Università Politecnica delle Marche

Dipartimento di Scienze Economiche e Sociali

# Automation Imports and Upgrading in Firm Production Networks

Seda Köymen Özer, Alessia Lo Turco, Daniela Maggioni

QUADERNI DI RICERCA n. 495
ISSN: 2279-9575

March 2025

**Abstract**

We investigate how the import of automation impacts upgrading within firm production networks. We use comprehensive data on product mix, foreign trade, balance sheets, employment, and firm-to-firm transactions for Turkish manufacturing firms from 2009 to 2020.
By employing Propensity Score Matching (PSM) alongside event study analyses and an instrumental variable (IV) approach, our research provides robust evidence that firms importing automation enhance the quality and lower quality-adjusted prices of their products. Importantly, the benefits of automation extend downstream throughout the supply chain to firms sourcing inputs from suppliers that have adopted automation. No significant effects propagate, instead, to upstream firms supplying automation adopters.

**JEL Class.:** O14, 033, F61, F63.
**Keywords:** buyer-supplier links, product upgrading, manufacturing, Türkiye.

**Indirizzo:** Seda Köymen Özer - Başkent University, Ankara, Turkey. Email: skozer@baskent.edu.tr
Alessia Lo Turco -Department of Economics Polytechnic University of Marche, Ancona, Italy. Email: a.loturco@univpm.it.
Daniela Maggioni - Corresponding Author: Daniela Maggioni, Department of Economics, Catholic University of the Sacred Heart, Milan, Italy. Email: daniela.maggioni@unicatt.it.

# Automation Imports and Upgrading in Firm Production Networks*

*Seda Köymen Özer, Alessia Lo Turco, Daniela Maggioni*

*The data used in this work are from the Foreign Trada Data, the Annual Business Statistics and the Production Surveys provided by Turkish Statistical Office (TurkStat) and by the Ministry of Industry and Technology. The analysis conducted at the Microdata Research Centre of TurkStat has been in accordance with the law on the statistical confidentiality and personal data protection. The results and the opinions expressed in this article are those of the authors and do not represent the official statistics.*

*The authors thank Pascual Restrepo for kindly providing the HS-2012 codes. The authors also thank participants to the following conferences and workshops: ETSG 2023 Surrey, 64$^{th}$ Annual Conference of the Italian Economic Association, 19$^{th}$ ISGEP conference in Maastricht, Midwest International Trade and Theory Conference 2024 in Rochester.*

# 1 Introduction

The process of firm upgrading is vital for the development of low and middle income countries (Verhoogen, 2023), but it may be hindered by limited local access to advanced knowledge and technologies. To address this challenge, firms in these contexts can source technologies from industrialized countries, thus leveraging some sort of advantages of backwardness. This is particularly relevant for automation technologies, which are largely sourced from industrialized countries that serve as key hubs for their development and innovation.

Automation, such as the use of numerical control machines, Iot sensors and robots, has the potential to significantly change production processes and outcomes, becoming a key driver of production upgrading. In recent decades, the adoption of automation technologies has seen a significant surge. The International Federation of Robotics, for example, reports that the number of robots per 10,000 employees in Europe increased from 88 in 2016 to 129 in 2021 (IFR, 2022), and this upward trend is also evident in middle-income countries (e.g. the case of Mexico after the 2000s, Faber, 2020).

This growing integration of automation into production has drawn considerable attention from economists, leading recent literature to study the impact of robots and automation adoption on both labour markets and firms' economic performance. In this paper, we present, to the best of our knowledge, the first study that investigates the impact of automation adoption on firm upgrading by exploring how automation influences firms' production outcomes and how these effects ripple through the economy via production networks.

Modern industrial automation-related capital goods can be programmed to perform a wide range of tasks with consistent precision, potentially replacing workers who perform similar roles (Artuc et al., 2023). As a result, automation can have disruptive effects on the labour market, particularly when it replaces tasks typically performed by lower-skilled workers. At the same time, automation can enhance productivity, reduce costs, and lead to the improvement of goods produced by firms. By ensuring precision, time savings, and consistency, automation improves manufacturing processes, reduces errors, and minimizes defects. Despite these potential benefits, there is currently little evidence on the impact of automation on firms' production, likely due to the limited availability of highly disaggregated production data as well as information on automation adoption.

Understanding the consequences of automation on production calls for the consideration of the potential propagation of its effects outside the boundaries of the adopting firms. Indeed, if automation fosters quality upgrading and price reduction of adopting firms' products, there is ample scope for a positive trickle-down effect on buyers which employ these products as intermediates and components. The adoption of automation by upstream input suppliers can lead to more efficient production and faster deliveries, which positively affect downstream firms' economic performance by ensuring a timely and consistent supply of inputs. Furthermore, if the adoption of automation contributes to enhanced input quality, then it can positively impact the quality of the final products produced by downstream buyers. Literature, indeed, suggests a significant role of inputs - both domestic and imported - in affecting firm upgrading (Kugler and Verhoogen, 2011; Bas and Strauss-Kahn, 2015; Boehm et al., 2022). Bas and Paunov (2021) show, for example, that firms' output quality is positively affected by the upstream sectors' imports of high-quality inputs. Also, if automation in upstream processes results in cost savings, downstream firms may benefit from lower input costs. This could improve overall cost efficiency and potentially lead to more competitive pricing. Hence, the effects of automation on the product quality and price of firms may flow over to downstream firms.

The expected impact on upstream - adopters' supplying - firms, instead, is less clear-cut. On one hand, the automation-induced product upgrading could drive the demand for higher quality domestic inputs. However, on the other hand, the upgrading could be just associated to internal changes in the procedures and production processes, without involving a change in the types of purchased inputs. Also, automation could even lead to substitution between inputs' internal production and their purchase from third parties.

To thoroughly unravel the complex dynamics of automation on the upgrading of firm production, we focus on the context of the Turkish manufacturing sector for the period 2009-2020. By adopting nearest-neighbor PSM in combination with dynamic event study analysis, we first inspect the direct effect of automation imports on the product quality and quality-adjusted price of adopting firms. Second, we use firm-to-firm transaction data to uncover the upstream and downstream propagation of automation effects through the adopting firms' production network. In this respect, we compare the evolution of product quality and adjusted price of adopters' customers/suppliers with that of customers/suppliers of adopters' matched controls.

Anticipating our findings, firms that start to import automation capital experience quality growth and a decline in the quality-adjusted prices of their products. Importantly, the benefits of automation extend downstream throughout the supply chain to buyers of adopting firms. Instead, no significant effects are propagated to the upstream firms supplying automation adopters.

The emphasis on Türkiye offers, for the first time, a perspective on the consequences of automation for upgrading in an emerging and middle-income country, and this proves advantageous for several reasons. First, the effects of automation can be even more significant and disruptive in the context of emerging countries, compared to the advanced economies typically analysed by the extant literature. And this is particularly relevant for upgrading dynamics, where emerging countries must overcome a lag in technological development. Second, differently from advanced countries, emerging and middle income economies usually purchase a significant portion of their automation-related capital goods from abroad due to their higher technological content with respect to those domestically available. This corroborates the need to investigate the role of automation capital imports in upgrading in the context of a middle income country as Türkiye, and supports the use of imported automation goods to capture the adoption of automation (including robotics) as commonly done in the literature even in the context of advanced economies (Acemoglu and Restrepo, 2020; Bonfiglioli et al., 2024). Specifically, in a robustness check, we show that our results remain consistent even after addressing the potential confounding effect of domestically sourced automation technology, for which we develop a proxy.

By focusing on the sources and network effects of firm upgrading, this work primarily contributes to the literature exploring the implications of granularity and production networks on income and growth (Ciccone, 2002; Acemoglu and Azar, 2020; McNerney et al., 2021). In this paper, we study the interaction of granularity with technology. More specifically, we aim at shedding light on the mechanisms through which automation adoption strategies of a firm can modify its product outcomes - especially in terms of quality and prices - and propagate through its production network with potential positive repercussions on a country's aggregate growth perspectives. In this respect, this paper contributes to extend to a long-term perspective the existing work and evidence on the propagation of shocks and on the importance of second order - through the production network - effects in the business cycle evolution (Baqaee, 2019; Bigio, 2020). Existing empirical work has shown that localised exogenous shocks, such as natural disasters, transmit to firms in other locations through the global production network of firms (Barrot and Sauvagnat, 2016; Bohem et al., 2019; Carvalho et al., 2021). More directly related to our work, Demir et al. (2024) show that a firm-specific export demand shock from a rich country increases the firm's skill intensity and shifts firms toward skill-intensive domestic suppliers in the context of a middle income country, i.e. Türkiye. In a quantitative model with heterogeneous firms, quality choices, and endogenous network, they find that an economy-wide export demand shock of 5 percent induces exporters and non-exporters to raise the average wage by 1.2 percent, that is interpreted being associated to a quality improvement. We add to this literature by inspecting the propagation effects of a firm level technology rather than demand shock and by inspecting in detail product quality and price consequences of this shock.

By identifying technology adoption as automation capital, we also contribute to the recent burgeoning literature on the firm level effects of automation and robotization on productivity (Dixon et al., 2021; Stapleton and Webb, 2020; Koch et al., 2021; Ballestar et al., 2020), employment (Acemoglu et al., 2023; Aghion et al., 2020; Bonfiglioli et al., 2024) and trade (Artuc et al., 2023; Krenz et al., 2021; De Backer et al., 2018; Faber, 2020; Acemoglu et al., 2020; Stapleton and Webb, 2020; Alguacil et al., 2022).[1]

[1]While automation and robotics are closely related, they differ in both technological and procedural terms. Automation refers broadly to the use of technology to perform tasks automatically, while robots specifically are physical machines designed to carry out actions autonomously or semi-autonomously. Our study focuses on the broader economic impact of automation adoption, examin-

This stream of literature, so far, has been largely silent about the consequences of automation adoption for firms' production[2] and supply network. In light of this, the current study seeks to fill this void by conducting an in-depth analysis that extends beyond the existing literature, shedding light on the intricate interplay between automation adoption, firm-level production dynamics, and the configuration of supply networks.

The rest of the paper is structured as follows. Section 2 presents the data and the measurement of variables. Section 3 reports some firm and firm-product level descriptive statistics on automation adoption in Türkiye. Section 4 describes the empirical methodology to detect the direct nexus between automation and firm upgrading and discusses the results and robustness. In Section 5, we extend our focus to the propagation effects through the product network. Finally, Section 6 reports concluding remarks.

# 2 Data sources and measurement of variables

## 2.1 Data sources

In order to implement our empirical analysis on the impact of automation on firm production and supply network effects, we exploit a rich set of information retrieved from different firm-level sources.

We use three administrative firm level datasets provided by and available at the Turkish Statistical Office (TurkStat). The first data set is the Turkish Annual Industrial Product Statistics (AIPS). The AIPS provide insights into firms' production based on the 10-digit PRODTR classification[3]. For each product code, TurkStat collects the value and volume of production and sales over the 2006-2021 period for all firms with more than 20 persons employed in the Turkish manufacturing sector. We exploit this data source to estimate quality and quality-adjusted prices for each firm-product pair. The dataset also allows to obtain a measure of number of products, and newly introduced products at firm level. Second, we exploit firm level Foreign Trade Statistics collected from customs data. This data set enables us to identify all export and import transactions of Turkish firms across 12-digit GTIP

ing a range of capital goods associated with automation, including but not limited to robots.

[2]Macro level evidence seems to suggest the existence of a positive nexus between automation and robotics and quality of production (DeStefano and Timmis, 2024). At the micro level, Aghion et al. (2020) demonstrates a decrease in export prices for French exporters after investments in modern manufacturing capital. However, they do not delve into the impact on product quality, do not investigate the propagation of the effect and focus on an advanced country.

[3]The PRODTR, 2017-2018 update, is a national product classification whose first 6-digits correspond to CPA (Classification of Products by Activity) codes (the last 4 digit are national) and which includes about 3,700 different products.

products (where the first 6 digits correspond to HS codes) and destination/origin countries. This information is key for our empirical analysis to retrieve the imports of automation-related capital products as explained in the following subsection. Third, TurkStat provides balance sheet data from 2009 onward which allow us to get information on firm-level sales and costs, financial variables, as well as NACE sector of activity and province of location. Balance sheet data are complemented by Structural Business Statistics (SBS) which provide further relevant firm level economic variables such as employment.

To analyse the propagation of automation effects through a firm's production network, we use data on firm-to-firm transactions available at the Ministry of Industry and Technology (MoIT) for the period 2006-2020. This data set encompasses all domestic transactions involving a seller-buyer pair with transaction amounts exceeding 5,000 Turkish liras.[4] This additional data source is key for the analysis of the propagation of automation effects through the supply networks as it allows to identify suppliers and customers associated with each firm and their economic relevance. From the MoIT we can also access information regarding firm-level trade flows, workforce composition and balance sheet. Therefore, although the Turkstat sources cannot be combined with those of the MoIT, we are still able to identify the firms that adopt automation and to analyse the effects on the upgrading of the production of their suppliers and customers. More specifically, as information on firm-product level production is not available at the MoIT, when analysing propagation effects we proxy information on the product quality and adjusted price of automation adopters' customers and suppliers with information on the quality and adjusted price of 6-digit 2007 HS exported products. In this part of the analysis, we will exclude firms that export less than 10% of their sales, as for these smaller exporters the export basket may not accurately reflect their production quality and price.

Combining the sources at our disposal, our starting sample for the direct effect of automation adoption is made up of more than 38,000 manufacturing firms with more than 20 employees operating in Türkiye between 2009 and 2020 and for which we can observe production data and relevant economic variables that will enter our analysis.

## 2.2 Identifying automation imports and automation adoption

The adoption of automation-related capital goods has experienced an upsurge in the last two decades. Firm level information on this adoption is usually collected by means of surveys, that do not cover the whole population of firms. One of the few exception is the paper by Acemoglu et al. (2022) which, for the US case, exploits the Annual Business Survey but focus just on one year. Thus, most of the existing literature on the study of automation technologies rests on imports of selected product categories as a proxy of their adoption. This strategy is jus-

[4]The threshold was slightly higher - 8.000TL - in 2008/2009.

tified by the consideration that the supply of industrial robots as well as of other automation-related capital goods is highly concentrated in few actors in the world and, importantly, in few exporting countries. To measure automation capital, we then pursue this strategy and follow Acemoglu and Restrepo (2022) by taking their list of HS-2012 product codes that identify automation capital goods.[5] We then convert HS-2012 (as well as HS-2017) codes to HS-2007 codes by resting on the UNCTAD official conversion tables and retain just codes related to capital goods (based on the BEC4 classification). By exploiting firm level trade data at HS product level, we then identify import flows of automation-related capital goods, thus ending up with a measure of firm level automation imports. More specifically, since imports of automation-related capital goods represent fixed investments that are expected to play a role in the following years, we build a measure of the capital stock of imported automation-related capital goods at the firm level. We sum up the real investments in automation over time and we apply a 10% depreciation rate. We then define a dummy, $adopter_{it}$, that takes value one when firm $i$ shows a positive value of automation capital stock at time $t$ and zero otherwise.
In emerging economies, such as Türkiye, a significant portion of automation technologies is typically imported and the use of imports of these specific products can be considered a reliable proxy for automation adoption in the Turkish context. Aggregate trade data (WITS-COMTRADE) supports a high concentration of the supply of automation-related capital goods in few countries, namely Germany, Japan, United States, China, Italy, South Korea, Netherlands and Singapore. Within this context, Türkiye plays a minor role as a producer of these capital goods. Furthermore, even though we cannot observe the adoption of domestically produced automation-related capital goods, it is highly likely - particularly in the case of Türkiye - that these goods are of lower quality and performance compared to their imported counterparts.

## 2.3 Measuring product quality and adjusted price

To retrieve a measure of quality at the firm-product level, we adopt the methodology proposed by Khandelwal et al. (2013). Exploiting the AIPS firm-product level dataset, we estimate the following equation:

$$lnq_{ipt} + \sigma_s lnp_{ipt} = \alpha_p + \alpha_t + \epsilon_{ipt} \tag{1}$$

where $q_{ipt}$ and $p_{ipt}$ are the quantity and price (unit value) of a 10-digit product $p$ produced by firm $i$ at time $t$ and $\sigma_s$ is the median elasticity of substitution at sector

[5]To better isolate the impact of automation capital, we retain the subset of capital goods from their original list of 142 HS codes, based on the BEC classification. This led to the exclusion of 29 codes related to generic goods, which are minor parts and accessories of automation capital. For example, we excluded the code 845230, which refers to *Sewing machine needles*.

$s$ (the 2-digit NACE Rev. 2 which product $p$ belongs to) level for Türkiye retrieved from Broda and Weinstein (2006).[6]
After estimating equation 1, we take the regression residuals as a measure of the log quality of product $p$ produced by firm $i$ at time $t$, $qual_{ipt}$, and we also compute the quality-adjusted price, $p_{ipt}^{adj}$, by subtracting the log $qual_{ipt}$ from the firm-product log price.

## 3 Automation adoption in the Turkish manufacturing sector

In this section, we provide some descriptive statistics on the automation adoption in the Turkish manufacturing sector. Table A.1 in the Appendix shows the distribution of the total imports of automation capital by manufacturing firms among 2 digit NACE sectors over the sample period between 2009 and 2019. As we can see, most import flows are accounted for by the sectors of Manufacture of textiles (NACE 13), Manufacture of electrical equipment (NACE 27), Manufacture of machinery and equipment (NACE 28) and Manufacture of fabricated metal products (NACE 25). These statistics reflect in part the economic relevance of these sectors within the Turkish manufacturing. When we look at the firm propensity to import automation capital, in Table A.2 in the Appendix we find that the highest percentages of automation importers are recorded by Manufacture of basic pharmaceutical products (NACE 21), Manufacture of computer, electronic and optical products (NACE 26), Manufacture of machinery and equipment (NACE 28), Manufacture of motor vehicles, trailers and semi-trailers (NACE 29), Manufacture of other transport equipment (NACE 30). Thus, for the whole population of firms in the Turkish manufacturing, a firm's probability to import automation in a given year is on average equal to 1.57%.

A similar ranking across sectors is confirmed when we restrict the sample to firms with more than 20 persons employed, which is the relevant sample of our analysis and for which production data are collected. As we can see from column 2 of the Table, in this sub-sample of relatively larger firms the propensity to adopt imported automation technologies increases to 15%.
We then present some preliminary evidence on the premia experienced by automation adopters, both for some selected firm level characteristics and for product quality and price. We estimate the following regressions:

$$\begin{aligned} y_{it} &= \alpha + \beta adopter_{it} + \gamma size_{it-1} + \lambda_i + \mu_t + \epsilon_{it} \\ y_{ipt} &= \alpha + \beta adopter_{it} + \gamma size_{it-1} + \lambda_{ip} + \mu_{pt} + \epsilon_{ipt} \end{aligned} \tag{2}$$

where the dependent variable is either a firm level characteristic $y_{it}$ - size, sales, total factor productivity (Ackerberg et al., 2015), import and export status of firm

[6] We converted SITC codes into NACE codes.

$i$ at time $t$ - or firm-product level measures of quality and quality-adjusted price, $y_{ipt}$. Our variable of interest is the the dummy $adopter_{it}$ which denotes those firms with positive automation capital stock, as explained in subsection 2.2. In the regressions, we control for the lagged size (log of the number of employees), firm (or firm-product) fixed effects and 4digit NACE-year (or product-year) fixed effects.

Panel A of Table A.3 in the Appendix shows the premia enjoyed by automation adopters for firm level indicators. We observe that, compared to non-adopters, automation adopters are larger, record larger values of sales, are more involved in import and export activities and are more productive.

We then move to explore firm-product level characteristics, i.e. quality and quality-adjusted price, in Panel B. Automation adopters produce products characterised by a higher quality and charge lower quality-adjusted prices. This is confirmed when we control for firm-product and product-year fixed effects. Since our measure of automation is based on imports, we also replicate these descriptive statistics for the sample of importers and we get a similar evidence (columns 5-8).

# 4 The direct effects of automation on firm product quality and prices

## 4.1 Empirical strategy

Since the decision to adopt any technology is not random, we implement a propensity score matching approach (PSM) combined with event study analyses to test the direct causal impact of automation imports on the quality and prices of products in adopting firms.

Automation is considered a treatment a firm may undergo, and we focus on the sample of firms that start importing automation and those that never import such technologies during the period of our analysis. A firm is defined as starting to adopt automation if it registers an import flow of automation related capital goods at time *t*, having not imported such goods in at least the three preceding years, and in any earlier year for which data is available.[7] We just retain firms that remain in the dataset and are active in the year following the adoption, or the matching in case of a control firm.

Considering that the initial data availability spans from 2009 to 2020, we identify eight distinct cohorts of adopters ranging from 2012 to 2019.

In order to compare treated and control firms that are similar in their probability to overcome national borders and access goods from foreign markets, the control group is made up of firms that never adopt imported automation and, nonetheless,

[7] This corresponds to firms registering a value 1 in the dummy $adopter$ in $t$ and 0 for at least the three preceding years and in any preceding year we observe the firm.

have imported any kind of goods at least once in the period of our analysis (Acemoglu et al., 2023).[8]

We further exclude from the sample of adopters and potential controls those firms that in the same year start importing intermediates or any kind of other - not automation-related - capital goods for the first time in our sample (and were not importing those goods in the previous year). This allows us to isolate the role of imported automation.

Through PSM, we then select as control firm the nearest neighbour among those firms in the same 3-digit NACE sector and year which never import automation in the period of our analysis on the basis of a predicted propensity score. The propensity score is obtained from a probit model of importing for the first time automation-related capital goods where the following firm level variables measured at time *t-1* are considered as determinants: employment, sales, TFP level, unit labour cost, total fixed assets, number of products in the firm basket, export status, import status, import share of intermediate goods, import share of capital goods other than automation. For employment, sales and TFP levels we also control for their lag in $t-2$ and $t-3$. We add year fixed effects and 2-digit NACE Revision 2 sector fixed effects.

When implementing the matching, we drop firms active in 4-digit sectors where no firm ever adopts automation technologies in the period of our analysis and in order to exclude poor matches, we apply a caliper equal to 25% of the standard deviation of the propensity score.[9]

In the Appendix, Table A.4 reports the results from the probit regression of the probability to import automation-related capital goods for the first time, before and after the matching. This set of results corroborates the validity of our matching procedure as by focusing on the matched sample no pre-treatment covariate significantly predicts the probability of importing automation for the first time and the $R^2$ is statistically near to zero. The validity of the matching is also confirmed when looking at the balancing tests of pre-treatment covariates before and after matching (Table A.5), as well as the distribution of the propensity score of treated and control firms before and after the matching (Figure A.1).

The empirical analysis of the automation-production nexus is thus based on a dataset comprising 1,358 automation adopters across eight waves, paired with the most comparable controls. By focusing on this matched sample, we investigate the impact of imported automation on the quality and quality-adjusted prices of goods produced by automation adopters in an event study analysis as follows:

$$y_{ipt} = \alpha_{ip} + \sum_{l=-3}^{5} \mu_l D_{it+l} + \lambda_t + \epsilon_{ipt} \qquad (3)$$

where $y_{ipt}$ is a firm-product level outcome variable, either the quality or the quality-

[8]Our results are robust when we expand the sample of control firms to non importers.

[9]We tried different values and without applying any caliper and results are unaffected.

adjusted price of product $p$ produced by firm $i$ at time $t$, and $D_{it+l}$ is a set of dummy variables which denote the time to treatment for the treated firms. We include firm-product fixed effects ($\alpha_{ip}$), time fixed effects ($\lambda_t$) and relative time period dummies.

For the event study analysis, our preferred approach is the one recommended by Sun and Abraham (2021), which accommodates heterogeneity in dynamic absorbing treatment effects across waves of adoption. We consider a 9 year time window from three years before the adoption till five years after the adoption. We cluster standard errors at firm level, as automation adoption is a firm level treatment.

In order to test the robustness of our findings, we will also rest on different empirical approaches, which are the estimators suggested by Borusyak et al. (2024), by Callaway and Sant'Anna (2021), as well as the two-way fixed effects OLS.

## 4.2 Event study results

Figure 1 provides evidence of a process of quality upgrading triggered by automation. Panel *a* plots coefficient estimates and 90% confidence intervals from model 3 showing that one year after the adoption, product quality increases by approximately 8%on average, with further improvements in the following year.[10] After importing automation, firms produce products which are characterised by a quality level that is about 15% higher between $t + 2$ and $t + 5$.

In panel *b* we find that automation also contributes to a reduction in the quality-adjusted price of products. This effect is likely to originate from cost savings achieved through automation, as increased efficiency and productivity can lead to lower production costs. The adoption of automation technologies allows firms to streamline processes, to enhance production capabilities, and ultimately to offer products at a more competitive price without compromising quality. The effect is significant right at the adoption year and further improves afterward. In terms of economic magnitude, we detect a reduction by 8% of the quality-adjusted price after two years from the adoption, an effect that persists in the following years.

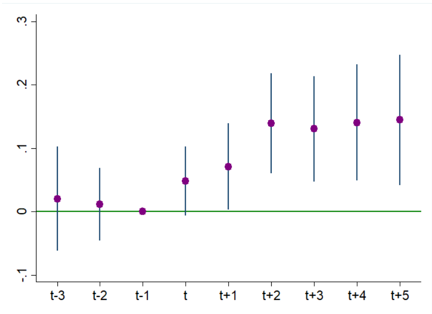
Similar results are obtained when we just focus on the three most significant products in terms of firm production share in the year before the adoption (panel *c* and *d* of Figure 1).

The evidence presented above also suggests the importance of identifying quality levels and quality-adjusted prices and focusing on their separate evolution. Indeed, relying on the observed unit values (production value divided by quantity) reveals much milder effects of automation, as shown in the Appendix in Figure A.3. The estimates of the effects are also imprecise.

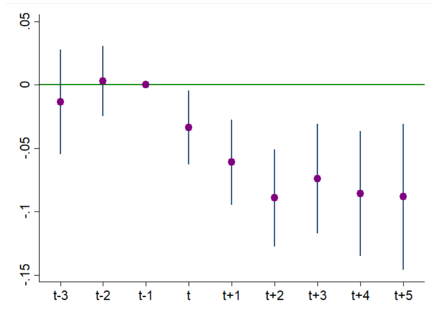
Extending our focus to include additional outcomes associated with firm production activity, we find a within-product increase in the quantity produced by the firm even if the effect is not precisely estimated (see Figure 2a). Instead, we do not find

[10] The 95% confidence intervals are shown in Figure A.2 in the Appendix.

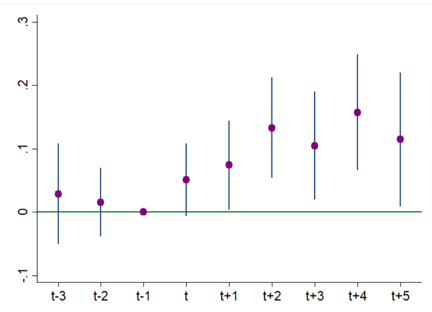
Figure 1: Automation and firm product upgrading



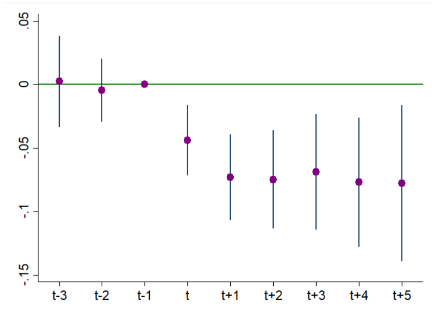

(a) Quality - All products




(b) Quality-Adjusted Price - All products




(c) Quality - Top 3 products



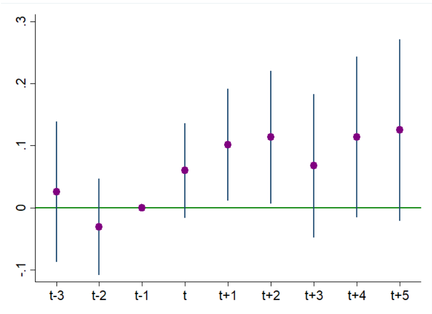

(d) Quality-Adjusted Price - Top 3 products

Observations: 29.568 in (a) and (b); 18.114 in (c) and (d). Figures (a) and (b) report estimates of the response of firm product quality and quality-adjusted price, respectively, to automation imports and pre-trend coefficients, using specification 3 with the estimator proposed by Sun and Abraham (2021). Figures (c) and (d) replicate the same analysis on the sub-set of the top three products. Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

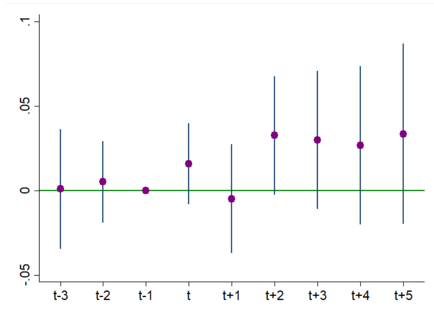
any significant effect on product scope, the introduction of new products,[11] and a change in the product diversification, as measured by the Herfindahl index computed across products (see Figures 2b, 2c and 2d). Therefore, automation adoption drives within-product changes rather than between-product changes within a firm. The upgrading process that we highlight occurs together with a general improvement of firms' economic performance. In the Appendix, in figure A.4 we report the event studies for a number of firm level outcomes. Following automation adop-

[11] We show in the text the impact on the number of new products, but a similarly non-significant effect is observed when considering the share of production accounted for by new products, as well as their share relative to all current products or to those from the previous year.

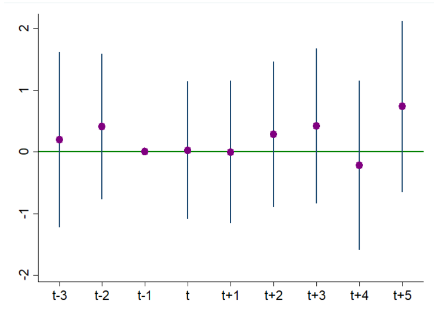
Figure 2: Automation and other changes in firm production



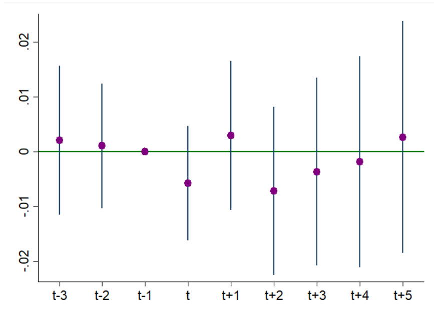

(a) Product level Quantity




(b) Product scope




(c) Newly introduced Products




(d) Herfindahl index across products

The Figure reports the impact of automation imports on the log of the produced quantity at firm-product level (a), the log number of products in the firm portfolio (b), the log of newly introduced products (c), the Herfindahl index across products (d). Firm-product fixed effects (firm fixed effects in panels b,c,d), time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

tion, firms experience an increase in their scale - both in terms of employment and sales - and enjoy productivity gains. In terms of input use, they become more capital intensive and pay higher wages. Figure A.5 further shows a change in the age composition of the workforce. By exploiting employer-employee data made available from the MoIT, we find an increase in the employment of young people (under 35 years old) and a (slight) decrease in the employment of older people (over 50 years old), both measured as a share with respect to total employment.[12]

[12]While we have employer-employee data for the whole period of our analysis, information on the occupational codes is not reliable till 2017. This prevented us from conducting any more detailed analysis of the effects of automation on the task composition of the adopting firms.

### 4.3 Sensitivity Checks

To assess the robustness of the above findings we run a large set of sensitivity checks available in the online Appendix that confirm our baseline findings and are listed here.
***Alternative matching procedure*** - i) we repeat the PSM procedure with a less demanding selection of controls by applying no caliper; ii) we repeat the PSM procedure with a more demanding selection of controls that is based on a narrower caliper equal to 10% of the propensity score standard deviation; iii) we run the matching at the 4- rather than 3-digit industry level as well as at the 2-digit level.
***Firm sample definition*** - i) we exclude those firms which record exports of automation-related capital goods in our sample period; ii) we expand the control group to include all firms, rather than limiting it to importers only (i.e., firms importing at least once along their life); iii) we define as treated firms just those firms with relevant investments in automation and we test for different thresholds.
***Event Study Analysis*** - i) we use different estimators (Borusyak et al., 2024, Callaway and Sant'Anna, 2021 and the two-way fixed effects OLS); ii) we just focus on products produced in the pre-treatment period (one, two, or even three years before automation); iii) we control for the lagged share of the product over the total firm production as a covariate; iv) we control for 10digit PRODTR product-year fixed effects; v) we extend the pre-treatment period to 4 and 5 years before the matching.
***Quality estimation*** - we get quality and quality-adjusted price measures when equation 1 is i) run on production values deflated by employing 3-digit sectoral deflators; ii) run on separate regressions by 2-digit NACE sector.

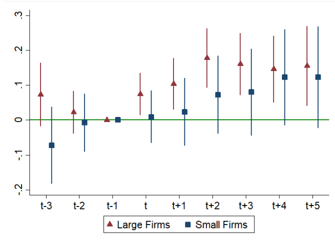
### 4.4 Heterogeneous effects across firms

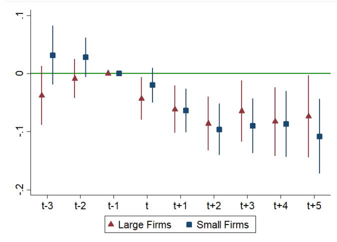
In this section, we test whether automation adoption plays a different role for firms that are heterogeneous in a number of dimensions. We split the sample of treated firms into two groups of firms presenting values above or below the median of the following variables in the pre-treatment year ($l = -1$): size, unit wage, capital intensity, total factor productivity. The results of these analyses are reported in Figure 3. Automation fosters the quality upgrading process, especially for large firms and high-wage firms. Instead, there are no large differences according to the initial capital intensity and the firm's productivity. The reduction of price following automation is, instead, a common effect among all firms, even if with some mild differences. Low-productivity firms, in particular, enjoy a faster reduction in their prices.
Interestingly, automation is beneficial for firms that start with a lower intensity of capital. The use of such capital goods could be especially disruptive for the production processes and performance of firms that were previously relying on more labour intensive production techniques.[13]

[13] In a robustness check, we also test whether firms that import robotics in any period after the first-time automation investment (since l=0) present an evolution of their products' quality and quality-

Figure 3: Automation and firm product upgrading: heterogeneity across firms

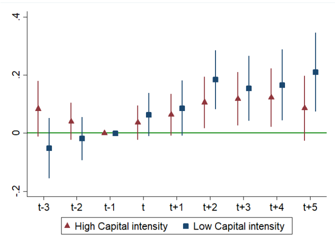
**A - Small vs Large Firms**

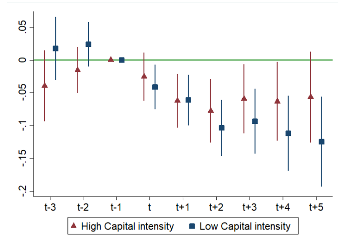



Quality Quality-Adjusted Price

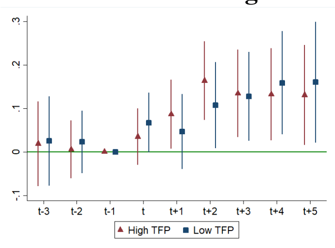
**B - High vs Low Capital Intensity Firms**

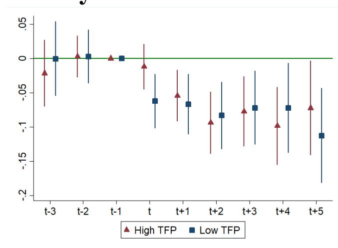



Quality Quality-Adjusted Price

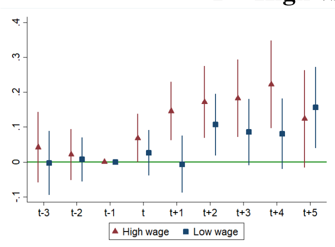
**C - High vs Low Productivity Firms**

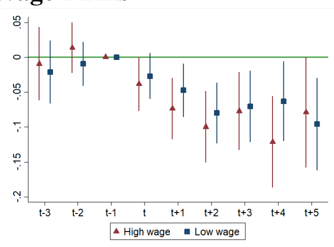



Quality Quality-Adjusted Price

**D - High vs Low-Wage Firms**




Quality Quality-Adjusted Price

The Figure replicates the baseline event study analysis by splitting between firms that in the pre-treatment year ($l = -1$) were displaying a value above or below the median for: size (Panel A); capital intensity (Panel B); tfp (Panel C); unit wage (Panel D) . Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

## 4.5 Accounting for endogeneity issues - placebo tests and an IV approach

To further take into account the potential endogeneity concerns associated with firms' decision of importing automation, we implement a placebo test. We randomly assign the treatment status and year to automation adopters and control firms, that is we allow automation adopters to act as control units and control firms to be treated units. The results, presented in Figure A.6 in the appendix, show no significant effect, either for quality or for quality-adjusted price, associated with this random treatment.[14]

We then move to an instrumental variable (IV) approach. We rest on the strategy used by existing works on the effects of robot adoption which exploits sector and time variation of robot adoption observed in other countries with comparable income levels or that are ahead in the use of robotics (Acemoglu and Restrepo, 2020; Acemoglu et al., 2023). Building on this literature, we exploit the availability of French micro-level trade and production data (trade and PRODCOM data made available by INSEE), which enable us to observe imports of automation-related capital goods by French manufacturing firms, based on their product basket. Using these micro-level data, we compute the share of firms importing automation technologies for each 6-digit CPA product. While it is plausible that firms producing the same products across countries exhibit similar propensities to adopt automation, it is highly unlikely that the evolution of automation among French firms is directly affected by changes in the quality and prices of goods produced by Turkish firms.

Therefore, we extend our analysis to include all firms available in our dataset and test whether importing automation leads to changes in the firm-product level quality over a 5-year time interval. Our empirical model becomes the following cross-sectional specification:

$$\Delta^{\tau_1/\tau_0}\ quality_{ip}^{average} = \alpha + \beta Automation_{\tau_1,i} + \epsilon_{ip} \tag{4}$$

where $\tau_1$ is the five-year time span 2015-2019 ($\tau_0$=2010-2014). $\Delta^{\tau_1/\tau_0}\ quality_{ip}^{average}$ is

adjusted price different with respect that of firms that never invest in robotics and import just other kind of automation capital. Despite the small number of firms in the former group, our findings suggest that investing in robotics is significantly associated with higher benefits both in terms of price reductions and in terms of quality upgrading. Results are available upon request.

[14] As a further placebo test, we retain only control firms (non-adopters), consider half of this sample as treated firms and replicate our analysis of the baseline event study. In this case, as well as in the one discussed in the text, we further run placebo tests where the treatment year is assigned to match the distribution of treatment years in our original matched sample. In all placebo tests, no significant effect emerges either for quality or for quality-adjusted price. Results are available upon request.

the change between $\tau_1$ and $\tau_0$ in the average quality of product $p$ produced by firm $i$. A similar analysis is run by focusing on the change in the quality-adjusted-price. Our variable of interest is $Automation_{\tau_1,i}$, a dummy denoting whether firm $i$ has imported automation-related capital goods over the period $\tau_1$.

OLS estimations of equation 4 confirm the positive association of automation adoption on quality upgrading (column 1) and its role in reducing prices (column 3). We then implement an IV analysis, where we instrument the automation adoption of firm $i$ using the average share of French firms importing automation technologies during the time span $\tau_0$ and producing the core CPA product of the Turkish firm $i$ under analysis, as denoted by $\hat{p}$.[15]

As reported in column 2 and 4, IV estimations confirm OLS findings. We find a positive effect on quality upgrading which is larger, thus pointing at a downward bias in the OLS regression. First-stage estimations are available in column 5. The adoption of automation technologies by Turkish firms is positively related to the share of French firms producing the same products and importing automation-related capital goods. The Kleibergen-Paap F-test reported at the bottom of the Table supports the strength of the instrument. Results are confirmed when in Panel B we focus on the subsample of importers.[16]

### 4.6 Automation *versus* other capital goods

To explore whether the beneficial effect on product upgrading is specific to imports of automation-related capital goods only, we further replicate the same PSM strategy explained in section 4.1, but with the treatment being the first-time import of any kind, rather than just automation-related, capital goods. Thus, we end up with a sample made up of two mutually exclusive groups of treated firms - automation adopters and any other kind of capital good adopter - and their matched controls.[17]

On this sample we implement an event study analysis as done in section 4.2, and test for heterogeneous effects associated with the two events. More specifically, we include two sets of dummies $D_{it+l}$ which denote time to the two treatments

[15] A Turkish firm's core product is defined at 6-digit CPA and is the one accounting for the largest share of production in a year. The evidence is unchanged when we build the IV as a simple or weighted average across all goods produced by the firm $i$.

[16] Results are further corroborated when, instead of considering all firms regardless of their automation adoption in $\tau_0$, we just focus on firms that were not importing automation in $\tau_0$. On this sample, the variable $Automation_{\tau_1,i}$ denotes the probability to start importing automation between $\tau_0$ and $\tau_1$. Finally, results are confirmed when we further control for the following firm level covariates all measured in the pre-treatment year 2014: employment, TFP, sales, import dummy, export dummy, unit wage and capital stock. This set of results is available from the authors upon request.

[17] We drop just few firms that start importing both kinds of capital goods at the same year. Re-including them in the analysis does not substantially change our results.

Table 1: An IV approach

| | Panel A: All firms | | | | |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| | ols | 2sls | ols | 2sls | 1st stage |
| | $\Delta^{\tau_1/\tau_0}$ | $quality$ | $\Delta^{\tau_1/\tau_0}$ | $q\text{-}adjusted\, price$ | $Automation_{\tau_1,i}$ |
| $Automation_{\tau\_1,i}$ | 0.221*** | 0.306*** | -0.093*** | -0.218*** | |
| | [0.016] | [0.045] | [0.012] | [0.033] | |
| $shfirms\_Automa^{FRA}_{\hat{p}_i\tau_0}$ | | | | | 0.009*** |
| | | | | | [0.000] |
| Observations | 10.799 | 10.799 | 10.799 | 10.799 | 10.799 |
| Shea | | 0,121 | | 0,121 | |
| 1st stage Ftest | | 548,5 | | 548,5 | |
| | **Panel B: Importers** | | | | |
| | ols | 2sls | ols | 2sls | 1st stage |
| | $\Delta^{\tau_1/\tau_0}$ | $quality$ | $\Delta^{\tau_1/\tau_0}$ | $q\text{-}adjusted\, price$ | $Automation_{\tau_1,i}$ |
| $Automation_{\tau_1,i}$ | 0.203*** | 0.261*** | -0.075*** | -0.171*** | |
| | [0.017] | [0.049] | [0.012] | [0.036] | |
| $shfirms\_Automa^{FRA}_{\hat{p}_i\tau_0}$ | | | | | 0.009*** |
| | | | | | [0.000] |
| Observations | 9.758 | 9.758 | 9.758 | 9.758 | 9.758 |
| Shea | | 0,113 | | 0,113 | |
| 1st stage Ftest | | 456,7 | | 456,7 | |

*Notes:* *** p<0.01, ** p<0.05, * p<0.1.

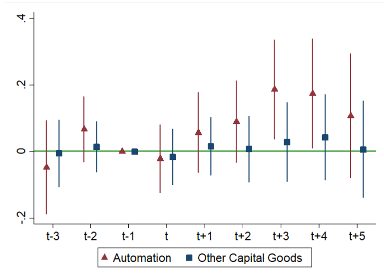
The dependent variable is the change in the average quality (price) of product $p$ produced by firm $i$ between $\tau_0$ and $\tau_1$. $Automation_{\tau_1,i}$ is a dummy denoting whether firm $i$ has imported automation-related capital goods over the period $\tau_1$. The instrument $shfirms\_Automa^{FRA}_{\hat{p}_i\tau_0}$ is the average share of French firms importing automation technologies during the time span $\tau_0$ and producing the core CPA product - $\hat{p}$ - of the Turkish firm $i$ under analysis. Panel A presents the results for the sample of all firms (for which the variables under analysis are available), while Panel B focuses just on importers.

for treated units: import of automation related capital goods; imports of any other kind of capital goods. We thus test whether these two events play a different role on quality upgrading and price reduction.

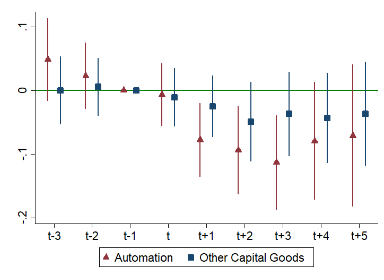
Results from this analysis are reported in Figure 4 which plots the heterogeneous effects of the two treatments on both firm product quality and quality-adjusted price. We consider both all products and the top three products in the firm portfolio (in the pre-treatment period).

Although the effects are less precisely estimated, it is clear that importing automation-related capital goods is a superior strategy compared to importing other types of capital goods in driving the upgrading process and enhancing price competitiveness. Imports of other capital goods show no significant role or only mild effects. The difference between the two events as well as the role of automation is especially straightforward when we focus on firms' top products.

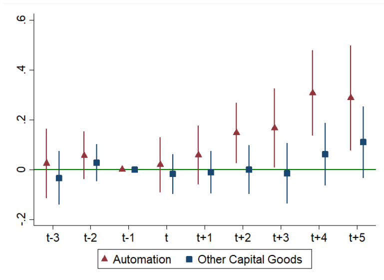
Figure 4: Imports of automation-related capital goods vs. other capital goods



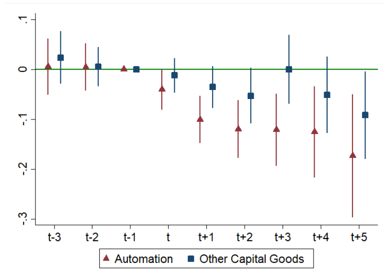

(a) Quality - All products




(b) Q-adjusted Price - All products




(c) Quality - Top 3 products




(d) Q-adjusted Price - Top 3 products

The Figures compare the effect of importing automation-related capital goods (defined according to Acemoglu and Restrepo (2022)), with respect to importing other capital goods on both product quality and quality-adjusted price. Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

# 5 Propagation effects of automation adoption through the production network

## 5.1 The effects on buyers: baseline results

In this section, we proceed to explore whether and how automation, acting as a catalyst for quality improvements and cost efficiencies, extends beyond the firm boundaries, shaping product dynamics within downstream buyers.
The hypothesis is straightforward: since a firm adopting automation improves the quality of its products and enjoys a reduction in their quality-adjusted price, these effects may positively affect the firm's downstream buyers which use these cheaper and better products in their production processes. In order to shed light on these

indirect effects, we exploit the data sources made available by the MoIT, as it provides information on firm-to-firm level domestic transactions which allow us to retrieve the set of suppliers as well as customers for each firm.

We first implement a preliminary analysis aimed at testing how the exposure to automation technologies by suppliers is correlated with the quality and prices of downstream firms' production. We proceed in the following steps. By combining firm-to-firm transactions with firm level trade data, for each firm we identify the set of manufacturing domestic suppliers that are automation adopters - i.e. for which the dummy $adopter_{it}$ is equal to 1 -, compute the total purchases from them and normalise these purchases by the total cost of sales (or the total purchases, or the total sales). We then compute

$$shPurch_{j\ t}^{K\_automation} = \frac{\sum_{i \in \Omega^{adopter}} purchases_{jit}}{costofsales_{jt}}$$

where $purchases_{jit}$ are the total purchases of firm $j$ from suppliers $i$, and $\Omega^{Automation}$ is the set of manufacturing suppliers that are identified as automation adopters.

We then test whether the product quality and quality-adjusted price of manufacturing firms are affected by suppliers' automation adoption. As mentioned in Section 2.1, information on firms' production is not available at MoIT, hence we proxy for the quality and quality-adjusted price of the firm produced goods on the basis of exported products,[18] and we focus on firms exporting at least 10% of their sales.

The preliminary model we estimate is the following:

$$y_{jpt} = \alpha + \beta shPurch_{j\ t}^{K\_automation} + \iota X_{jt-1} + \gamma_{jp} + \phi_t + \epsilon_{jpt}$$

where $y_{jpt}$ is either the quality or the quality-adjusted price of product $p$ exported by buyer firm $j$, and $shPurch_{j\ t}^{K\_automation}$ is the share of purchases that firm $j$ buys from suppliers that are automation adopters. We control for a number of firm level covariates $X_{jt-1}$, as well as for firm-(HS)product fixed effects and year fixed effects.

Results of this analysis are reported in Table 2. We find that firms' exposure to suppliers that adopt automation technologies is positively correlated to the quality of their products and negatively correlated to the quality-adjusted price. These findings are confirmed when, instead of $shPurch_{j\ t}^{K\_automation}$, we test for the average imported automation capital stock across all manufacturing suppliers, $K\_automation_{j,t}^{Suppliers}$. The same significant relations are not disclosed for the average stock of other imported capital goods across manufacturing suppliers, $K\_other_{j\ t}^{Suppliers}$. For the latter, just a weaker significant correlation is displayed with the customers' quality-adjusted price.

[18]The replication of the baseline analysis of the direct automation effects on the quality and adjusted price of exported goods corroborates the validity of this strategy. Results are available in the online Appendix.

Table 2: Suppliers' automation and downstream buyers' quality and prices: preliminary analysis

| | quality | | | quality-adjusted price | | |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| $\text{shPurch}_{i\ t}^{K\_automation}$ | 0.086** | | | -0.103*** | | |
| | [0.036] | | | [0.025] | | |
| $K\_automation_{j\ t}^{Suppliers}$ | | 0.010*** | 0.008*** | | -0.011*** | -0.008*** |
| | | [0.002] | [0.002] | | [0.001] | [0.002] |
| $K\_other_{j\ t}^{Suppliers}$ | | | 0.003 | | | -0.004*** |
| | | | [0.002] | | | [0.002] |
| Observations | 534,762 | 534,762 | 534,762 | 534,762 | 534,762 | 534,762 |
| R-squared | 0.809 | 0.798 | 0.798 | 0.948 | 0.948 | 0.948 |
| firm covariates | yes | yes | yes | yes | yes | yes |
| firm-HSproduct FE | yes | yes | yes | yes | yes | yes |
| year FE | yes | yes | yes | yes | yes | yes |

*Notes:* *** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered at the firm level.

The dependent variable is either the quality or the quality-adjusted price which are estimated at the firm - HS product level and refer to exported products. Regressions are run on the sample of firms exporting at least 10% of their sales. Columns [1] and [4] test the role of $shPurch_{i\ t}^{K\_automation}$, i.e., the share of purchases that firm $j$ under analysis buys from suppliers that are automation adopters. Columns [2] and [5], instead, test $K\_automation_{j\ t}^{Suppliers}$, which represents the average imported automation capital stock across all manufacturing suppliers. Columns [3] and [6] include a similar measure for other imported capital goods, $K\_other_{j\ t}^{Suppliers}$.

The following covariates in $t-1$ are controlled for in the estimation but not reported: export share accounted by the product, importer dummy, productivity, unit wage, sales, capital stock.

The above evidence is in line with potentially significant propagation effects of automation along the supply network. In order to account for endogeneity issues we take a step forward and, on the basis of data available at the MoIT, we match automation adopters to selected control units, closely following the strategy described in Section 4.[19]

For this sample of matched treated and control firms, we identify all manufacturing domestic buyers in $t$, that is the year of the treatment for treated and controls.[20]
Focusing on this sample of buyers, we create a dummy variable, $Exposed_j^{Upstream}$,

[19]The strategy is kept as similar as possible to the one presented in Section 4. However, at MoIT, while we cannot control for the number of products in the firm's basket when estimating the propensity scores, we can control for the supplying industries' routine intensity.

[20]We consider only buyers sourcing at least 1% of their purchases from the selected suppliers in the year of adoption (or potential adoption for matched controls). Buyers for whom firms in the

to categorise them into two exclusive groups: (i) firms that were purchasing inputs in year $t$ from an upstream supplier that started importing automation related capital goods at the same time ($Exposed_j^{Upstream} = 1$); (ii) firms that were purchasing inputs in year $t$ from upstream suppliers that never imported automation technologies ($Exposed_j^{Upstream} = 0$) but are similar to automation-adopting suppliers based on our matching procedure. Few firms purchasing inputs from both automation adopters and their matched controls are excluded from the analysis. We also drop firms in years when they stop buying inputs from the selected sample of suppliers.

To rule out the possibility of differences between the two groups of firms in relevant variables during the period before their suppliers' treatment, Table A.6 in the Appendix shows that there are no substantial significant differences. This reassures us that any difference in the years following the (suppliers') treatment can be attributed to the treatment itself.[21]

We, thus, run a set of event studies with dynamic treatment effects where the treatment is defined as the supplier's adoption of automation, while the control group is made up of buyers that purchase from suppliers matched to those adopting automation. Figure 5 shows our findings. In the upper panel, we consider all buyers sourcing at least $1\%$ of their purchases from the selected firms in the matched sample.[22] In the lower panel, we further restrict the analysis to those buyers sourcing at least 5% of their inputs from the selected firms in the matched sample in the year of adoption (or potential adoption).

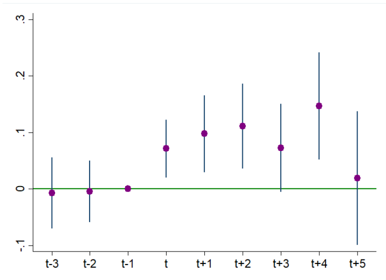
Following the supplier's automation adoption we observe a positive dynamic effect on the quality of goods exported by downstream buyers. Benefits of automation on the price do not seem, instead, to propagate downstream unless the suppliers account for a significant share of the customers' purchases (higher than 5% in the adoption year). In the latter case, a reduction in the price emerges.

matched sample are only minor suppliers are excluded, as their automation activities are unlikely to have a significant impact on the buyers' performance.

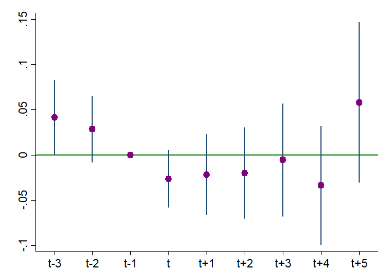
[21] Indeed, the only significant pre-treatment differences are mild and suggest a superiority of buyers of untreated suppliers during the pre-treatment period. Therefore, at worst, this would imply an underestimation of the impact of sourcing from suppliers that adopt automation on buyers' product quality and price.

[22] The analysis is based on more than 214,000 firm-product-year observations, around $58\%$ refer to firms sourcing from adopters, while $42\%$ refer to firms sourcing to non adopters. We end up with 2,340 firms sourcing from firms that start importing automation and 1,759 firms sourcing from firms which never import automation and that are similar to adopters.

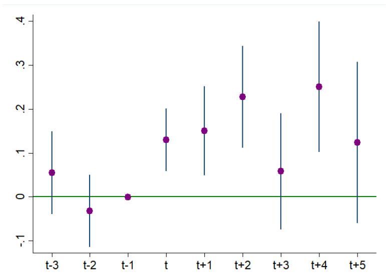
Figure 5: Transmission effects to buyers: an event study



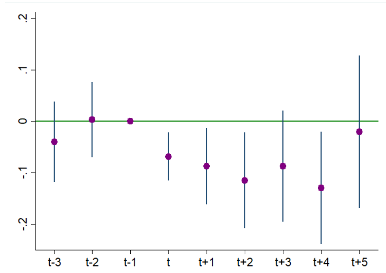

(a) Quality




(b) Q-adjusted Price




(c) Quality - purchase share > 5%




(d) Q-adjusted Price - purchase share > 5%

Observations: 214,957 in the upper panel, and 88,585 in the lower panel. The Figure shows the impact of suppliers' automation adoption as the treatment on the quality and price of buyers' export products. Firm-HSproduct fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

### 5.2 The effects on buyers: sensitivity and placebo tests

Results on the propagation of automation effects on buyers prove robust to a number of sensitivity checks.

***Alternative matching procedure*** - i) we account for the automation adoption by customers and suppliers as additional pre-treatment covariates included in the probit both as a dummy and a measure of automation capital stock; ii) we account for potential domestic purchases of automation-related capital goods in our matching procedure by defining a proxy based on firm-to-firm transaction data and the sector of activity of suppliers. This control helps isolate the role of foreign automation technology. Specifically, in the matching procedure, we include the shares of purchases from potential domestic suppliers of automation-related capital goods in the three years preceding the treatment. Additionally, we refine this approach by excluding firms from the matching that start purchasing goods from these domestic suppliers of automation in the same year as the treatment.[23]

***Sample of buyers*** - i) we consider those buyers sourcing inputs from the selected firms in the matched sample at least in the treatment year and in the previous year, as well as in the treatment year and one year before and after, or three years before and after; ii) we drop buyers that were importing automation in the three years before the supplier's treatment; iii) we consider buyers exporting at least 25% of their sales instead of 10% as in the baseline.

***Event study analysis*** - i) we control for a dummy for buyers that in the post treatment period start adopting automation; ii) we include a set of buyers' variables in the pre-treatment year ($l = -1$) interacted by a time trend among the covariates; iii) we include the share of exports accounted for by each product among the covariates; iv) we control for HS product-year fixed effects; v) we just focus on products that were in the export portfolio of buyers under analysis in the year before the suppliers' treatment, $l = -1$.

All these controls confirm our baseline findings and are reported in the online Appendix.

***Placebo*** - As in the case of the analysis of the direct effect of automation, we implement a placebo test. More specifically, we implement a test based on treatment and time falsification. We randomly assign the treatment status and a treatment year to all buyers included in the above estimation. Figure A.7 in the Appendix show the results from this placebo test: no significant effect is found, either for quality or for quality-adjusted price.[24]

We then test whether product dynamics of firms guide the automation adoption by suppliers. We regress the first-time imports of automation-related capital goods of firm $i$ at time $t$ on the past average change of quality and adjusted price of its customers.[25] The change of product quality (and quality-adjusted price) experienced by (exporting) buyers in $t-1$ is alternatively computed over a 3-year time span, between $t-3$ and $t-1$, over a 4-year time span, between $t-4$ and $t-1$ and over a 5-year time span between $t-5$ and $t-1$. This analysis cannot be extended to firms whose buyers are exclusively non-exporters. As shown in Table 3, in all cases we do not find any significant role of customers' product upgrading (and customers' price reductions) in driving the following automation adoption by suppliers. This evidence, thus, does not support the existence of a potential reverse causality issue.

[23]More details on this procedure can be found in the online appendix.

[24]Alternatively, the treatment is randomly assigned only to buyers sourcing inputs from suppliers that do not import automation (suppliers that are not treated). All placebo tests are implemented without restrictions, however the baseline findings are corroborated when the original distribution of treatment across years is preserved in the assignment.

[25]Each buyer is weighted on the basis of its importance in the supplier i's sales in $t-1$.

Table 3: Buyers' product upgrading and suppliers' first time automation adoption

| | [1] | [2] | [3] | [4] | [5] | [6] |
|---|---|---|---|---|---|---|
| | Dependent Variable: First Time Probability of Importing Automation | | | | | |
| $\Delta\ qual^{Buyers}_{t-1/t-3}$ | -0.020 | -0.026 | | | | |
| | [0.034] | [0.039] | | | | |
| $\Delta\ qual^{Buyers}_{t-1/t-4}$ | | | -0.026 | -0.026 | | |
| | | | [0.034] | [0.038] | | |
| $\Delta\ qual^{Buyers}_{t-1/t-5}$ | | | | | -0.032 | -0.057 |
| | | | | | [0.031] | [0.035] |
| Observations | 26,892 | 24,823 | 24,122 | 22,381 | 21,736 | 20,240 |
| Controls | no | yes | no | yes | no | yes |
| | Dependent Variable: First Time Probability of Importing Automation | | | | | |
| $\Delta\ p^{Adj\ Buyers}_{t-1/t-3}$ | 0.004 | 0.018 | | | | |
| | [0.059] | [0.067] | | | | |
| $\Delta\ p^{Adj\ Buyers}_{t-1/t-4}$ | | | -0.015 | 0.007 | | |
| | | | [0.055] | [0.061] | | |
| $\Delta\ p^{Adj\ Buyers}_{t-1/t-5}$ | | | | | -0.019 | 0.027 |
| | | | | | [0.050] | [0.054] |
| Observations | 26,892 | 24,823 | 24,122 | 22,381 | 21,736 | 20,240 |
| Controls | no | yes | no | yes | no | yes |

*Notes:* *** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered at the firm level.

The dependent variable is the probability of importing automation for the first time, defined for firms that have never adopted automation until $t-1$. This is the same variable used to estimate the propensity score in the matching approach. $\Delta\ qual^{Buyers}$ ($\Delta\ p^{Adj\ Buyers}$) represents the average change in product quality (quality-adjusted price) experienced by (exporting) buyers in $t-1$, computed over different time windows (t-3/t-1, t-4/t-1, t-5/t-1). Year and 3-digit NACE sector fixed effects are included in each specification. The following firm-level controls in $t-1$ are included in the estimations of columns [2], [4] and [6]: employment, sales, TFP level and growth, unit labour cost, total fixed assets, export status, import status, import share of intermediate goods, import share of capital goods other than automation, supplying industries' routine intensity.

### 5.3 The effects on suppliers

From a theoretical perspective, the positive effects of automation could also propagate upstream to suppliers, as the automation adoption by downstream firms may call for higher quality inputs. The upstream propagation of the automation-induced price reduction to domestic suppliers is, instead, less straightforward. Automation could rather lead to the replacement of suppliers.

In order to test these hypotheses, we repeat the same event study analysis implemented above, by focusing on suppliers of firms included in the matched sample instead of customers. We substitute $Exposed_i^{Upstream}$ for $Exposed_i^{Downstream}$, a dummy equal to 1 for firms that are suppliers of downstream firms that start importing automation-related capital goods at time $t$, and 0 for those firms that are suppliers of matched control units.

Results in Figure A.8 in the Appendix show that firms' automation adoption has no significant effect on the quality and quality-adjusted price of products exported by their suppliers.

## 6 Conclusions

This study has shed light on the impact of automation adoption on production upgrading in the Turkish manufacturing sector from 2009 to 2020. Building on fine-grained information retrieved from several firm, firm-product and firm-to-firm level data sources, our work has made several key contributions to the understanding of this crucial phenomenon. More specifically, for the first time to our knowledge, we provide evidence on the consequences for a firm's quality upgrading process and price competitiveness as well as on the propagation of these effects along the supply chain.

Automation adoption improves firm-level outcomes, boosting sales, productivity, capital intensity, and overall employment. This aligns with existing research and reinforces the economic benefits of automation.

Importantly, we find that firms adopting automation experience a decrease in the quality-adjusted price of their products and a product quality upgrading.

The positive effects of automation extend beyond the adopting firm. This study reveals that downstream firms whose suppliers adopt automation also experience an improvement of the quality of their products and some evidence also emerges in favour of a reduction in the quality-adjusted price. This effect demonstrates the considerable potential of automation adoption to foster development.

# Appendix

Table A.1: Distribution of automation imports across manufacturing sectors - 2009/2019

| | NACE Rev.2: Manufacture of | % |
|---|---|---|
| 10 | food products | 0.45 |
| 11 | beverages | 0.12 |
| 12 | tobacco products | 0.30 |
| 13 | textiles | 21.23 |
| 14 | wearing apparel | 2.30 |
| 15 | leather and related products | 0.28 |
| 16 | wood and of products of wood | 1.14 |
| 17 | paper and paper products | 0.98 |
| 18 | Printing and reproduction of recorded media | 0.06 |
| 19 | coke and refined petroleum products | 0.59 |
| 20 | chemicals and chemical products | 2.29 |
| 21 | basic pharmaceutical products and preparations | 0.82 |
| 22 | rubber and plastic products | 1.80 |
| 23 | other non-metallic mineral products | 2.95 |
| 24 | basic metals | 3.48 |
| 25 | fabricated metal products | 5.66 |
| 26 | computer, electronic and optical products | 2.74 |
| 27 | electrical equipment | 7.31 |
| 28 | machinery and equipment | 12.82 |
| 29 | motor vehicles, trailers and semi-trailers | 28.94 |
| 30 | other transport equipment | 2.62 |
| 31 | furniture | 0.57 |
| 32 | Other manufacturing | 0.53 |
| | | 100 |

The table reports the distribution of total import flows in automation-related capital goods across 2-digit NACE manufacturing sectors over the period 2009-2019.

Table A.2: Propensity of firms to import automation technologies - by 2 digit NACE sectors, 2009-2019

| NACE Rev.2: Manufacture of | | All firms | Our sample |
|---|---|---|---|
| | | [1] | [2] |
| 10 | food products | 0.44 | 4.57 |
| 11 | beverages | 4.77 | 13.87 |
| 12 | tobacco products | 62 | 25.10 |
| 13 | textiles | 3.85 | 22.89 |
| 14 | wearing apparel | 0.36 | 3.94 |
| 15 | leather and related products | 1.11 | 9.70 |
| 16 | wood and of products of wood | 0.30 | 8.15 |
| 17 | paper and paper products | 3.32 | 12.53 |
| 18 | Printing and reproduction of recorded media | 0.32 | 4.64 |
| 19 | coke and refined petroleum products | 9.13 | 2.41 |
| 20 | chemicals and chemical products | 2.83 | 13.49 |
| 21 | pharmaceutical products | 17.47 | 35.20 |
| 22 | rubber and plastic products | 1.87 | 11.45 |
| 23 | other non-metallic mineral products | 1.57 | 8.25 |
| 24 | basic metals | 4.78 | 19.67 |
| 25 | fabricated metal products | 1.17 | 13.11 |
| 26 | computer, electronic and optical products | 13.28 | 40.28 |
| 27 | electrical equipment | 4.34 | 24.89 |
| 28 | machinery and equipment | 6.38 | 23.74 |
| 29 | motor vehicles, trailers and semi-trailers | 6.65 | 23.85 |
| 30 | other transport equipment | 9.62 | 26.58 |
| 31 | furniture | 0.35 | 5.01 |
| 32 | Other manufacturing | 1.32 | 13.88 |
| | | 1.57 | 13.15 |

The table reports the firm propensity to import automation-related capital goods by 2digit NACE sector over the period 2009-2019. Column 1 shows the propensity computed on all Turkish firms. Column 2, instead, focuses on the sample of firms considered in our analysis, i.e. firms with more than 20 employees for which production data is available.

## Table A.3: Automation Adoption: Premia

PANEL A: firm level variables

| | [1] | [2] | [3] | [4] | [5] | [6] |
|---|---|---|---|---|---|---|
| | *size* | *sales* | *tfp* | *import status* | *export status* | *unit wage* |
| $adopter_{it}$ | 0.162*** | 0.104*** | 0.040*** | 0.180*** | 0.047*** | 0.030*** |
| | [0.008] | [0.008] | [0.006] | [0.006] | [0.006] | [0.003] |
| $size_{i\ t-1}$ | | 0.574*** | -0.060*** | 0.073*** | 0.066*** | 0.019*** |
| | | [0.007] | [0.004] | [0.003] | [0.003] | [0.002] |
| Observations | 234,139 | 210,182 | 195,073 | 211,015 | 211,015 | 211,015 |
| $R^2$ | 0.906 | 0.945 | 0.906 | 0.731 | 0.714 | 0.897 |
| *Fixed effects* | | | | | | |
| Firm | y | y | y | y | y | y |
| 4d sector-year | y | y | y | y | y | y |

PANEL B: firm-product level variables

| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
|---|---|---|---|---|---|---|---|---|
| | All firms | | | | Importers | | | |
| | *quality* | | *quality-adjusted price* | | *quality* | | *quality-adjusted price* | |
| $adopter_{it}$ | 0.232*** | 0.051*** | -0.159*** | -0.041*** | 0.194*** | 0.051*** | -0.140*** | -0.040*** |
| | [0.020] | [0.016] | [0.013] | [0.009] | [0.021] | [0.016] | [0.014] | [0.009] |
| $size_{i\ t-1}$ | 0.313*** | 0.218*** | -0.302*** | -0.196*** | 0.299*** | 0.215*** | -0.290*** | -0.196*** |
| | [0.009] | [0.011] | [0.007] | [0.007] | [0.010] | [0.012] | [0.007] | [0.009] |
| Observations | 312,312 | 292,775 | 312,312 | 292,775 | 254,113 | 238,806 | 254,113 | 238,806 |
| $R^2$ | 0.167 | 0.795 | 0.921 | 0.985 | 0.173 | 0.804 | 0.92 | 0.985 |
| *Fixed Effects* | | | | | | | | |
| firm-product | n | y | n | y | n | y | n | y |
| product-year | y | y | y | y | y | y | y | y |

The table reports the automation premia obtained from the estimation of equation 2 where the dummy variable $adopter_{it}$ identifies firms with a positive imported automation capital stock. All estimations include firm size in $t-1$ as a control (with the exception of column 1 in Panel A). The set of fixed effects included in the estimations is reported at the bottom of each panel.

Panel A presents premia for the following firm level variables: *size* is the log of firm employees; *sales* is the log of sales; *tfp* is obtained following Ackerberg et al. (2015) and using intermediates as a proxy; *import/export status* is a dummy variable taking value 1 if a firm import purchases/export sales are higher than 0 and takes value 0 otherwise; *unit wage* is the log of total wages divided by employment.

Panel B presents premia for firm-product quality and quality-adjusted price that are reported for all firms with available production data and separately for importers (firms that import at least once according to available data).

Table A.4: Predicting the first-time probability of importing automation - unmatched and matched sample

| | Unmatched Sample [1] | Matched Sample [2] |
|---|---|---|
| $lab_{t-1}$ | 0.024*** | -0.066 |
| | [0.005] | [0.062] |
| $lab_{t-2}$ | -0.01 | -0.004 |
| | [0.007] | [0.088] |
| $lab_{t-3}$ | -0.003 | 0.026 |
| | [0.005] | [0.059] |
| $tfp_{t-1}$ | -0.001 | -0.043 |
| | [0.004] | [0.042] |
| $tfp_{t-2}$ | 0.000 | -0.034 |
| | [0.004] | [0.049] |
| $tfp_{t-3}$ | -0.001 | 0.036 |
| | [0.003] | [0.037] |
| $sales_{t-1}$ | 0.018*** | 0.004 |
| | [0.004] | [0.043] |
| $sales_{t-2}$ | -0.008* | 0.014 |
| | [0.004] | [0.051] |
| $sales_{t-3}$ | -0.009*** | 0.015 |
| | [0.003] | [0.042] |
| $import\_dummy_{t-1}$ | 0.024*** | 0.038 |
| | [0.002] | [0.024] |
| $export\_dummy_{t-1}$ | 0.005** | -0.019 |
| | [0.002] | [0.022] |
| $unit\_wage_{t-1}$ | 0.024*** | -0.052 |
| | [0.003] | [0.037] |
| $capital_{t-1}$ | 0.009*** | 0.011 |
| | [0.001] | [0.014] |
| # $products_{t-1}$ | -0.002 | 0.008 |
| | [0.001] | [0.016] |
| $imp\_share_{t-1}^{intermediates}$ | 0.044*** | -0.038 |
| | [0.007] | [0.080] |
| $imp\_share_{t-1}^{otherK}$ | 0.168*** | -0.308 |
| | [0.021] | [0.291] |
| Observations | 38,137 | 2,716 |
| Pseudo-$R^2$ | 0.164 | 0.004 |

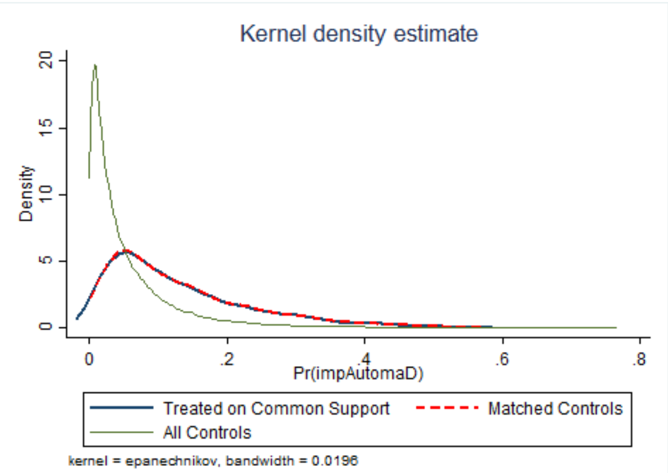
Standard errors in brackets: *** $p < 0.01$; * $p < 0.05$, * $p < 0.10$. Column [1] reports the results of the probit regression used to predict the propensity scores that are exploited in the matching strategy. Column [2] shows the results of the same regression run on the matched sample made up of treated firms on the common support and their matched controls.

Table A.5: Balancing Tests of covariates

| | Unmatched Sample | | | Matched Sample | | |
|---|---|---|---|---|---|---|
| | Treated firms | Control firms | t | Treated firms | Control firms | t |
| $\text{lab}_{t-1}$ | 4.013 | 3.817 | 11.69 | 3.920 | 3.926 | -0.22 |
| $\text{lab}_{t-2}$ | 3.930 | 3.784 | 8.75 | 3.843 | 3.843 | 0.03 |
| $\text{lab}_{t-3}$ | 3.832 | 3.724 | 6.24 | 3.750 | 3.744 | 0.24 |
| $\text{tfp}_{t-1}$ | 8.809 | 8.788 | 1.04 | 8.754 | 8.747 | 0.21 |
| $\text{tfp}_{t-2}$ | 8.791 | 8.789 | 0.10 | 8.740 | 8.734 | 0.18 |
| $\text{tfp}_{t-3}$ | 8.777 | 8.785 | 0.39 | 8.735 | 8.715 | 0.61 |
| $\text{sales}_{t-1}$ | 15.546 | 15.333 | 8.37 | 15.399 | 15.359 | 1.09 |
| $\text{sales}_{t-2}$ | 15.418 | 15.270 | 5.85 | 15.279 | 15.234 | 1.18 |
| $\text{sales}_{t-3}$ | 15.265 | 15.173 | 3.57 | 15.140 | 15.084 | 1.43 |
| $\text{import\_dummy}_{t-1}$ | 0.785 | 0.509 | 22.60 | 0.740 | 0.716 | 1.38 |
| $\text{export\_dummy}_{t-1}$ | 0.703 | 0.589 | 9.48 | 0.675 | 0.687 | -0.66 |
| $\text{unit\_wage}_{t-1}$ | 9.140 | 9.082 | 7.18 | 9.090 | 9.099 | -0.67 |
| $\text{capital}_{t-1}$ | 14.321 | 13.919 | 13.97 | 14.184 | 14.148 | 0.91 |
| # $\text{products}_{t-1}$ | 0.504 | 0.666 | 8.75 | 0.499 | 0.487 | 0.45 |
| $\text{imp\_share}_{t-1}^{intermediates}$ | 0.089 | 0.041 | 17.28 | 0.068 | 0.067 | 0.26 |
| $\text{imp\_share}_{t-1}^{otherK}$ | 0.015 | 0.004 | 17.35 | 0.009 | 0.010 | -0.7 |

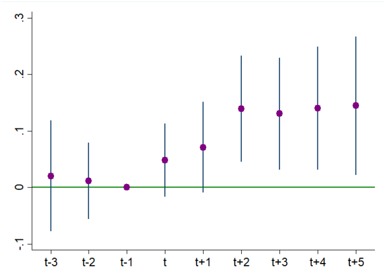
Statistics for treated firms differ between the unmatched and matched samples due to some treated firms (381 firms) being out of the common support and which cannot be matched with any control unit.

Figure A.1: Propensity Score distribution - unmatched and matched sample

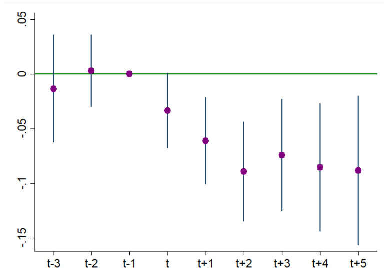



The figure shows the propensity score distribution of the three following samples: treated firms (firms that start importing automation) on common support; all control firms (non adopters); control firms that are matched with treated firms.

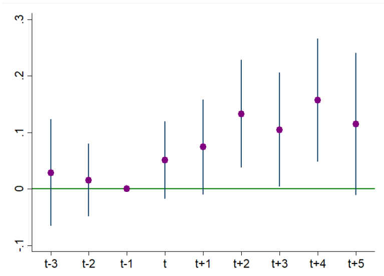
Figure A.2: Automation and firm product upgrading - 95% confidence intervals



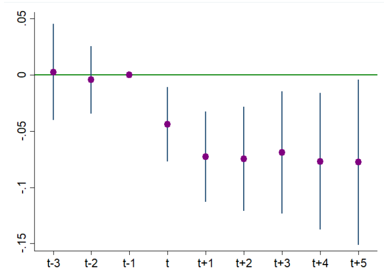

(a) Quality - All products




(b) Quality-Adjusted Price - All products



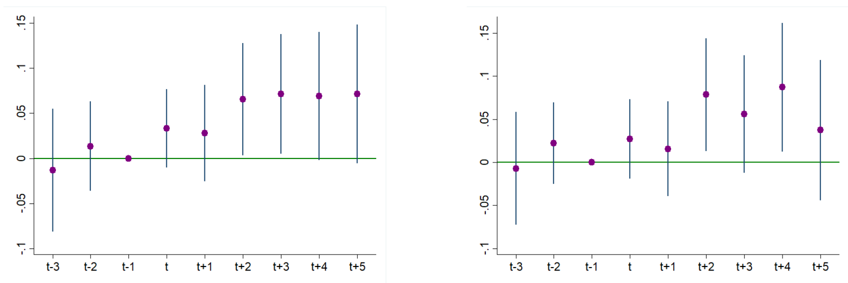

(c) Quality - Top 3 products




(d) Quality-Adjusted Price - Top 3 products

Observations: 29.568 in (a) and (b); 18.114 in (c) and (d). Figures (a) and (b) report estimates of the response of firm product quality and quality-adjusted price, respectively, to automation imports and pre-trend coefficients, using specification 3 with the estimator proposed by Sun and Abraham (2021). Figures (c) and (d) replicate the same analysis on the sub-set of the firm's top three products in its basket. Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 95% confidence intervals are displayed. Standard errors are clustered at the firm level.

Figure A.3: Automation and product unit values

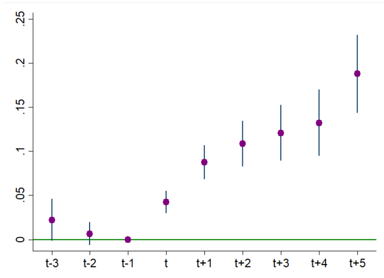



(a) Unit Value - All products

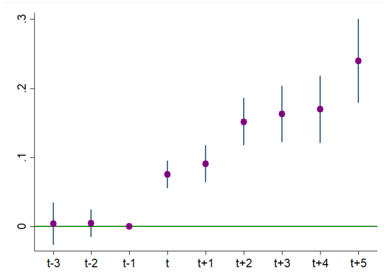
(b) Unit Value - Top 3 products

The figures report estimates of the response of firm product unit value to automation imports and pre-trend coefficients, using specification 3 with the estimator proposed by Sun and Abraham (2021). Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

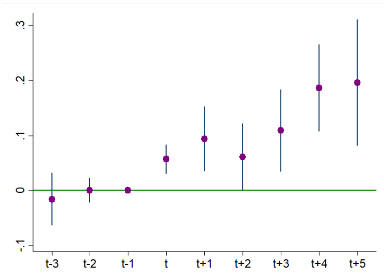
Figure A.4: Automation and firm economic outcomes



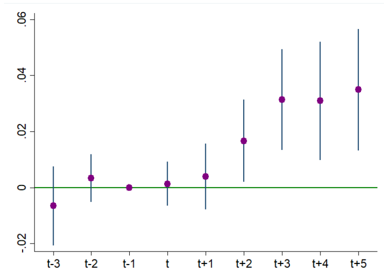

(a) Employment



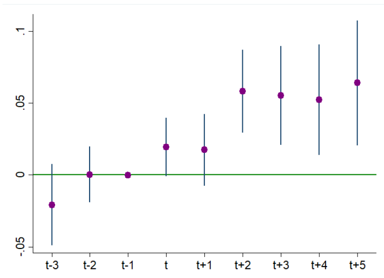

(b) Sales



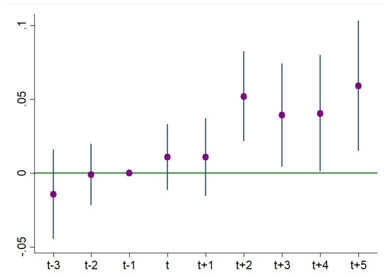

(c) Capital Intensity




(d) Unit wage



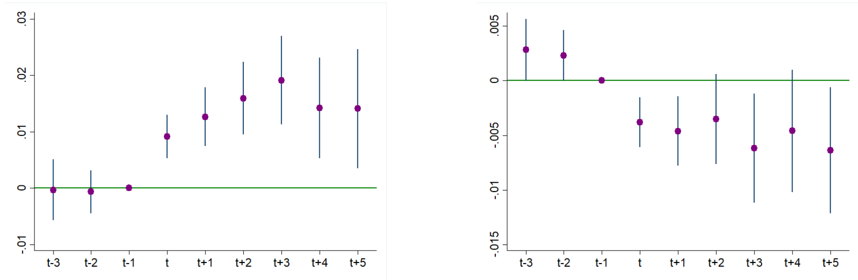

(e) Labour Productivity




(f) TFP

Observations: 19,624 in panel a,c and d, 19,516 in panel b, 19,497 in panel e, 19,418 in panel f. Figures report estimates of the response of a set of firm level variables to automation imports and pre-trend coefficients, using specification 3. Firm fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

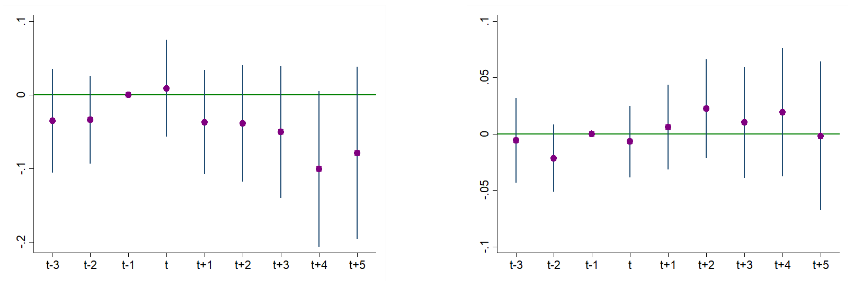
Figure A.5: Automation and workforce composition




(a) employees younger than 35 (b) employees older than 50

The Figure reports estimates of the response of firms' workforce composition to automation imports and pre-trend coefficients, using specification 3. Firm fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level. Panel a) and b) show the effects on the ratio of employees younger than 35 and employees older than 50, respectively. These results are obtained by exploiting employer-employee data made available from the MoIT.

Figure A.6: Automation and direct effects on upgrading: Placebo test - Random treatment assignment




(a) Quality (b) Q-adjusted Price

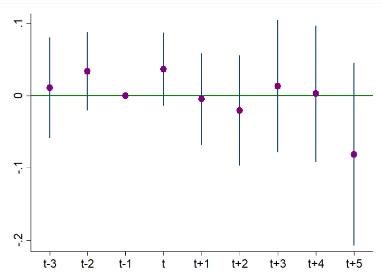
Figures report the results of a placebo test where treatment status and treatment year are randomly assigned to half of the baseline sample of firms, including both treated and control groups. Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

Table A.6: Buyers of Treated and Untreated suppliers: balancing tests before the suppliers' treatment

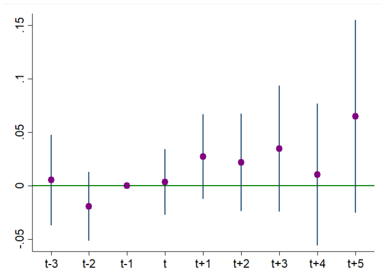
| | BUYERS of Treated suppliers $Exposed_j^{Upstream}$=1 | BUYERS of Untreated suppliers $Exposed_j^{Upstream}$=0 | t-test |
|---|---|---|---|
| $\text{lab}_{t-1}$ | 3.197 | 3.169 | -0.558 |
| $\text{lab}_{t-2}$ | 3.272 | 3.200 | -1.371 |
| $\text{lab}_{t-3}$ | 3.286 | 3.188 | -1.741 |
| $\text{tfp}_{t-1}$ | 4.303 | 4.333 | 0.942 |
| $\text{tfp}_{t-2}$ | 4.269 | 4.281 | 0.334 |
| tfp$t-3$ | 4.203 | 4.274 | 1.913 |
| $\text{sales}_{t-1}$ | 10.327 | 10.259 | -0.984 |
| $\text{sales}_{t-2}$ | 10.366 | 10.328 | -0.587 |
| $\text{sales}_{t-3}$ | 10.360 | 10.334 | -0.368 |
| import_dummy$_{t-1}$ | 0.573 | 0.577 | 0.230 |
| import_dummy$_{t-2}$ | 0.605 | 0.596 | -0.444 |
| import_dummy$_{t-3}$ | 0.609 | 0.607 | -0.096 |
| unit_wage$_{t-1}$ | 5.090 | 5.143 | 3.167 |
| unit_wage$_{t-2}$ | 5.015 | 5.037 | 1.295 |
| unit_wage$_{t-3}$ | 5.039 | 5.059 | 1.087 |
| $\text{capital}_{t-1}$ | 8.594 | 8.679 | 1.226 |
| $\text{capital}_{t-2}$ | 8.686 | 8.689 | 0.044 |
| $\text{capital}_{t-3}$ | 8.725 | 8.695 | -0.361 |

The treatment here is the automation adoption by suppliers. Statistics refer to buyers of both suppliers starting to import automation ($Exposed_j^{Upstream}$=1) and their matched controls that never imported automation ($Exposed_j^{Upstream}$=0).

Figure A.7: Automation and effects on buyers: Placebo tests



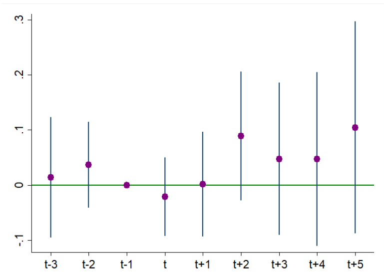

(a) Quality



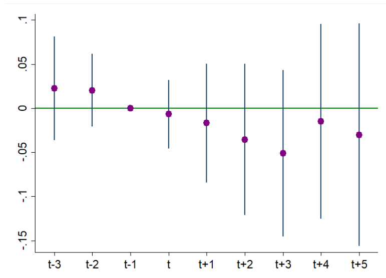

(b) Q-adjusted Price

Figures report the results of a placebo test where we randomly assign the treatment status and a treatment year to half of the baseline sample of buyers from treated and control firms. 90% confidence intervals are shown and standard errors are clustered at the firm level.

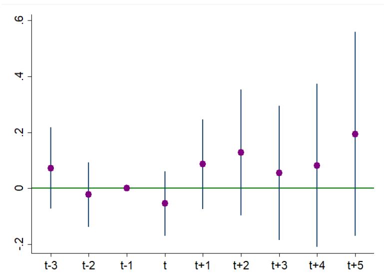
Figure A.8: Transmission effects to suppliers: an event study



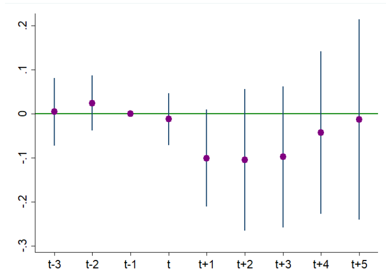

(a) Quality




(b) Q-adjusted Price




(c) Quality - purchase share>5%




(d) Q-adjusted Price - purchase share>5%

The Figure shows the impact of customers' automation imports as the treatment on the export quality and price of their suppliers. Firm-product fixed effects, time fixed effects and time-to-treatment fixed effects are included in each specification. 90% confidence intervals are displayed. Standard errors are clustered at the firm level.

## References

Acemoglu, D., Anderson, G.W., Beede, D.N., Buffington, C., Childress, E.E., Dinlersoz, E., Foster, L.S., Goldschlag, N., Haltiwanger, J.C., Kroff, Z., Restrep, P., 2022. Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey. NBER Working Papers 30659. National Bureau of Economic Research, Inc.

Acemoglu, D., Azar, P.D., 2020. Endogenous production networks. Econometrica 88, 33–82.

Acemoglu, D., Koster, H.R.A., Ozgen, C., 2023. Robots and Workers: Evidence from the Netherlands. Working Paper 31009. National Bureau of Economic Research.

Acemoglu, D., Lelarge, C., Restrepo, P., 2020. Competing with robots: Firm-level evidence from france. AEA Papers and Proceedings 110, 383–88.

Acemoglu, D., Restrepo, P., 2020. Robots and Jobs: Evidence from US Labor Markets. Journal of Political Economy 128, 2188–2244.

Acemoglu, D., Restrepo, P., 2022. Demographics and Automation [Automation and Demographic Change]. Review of Economic Studies 89, 1–44.

Ackerberg, D.A., Caves, K., Frazer, G., 2015. Identification Properties of Recent Production Function Estimators. Econometrica 83, 2411–2451.

Aghion, P., Antonin, C., Bunel, S., Jaravel, X., 2020. What Are the Labor and Product Market Effects of Automation? New Evidence from France. SciencePo Working papers Main hal-03384668. HAL.

Alguacil, M., Lo Turco, A., Martinez-Zarzoso, I., 2022. Robot adoption and export performance: Firm-level evidence from Spain. Economic Modelling 114.

Artuc, E., Bastos, P., Rijkers, B., 2023. Robots, tasks, and trade. Journal of International Economics 145.

Ballestar, M.T., Diaz-Chao, A., Sainz, J., Torrent-Sellens, J., 2020. Knowledge, robots and productivity in SMEs: Explaining the second digital wave. Journal of Business Research 108, 119–131.

Baqaee, D, F.E., 2019. The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem. Econometrica 87, 1155–1203.

Barrot, J.N., Sauvagnat, J., 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. Quarterly Journal of Economics 131, 1543–1592.

Bas, M., Paunov, C., 2021. Input quality and skills are complementary and increase output quality: Causal evidence from Ecuador's trade liberalization. Journal of Development Economics 151.

Bas, M., Strauss-Kahn, V., 2015. Input-trade liberalization, export prices and quality upgrading. Journal of International Economics 95, 250–262.

Bigio, S, L.J., 2020. Distortions in production networks. Quarterly Journal of Economics 135, 2187–1253.

Boehm, J., Dhingra, S., Morrow, J., 2022. The comparative advantage of firms. Journal of Political Economy 130, 3025–3100.

Bohem, C., Flaaen, A., Pandalai-Nayar, N., 2019. Input linkages and the transmission of shocks: Firm level evidence from the 2011 tohoku earthquake. Review of Economics and Statistics 101, 60–75.

Bonfiglioli, A., Crino, R., Fadinger, H., Gancia, G., 2024. Robot Imports and Firm-Level Outcomes. The Economic Journal 134, 3428–3444.

Borusyak, K., Jaravel, X., Spiess, J., 2024. Revisiting Event-Study Designs: Robust and Efficient Estimation. The Review of Economic Studies 91, 3253–3285.

Broda, C., Weinstein, D.E., 2006. Globalization and the gains from variety. The Quarterly Journal of Economics 121, 541–585.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-Differences with multiple time periods. Journal of Econometrics 225, 200–230.

Carvalho, V.M., Nirei, M., Saito, Y.U., Tahbaz-Salehi, A., 2021. Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. The Quarterly Journal of Economics 136, 1255–1321.

Ciccone, A., 2002. O-ring production networks. Review of Economic Studies 69, 565–587.

De Backer, K., DeStefano, T., Menon, C., Suh, J.R., 2018. Industrial robotics and the global organisation of production. OECD Science, Technology and Industry Working Papers .

Demir, B., Fieler, A.C., Xu, D.Y., Yang, K.K., 2024. O-Ring Production Networks. Journal of Political Economy 132, 200–247.

DeStefano, T., Timmis, J., 2024. Robots and export quality. Journal of Development Economics 168.

Dixon, J., Hong, B., Wu, L., 2021. The Robot Revolution: Managerial and Employment Consequences for Firms. Management Science 67, 5586–5605.

Faber, M., 2020. Robots and reshoring: Evidence from mexican labor markets. Journal of International Economics 127, 103–384.

IFR, 2022. World Robotics - Industrial Robots. Technical Report. International Federation of Robotics.

Khandelwal, A.K., Schott, P.K., Wei, S.J., 2013. Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters. American Economic Review 103, 2169–2195.

Koch, M., Manuylov, I., Smolka, M., 2021. Robots and Firms. The Economic Journal 131, 2553–2584.

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

Kugler, M., Verhoogen, E., 2011. Prices, Plant Size, and Product Quality. The Review of Economic Studies 79, 307–339.

McNerney, J., Savoie, C., Caravelli, F., Carvalho, V.M., Farmer, J.D., 2021. How production networks amplify economic growth. Proceedings of the National Academy of Sciences 119, 2106031118–.

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

Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics 225, 175–199.

Verhoogen, E., 2023. Firm-level upgrading in developing countries. Journal of Economic Literature 61, 1410–64.