-income countries. Using a measure of robot exposure based on robotics patent data and occupation–task similarity, they find that Spanish firms are more likely to adopt robots prior to initiating offshoring activities. For firms that had not yet offshored to lower-income countries, robot adoption increased both the likelihood and intensity of such offshoring. In contrast, for firms already engaged in offshoring, automation had no sizeable effect. Stapleton and Webb (2023) underscore the importance of firm heterogeneity, sequencing, and scale effects. Cilekoglu et al. (2024) similarly show that robot adoption increases foreign sourcing, particularly through outsourcing, while leaving domestic sourcing largely unaffected.

The remainder of the paper is organized as follows. Section 2 describes the data sources, the construction of key variables, and the sample selection procedure. Section 3 outlines the empirical strategy. Section 4 presents the main results on the effect of robot adoption on offshoring. Section 5 provides a series of robustness checks and refinements, including instrumental variable estimates, alternative offshoring and robot adoption definitions and subsample analyses. Section 6 concludes.

2 Data

Our analysis combines administrative datasets from Statistics Denmark that cover the full population of firms and employees in Denmark. This unique data setup allows us to construct detailed firm-level measures of offshoring and robot adoption and to control for a wide range of firm and workforce characteristics.

2.1 Sample

We construct a firm-level panel spanning the period 1995–2022 using data from the Firm Statistics Register (FIRM), which provides annual information on firm sales, employment and industry. Each firm is linked to its employees using the Firm-Integrated Database for Labor Market Research (FIDA), a matched employer–employee register built by linking FIRM to the Integrated Database for Labor Market Research (IDA). IDA contains detailed demographic and job-related information on all employees, including age, gender, education, tenure, occupational classification and location of employment.[4]

Robot adopters differ from non-adopters along several dimensions (Mann and Pozzoli, 2024). To attenuate potential selection bias in the adoption of robots, all empirical analyses will be based on a matched sample that ensures comparability between treated and control firms based on observable characteristics. We follow a two-step procedure to estimate firm-level propensity scores and define a subsample of firms that are comparable in terms of their likelihood to adopt robots. We begin by estimating firm-level propensity scores that reflect the likelihood of robot adoption given a rich set of observed characteristics. In the second step, we construct the final analysis sample by combining all treated firms (those that ever adopt a robot during the sample period) with a restricted control group composed only of non-adopting firms whose estimated propensity scores are above the 75th percentile of the year-specific distribution.[5] This restriction ensures that control firms are comparable in terms of their likelihood of adopting a robot, and it reduces imbalance on observables between treated and control groups. Further details of this procedure are provided in Appendix A.2.

This approach has several advantages. First, it focuses the comparison on firms that

[4]Given the presence of a large fraction of multi-establishment firms, we identify each firm's location as the municipality where the largest fraction of employees is employed. When we identify firms' location using the municipality of the headquarters from FIRM, we obtain almost identical results for the entire analysis. Our results are robust to the exclusion of multi-establishment firms, and the findings focusing on mono-establishment firms are discussed in Section 5.3.

[5]As robustness checks, we also rely on alternative control groups, including later adopters (Bessen et al., 2025), and on a caliper-based matched sample that only retains treated firms for which non-treated firms exist within a range of 25% of the propensity-score standard deviation (Köymen Özer et al., 2025).

are at the margin of adoption, thereby improving the internal validity of our treatment effect estimates. It avoids bias that can arise when comparing robot adopters to firms that have a very low likelihood of adoption (e.g., low productivity, low tech firms). Second, the propensity scores are estimated in a data-driven way using Lasso regularization, which is well suited for cases with a large number of covariates like ours and helps prevent overfitting. Third, it mitigates measurement error from using robot imports as a proxy for adoption. Since sourcing depends on exporter status and firm size (Mann and Pozzoli, 2024), both of which are included in the propensity score, the retained control firms are more likely than excluded firms to appear as importers if they adopted, thereby reducing misclassification bias.

Our final sample covers private-sector firms across all industries, excluding mono-employee firms, firms with missing values, exporters of robots (to avoid mechanical correlation between adoption and offshoring), robot installers, firms in the wholesale industry specialized in machinery (to reduce false positives), firms in 2-digit industries with no robot adoption, and firms in 2-digit industries with no offshoring activity. Some of these sample selection criteria are discussed in greater detail later in Section 2.3, which describes the construction of the robot adoption variable. These exclusions, applied prior to the propensity score estimation, remove about 300,000 observations. The subsequent propensity score restriction then eliminates roughly 2 million firm-year observations, providing a sample in which treated and non-treated firms are more comparable to each other than in the original sample.

2.2 Offshoring Measures

We follow the methodology of Olney and Pozzoli (2021) to construct a narrow measure of offshoring based on transactional trade data. Specifically, we identify offshoring as occurring when a firm imports and exports goods within the same 8-digit HS product category. This approach captures the cross-border relocation of stages of production more precisely than broader measures of trade openness or imports of intermediate goods. The trade data are obtained from the Foreign Trade Statistics Register, which records every import and export transaction, including product codes, trade values, and partner countries.

We define the extensive margin of offshoring as a binary indicator equal to 1 if the firm engages in matched import–export activity within any HS8 category in a given year, and 0 otherwise. Conditional on offshoring, the intensive margin is measured as the (log of) total value of such matched transactions, expressed in constant 2015 Danish kroner. In a refinement analysis, we also examine, among other outcomes, the number of products offshored and the number of offshoring destinations, as well as offshoring probabilities disaggregated by destination, i.e., whether firms offshore to countries in the North or South.[6] Our approach is related to the methodology in Bernard et al. (2020), who identify offshoring using firm-level overlap between imports and domestic production within the same detailed product codes. They show that this narrow, product-level definition of offshoring captures fundamentally different economic behavior than aggregate import penetration measures, which confound offshoring with import competition. While their measure relies on the overlap between imports and domestic production data, ours exploits the overlap between imports and exports within the same HS8 category.

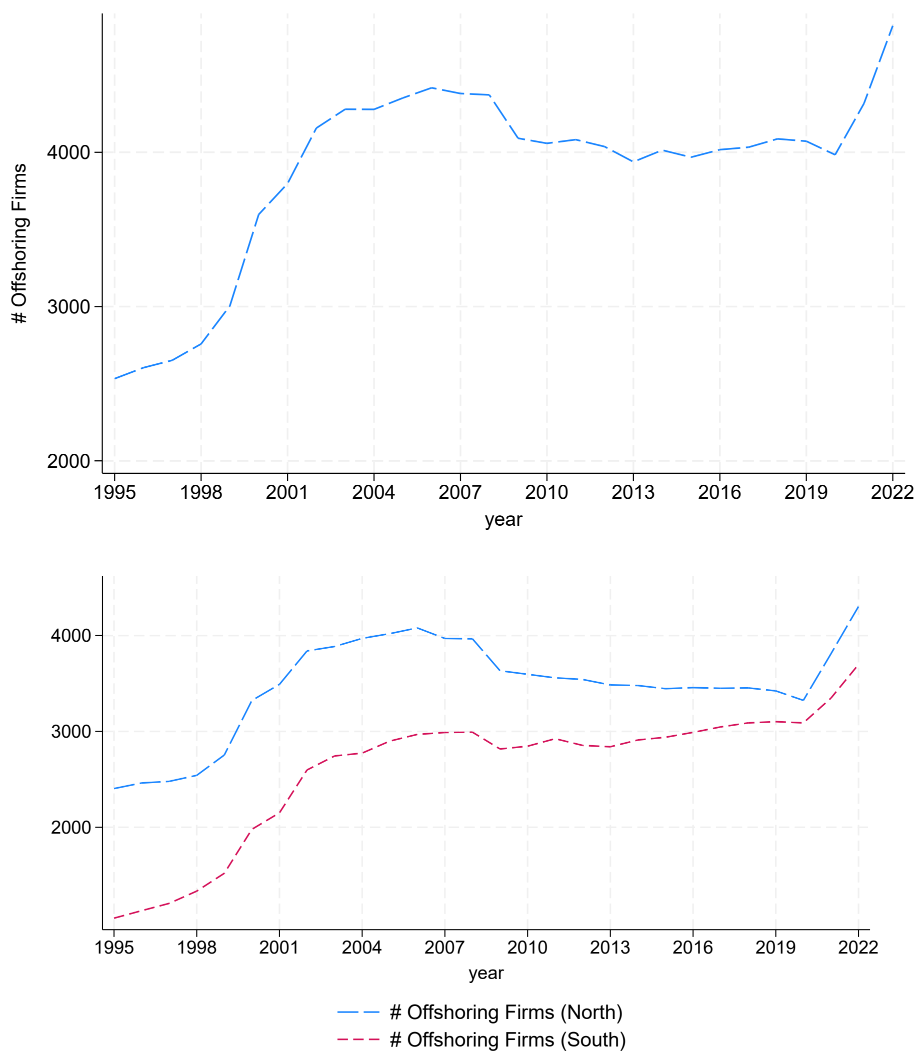
Figure 1 shows an upward trend in the number of offshoring firms in our sample over the period considered, particularly with respect to offshoring to Southern destinations after 2000.[7] The gap between offshoring to the North and the South has been narrowing since the early 2000s, suggesting that developing (low-wage) economies, such as China, have become increasingly attractive locations for relocating production stages. This trend may reflect cost considerations, evolving global supply chains, or improvements in infrastructure and institutional quality in the South (Moriconi et al., 2020). While there are some fluctuations, especially a temporary drop during the Covid-19 pandemic in 2020, the long-term trend

[6] North covers EU member states that joined before 2004 (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden), as well as the United Kingdom, the United States, Canada, Japan, South Korea, Norway, Switzerland, Australia, and New Zealand. All other countries are classified as part of the South.

[7] Half of the firms in the sample that offshore to either the North or the South offshore to both the North and the South.

points to increasing integration of Danish firms into global value chains, particularly with countries in the South. Among the broad category "North," the most popular offshoring destinations are the neighboring countries Germany and Sweden, followed by other countries such as the UK, Norway, the Netherlands, and the US. In the "South", the top offshoring destinations are China, Poland, India, and Turkey, along with other Eastern European countries such as the Czech Republic, Bulgaria, and Lithuania.

Figure 1: Offshoring Firms: Total and by Destination (North vs. South)



Notes: The first panel plots the annual number of firms engaged in offshoring 1995–2022. The second panel shows the same number disaggregated by destination: developed economies ("North") and developing economies ("South").

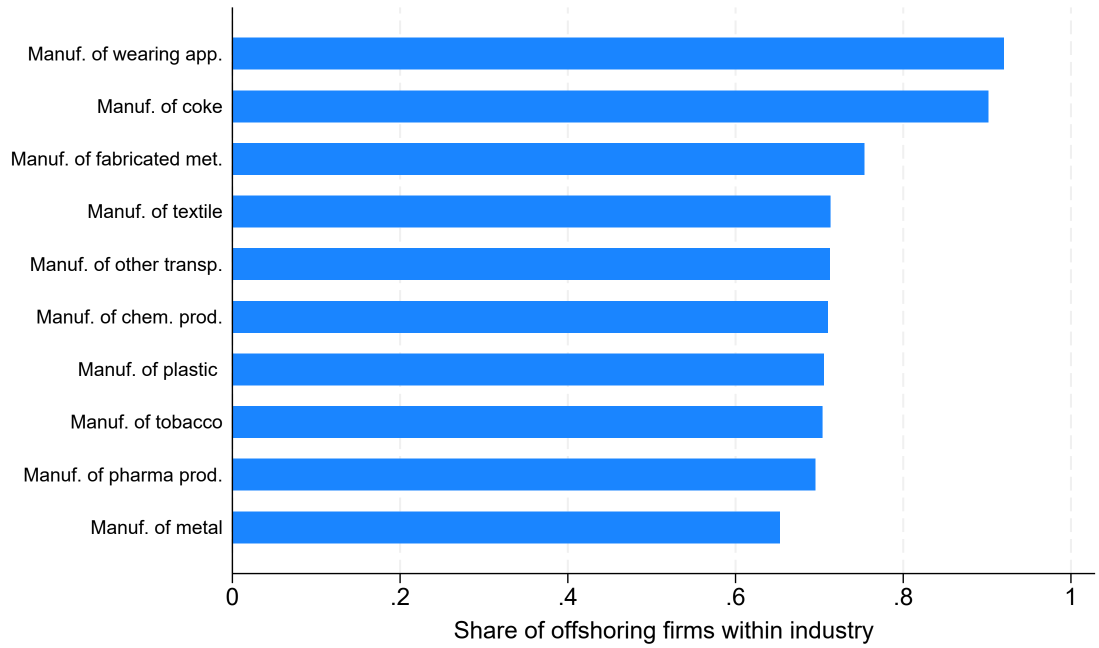
Figure 2 presents the average industry-level share of offshoring firms from 1995 to 2022 for the ten industries with the highest incidence of offshoring. All of these are manufacturing industries. Offshoring is most prevalent in sectors such as manufacture of wearing apparel, chemical and pharmaceutical products, where high tradability and global supply networks are defining features. These patterns are consistent with prior evidence showing that offshoring tends to be more common in industries reliant on routinizable tasks or modular production processes (Hummels et al., 2014a; Ebenstein et al., 2014; Becker et al., 2013). Although our measure is based on matched trade transactions rather than survey responses, the sectoral distribution is consistent with results from alternative approaches, such as those used by Bernard et al. (2020), thereby lending external validity to our method. Conversely, among the 10 industries with the lowest shares of offshoring are the industries of waste management and recycling, transport, and other services, highlighting the heterogeneity in firms' global sourcing strategies.[8] This variation supports the view that our measure captures meaningful cross-industry differences in offshoring behavior and provides useful insights into firm-level responses in terms of offshoring activities.

2.3 Robot Adoption Measure

To measure robot adoption, we use firm-level customs data on robot imports following the approach of Mann and Pozzoli (2024) as well as a large literature on the effects of robot adoption (see e.g. Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Bonfiglioli et al., 2020; Dixon et al., 2021; Humlum, 2021). Robots are identified using HS6 codes 847950 (industrial robots) and 847989 (other mechanical appliances with individual functions). Robot adoption is measured at the extensive margin as a binary indicator equal to 1 if the firm imports a robot in a given year, and 0 otherwise. Data

[8]In compliance with Statistics Denmark's data confidentiality policy, we do not show in the paper industry-level bars for sectors with the lowest shares of offshoring firms. On average, these industries have an offshoring rate of 2 percent.

Figure 2: Offshoring Intensity by Industry



Notes: This figure shows the average share of offshoring firms in our sample over the period 1995-2022 by 2-digit industry.

are available from 1995 onwards. Prior to 1995, robot adoption was very scarce.[9] For this reason, in our event study design we assume that the first time we observe a firm importing a robot in our dataset corresponds to the first time it adopted a robot.

Using imports data as a proxy for adoptions creates several challenges. First, some robots get imported by distributors, who sell them to the end users. As mentioned in the previous section, we address this issue by excluding firms in the wholesale industry specializing in machinery.[10] Second, some importers are robot integrators, i.e. they program and outfit industrial robots in order to sell them to other firms. We identify robot integrators using a list of six-digit industry codes provided by Humlum (2021), and exclude them from the analysis. We also exclude any firm that exports robots, i.e., firms that export products under HS6 codes 847950 and 847989.

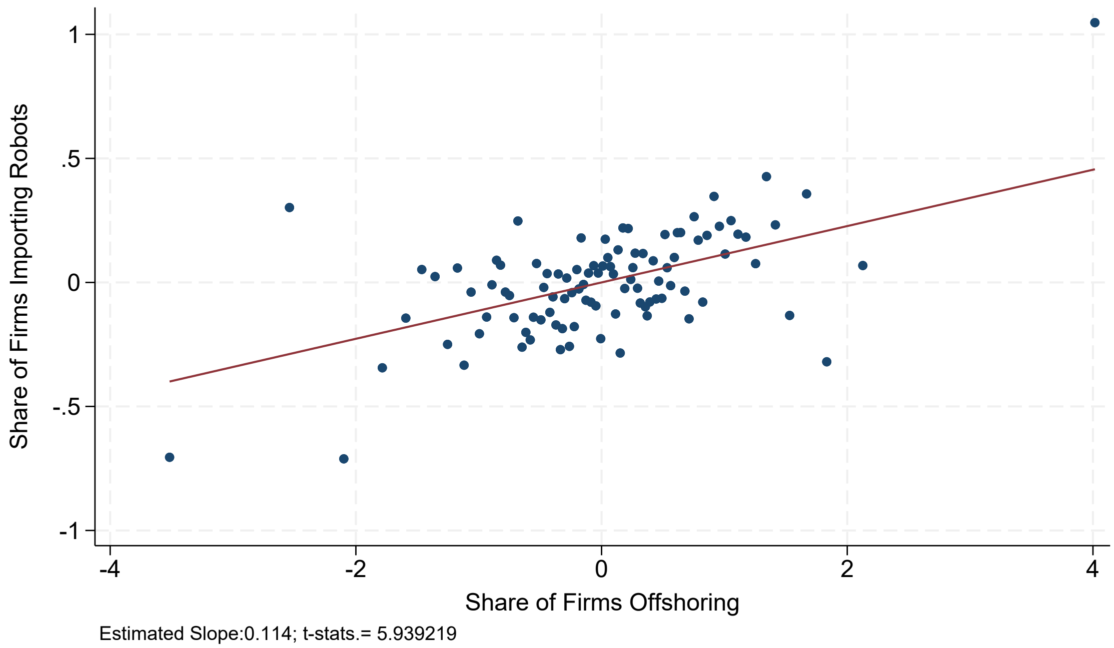
[9]For example, the International Federation of Robotics reports that in 1993 only 35 robots were adopted across all Danish firms (IFR, 2006).

[10]Industries codes: 466100, 466200, 466300, 466400, 466900.

A concern with the trade-based approach is that it may systematically under-identify firms that source robots domestically, classifying them as non-adopters simply because they do not engage in international trade. This is particularly relevant as such firms may also be less likely to offshore, potentially biasing our estimates by conflating robot non-adoption with general non-participation in global trade. To mitigate this issue, we validate our import-based measure against two alternative data sources, and we also report results using the validated version of the robot adoption variable in the refinement analysis. Both sources are independent of firms' sourcing channels. First, we use a firm-level survey carried out by Statistics Denmark (Virksomheders IT-anvendelse, VITA). This survey, conducted annually since 2018, covers about 4,000 firms. One survey question asks firms whether they purchase robot(s). Second, we validate our import-based variable with a measure of robot usage based on job vacancy postings from HBS Economics, which covers the period from 2007 through 2022. This measure reflects operational needs for robotics-related tasks. We identify firms likely engaged in robot-related activities by analyzing the text of job advertisements. Appendix A.3 provides additional details on the construction of both datasets and their overlap with our main, import-based measure. While these datasets have the advantage of being independent of firms' sourcing channels, they also have limitations. For the VITA survey, the main limitation is the small sample size and the short period it covers. For the vacancy data, limitations include that we cannot observe whether the advertised positions are actually filled. Thus, the vacancy-based measure by itself reflects firms' intent or need for robot-related capabilities rather than confirmed adoption. We therefore use it for validation rather than as an independent alternative measure.

Figure 3 plots the relationship between the municipality by year share of offshoring firms and robot adoption rate, controlling for year and municipality fixed effects. Results show a statistically significant positive relationship, providing preliminary descriptive evidence that an increase in the share of firms adopting industrial robots is associated with a higher likelihood of offshoring, in line with the hypothesis that industrial robots complement rather than substitute offshoring activities. We further examine this relationship in the next section using more rigorous empirical approaches.

Figure 3: Robot Adoption and Offshoring



Notes: Vertical axis reports standardized residuals obtained from regressing the share of firms that adopt robots on year and municipality dummies. The standardized residuals from regressing the share of offshoring firms on year and municipality dummies are reported on the horizontal axis.

2.4 Additional Variables and Descriptive Statistics

Table 1 presents descriptive statistics for all variables used in the empirical analysis over the period 1995–2022. Approximately 24% of firms in our sample engage in offshoring. Among these, the average log offshoring value is around 17 (corresponding to a value of 9 million DKK, approximately 1.5 million USD), though there is substantial heterogeneity across firms. Our main treatment variable is the binary indicator of robot adoption based on imports data. While robot adoption is relatively rare (only 2% of firms import robots annually during the full sample period), the cumulative share of adopters increases markedly over time, from less than 1% in 1995 to 14% in 2022.

Leveraging our rich employer-employee dataset, we control for a wide range of time-varying firm and workforce characteristics in the regression analysis, which are also described in Table 1. Specifically, we include the firm-level shares of female, college-educated, and foreign workers, as well as the share of workers employed in routine-intensive occupations. Routine intensity is measured using the classification developed by Mihaylov and Tijdens (2019), based on the task-based framework of Autor and Dorn (2013). An occupation is classified as routine-intensive if at least 70% of its tasks are routine. According to Table 1, on average, 30% of workers are female, 6% are foreign, and 13% are employed in routine jobs. Workers have, on average, 18 years of work experience and are 41 years old.

We also account for several firm-level characteristics, including sales, firm size, multi-establishment status, and export participation. Table 1 shows that our sample includes a wide range of firm sizes, with a focus on small and medium-sized firms: the average firm employs 39 workers, and one-third are single-establishment firms. More than half of firms export, and average annual sales are DKK 31 million (approximately USD 4 million).

3 Methodology

This section outlines our empirical strategy to estimate the relationship between robot adoption and offshoring at the firm level. We employ two complementary approaches: a linear fixed effects model, which we refer to as static difference-in-differences model, and a dynamic event study specification that accounts for heterogeneous adoption timing. Throughout, the analysis is conducted on a matched sample derived from the matching procedure described in Section 2, which ensures comparability between treated and control firms based on their propensity to adopt robots.

Table 1: Descriptive Statistics

Variables	Definition	Mean	Sd
Offshoring variables			
Extensive margin of offshoring	1, if the firm offshores (narrow definition)	0.243	0.429
Intensive margin of offshoring	log of offshoring values, conditional on offshoring (narrow definition)	16.727	3.372
Robot variables			
Robot adoption	1, if the firm imports a robot (product code=847950; 847989)	0.020	0.143
Share of robot installers (IV)	mun. share of robot installers in 1995	0.047	0.012
Workforce variables			
Female	female employees as a proportion of all employees	0.313	0.251
Foreign	foreign employees as a proportion of all employees	0.059	0.117
Routine	employees with routine intensive occupations as a proportion of all employees	0.129	0.181
Tertiary	college educated workers as a proportion of all employees	0.140	0.205
Work experience	average employees' work experience	18.197	6.682
Age	average employees' age	40.531	7.495
Firm variables			
Sales	log of sales	17.253	1.283
Size	log of number of employees	2.695	1.754
Multi-establishment	1, if the firm is a multi-establishment company	0.675	0.468
Exporter	1, if the firm exports	0.645	0.478
Number of firm-year obs.		440,601	
Number of firms		48,206	

Notes: All descriptive statistics are calculated as averages of the matched sample over the period 1995-2022. Trade and accounting variables are in real Danish Kroner (using 2015 as the base year). 1 Danish krone is approximately 0.15 US Dollar in 2015.

3.1 Static Models

Our baseline specification estimates the effect of robot adoption on firm-level offshoring outcomes using the following linear regression model:

$$Offshoring_{ijt} = \beta Robot_{it} + X'_{it}\delta + \gamma_i + \gamma_j + \gamma_m + \gamma_t + \epsilon_{it}, \quad (1)$$

where the dependent variable $Offshoring_{it}$ denotes the extensive or intensive margin of offshoring for firm i, in industry j, located in municipality m, and year t. The main explanatory variable, $Robot_{it}$, is an indicator equal to one if the firm imports at least one robot in year t, as measured by the import of industrial robots under HS codes 847950 or 847989.[11]

[11] In the main analysis, $Robot_{it}$ is defined as a flow indicator equal to one if the firm imports at least one industrial robot in year t, and zero otherwise. We also estimate specifications using an absorbing adoption indicator that switches to one in the year of first robot purchase and remains equal to one for up to 12 years thereafter, reflecting the typical economic lifespan of industrial robots as reported by the International

The vector X_{it} includes a rich set of time-varying firm-level covariates as described in Table 1. We include firm fixed effects γ_i to control for time-invariant firm heterogeneity, as well as 2-digit industry fixed effects γ_j and municipality fixed effects γ_m to account for industry and location heterogeneity. Year fixed effects γ_t are included to capture common trends in robot imports and offshoring activity.[12] Standard errors are clustered at the firm level.

While we label this specification a "static model" for expositional purposes, it is more precisely interpreted as a staggered difference-in-differences design estimated with two-way fixed effects (TWFE), following the terminology in Baker et al. (2022). A potential limitation of TWFE estimators is their vulnerability to "bad comparisons" when there are few never-treated units. In our context, however, this concern is mitigated by the fact that the fraction of never-treated firms is very large as the cumulative share of adopters is only 14% in 2022, which reduces the scope for problematic weighting across treatment cohorts. To further address this issue, we also extend the analysis with an eventstudy approach that explicitly deals with problematic weighting across treatment cohorts. In addition, the event study analysis estimates dynamic treatment effects over time, including pre-treatment effects, and shows that robot adoption precedes offshoring.

3.2 Event Study and Dynamic Effects

To examine the dynamic relationship between robot adoption and offshoring behavior, we implement an event study design that accounts for variation in the timing of adoption across firms. Specifically, we estimate dynamic treatment effects using the estimator developed by Sun and Abraham (2021), which is designed for settings with staggered treatment adoption and heterogeneous treatment effects. The key idea of this approach is to group firms into cohorts based on their year of first robot adoption and to estimate cohort-specific event-time

Federation of Robotics (IFR). The results using this alternative definition are virtually identical and are available upon request.

[12]Industry and municipality fixed effects are identified from firms' changes in industry and location over time.

effects. For each cohort, we construct a set of relative time indicators denoting the number of years ℓ before or after adoption. Put differently, we compare treated firms to never-treated firms and construct cohort-specific event-time effects, which are aggregated into average dynamic treatment effects. We then estimate the following event study specification:

$$Offshoring_{it} = \sum_{g \in \mathcal{G}} \sum_{\ell \neq -1} \beta_{g,\ell} \cdot 1\{A_i = t - \ell\} \cdot 1\{G_i = g\} + X'_{it}\delta + \gamma_i + \gamma_j + \gamma_m + \gamma_t + \epsilon_{it}, \quad (2)$$

where A_i is the year of first robot adoption for firm i, $1\{A_i = t - \ell\}$ is a set of relative time indicators and $1\{G_i = g\}$ is the set of group indicators. We then derive the coefficients:

$$\hat{\beta}_\ell = \sum_{g \in \mathcal{G}} w_g \hat{\beta}_{g,\ell},$$

which calculates the weighted average treatment effect ℓ years after adoption (or -ℓ years before adoption), relative to the omitted baseline period $\ell = -1$. The weights w_g are proportional to the number of treated firms in cohort g that contribute observations at event time ℓ, and they sum to one. Intuitively, this means that larger cohorts and cohorts observed more frequently at the relevant relative time receive more weight in the aggregation.

Pre-treatment coefficients ($\ell < -1$) are used to assess the validity of the parallel trends assumption. The estimator avoids the bias present in traditional two-way fixed effects models by fully interacting cohort and event time dummies and appropriately aggregating cohort-specific effects. We define our control group as never-treated firms, i.e. firms that did not adopt any robots during the sample period. These firms serve as a stable comparison group across all event times. In a refinement analysis, we also report results obtained using alternative strategies. For example, one approach uses later adopters as a control group in a stacked difference-in-differences framework, following Bessen et al. (2025).

We include the same set of firm-level covariates and fixed effects as in the baseline specification to control for time-varying characteristics and unobserved heterogeneity and cluster standard errors at the firm level.

4 Main Results

This section presents the main empirical findings on the relationship between robot adoption and offshoring. We begin by estimating static linear models that evaluate the average effect of adoption on the extensive and intensive margins of offshoring. We then turn to event study models that exploit variation in adoption timing to trace the dynamic evolution of offshoring outcomes around the time of adoption.

4.1 Static Models Results

Table 2 reports the results from the static linear models, estimating equation (1). In Column (1), we estimate the relationship between robot adoption and the likelihood of offshoring without including time-varying covariates. The coefficient on robot adoption is 0.097, implying a positive association with offshoring of approximately 10 percentage points relative to a baseline mean of 24%. This represents a sizable association, though the omission of potentially endogenous controls may lead to an overestimation of its magnitude.

Column (2) adds the full set of firm-level controls. The coefficient on robot adoption drops to 0.080, suggesting some upward bias in the unadjusted specification due to omitted variables. Column (3) introduces a lagged indicator for offshoring to capture firms' prior exposure to global sourcing. The coefficient further declines to 0.057, implying that part of the coefficient of robot adoption reflects path dependence in offshoring behavior. Nevertheless, the coefficient remains statistically and economically significant. To further account for this dynamic, Column (4) restricts the sample to firms that were already offshoring at least once prior to their first robot adoption. In this subset, the coefficient decreases to 0.048 relatively to the one reported in column (2), indicating a weaker association between robot adoption and offshoring, though the relationship remains positive even among firms with pre-existing experience with international production. This finding suggests that automation and offshoring are complements, rather than substitutes, and that robots may facilitate the expansion of global sourcing strategies even among offshorers with prior offshoring experience.

Turning to the intensive margin (Columns 5–6), we find qualitatively similar results, conditional on firms already offshoring. Column (5) shows that robot adoption is associated with a 33% increase in the (log) value of offshored goods, relative to a baseline mean log value of 17.[13] Adding controls in Column (6) reduces the estimate to 18%. These results confirm that robot adoption may not only encourage firms to offshore but also lead existing offshorers to expand the scale of their sourcing abroad.

Table 2: Robot Adoption and Offshoring

	Extensive Margin				Intensive Margin	
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	0.097***	0.080***	0.057***	0.048***	0.334***	0.179***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.042)	(0.038)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	No	Yes	Yes	No	No	Yes
$Offshoring_{it-1}$	No	No	Yes	No	No	No
Mean Dep. Var.	0.243	0.243	0.265	0.735	16.727	16.727
R^2	0.748	0.754	0.788	0.488	0.705	0.733
N	440,601	440,601	359,281	38,472	105,180	105,180

Notes: The dependent variable is a binary offshoring indicator (cols 1–4) and the log value of offshoring (cols 5–6). Robot adoption is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition. Column 4 restricts the sample to firms that were already offshoring at least once prior to their first robot adoption. Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and average work experience and age. Standard errors clustered at the firm level in parentheses. Significance levels: ***1%, **5%, *10%.

Taken together, the static model results show a consistent positive relationship between robot adoption and offshoring. One plausible explanation for this positive correlation is that robot adoption goes hand in hand with the expansion and upgrading of firm activities. The

[13]The baseline mean log value of 17 corresponds to approximately 9 million Danish kroner in offshored goods. Thus, a 33 percent increase implies an average rise of about 3 million Danish kroner.

first three columns of Table A.1 in Appendix A.1 support this interpretation by documenting significant increases in sales (Column 1), employment (Column 2) and labor productivity, measured as sales per employee, (Column 3) around the time of robot adoption. These results suggest that automation is associated not only with labor-saving adjustments but also with broader changes in firms' scale, output, and productivity. Firms with larger scale and higher productivity tend to be better positioned to manage complex international supply chains and to exploit scale economies in global sourcing.

Columns (4) and (5) of Table A.1 further show that robot adoption is associated with an increase in the number of non-routine workers, while the relationship with the number of routine workers is negative but statistically insignificant. This pattern is consistent with a reallocation of labor toward roles specialized in non-routine tasks and aligns with prior research showing that automation is routine-biased, with disproportionately higher demand for non-routine cognitive and non-routine manual tasks and neutral or negative effects on routine (manual and cognitive) tasks (Autor et al., 2003; Acemoglu and Restrepo, 2019, 2020; Mann and Püttmann, 2023; Acemoglu et al., 2026). Furthermore, the estimated coefficient in Column (6) where the outcome variable is the number of establishments is positive and marginally significant, consistent with evidence that automation can lead to productivity gains and a moderate expansion in firms' geographic scope within the domestic economy (Koch et al., 2019). Finally, column (7) of Table A.1 shows that these same firm characteristics, such as sales, size, workforce composition and the number of establishments, are themselves strongly and positively correlated with the extensive margin of offshoring. This pattern suggests that robot adoption may increase offshoring partly by moving firms into a region of the firm scale distribution where offshoring is more likely.

Overall, while these results are consistent with scale, productivity, and organizational upgrading playing a role in the link between robot adoption and offshoring, we emphasize that the analysis does not isolate these variables as causal mediating channels. Rather, the evidence establishes that robot adoption is associated with a bundle of firm-level adjustments, such as growth in scale and shifts in task composition, that are themselves strongly correlated with offshoring.

4.2 Event Study Results

Figure 4 presents the results from the event study analysis, which estimates the dynamic relationship between robot adoption and firms' offshoring behavior. The estimated coefficients represent deviations in the outcome variable relative to the year immediately preceding adoption ($\ell = -1$), allowing us to assess both pre-treatment trends and post-adoption dynamics.[14] Panel (a) shows the estimated effects on the extensive margin of offshoring. The coefficients for the pre-treatment period ($\ell = -5$ to $\ell = -1$) are close to zero and statistically insignificant, supporting the parallel-trends assumption and lending credibility to our identification strategy. Following robot adoption, we observe a marked and persistent increase in the likelihood of offshoring. The estimated coefficient becomes statistically significant one year after adoption and peaks around $\ell = 3$, reaching approximately 5 percentage points relative to the pre-adoption mean. The coefficient remains positive and stable throughout the six-year post-event window, suggesting that automation has a lasting positive association with firms' propensity to offshore.

Panel (b) introduces a specification that accounts for whether firms had already engaged in offshoring prior to adopting robots. The results continue to show a persistent positive association between robot adoption and offshoring, although the magnitude is somewhat smaller than in Panel (a). The estimated coefficient peaks around $\ell = 1$ at roughly 4 percentage points and gradually declines to about 2–3 percentage points toward the end of the event window. Despite slightly wider confidence intervals, the post-event coefficients remain positive throughout, indicating that robot adoption continues to be associated with an increase in the likelihood of offshoring even after controlling for firms' previous offshoring

[14] We restrict the event-time window to $\ell \in \{-5, \ldots, 6\}$. The indicators $\ell = -5$ and $\ell = 6$ correspond to exactly five years before and six years after adoption, respectively; earlier and later years are excluded rather than pooled.

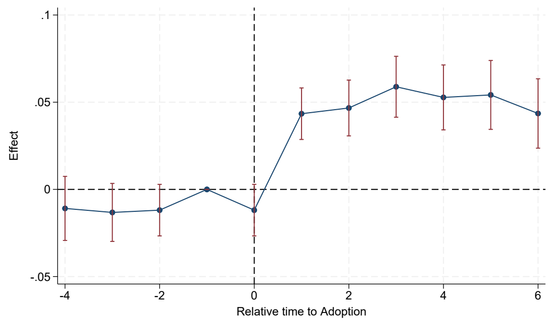
experience.

Panel (c) of Figure 4 examines the intensive margin of offshoring, measured as the log value of offshored goods. The pre-treatment coefficients ($\ell = -5$ to $\ell = -1$) are statistically indistinguishable from zero, indicating no differential pre-trends. Following robot adoption, the coefficients turn positive and become statistically significant, pointing to an increase in offshoring intensity. By $\ell = 6$, the estimated association reaches just above 0.3 log points, corresponding to roughly a 30 percent increase relative to baseline levels. While the point estimates generally rise over the post-treatment horizon, the confidence intervals overlap considerably across years, meaning the individual post-adoption coefficients are not statistically different from one another. Overall, the results indicate that robot adoption is associated with a sustained increase in the scale of offshoring, even though the year-to-year growth in the estimated effects cannot be precisely distinguished.

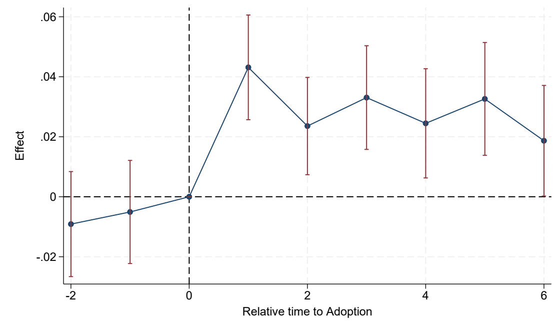
Taken together, the event study results provide robust evidence that robot adoption has a dynamic and persistent association with firms' offshoring behavior. These findings reinforce the interpretation that automation and offshoring are strategic complements rather than substitutes. Instead of inducing reshoring or withdrawal from global value chains, robot adoption appears to be associated with deeper integration into international production networks, presumably by increasing firms' scale and productivity, as shown in the previous section, which in turn supports the expansion of production activities abroad. The persistence of the estimated coefficients suggests that the consequences of automation materialize soon after initial adoption and remain stable over time, reflecting both the immediate adjustments after robot implementation and the longer-run reorganization of production associated with offshoring expansions (Artuç and McLaren, 2015; Bloom et al., 2020).

In Appendix Section A.4, we re-estimate the dynamic relationship between robot adoption and offshoring using an alternative event definition and control group construction, following Bessen et al. (2025). Instead of defining the event as the year of first robot adoption, we identify "robotization spikes" based on sudden surges in robot investment intensity. To

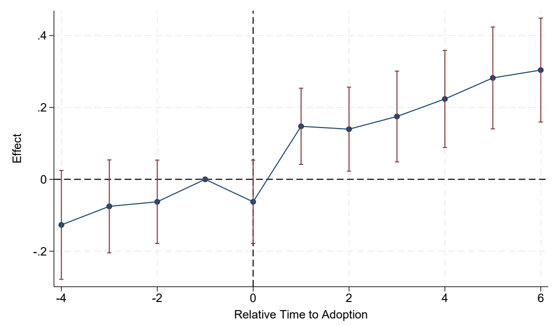
Figure 4: Robot Adoption and Offshoring: Event Study



(a) Offshoring (Extensive)



(b) Offshoring (Extensive), contr. for lagged off.



(c) Offshoring (Intensive)

Notes: This figure shows the coefficients of the time to treatment variables and their 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). The dependent variable in the first and the second panels is the extensive margin of offshoring. In the third, the dependent variable is the intensive margin of offshoring.

attenuate concerns about differences between adopters and never-adopters, we use a stacked difference-in-differences design, where we compare firms experiencing a robot spike in a given year (treated cohort) to firms that will have their first spike at least five years later (later adopters). The stacked event study results confirm that robot adoption has a positive significant association with offshoring, though the coefficients are smaller in magnitude than our baseline estimates. This difference is also consistent with refinement findings reported below showing that the strongest offshoring response occurs at the point of first robot adoption. Since the spike-based design often captures subsequent investment rounds rather than the initial adoption, it may underestimate the full and immediate association between robot adoption and firms' offshoring.

4.3 Channels: Robot Adoption and the Expansion of Global Supply Chains

The results presented so far establish that robot adoption is associated with an increase in both the likelihood and the intensity of offshoring. In this subsection, we explore the channels through which robot adoption shapes firms' offshoring behavior. Specifically, we analyze how automation relates to different margins of global sourcing by disaggregating offshoring outcomes across products, destinations, and technological content. This approach allows us to distinguish between changes that reflect a reallocation of sourcing within existing relationships and those that refer to a broader restructuring of firms' offshoring.

Table 3 examines alternative offshoring outcomes that shed light on the channels underlying the main results. Column (1) considers the number of offshored products, and Column (2) analyzes the number of offshoring destinations, conditional on offshoring. In both cases, we find positive and significant coefficients on robot adoption, suggesting that automation is associated not only with offshoring participation but also with more extensive and geographically diversified global sourcing. These results are consistent with the static and dynamic evidence reported above, which shows that robot adoption is followed by a sizable increase in the intensive margin of offshoring. These refinement results strengthen the interpretation that robot adoption expands not only the likelihood of offshoring (extensive margin) but also the depth and complexity of global production networks (intensive margin), through a greater variety of offshored products and a broader set of sourcing destinations. This is consistent with Stapleton and Webb (2023), who also find that robot adoption increases the number of products imported from lower-income countries, suggesting that automation can complement rather than replace offshoring.

Next, Columns (3)–(6) distinguish between the extensive margin of offshoring to advanced economies (North) and developing countries (South). Given the increasing debate over whether automation induces reshoring, particularly from developing to high-income economies, we further disaggregate the effects of robot adoption by destination. If automation were eroding the cost advantages of offshoring to low-wage countries, we would expect a decline in sourcing from the Global South. Instead, our results show that robot adoption is associated with higher levels of offshoring to both high-income and low- and middle-income countries, with somewhat stronger coefficients toward Northern destinations. To further assess whether robot adoption is associated with a simultaneous expansion of sourcing across income groups, Column (7) of Table 3 focuses on firms that offshore to both Northern and Southern destinations in the same year. The positive and statistically significant coefficient indicates that robot adoption increases the likelihood that firms engage in multi-region offshoring, rather than substituting sourcing from one group of countries to another. While this result does not provide direct evidence for complementarity between Northern and Southern sourcing at the firm level, it nevertheless suggests that automation is associated with more complex global sourcing strategies that span both high- and low-income locations simultaneously. This pattern is consistent with a supply-chain expansion mechanism: productivity gains from automation allow firms to scale operations and engage with a broader set of suppliers, including technologically advanced inputs from the North and cost-efficient production stages in the South. In this sense, automation complements global sourcing by enabling firms to coordinate more complex international production networks rather than by reversing offshoring decisions. Our firm-level evidence thus complements the results in Baur et al. (2025), who show that automation in advanced economies stimulates trade linkages between Northern and Southern industries.

Additional insight into this North–South pattern comes from Columns 8 and 9 of Table 3, which focus specifically on offshoring to the top nine Southern destinations. These cover Eastern European countries as well as China.[15] The results indicate a positive and statistically significant association between robot adoption and the likelihood of offshoring to these Southern locations. The magnitudes involved however remain smaller than those found for offshoring to the North: robot adoption is associated with increases of 5.9 and 4.4 percentage

[15]Eastern European countries include Bulgaria, Romania, Poland, Hungary, the Czech Republic, Slovakia, Slovenia, and the Baltic states (Estonia, Latvia, and Lithuania).

points, respectively, in the probability of offshoring to the top destinations in the South, with the latter specification controlling for lagged offshoring.

Finally, we broaden our definition of offshoring by constructing outcomes based on HS4 product codes. This more aggregated measure captures a wider range of internationally sourced inputs than our baseline HS8-based definition, which restricts offshoring to narrowly defined industry–product categories. By using HS4 codes we allow for the possibility that firms offshore inputs that are technologically or functionally related but not classified within the same detailed HS8 product line. This broader measure therefore aligns more closely with the concept of industry-level offshoring used in Baur et al. (2025). Our results based on HS4 offshoring outcomes, reported in Columns (10) and (11) of Table 3, confirm that robot adoption is also positively associated with increases in this wider measure of global sourcing.

Table 4 provides the most direct evidence on the mechanism underlying the main findings by examining how robot adoption relates to offshoring along the product margin, conditional on offshoring. The results show that robot adoption is disproportionately associated with the expansion of offshoring into new products. Column (1) indicates a 32% increase in the value of offshoring of newly introduced products, compared with a smaller but still significant 8% increase for existing products in Column (2).[16] To address the concern that these results may be driven by changes in the product classification system rather than actual expansion into new products, we take two robustness approaches. First, we exclude the years in which the HS product classification underwent the most substantial revisions, as measured by spikes in the number of new codes introduced or old codes removed.[17] The results, reported in

[16]Intensive-margin regressions are estimated conditional on positive offshoring values. For new products, this restricts the sample to firm–year observations in which the firm offshores at least one newly introduced product. The estimated coefficient therefore captures within-firm increases in the value of offshoring of new products following robot adoption, rather than growth from zero. As a result, the 32% effect should be interpreted as an increase in the value of offshoring of new products within the same firm in years following robot adoption compared to years without adoption. When we estimate the coefficient on the extensive margin of starting to offshore a new product, the coefficient is 0.091 (0.006), relative to an average sample probability of offshoring a new product of 0.195.

[17]More details about these data breaks in the product classification can be found at: https://ec.europa.eu/eurostat/cache/metadata/en/ext$_{g}o_{a}gg_{e}sms.htm?utm_{s}ource = chatgpt.comshortcompar_{t}imeDisseminated$

Table 3: Robot Adoption and Offshoring (Alternative Outcomes)

	# Products (1)	# Destinations (2)	North (3)	North (4)	South (5)	South (6)	North & South (7)	East EU/China (8)	East EU/China (9)	HS4 Off. (Ext.) (10)	HS4 Off. (Int.) (11)
Robot Adoption	1.746***	0.691***	0.083***	0.061***	0.061***	0.043***	0.064***	0.059***	0.044***	0.081***	0.276***
	(0.454)	(0.105)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.037)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mun. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	No	No	Yes	No	Yes	No	No	Yes	No	No
Mean Dep. Var.	11.140	7.236	0.218	0.239	0.163	0.179	0.137	0.133	0.147	0.265	17.509
R^2	0.723	0.771	0.728	0.762	0.697	0.723	0.666	0.677	0.701	0.767	0.766
Observations	105,180	105,180	440,601	359,281	440,601	359,281	440,601	440,601	359,281	440,601	114,778

Notes: In columns (1)–(2), the dependent variable is the number of offshored products or destinations at the firm level. In columns (3)–(6), the dependent variable is a binary indicator for offshoring to the North or South, respectively. Column (7) reports an indicator for whether the firm offshores simultaneously to both the North and the South. Columns (8)–(9) report offshoring to Eastern Europe/China. Columns (10)–(11) report HS4-based extensive and intensive offshoring outcomes, respectively. Robot adoption is a binary variable indicating whether the firm imports at least one robot in year t. Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and average work experience and age. Standard errors are clustered at the firm level (in parentheses). Significance levels: *** 1%, ** 5%, * 10%.

Columns (1) and (2) of Table A.2 in Appendix A.1, are very similar, suggesting that our findings are not mechanically driven by classification updates. Second, we reclassify "new products" as "existing products" those product codes that appear in the sample for the first time in a given year and are offshored by at least 5 firms in that same year. This conservative filter is designed to capture product codes likely introduced due to systemic classification changes rather than genuine new offshoring decisions. Columns (3) and (4) in Table A.2 present the results of this alternative specification. The findings remain robust, with the largest offshoring increases still occurring for new products, confirming that the intensive-margin association is indeed concentrated along the product dimension.

Columns (3) and (4) of Table 4 split new products into high/medium-technology and low-technology categories. The results suggest that the intensive-margin association is particularly pronounced for high/medium-technology new products, where robot adoption is associated with a 24% increase in offshoring, compared with a smaller yet significant 16% increase for low-technology new products.[18] This pattern indicates that automation may disproportionately facilitate the offshoring of more technologically sophisticated goods, consistent with the idea that robots complement firms' capabilities to organize and manage complex international production processes.[19]

We also find that firms adopting robots expand their offshoring activity along the destination margin. Column (5) shows a 21% increase in offshoring to new destinations, compared with a 7% increase for existing destinations in Column (6). Finally, Column (7) of Table 4 focuses on offshoring flows that simultaneously involve the introduction of a new product to a new destination within the same firm-year. The large and positive coefficient indicates that robot adoption is associated not only with independent expansion along the product

[18]The high/medium- and low-technology product classification follows UNCTAD's SITC Rev.3 technology hierarchy: https://unctadstat.unctad.org/EN/Classifications/DimSitcRev3Products_Ldc_Hierarchy.pdf. To mitigate concerns about changes in product classifications over time, we aggregate product codes to the 4-digit level before assigning technology groups.

[19]When we estimate the coefficient on the extensive margin of starting to offshore a new high- [low-] technology product, the coefficient is 0.085 (0.006) [0.050 (0.005)], relative to an average sample probability of offshoring a new product of 0.090 [0.069].

Table 4: Robot Adoption and Offshoring: New vs. Existing Products and Destinations

	Intensive Margin						
	New Prod. Only	Ex. Prod. Only	New Prod., High Tech	New Prod., Low Tech	New Dest. Only	Ex. Dest. Only	New Prod. & New Dest. Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot adoption	0.320***	0.079**	0.242***	0.156**	0.206***	0.065*	0.234***
	(0.047)	(0.040)	(0.063)	(0.070)	(0.044)	(0.038)	(0.042)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	No	No	No	No	No	No
Mean Dep. Var.	14.205	17.357	12.856	12.758	15.092	17.208	15.957
R^2	0.407	0.730	0.368	0.375	0.514	0.751	0.577
N	83,054	80,431	37,081	32,449	78,629	85,397	68,165

Notes: The dependent variable is the log value of offshoring at the intensive margin. Column (7) captures offshoring flows that involve the introduction of a new product to a new destination within the same firm-year. Robot adoption is a binary variable indicating whether the firm imports at least one robot in year t. All specifications include firm fixed effects, year, 2-digit industry, and municipality fixed effects. Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and average work experience and age. Standard errors are clustered at the firm level (in parentheses). Significance levels: ***1%, **5%, *10%.

and destination margins, but also with coordinated expansions that introduce new products into new markets, consistent with automation facilitating broader value-chain adjustments.

Taken together, the results presented in Tables 3 and 4 show that the firm-level association between robot adoption and offshoring is largely driven by diversification into new products and destinations spanning the North–South divide, suggesting that automation enables firms not only to deepen existing supply relationships but also to broaden the scope of their global value chains across products and geographies.

5 Refinements

In this section, we extend the main analysis through a series of additional specifications. First, we further attenuate endogeneity concerns using an instrumental variable approach based on pre-existing local robot service capacity. Second, we present findings obtained using alternative measures of robot adoption. Finally, we conduct a set of subsample analyses to explore heterogeneity in effects across geography, firm size, firm duration, and sector. For brevity, we primarily present results from two versions of the static model for the extensive margin of offshoring, one without and one with a control for firms' previous offshoring experience, captured by their lagged offshoring status.

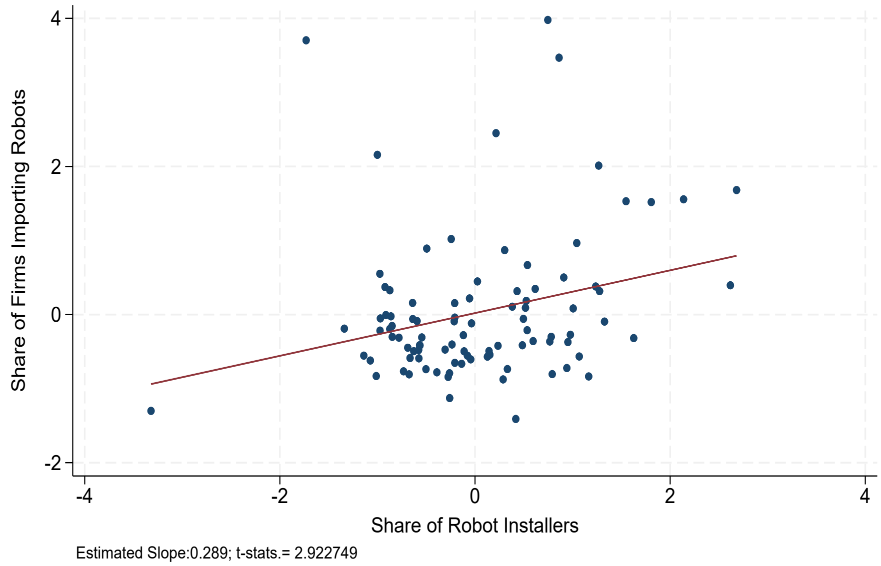
5.1 Instrumental Variable Approach

The previous analysis using the event study analysis shows that automation is positively correlated with increases in the probability of firm offshoring in the subsequent years and the association is persistent. The specification controls for a rich set of firm characteristics, together with firm, municipality, and year fixed effects. As a result, it controls for the possibility that, for example, more productive firms, located in more productive municipalities are more likely to automate and offshore at the same time. In addition, it also controls for the overall trends of offshoring and automation. Nevertheless, there may still be concerns that some unobservable shocks at the firm level are correlated with firm activities of automation and offshoring at the same time, although it requires that these shocks somehow affect automation first.

To further attenuate potential endogeneity concerns in the relationship between robot adoption and offshoring, we implement an instrumental variable (IV) strategy. We use the historical local density of robot installers and mechanical repair technicians in 1995 as an instrument for robot adoption. This instrument captures exogenous cross-sectional variation in the technical feasibility and local cost of adopting robots across municipalities, based on predetermined supply-side conditions. As reported in Table 1, the average municipal share of robot installers in the pre-sample period is 5 percent with a standard deviation of 1 percentage point.

To improve the reliability of this identification strategy, we estimate the IV regressions using data from the sample period 2005–2022. Since the instrument is measured a decade prior to the beginning of the sample period, it is unlikely to be correlated with unobserved shocks to firms' current global sourcing strategies, thereby plausibly satisfying the exclusion restriction and mitigating concerns over simultaneity or reverse causality. To address potential violations of the exclusion restriction arising from persistent differences in local economic structure, all IV specifications include municipality-level controls measured in 1995, such as the share of employment in manufacturing and the share of exporters and importers. These controls absorb pre-existing differences in industrial composition and trade orientation that could otherwise directly affect firms' offshoring decisions. To further attenuate potential persistence bias and ensure the validity of the exclusion restriction, we restrict the sample to firms that adopt robots and offshore production abroad for the first time between 2005 and 2022, along with firms that never adopt or never offshore. This exclusion of earlier adopters and offshorers helps avoid spurious correlation between pre-sample instrument values and persistent adoption and offshoring behavior. As a result, the IV strategy requires working with a more specific sample. Note that, as in the main analysis, we work with a

Figure 5: Robot Adoption and the Local Supply of Robot Installers (IV First Stage)



Notes: The horizontal axis reports the standardized share of robot installers in a given municipality in the pre-sample year (1995), while the vertical axis reports the standardized share of firms adopting industrial robots in that municipality.

matched sample and do not include firm or municipality fixed effects in the IV specification, as these would absorb the variation in the instrument.[20] Standard errors are clustered at the municipality level.

To assess the strength of our instrument, Figure 5 presents a plot of the share of firms' adopting industrial robots within a municipality between 2005 and 2022 against the share of robots' installers within a municipality in 1995. The plot clearly displays a strong positive correlation, confirming the ability of the instrument to predict adoption within a municipality. This provides a prima-facie and visual inspection of the first-stage IV results reported later.

Table 5 provides IV regression results. For comparison, column (1) shows re-estimates Column (2) of Table 2 without firm and municipality fixed effects, using data from 2005–2022 and excluding adopters and offshorers prior to 2005. Column (2) shows the IV estimate. The

[20] Less than 10 percent of firms change municipality during the sample period (2005–2022), so most of the instrument's identifying variation remains cross-sectional.

positive significant coefficient reinforces the baseline findings that robot adoption is positively associated with the probability of offshoring at the firm level. The estimated coefficient exceeds the corresponding OLS coefficient of 0.241 in column (1), suggesting that the baseline estimates may be attenuated due to measurement error or downward bias. This implies that our non-instrumented results likely serve as lower-bound estimates. There is, however, an additional interpretation for the larger IV estimates, stemming from the fact that IV captures a local average treatment effect (LATE) for compliers, that is, firms whose adoption decisions respond to variation in instrumented exposure. These compliers represent a specific subset of firms that are induced to adopt robots because of their proximity to historical clusters of robot installers. Such firms may particularly benefit from easier access to technical support, lower maintenance and installation costs. If these firms are therefore better positioned to reorganize production internationally or face lower frictions when expanding or initiating global sourcing, then the IV estimate will exceed the OLS estimate because it captures the treatment effect for the firms most responsive to the instrument.

The first-stage regression confirms the instrument's strength, with an F-statistic well above conventional thresholds. Finally, in Column (3), we again control for lagged offshoring to account for firms' prior exposure to global sourcing. Relative to the specification in column (2), the instrumented coefficient estimated on the adoption variable declines but remains significant and larger than the corresponding non-instrumented coefficient in Column (1).

Taken together, these IV results reinforce our baseline findings. While the IV sample is more restrictive, focused on first-time adopters/offshorers in a narrower time window, the results confirm the broader pattern of complementarity between automation and global production. Moreover, the fact that IV estimates are generally larger than OLS suggests that our main results likely understate the true effect of automation on firms' international sourcing strategies and can therefore be considered a lower-bound estimate.

Table 5: Robot Adoption and Offshoring (OLS and IV Estimates)

	OLS (1)	IV (2)	IV (3)
Robot Adoption	0.241***	0.846***	0.315***
	(0.011)	(0.090)	(0.106)
Firm FE	No	No	No
Mun. FE	No	No	No
Ind. (2-digit), Year FE	Yes	Yes	Yes
Firm and workforce variables	Yes	Yes	Yes
Municipality variables	No	Yes	Yes
$Offshoring_{it-1}$	No	No	Yes
Mean Dep. Var.	0.119	0.119	0.128
R^2	0.303	0.303	0.642
Observations	236,036	236,036	189,453
F-stat (1st Stage)	—	23.09	18.39

Notes: In columns 1–3 the dependent variable is a binary indicator of offshoring at the firm level at time t. Robot adoption is a binary variable indicating whether the firm adopts at least one robot in year t. The estimation sample includes only years from 2005 through 2022 and excludes firms that offshore and/or adopt a robot before 2005. The instrumental variable is the share of robot installers in a given municipality in the pre-sample year (1995). Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and workers' average experience and age. Municipality variables include the 1995 manufacturing employment share and the 1995 share of exporters and importers. Standard errors are clustered at the firm level in column 1 and at the municipality level in columns 2–3. Significance levels: *** 1%, ** 5%, * 10%.

5.2 Alternative Definitions of Robot Adoption

To further assess the robustness of our robot adoption measure, Table 6 reports results using alternative definitions. In Columns (1)–(2), we add the inverse hyperbolic sine of the value of imported robots to capture the intensive margin of investment. The coefficients on the linear and squared terms are small and statistically insignificant, suggesting that it is the act of adoption, rather than the scale of investment, that matters for offshoring.

To test whether robot quality influences offshoring, Columns (3) and (4) replicate the main analysis using a narrower definition of robot adoption: industrial robots imported specifically from Germany and Switzerland, two countries known for supplying high-quality automation equipment, as documented in Bilgin et al. (2024). This alternative definition offers a more restrictive but targeted proxy for technologically advanced adoption. The resulting coefficients (0.063 and 0.047) remain positive and significant, although slightly smaller than those reported in Table 2. These findings do not suggest that sourcing high-quality robots is associated with a larger increase in offshoring participation.

In Columns (5) and (6) of Table 6, we validate our robot adoption measure by combining administrative trade records with firm-level survey responses from Statistics Denmark's VITA dataset. Specifically, we restrict the sample to firms that both import robots (per customs data) and self-report robot use in the survey. Non-adopters are defined as firms that neither import robots nor report usage. This conservative classification, based on so-called "true positives" and "true negatives", is designed to reduce measurement error and improve the reliability of the adoption indicator. However, this approach comes at the cost of a much smaller sample[21] and a much shorter longitudinal dimension (from 2018 through 2022), which leaves us without sufficient power to include firm fixed effects. Despite this limitation, the estimated coefficients remain sizable and statistically significant. Column (5) reports a coefficient of 0.146, indicating that verified adopters are 14 percentage points more likely to offshore than non-adopters. When controlling for lagged offshoring in Column (6),

[21] The VITA survey covers only around 4,000 firms.

the coefficient falls to 0.045 but remains significant at the 1 percent level. These estimates are consistent with our baseline results and highlight the strong association between verified robot use and firms' global sourcing behavior.

Next, we validate our robot adoption measure using job vacancy postings, following the same procedure as in the survey-based validation. Specifically, we combine administrative trade records with firm-level vacancy data for 2007–2022 to identify firms that both import robots and post vacancies requiring robot-related skills using the strict definition described in Appendix A.3.[22] Firms that neither import robots nor post robot-related vacancies are classified as non-adopters.[23] This validation, which is based on overlapping signals from the two independent sources, focuses on verified adopters and verified non-adopters to minimize potential misclassification as we did with the survey before. Columns (7) and (8) of Table 6 show that the validated indicator is associated with an increase in the likelihood of offshoring by 4.2 and 2.5 percentage points, respectively, depending on whether lagged offshoring is controlled for. Although both coefficients remain positive and statistically significant, they are smaller than the baseline estimate reported in Table 2. The weaker coefficients may result from the validation procedure itself: by restricting the sample to firms consistently identified across both data sources, we exclude firms that adopt robots but do not explicitly advertise robotics-related positions, for example because they instead choose to retrain their workers. This narrows the treated group to a subset of confirmed adopters (the share of validated adopters is 2 percent in the validated sample, compared with 5 percent in the baseline sample). Accordingly, the smaller coefficient should be interpreted as reflecting this more selective definition of adoption.

Columns (9), (10), and (11) of Table 6 provide additional insights into the dynamics of the relationship between robot adoption and offshoring. Columns (9) and (10) focus

[22]Results based on the "extended" vacancy-based validation yield virtually identical coefficients and are available upon request.

[23]Note that if a firm does not post vacancies in a given year, it is not classified as a non-adopter. Instead, it is excluded from this validation exercise and the related regression. When we instead classify firms without online job postings as non-adopters, we obtain similar results (although slightly larger in magnitude for the robot adoption coefficient) to those reported in the paper.

specifically on first-time adopters, i.e., firms that adopt robots for the first time in year t, to explore whether the link between robotization and offshoring is immediate or develop cumulatively over time through multiple robot investment rounds. If offshoring were driven by sustained automation strategies, where firms gradually build robotic capabilities and realize productivity gains over time, we would expect a weaker coefficient among first-time adopters. Instead, the results indicate the opposite: the estimated coefficient in Column (9) is 0.104, which is slightly larger than the one estimated in the baseline specification in Table 2, and remains statistically significant even after controlling for lagged offshoring in Column (10). These findings suggest that the first robot investment plays a critical role in enabling firms to offshore. Rather than being a marginal add-on to an ongoing automation strategy, the initial adoption of robotics appears to be the tipping point that facilitates integration into global value chains. This evidence complements the dynamic event study results discussed above, which show that the association between automation and offshoring emerges quickly after first adoption and remains persistent over time and it is also consistent with the dynamic specification discussed in Appendix A.4 showing that investment-spike events have smaller correlation with offshoring than the adoption event itself.

Column (11) shifts focus to a different concern, namely, the possibility of reverse causality. A key critique of our baseline analysis is that the observed correlation between robot adoption and offshoring could reflect simultaneous decisions or even causality running from offshoring to adoption. For example, firms that start offshoring may gain access to foreign suppliers or lower-cost robot technologies abroad, which in turn prompts them to adopt automation. However, in Columns (3) and (4) of Table 2, we already showed that the coefficient estimated on robot adoption weakens when we control for previous offshoring or when we restrict the sample to firms that had already offshored prior to adoption.[24] These findings mitigate concerns that offshoring experience is driving both robot adoption and subsequent offshoring.

[24] Similarly, we focus on the sample of exporting firms, the coefficient estimated on adoption for the extensive margin of offshoring is slightly smaller than the one presented in the main results but still statistically significant at 1 percent level [0.059 (0.006)].

To probe this issue more directly, Column (11) restricts the sample to firms that offshore for the first time in year t. This stringent refinement ensures that offshoring activity was not already in motion prior to the observed treatment period, thereby removing any confounding influence of pre-existing offshoring behavior. The estimated coefficient in Column (11) is 0.087 and statistically significant, suggesting a strong association between robot adoption and offshoring even when offshoring activities are initiated for the first time at time t. While this result does not fully rule out very short-run simultaneity, since both robot adoption and offshoring are measured at the annual level, it substantially reduces concerns that the baseline estimates are driven by offshoring induced adoption. If offshoring were causing adoption, we would not expect the coefficient on robot adoption to persist in a sample restricted to first-time offshorers. Instead, the large and significant coefficient suggests that robot adoption may act as a triggering mechanism for firms to enter global sourcing for the first time. Moreover, the dynamic event study results show that robot adoption systematically precedes increases in offshoring, providing additional evidence against simultaneity as the primary explanation for our findings.

5.3 Sub-sample Results and Alternative Specifications

To explore heterogeneity in the relationship between robot adoption and offshoring, Table A.3 of Appendix A.1 reports estimates across firm subsamples. It also show the results obtained from a specification in which robot adoption is lagged by one year. These robustness checks assess whether our main findings hold across different segments of the Danish economy, firm types, and alternative model assumptions. The results show that the positive link between robot adoption and offshoring is not driven by urban agglomeration effects, as it persists when excluding firms in Greater Copenhagen. It also holds when restricting the analysis to large firms, firms with long activity durations (i.e., at least 12 years), and manufacturing firms, the sector most likely to adopt robots. The effects are not confined to manufacturing: robot adoption is also significantly associated with offshoring in services,

Table 6: Robot Adoption and Offshoring: Alternative Definitions of Robot Adoption

	Extensive and Intensive Margin		Industrial Robots (DE+CH)		VITA-Validated Robots	
	(1)	(2)	(3)	(4)	(5)	(6)
Robot Adoption	0.174***	0.166***	0.063***	0.047***	0.146***	0.045***
	(0.066)	(0.057)	(0.009)	(0.008)	(0.024)	(0.016)
Value Robots$_{t-1}$	-0.014	-0.018				
	(0.012)	(0.011)				
Value Robots$^2_{t-1}$	0.001	0.001				
	(0.001)	(0.000)				
Firm fixed effects	Yes	Yes	Yes	Yes	No	No
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	Yes	No	Yes	No	Yes
Mean Dep. Var.	0.243	0.265	0.243	0.265	0.308	0.307
R^2	0.754	0.788	0.753	0.788	0.510	0.733
Observations	440,601	359,281	440,601	359,281	10,976	6,062

	Job Ads-Based Robots		First-Time Adopters		First-Time Offshorers
	(7)	(8)	(9)	(10)	(11)
Robot Adoption	0.042**	0.025**	0.104***	0.082***	0.087***
	(0.017)	(0.010)	(0.008)	(0.007)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	Yes	No	Yes	No
Mean Dep. Var.	0.276	0.280	0.232	0.232	0.018
R^2	0.835	0.851	0.767	0.767	0.272
Observations	80,516	42,790	332,728	332,728	235,643

Notes: In all columns, the dependent variable is a binary indicator equal to one if the firm engages in offshoring in year t, and zero otherwise. Columns (1)–(2) use the main extensive margin measure with the asinh value of robot imports (1,000 DKK) and its square. Columns (3)–(4) use imports of industrial robots from Germany and Switzerland. Columns (5)–(6) use VITA-validated robot adoption and the sample period is 2018–2022. Columns (7)–(8) use job ads-based robot adoption measures (2007–2022). Columns (9)–(10) restrict the sample to first-time adopters, and column (11) further restricts to first-time offshorers. Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and average work experience and age. Standard errors clustered at the firm level in parentheses. Significance levels: ***1%, **5%, *10%.

despite lower overall adoption rates, showing that the global sourcing implications of automation extend beyond traditional factory-based production. The estimates are furthermore robust to the exclusion of multi-establishment firms, confirming that our findings are not driven by potential measurement error arising from assigning firms to the location of their largest establishment (in terms of employment) in the main analysis. This approach assumes that the largest establishment represents the central decision-making unit for both offshoring and robot adoption, yet the robustness checks indicate that this assumption does not drive our main results.

Additional results, reported in Table A.4 of Appendix A.1, show that the findings are similar when we restrict the sample to the years 2020 through 2022, the so-called pandemic years, during which the debate about reshoring gained traction. Our main results are also confirmed when we focus exclusively on firms that adopt robots at some point during the sample period, excluding never-adopters from the analysis, similarly to the stacked difference-in-differences discussed in Appendix A.4. In addition, re-estimating the models with inverse probability weighting based on propensity scores yields similar results, indicating that selection on observables does not drive our findings. Likewise, the results are robust to using a caliper-based matched sample that only retains treated firms for which non-treated firms exist within a range of 25% of the propensity-score standard deviation (Köymen Özer et al., 2025). Finally, the last two columns of Table A.4 of Appendix A.1 address the concern that the estimated effect of robot adoption may reflect a broader process of firm upgrading or forward-looking strategic reorganization rather than a technology-specific shock. To this end, we conduct falsification tests in which robot adoption is replaced by indicators for new investments in either tangible or intangible fixed assets, capturing general capital deepening and balance-sheet expansion. Unlike robot adoption, these alternative investment measures do not generate economically meaningful increases in offshoring and yield coefficients that are small in magnitude and of opposite sign. This pattern suggests that the main results are not driven by firms' general investment activity or anticipatory restructuring, but are specific to automation through industrial robot adoption.

6 Conclusion

This paper provides new firm-level evidence on the relationship between industrial robot adoption and offshoring. Using comprehensive matched employer–employee and customs data from Denmark between 1995 and 2022, we construct a direct measure of robot adoption based on import transactions and a narrowly defined offshoring indicator derived from product-level trade flows. Our findings reveal that robot adoption is associated with increases in both the likelihood and intensity of offshoring.

To estimate the relationship between adoption and offshoring, we implement multiple empirical strategies. Our static linear models control for a rich set of firm characteristics and fixed effects, while event study specifications allow us to trace the dynamic relationship between adoption and offshoring over time. Both approaches consistently show that robot adoption has a strong and persistent positive association with offshoring. Further, instrumental variable estimates, based on historical local variation in the supply of robot installers, confirm that our main results are not entirely driven by endogeneity or reverse causality.

Crucially, our analysis goes beyond documenting average relationships by examining the channels through which robot adoption is related to global sourcing decisions. When we disaggregate offshoring outcomes along product, destination, and technological dimensions, we find that robot adoption is associated with an expansion of firms' supply chains. Adopting firms offshore a broader range of products, source inputs from a more diverse set of countries, and disproportionately expand offshoring into new and technologically more sophisticated inputs. These patterns are consistent with automation being linked to firms' ability to scale production and manage more complex international sourcing relationships, rather than merely intensifying existing offshoring activities.

Our results are robust to alternative definitions of robot adoption. In particular, the results remain positive and significant when validating the import-based adoption measure using two independent external sources: firm-level survey data from Statistics Denmark's VITA survey and online job vacancy postings.

While our analysis provides clear evidence of complementarity between robot adoption and offshoring, the external validity of these findings should be interpreted with some caution. Denmark is a small, open, high-income economy characterized by high wages, strong specialization in skill- and capital-intensive activities, deep integration into global value chains, and labor market institutions that facilitate adjustment to technological change (Hummels et al., 2014b; Bernard et al., 2017; Gu et al., 2024). In such a setting, automation is likely to raise firm productivity and scale while reducing coordination and fixed costs, which can increase firms' demand for foreign inputs rather than substitute for offshore production stages. Our results are therefore most directly applicable to other small open economies with similar structural features.

Taken together, the evidence indicates that, in contexts similar to the Danish economy, automation is associated with firms' ability to scale and reorganize production across borders, deepening their participation in global value chains rather than triggering reshoring. For policymakers in similar small open economies, the results suggest that robot adoption is likely to reinforce international production fragmentation by lowering coordination costs and expanding firms' capacity to manage diversified sourcing networks. Future research should examine more closely how automation technology shapes the structure of supply chains and what this means for competitiveness, employment, and how the gains from automation are shared across firms, workers, and regions.

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A Appendix

A.1 Additional Tables and Figures

Table A.1: Robot Adoption and Firm Outcomes

	Sales (1)	Size (2)	Productivity (3)	Non-Routine (4)	Routine (5)	Establishments (6)	Offshoring (Ext. Marg.) (7)
Robot adoption	0.100***	0.078***	0.028***	0.025**	-0.002	0.178*	
	(0.008)	(0.008)	(0.008)	(0.011)	(0.008)	(0.095)	
Sales							0.049***
							(0.002)
Size							0.025***
							(0.003)
Non-Routine							0.009***
							(0.002)
Routine							0.002***
							(0.000)
Establishments							0.001**
							(0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes	No
Mean Dep. Var.	17.353	2.695	14.658	2.471	1.813	3.860	0.243
R^2	0.919	0.918	0.812	0.796	0.915	0.828	0.752
N	440,601	440,601	440,601	400,989	401,142	440,601	440,601

Notes: The dependent variable is respectively log sales (column 1), log size (column 2), log productivity (column 3), log number of non-routine workers (column 4), log number of routine workers (column 5), log number of establishments (column 6), and the extensive margin of offshoring (column 7). Robot adoption is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition. In column (1), firm variables include export status, firm size, and a multi-establishment dummy. In column (2), firm variables include log firm sales, export status, and a multi-establishment dummy. In column (3), firm variables include export status and a multi-establishment dummy. In columns (4) and (5), firm variables include log firm sales, export status, firm size, and a multi-establishment dummy. In column (6), firm variables include log firm sales, export status, and firm size. In column (1)-(6), workforce composition controls are included as described in the main text. Standard errors clustered at the firm level are shown in parentheses. Significance levels: ***1%, **5%, *10%.

Table A.2: Robot Adoption and Offshoring: Alternative Definitions of New Products

	Intensive Margin			
	New Products Only (alt. def. 1)	Existing Products Only (alt. def. 1)	New Products Only (alt. def. 2)	Existing Products Only (alt. def. 2)
	(1)	(2)	(3)	(4)
Robot adoption	0.313***	0.102**	0.307***	0.085**
	(0.059)	(0.049)	(0.048)	(0.040)
Firm FE	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	No	No	No
Mean Dep. Var.	14.187	17.410	14.022	17.336
R^2	0.441	0.744	0.397	0.734
N	52,342	51,394	81,260	82,329

Notes: The dependent variable is the log value of offshoring at the intensive margin at the firm level at time t. In columns 1 and 2, we exclude the following years from the sample: 2002, 2004, 2006, 2007, 2009, 2010, 2011, 2012, and 2017. In columns 3 and 4, we classify new products as existing ones if they appear for the first time in the sample period and are offshored by more than 2 firms in the same year (i.e., the first year in which the product code appears in the sample). Robot adoption is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition. All specifications include firm fixed effects, year, 2-digit industry, and municipality fixed effects. Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and average work experience and age. Standard errors are clustered at the firm level (in parentheses). Significance levels: ***1%, **5%, *10%.

Table A.3: Robot Adoption and Offshoring (Subsamples)

	Exclude Copenhagen		Big Firms Only		Firms ≥ 12 Years		Manufacturing Only	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot Adoption	0.078***	0.056***	0.026***	0.018***	0.078***	0.055***	0.033***	0.028***
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Offshoring_{ijt-1}$	No	Yes	No	Yes	No	Yes	No	Yes
Mean Dep. Var.	0.250	0.273	0.466	0.465	0.260	0.278	0.560	0.587
R^2	0.756	0.789	0.771	0.797	0.747	0.786	0.633	0.662
Observations	391,650	320,197	56,877	52,347	349,001	297,439	63,624	54,515

	Services Only		Lagged Adoption		Mono-establishment Firms	
	(9)	(10)	(11)	(12)	(13)	(14)
Robot Adoption	0.097***	0.069***	0.051***	0.027***	0.107***	0.079***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.011)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	Yes	No	Yes	No	Yes
Mean Dep. Var.	0.190	0.208	0.265	0.265	0.226	0.251
R^2	0.764	0.797	0.766	0.788	0.751	0.782
Observations	376,572	304,535	359,281	359,281	135,006	102,351

Notes: The dependent variable is a binary indicator of offshoring at the firm level at time t. Robot adoption is a binary variable indicating whether the firm adopts at least one robot in year t (columns 1–10) or year $t-1$ (columns 11–12). Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy (with the only exception of columns 13 and 14, where we exclude the multi-establishment dummy). Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and workers' average experience and age. Standard errors clustered at the firm level are shown in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Table A.4: Robot Adoption and Offshoring: Adopting Firms, Pandemic Years, Alternative Matched Sample, IPW Specification, and Falsification Tests

	All Robot-Adopting Firms		**Pandemic Years (2020–2022)**		**Alternative Matched Sample**		**IPW Specification**		**Falsification tests**	
	Extensive Margin									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robot adoption	0.057***	0.043***	0.031***	0.031**	0.067***	0.049***	0.073***	0.067***		
	(0.005)	(0.005)	(0.012)	(0.015)	(0.005)	(0.005)	(0.006)	(0.007)		
Investment in Material Assets									-0.002**	
									(0.001)	
Investment in Immaterial Assets										0.002**
										(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. (2-digit), Mun., Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and workforce controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Offshoring_{it-1}$	No	Yes	No	Yes	No	Yes	No	Yes	No	No
Mean Dep. Var.	0.617	0.628	0.259	0.295	0.503	0.510	0.243	0.265	0.243	0.243
R^2	0.602	0.649	0.886	0.931	0.654	0.704	0.798	0.806	0.753	0.753
N	55,959	50,192	45,875	24,072	107,994	98,980	440,601	359,281	440,601	440,601

Notes: The dependent variable is a binary offshoring indicator at the firm level. Robot adoption is a binary variable indicating whether the firm adopts at least one robot in year t according to our main definition. Columns (1)–(2) restrict the sample to robot-adopting firms, columns (3)–(4) restrict to the pandemic period (2020–2022), columns (5)–(6) use an alternative matched sample, columns (7)–(8) present results using inverse probability weighting (IPW), and columns (9)–(10) report falsification tests using indicators for whether the firm has undertaken new investments in tangible (column 9) or intangible (column 10) fixed assets. Firm variables include the log of firm sales, export status, firm size, and a multi-establishment dummy. Workforce composition variables include the share of female, college-educated, and foreign workers; the share of workers in routine-intensive occupations; and average work experience and age. Columns (2), (5), (8) and (10) additionally control for lagged offshoring. Standard errors are clustered at the firm level (in parentheses). Significance levels: ***1%, **5%, *10%.

A.2 Sample selection

This section describes the procedure used to create the matched sample. We begin by estimating firm-level propensity scores that reflect the likelihood of robot adoption, given a rich set of observed characteristics. The estimation is conducted on a sample from which we exclude mono-employee firms, exporters of robots and robot installers, firms with missing values, firms in the wholesale industry specializing in machinery, and firms in 4-digit industries where no robot adoption occurs. The data is split into a training set (70% of the data) and a test set (30%). This split is conducted with stratification on the adoption indicator, ensuring that the share of robot adopters and non-adopters is preserved across both sets. This balanced partition allows the model to learn from a representative mix of treated and untreated firms and ensures that the predicted probabilities of adoption generalize well to unseen data. A Lasso-penalized logistic regression model is estimated on the training set, using 10-fold cross-validation to select the optimal regularization parameter. The model includes a rich set of covariates: log sales, log employment size, export and import status, multi-establishment status, the shares of female, foreign-born, tertiary-educated, and routine-intensive workers, as well as average employee age and work experience. To account for heterogeneous adoption behavior across sectors and time, the model also includes 2-digit industry and year fixed effects. The selected model is then applied to the test set to generate out-of-sample predicted probabilities of adoption (i.e., propensity scores). In the second step, we construct the final analysis sample by combining all treated firms (those that ever adopt a robot during the sample period) with a restricted control group composed only of non-adopting firms whose estimated propensity scores are above the 75th percentile of the year-specific distribution. This restriction ensures that control firms are comparable in terms of their likelihood of adopting a robot, and it reduces imbalance on observables between treated and control groups as highlighted in Table A.5.

Table A.5: Summary Statistics by Robot Adoption and by Match Status

Variables	Adopters	Matched Non-Adopters	Non-Matched Non-Adopters
Female (share)	0.305 (0.190)	0.313 (0.251)	0.389 (0.334)
Foreign (share)	0.064 (0.105)	0.059 (0.117)	0.077 (0.188)
Routine (share)	0.137 (0.197)	0.129 (0.179)	0.075 (0.154)
Tertiary (share)	0.144 (0.183)	0.139 (0.205)	0.131 (0.230)
Work experience (avg.)	19.624 (5.921)	18.145 (6.688)	15.255 (8.239)
Age (avg.)	41.034 (6.260)	40.477 (7.510)	38.721 (9.893)
Sales (log)	17.616 (1.760)	17.330 (1.158)	15.643 (1.296)
Size (log)	3.48 (1.75)	2.79 (1.12)	1.53 (0.97)
Exporter (dummy)	0.734 (0.371)	0.641 (0.479)	0.222 (0.415)
Multi-establishment (dummy)	0.738 (0.439)	0.674 (0.468)	0.532 (0.498)
Number of observations	9,227	431,374	1,910,452

Notes: This table presents summary statistics for firm-year observations over the period 1995–2022. "Adopters" refers to firms that imported at least one industrial robot (product codes 847950 or 847989). "Matched Non-Adopters" are firms that never adopted but were selected using the matching procedure described in the Data section to ensure comparability on pre-treatment covariates. "Non-Matched Non-Adopters" include all non-adopters firms excluded from the final sample. All variables are defined in Table 1.

A.3 Additional Details on the Data

VITA Survey

The VITA (Virksomheders IT-anvendelse) survey is conducted annually since 2018. Firms in the survey are presented with a definition of robots and are asked whether they have been using any of these in the previous year. The survey covers Danish firms with 10 or more employees in all private sectors except the primary industry and the financial industry. It works as a form of rotating panel. Large firms are included every year, smaller firms only at irregular intervals. Overall, about 4,000 firms participate in the survey each year. The response rate is about 95%. Table A.6 shows the performance of the robot import data for the sample of firms participating in the VITA survey. The weighted false positive rate is 7%, the weighted false negative rate is 79%, resulting in an accuracy of 84%.[25]

[25] Using survey weights provided by Statistics Denmark, approximately 12% of firms are robot users according to the VITA survey.

Table A.6: External Validity of Import-Based Robot Adoption with VITA Survey

		Survey		
		Yes	**No**	**Total**
Imports	**Yes**	905	1,202	2,107
	No	1,900	10,138	12,038
	Total	2,805	11,340	14,145

Notes: Cell entries report unweighted counts of firms. The false positive rate (7%), false negative rate (79%), and overall accuracy (84%) reported in the text are computed using survey weights provided by Statistics Denmark.

Job Postings Data

We obtain job vacancy data from HBS Economics for the period 2007 through 2022. We identify firms likely engaged in robot-related activities by analyzing the text of job advertisements. We begin by identifying a core set of robot-related keywords and competencies that frequently co-occur with terms such as "robot" or "CNC" in Danish job postings. These co-occurring terms are identified statistically by comparing their frequency in robot/CNC-related job ads relative to their prevalence in the broader labor market. Based on this analysis, we construct two dictionaries: (1) a "strict" list containing 45 keywords that are highly indicative of robot-related activities (e.g., *robotanlæg*, *maskinautomatik*, *laserskærer*, *robotgriber*); and (2) an "extended" list that includes 72 terms, comprising both the secure keywords and additional terms with a weaker but still meaningful robot association (e.g., *PLC*, *KUKA*, *Mazak*, *Fanuc*, *procesudstyr*, *forstår arbejdstegning*). In addition, we identify a set of 18 job titles that reliably indicate robot use (e.g., *robotoperatør*, *robottekniker*, *CNC-fræser*, *CNC-operatør*). A job posting is then classified as involving robot adoption if it contains at least one keyword from one of the two lists or matches one of the robot-specific job titles. Specifically, we define two binary indicators for each firm-year: (i) a "strict indicator", which is equal to 1 if a robot-related job title or strict keyword is present in any of the firm's job postings in a given year; and (ii) an "extended indicator", which is equal to 1 if a robot-related job title or extended keyword is present in any of the firm's job postings in a given year. Table A.7 shows the performance of the robot import data when combined with

Table A.7: External Validity of Import-Based Robot Adoption with Job Vacancy Data

		Job Vacancy Data Yes	No	Total
	Yes	1,720	8,195	9,915
Imports	**No**	3,928	85,453	89,381
	Total	5,648	93,648	99,296

the job vacancy data. The false positive rate is 9%, the false negative rate is 69%, resulting in an accuracy of 88%.

A.4 Alternative Event Study Design

We re-estimate the dynamic coefficients shown in Section 3.2 using an alternative event definition and control group construction. Instead of defining the event as the year of first robot adoption, we follow Bessen et al. (2025) and identify "robotization spikes" based on sudden surges in robot investment intensity. Specifically, we define a spike year τ for firm i as one in which its real robot import costs relative to total operating costs (excluding robot import costs) are at least three times larger than the average cost share over all other years:

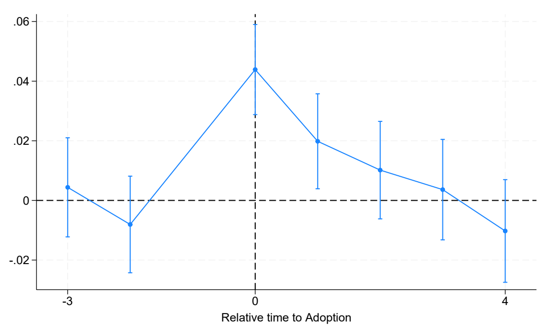
$$\text{spike}_{i\tau} = \mathbb{1}\left\{\frac{RC_{i\tau}}{TC_i} \geq 3 \times \frac{1}{T-1}\sum_{t\neq\tau}\frac{RC_{it}}{TC_i}\right\}, \tag{3}$$

where RC_{it} denotes robot import costs and TC_i is average total operating costs net of robot spending. The adoption event is the first year in which a firm experiences such a spike.

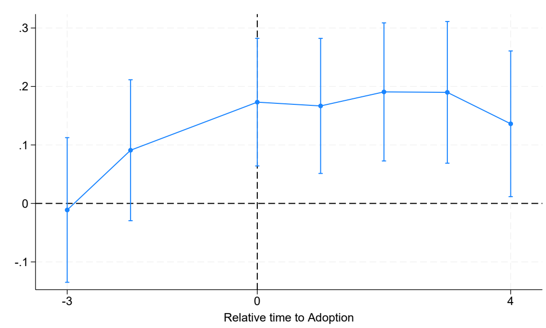
To address concerns about differences between adopters and never-adopters, we use an alternative identification strategy based on a stacked difference-in-differences design. We compare firms experiencing a robot spike in a given year (treated cohort) to firms that will have their first spike at least five years later (later adopters). This alternative control design hinges on the assumption that control firms are on similar pre-trends and are not already affected by robot adoption during the event window. For each treatment cohort, we define an event window of $\tau \in -3, \ldots, 4$, align event time across cohorts, and stack the datasets to estimate a balanced-panel event study.

Panel (a) of Figure A.1 presents results for the extensive margin of offshoring. The coefficients are normalized to zero at $\tau = -1$. The pre-treatment coefficients ($\tau = -3$ to $\tau = -1$) are close to zero and statistically insignificant. In the year of the spike ($\tau = 0$), we observe a statistically significant increase in the likelihood of offshoring of roughly 4 percentage points relative to the pre-spike baseline. This coefficient gradually declines over the subsequent years. Panel (b) of the same figure shows the corresponding estimates for the intensive margin of offshoring. Again, there is no evidence of pre-trends prior to the automation spike. At $\tau = 0$, the point estimate implies an increase of approximately 0.2 log points (about 20%) in offshoring intensity. The coefficient remains positive for several years after the investment spike.

Figure A.1: Robot Investment Spikes and Offshoring: Later Adopters as Controls



(a) Offshoring (Extensive)



(b) Offshoring (Intensive)

Notes: This figure shows event study estimates from a stacked difference-in-differences design, where treatment is defined as the first occurrence of an automation spike in robot investment intensity. Treated firms are compared to firms that experience their first spike at least five years later. We include a full set of cohort by firm fixed effects and a set of 2-digit industry, municipality, calendar year fixed effects. Coefficients are normalized to zero at $\tau = -1$; 95% confidence intervals shown.