Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France*

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Abstract

This paper estimates the labor and product market effects of a fall in the cost of investments in modern manufacturing capital, including modern automation technologies. Causal effects are estimated with a shift-share IV design leveraging pre-determined supply linkages and productivity shocks. At both the firm and industry levels, we find that capital investments lead to higher labor demand, higher sales, higher exports, and lower labor shares, while wage inequality remains unchanged. The industry-level labor demand response is positive only in industries that are exposed to import competition, due to business-stealing across countries.

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I Introduction

What are the effects of lowering the costs of investments in modern manufacturing capital, e.g. in automation technologies (numerically-controlled machine tools, automatic conveyor systems, industrial robots, etc.), on the labor and product markets? There are growing concerns that investments in modern manufacturing capital, which often benefit from tax incentives for business investments, could occur at the expense of workers. Indeed, modern manufacturing capital may displace certain workers by replacing them with machines, raising the possibility of technological unemployment (e.g., Keynes (1930), Leontief (1952), Brynjolfsson and McAfee (2014)). However, these displacement effects could potentially be offset by a productivity effect: capital investments may induce productivity gains, increase market demand and the scale of production, and in turn increase labor demand (e.g., Bowen and Mangum (1966), Zeira (1998), Autor (2015), Acemoglu and Restrepo (2018c)). Depending on the extent to which productivity gains are passed through to consumers by producers, consumers could benefit from lower prices or producers could retain higher profits (e.g., Caselli and Manning (2019) and Moll et al. (2022)). Finally, because of business stealing effects arising from firms that invest and displace their competitors, the industry-level employment, price and profit effects of modern manufacturing capital investments may differ from their firm-level impacts (e.g., Baqaee and Farhi (2019)).

Because of these multiple and countervailing economic forces, understanding the aggregate and distributional impacts of modern capital investments across workers, consumers and producers is fundamentally an empirical question. To design appropriate policies – e.g., to what extent should investment be subsidized or taxed? – the relative magnitudes of these mechanisms must be estimated in a unified empirical framework. Despite extensive research, the employment effects of investments in manufacturing capital remain debated, little is known about the impacts on consumer prices and profits, and most of the existing evidence is provided at the industry level rather than at the firm level, obscuring the channels at play.[1] Data limitations explain the relative scarcity of evidence on these questions, which can only be answered with comprehensive data on modern manufacturing capital investments and the labor and product markets.

In this paper, we leverage micro data on the population of firms in the French manufacturing

[1]For example, Chiacchio et al. (2018), Webb (2019) and Acemoglu and Restrepo (2019) find evidence in line with the view that various forms automation reduce labor demand, while Graetz and Michaels (2018), Mann and Püttmann (2021) and Klenert et al. (2023) document positive employment effects. At the end of this section, we discuss the emerging literature on the firm-level effects of robotization, which has grown in recent years and ran parallel to this paper.

sector between 1995 and 2017 to provide a unified analysis of the effects of such investments on employment, sales, prices, wages, the labor share, and profits at several levels of aggregation — firms and industries. We use several complementary measures of investments in modern manufacturing capital, including the balance-sheet value of industrial equipment and Acemoglu and Restrepo (2022)'s measure of imported automation technologies.

Recent theoretical contributions highlight that the effects of modern manufacturing capital investments on the economy depend crucially on whether it primarily consists in factor-augmenting technological change or rather in task-based automation (e.g., Acemoglu and Restrepo (2018b)), as well as on reallocation effects (e.g., Baqaee and Farhi (2019)).[2] With these motivations in mind, our empirical analysis proceeds in three steps. We first present descriptive evidence on the population of firms using event studies. We then estimate causal effects using a shift-share research design that can be applied to the subset of firms importing industrial automation technologies from abroad. Finally, we repeat the estimation of causal effects at the level of industries.

In the first part of the paper, we use event studies that exploit the timing of adoption of industrial equipment across firms in the same 5-digit industry. We find that firm-level employment increases after investments in modern manufacturing capital, including for unskilled industrial workers. We obtain similar result in an extension at the plant level. In line with the hypothesized productivity effect, we find that sales and exports increase when firms invest, while export prices and competitors' employment fall. Firm-level wage inequality remains unchanged, while there is a fall in the share of labor in value-added and an increase in the rate of job creation and destruction within the firm – consistent with the idea that these investments lead to automation of the production process and thus induce a change in the production function.[3]

A causal interpretation of these patterns would suggest that the productivity effect may outweigh the displacement effect, resulting in a net increase in firm-level labor demand. However,

[2]In this paper, we do not focus on a particular technology that may *a priori* be viewed as automation, like previous work has done (e.g., Graetz and Michaels (2018) and Acemoglu and Restrepo (2019) focused on industrial robots). Instead, we assess more broadly whether the effects of typical investments in modern industrial capital are consistent with factor-augmenting technological change or a task-based framework. Answering this question speaks to ongoing policy debates, e.g. to assess whether modern manufacturing capital investments should be taxed or subsidized, either in general (e.g., Curtis et al. (2022)) or focusing on specific technologies like robots (e.g., Guerreiro et al. (2022) and Acemoglu et al. (2020a)).

[3]The finding that there is no change in relative labor demand across skill groups may seem surprising. However, distributional effects may occur within each skill group, depending on the set of tasks performed across detailed occupations, even though we do not find that the firm-level wage distribution is affected by modern manufacturing capital investments. Other studies analyzing the effects of technological change have emphasized the importance of within-skill heterogeneity. For example, Hummels et al. (2014) documented that the distributional effects of offshoring occurred primarily within skill groups, rather than across. In this sense, our finding is in line with prior work.

potential unobserved shocks may confound the observed relationships. The event studies show no sign of pre-trends, which restricts the potential set of confounders to other shocks occurring exactly at the same time as the increase in capital investment. Absent a quasi-experiment, potential concerns over omitted factors cannot be addressed. For example, demand shocks or competition shocks could be at play. Increased demand or increased competition have a direct impact on employment but may also lead a firm to invest more, exactly at the time when the unobserved shock occurs.

To address these concerns, in the second part of the paper we develop a shift-share IV design. We implement this research design for the subset of firms that import automating technologies from abroad, using Acemoglu and Restrepo (2022)'s measure of automation. Identification stems from changes over time in the productivity of foreign suppliers of automation technologies, which French firms are differentially exposed to through pre-determined importer-supplier relationships. This identification strategy approximates an ideal experiment that would randomly assign the prices of automation technologies across firms. Because changes in machines' quality-adjusted prices are not directly observed, it is convenient to use changes in the market shares of foreign suppliers over time to infer productivity shocks across suppliers. Specifically, we use supply shocks across HS6 product categories measured in EU countries (except France) and Switzerland as instruments for the adoption of machines in France. We implement the shift-share IV design following the latest advances in the applied econometrics literature (Adao et al. (2019), Borusyak et al. (2022)).

The exclusion restriction underlying this design is that firms linked to increasingly productive suppliers should not have unobservable features affecting our outcomes. To test this assumption, we run falsification tests using the lagged outcome variable. Across a range of specifications, we can never reject that there is no relationship.

We find that, when their international suppliers of machines become more productive, firms increase their usage of automation technologies (in the sense of Acemoglu and Restrepo (2022)), their sales, and their labor force. The baseline specification with 4-digit product-by-trading-partner-by-year and 2-digit industry-by-year fixed effects yields an elasticity of firm employment to automation of 0.18 (s.e. 0.07). The point estimates remain comparable in magnitudes with alternative sets of controls. We find that sales also increase substantially in response to increased automation, with elasticities around 0.33 (s.e. 0.14) across specifications. In addition, we cannot reject that there is no impact of automation on wages, we estimate a fall in the labor share, an increase in productivity, and a significant fall in competitors' employment.[4]

[4]We obtain similar results in a complementary research design isolating "extensive margin investments in automa-

These findings are consistent with the role of the productivity effect of automation. Increased automation allows the firm to expand its sales and scale, which requires hiring additional workers for production. However, the firm-level relationships paint an incomplete picture as business-stealing effects across firms may affect the industry-level impacts of automation. Indeed, the shift-share IV design shows that automation in a firm causes a fall in competitors' employment.

In the third part of the paper, we repeat the analysis at the industry level to account for business stealing and other equilibrium effects. We develop an industry-level shift-share design to estimate the causal impact of automation on industry-level employment, using Acemoglu and Restrepo (2022)'s measure of automation. The shift-share design leverages the same productivity shocks across foreign suppliers of machines, as the firm-level shift-share design, but we now measure outcomes across 5-digit industries rather than at the firm level. The industry-level causal estimates are close to the firm-level responses described above. The elasticity of industry-level employment to industry-level automation is positive at 0.41 (s.e. 0.11),[5] compared with 0.48 (s.e. 0.15) for industry sales; these point estimates are statistically indistinguishable from the firm-level estimates. Like in the firm-level analysis, we cannot reject the hypothesis that wages remain unchanged, while the labor share falls and profits increase.[6]

The finding that the employment response remains positive at the industry level may appear surprising given the potential for business stealing effects. To understand the mechanism, we examine the role of international business stealing effects, proceeding in two steps.

In the first step, we assess the heterogeneity in the industry-level changes in employment and sales depending on exposure to international trade. While the relationship between industry-level manufacturing capital investments and sales or employment is positive and significant in sectors that are exposed to import competition, there is no significant relationship in sectors with low exposure to international competition (below median). This finding is consistent with the view that the business-stealing effect induced by investments mainly affects foreign competitors' employment in sectors facing international competition, whereas it mainly affects domestic competitors' employment in less open sectors. To assess whether this finding may be confounded by other factors

tion"– see Section IV.B.4.

[5]When restricting attention to incumbent firms only, i.e. without accounting for entry and exit, the point estimate is reduced to 0.22 (s.e. 0.11).

[6]We also provide descriptive evidence, using industry-level event studies to estimate the relationship between modern manufacturing capital investments and a range of outcomes, including employment, wage inequality and sales. The relationships turn out to be the same as in the event studies implemented at the level of firms. Industry-level capital investments remain associated with higher employment for all skill groups and with higher sales, while average wages and industry-level wage inequality remain stable.

that correlate with trade openness and could drive the estimated heterogeneity, we implement a falsification test by examining firm-level heterogeneity. At the firm-level, there is no such heterogeneity and the relationship with employment and sales remains positive and significant regardless of the degree of exposure to import competition in the firm's industry.

In the second step, using our estimated elasticities for the response of sales and consumer prices, we assess whether the industry-level patterns can be explained by a demand reallocation channel. We use a simple monopolistic competition model with CES demand, where consumers reallocate demand toward domestic firms with increased productivity and lower prices, at the expense of international competitors. We find that, in an open economy, standard consumer demand elasticities (Broda and Weinstein (2006)) can account jointly for the estimated elasticities of sales and prices. In contrast, it would be difficult to rationalize the industry-level results on sales and employment in a closed economy. Indeed, industry-level substitution would need to operate between industries (rather than between products within the same industry, produced either by domestic firms or by international competitors); because demand elasticities of substitution between industries are relatively small (Costinot and Rodríguez-Clare (2014)), explaining the observed sales response would require very large price changes that we do not observe in the data. Competition with international suppliers providing close substitutes can explain why the employment response can remain positive even at the industry level, because the reallocation of consumer demand to a change in productivity and prices can be large.

Related literature This paper builds on and contributes to several strands of literature. A large literature provides estimates of industry-level relationship between employment and various forms of automation, where signs and magnitudes vary across studies, potentially due to the empirical challenges raised by causal identification at the industry level (e.g., Autor and Dorn (2013), Chiacchio et al. (2018), Dauth et al. (2018), Graetz and Michaels (2018), Mann and Püttmann (2021), Acemoglu and Restrepo (2019), Aghion et al. (2019), Cheng et al. (2019), Webb (2019), Adachi et al. (2020), Klenert et al. (2023)). A more recent line of work, parallel to ours, uses event studies to estimate the firm-level employment effects of automation and robotization: a majority of studies documents a positive reponse (e.g., Acemoglu et al. (2020b), Dixon et al. (2019), Domini et al. (2021), Humlum (2021), Koch et al. (2021), Acemoglu et al. (2023)), with a few studies estimating a negative response (Bessen et al. (2020), Bonfiglioli et al. (2022)).[7] Furthermore, our analysis

[7]We provide a review of the literature to date and the divergence between existing estimates in a companion survey paper, Aghion et al. (2022). Jaimovich and Siu (2019) review the literature on the impacts of automation and

speaks to a broader literature on the estimation of the micro and macro capital-labor elasticities of substitution (e.g., Oberfield and Raval (2021), Hubmer (2023), Houthakker (1955)) and capital-skill complementarities (e.g., Goldin and Katz (1998), Doms et al. (1997), Baqaee and Farhi (2019), Curtis et al. (2022)).[8]

We contribute to this literature in four ways. First, we introduce a quasi-experimental shift-share design to provide causal estimates. In contrast, existing firm-level event study approaches cannot rule out potential unobserved confounding shocks. Second, we extend our analysis to product market outcomes, including sales, prices, business stealing, and firm profits, while the existing literature has focused on labor market impacts. Third, we study industry-level and firm-level responses in a unified setting, which helps isolate the relevant mechanisms.[9] The shift-share IV design implemented at the industry-level allows us to quantify the impact on domestic employment accounting for business-stealing across domestic firms. We view the ability of studying firm-level and industry-level dynamics in a unified empirical setting as one of the main contributions of this paper.[10] Fourth, the heterogeneity we uncover depending on trade exposure can help reconcile some of the diverging industry-level estimates in prior work.[11]

Furthermore, our estimates can be used by a growing literature that uses quantitative models to assess the macroeconomic impacts of automation on inequality (e.g., Moll et al. (2022), Jaimovich et al. (2021)) or to prescribe optimal technological regulations (e.g., Costinot and Werning (2022) and Guerreiro et al. (2022)). Our results provide a set of identified moments at various levels of aggregation (industry and firm) for a large set of manufacturing capital investments, which the

IT on the middle class.

[8]The paper closest to ours is perhaps Curtis et al. (2022), who estimates the causal effet of a major tax policy incentivizing manufacturing capital investments in the U.S., called bonus depreciation, on labor demand across manufacturing establishments. Consistent with our results, they find that the policy led to an increase in manufacturing capital and in employment, including for production workers, and that wages did not increase. Compared to them, we provide quasi-experimental evidence for both firm-level and industry-level effects of modern manufacturing capital investments on labor demand, highlighting the importance of international business-stealing effects. Using a model to aggregate their firm-level estimates, Curtis et al. (2022) show that the labor demand response remains positive when accounting for reallocation, which is consistent with our empirical industry-level estimates. In earlier work, Garrett et al. (2020) took a local labor market approach and showed that places that experience larger decreases in investment costs see an increase employment and earnings. Thus, a consistent empirical picture emerges: capital investments lead to an increase in labor demand.

[9]We conjecture that our methodological approach, which uses the same shocks to study outcomes at different levels of aggregation in a unified shift-share IV framework, could be applied to advance research on several other topics beyond automation, as well as to test the predictions or calibrate state-of-the-art theoretical models (e.g., Baqaee and Farhi (2019)).

[10]In a companion short paper, we document employment dynamics at the local labor market level (Aghion et al. (2023)), which paint a consistent picture with the findings reported here.

[11]For example, Acemoglu and Restrepo (2019) report a negative relationship in the United States, where domestic firms have a larger domestic market and are less exposed to international competition (i.e., business-stealing effects operate primarily between domestic firms rather than internationally). By contrast, exposure to international competition is higher in the sample of European countries studied by Klenert et al. (2023), including France.

next generation of quantitative models could target.

The remainder of the paper is organized as follows. Section II presents the conceptual framework motivating our empirical analysis. Section III describes the data, variables and summary statistics. Section IV reports the firm-level analyses, while Section V analyzes industry-level dynamics. The Online Appendix reports additional results as well as a survey of the theoretical literature that helps guide the interpretation of our empirical estimates.

II Conceptual Framework

In this section, we discuss how prior theoretical work motivates our research question and empirical analysis. We discuss why, both from a modeling and a policy perspective, it is essential to estimate the impact of typical modern manufacturing capital investments on labor demand,[12] and to compare the empirical estimates to the predictions of the canonical model of factor-augmenting technological change and of task-based models of automation. In particular, existing theoretical frameworks motivate the idea that substitution of "modern" capital with labor (as in the task model) may be different from substitution of "traditional" capital with labor (as in the canonical model). We then discuss implications for measurement and for our experimental ideal. Appendix A provides a more comprehensive survey of theoretical predictions, including the role of reallocation effects.

While the discussion below may help some readers interpret our empirical findings in light of existing theories, a reader solely interested in our main empirical contributions can safely skip this section.

Factor-augmenting technological change. Canonical models used in macroeconomics and labor economics assume a production function that can be represented by a function of the form $F(A_L L, A_K K)$, where L denotes labor and K capital. Technology is assumed to be "factor-augmenting", i.e. it multiplies factors of production, denoting labor-augmenting technologies by A_L and capital-augmenting technologies by A_K.

This standard modeling approach delivers stark predictions (see, e.g., Acemoglu and Restrepo (2018b)): (i) capital-augmenting technological change always increases labor demand (and wages); (ii) labor-augmenting technological change also increases labor demand (and wages) for realistic parameter values (namely, the elasticity of substitution must be greater than the share of capital

[12] By "impact of modern manufacturing capital investments", we mean the response of labor demand to supply shifts affecting the cost of modern manufacturing capital, which can lead to changes in capital investments at the intensive or extensive margins.

in national income, a condition typically satisfied in the data); (iii) the impact of technological change on the labor share depends on the elasticity of substitution between capital and labor: for example, if the elasticity of substitution between capital and labor is smaller than one,[13] then capital-augmenting (resp. labor-augmenting) technological change leads to an increase (resp. a fall) in the labor share. Thus, if modern manufacturing capital is modeled as capital-augmenting technological change, the canonical framework predicts that it should lead to an increase in both labor demand and the labor share.

Automation in a task-based framework. A growing body of work studies automation in a task-based framework following the seminal contributions of Acemoglu and Restrepo (2018c) and Acemoglu and Autor (2011). Automation is conceptualized as the expansion of the set of tasks that can be produced by machines, instead of relying solely on labor. In this modeling approach, automation transforms the production process in a way that allows more tasks to be performed by machines. The task-based automation framework makes several distinctive predictions contrasting with those of the canonical framework: (i) automation may *reduce* the demand for labor, wages, and employment, because it assigns to capital tasks that used to be performed by labor; (ii) this displacement effect could cause a decoupling of labor demand/wages and output per worker (i.e., output per worker could rise while wages could fall), as well as (iii) a *decline* in the labor share.

However, these patterns are not a foregone conclusion in the model, as automation may lead to an *increase* in labor demand through four counteracting forces: (i) the endogenous creation of new tasks in which labor has a comparative advantage relative to machines; (ii) a productivity effect whereby the demand for non-automated tasks increases as the cost of automated tasks falls; (iii) automation at the "intensive margin" (i.e., an increase in the productivity of machines in tasks that were previously automated, a phenomenon sometimes called "automation deepening"); (iv) endogenous capital accumulation triggered by increased automation, which raises the demand for capital and in turn the productivity of labor. Furthermore, Acemoglu and Restrepo (2018c) highlight the creation of new tasks as a powerful force whereby automation could lead to a *stable* or potentially *increasing* labor share.

Thus, in a task-based framework the impact of investment on automation technologies on labor demand, wages and the labor share is an empirical question depending on the relative strength of several forces. In contrast, models of automation make an unambiguous prediction about the fact

[13] Most of the literature places the elasticity of substitution between capital and labor in the range between 0.5 and 1 (e.g., Oberfield and Raval (2021)), with some exceptions (e.g., Karabarbounis and Neiman (2014)).

that automation should be associated with a change in the production function and is thus distinct from a pure scale effect. For example, automation leads to a change in the composition of tasks allocated to labor, which should translate into an increase in the rates of both job creations and destructions.[14]

Open empirical questions and policy relevance. Are the effects of typical investments in modern manufacturing capital consistent with the predictions of the canonical model of factor-augmenting technological change, or rather with those of the task model? Despite extensive research, this question remains open, for two main reasons.[15]

First, several papers have studied particular instances of automation, e.g. industrial robots (Acemoglu and Restrepo (2019), Dauth et al. (2021)) or automated teller machines (Bessen (2015)). This line of work highlights the relevance of the task-based framework of automation in specific contexts: for example, productivity-enhancing technologies like robots in the United States may lead to a fall in labor demand (Acemoglu and Restrepo (2019)). Although this line of work made an important contribution by demonstrating that the canonical framework may be incomplete, it is not known whether the canonical framework of factor-augmenting technological change or the alternative task-based framework of automation is more appropriate for predicting the effects of typical investments in modern manufacturing capital. For example, Benmelech and Zator (2022) show that investments in robots accounts for less than 0.30% of aggregate expenditures on equipment and that recent increases in robotization do not resemble the explosive growth observed for IT technologies in the past. Futhermore, other case studies found that certain automation technologies led to an increase in labor demand.[16]

Thus, instead of focusing on a particular technology that may *a priori* be viewed as automation, in this paper we provide novel evidence to assess more broadly whether the effects of typical investments in modern manufacturing capital are consistent with factor-augmenting technological

[14] We test this prediction below (Figure 2). In addtional to finding an increase in the rates of job creation and destruction, we also find a fall in the share of labor in value-added, which is in line with one of the distinctive prediction from the task model.

[15] As shown in Appendix A.B, shocks to the quality-adjusted price of capital on the intensive margin in the task-based framework have implications that are identical to those of the canonical framework. In this sense, the task-based framework nests the canonical framework. Through the lens of the task model, our analysis could be interpreted as an inquiry into the relative importance of "capital deepening at the intensive margin" and "extensive margin automation" shocks.

[16] For example, Bessen (2015) studies the effect of automated teller machines (ATM) on bank tellers, a routine-intensive occupations. Bessen (2015) explains that the ATM can be viewed as a paradigmatic case of technology substituting for workers, taking over cash handling tasks; however, Bessen (2015) documents that this technology led to an *increase* in the demand for bank tellers, because the ATM allowed banks to operate branch offices at lower cost and thus to open many more branches.

change or a task-based framework. Answering this question is of direct policy relevance, in particular to determine whether it is optimal to tax modern manufacturing capital investments — either in general or focusing on specific technologies like robots (e.g., as in the frameworks of Guerreiro et al. (2022) or Acemoglu et al. (2020a)).[17]

Second, it is well-known that the appropriate model for the production function may differ depending on the level of aggregation (e.g., Houthakker (1955), Baqaee and Farhi (2019)). To the best of our knowledge, there exist no quasi-experimental evidence estimating the both firm-level and industry-level effects of investments in modern manufacturing capital. Given the potential role of business stealing effects across firms, both domestically and internationally (e.g., Acemoglu and Guerrieri (2008)), a key goal of our paper is to provide causal estimates of the effects of investment in modern industrial capital at both the firm level and industry level, in a unified empirical framework. These results are directly informative about policy, for example to assess the effects of policies lowering the costs of investment in modern manufacturing capital (e.g., through tax incentives and accelerated depreciation, as in Zwick and Mahon (2017) or Curtis et al. (2022)).

Implications for Measurement and Ideal Experimental Research Design. To answer the modeling and policy questions motivated by the preceding discussion, we will rely on both broad measures of capital investments in manufacturing and standard measures of automation, following Acemoglu and Restrepo (2022), which we describe in detail in Section III.

Our research design attempts to approximate an ideal experiment which consists in lowering the cost of investment in manufacturing capital. Importantly, we do not attempt to isolate "extensive margin automation events" (Acemoglu and Restrepo (2018a)). Instead, we aim to estimate whether the effects of typical investments in manufacturing capital are consistent with the canonical model of factor-augmenting technological change or, rather, require a task-based framework to be rationalized. In particular, we must account for "intensive margin automation effects", i.e. increasing the productivity of machines in tasks that were previously automated.[18] From a policy perspective, our approach is informative about the effects of policies that reduce the costs of investment in

[17] Specifically, our descriptive evidence using event studies is based on broad measures of modern manufacturing capital. Our causal analysis, with the shift-share design, uses a more specific measure, Acemoglu and Restrepo (2022)'s measure of imported automation technologies. See Section III for a complete description of all measures.

[18] In this way, we can assess the extent to which investments in "so-so technologies" (Acemoglu and Restrepo (2018a)) is widespread in overall investments in modern industrial capital. Acemoglu and Restrepo (2018a) call "so-so technologies" instances where automation technologies are just productive enough to be adopted and cause displacement, but not sufficiently productive to bring about powerful productivity effects, leading to a fall in labor demand.

modern manufacturing capital, such as accelerated depreciation, or to the contrary that raise this cost, e.g. a tax on robots. These policies operate at both the intensive and extensive margins.

III Data, Variable Descriptions and Summary Statistics

In this section, we describe the data sources, define the sample and key variables used in the analysis, and present summary statistics.

III.A Data Sources

To obtain a comprehensive picture of the relationship between capital investments, employment and firm dynamics, we combine several measures of investment to a matched employer-employee dataset. We then supplement this linked dataset with additional information on trade, prices, and consumption patterns.

Matched employer-employee data set. We obtain detailed information on workers and firms from French administrative datasets, the DADS and FICUS-FARE databases. These databases cover the universe of firms in the manufacturing sector in France from 1995 to 2017. For each firm, we observe total sales, balance sheet records, and detailed industry codes. We also observe the composition of the workforce, notably the number of hours worked, total compensation and occupation codes for each worker (Charnoz and Orand (2017)).

Measuring manufacturing capital investments. Our first measure of investment leverages detailed balance sheet information available for the universe of French firms. Following French accounting standards, our balance-sheet measure of investments in modern manufacturing capital is the aggregation of (i) industrial equipment and (ii) industrial tools. Industrial equipment includes "all equipment and machines used for extraction, processing, shaping, packaging of materials or supplies or for services", while industrial tools include "instruments which, combined with an industrial equipment, specialize this equipment into a specific task." Our balance-sheet measure of manufacturing capital thus includes all machines used during the production process of manufactured products, which are specialized into a specific task by industrial tools. This measure excludes transport equipment, which corresponds to "all vehicles and devices used to transport people and goods, materials and products," as well as office and IT equipment that includes "typewriters, accounting machines, computers, etc."[19]

Three proxies for automation. We also use three proxies that isolate automation technologies, which correspond to a subset of the manufacturing capital used in production. Our first and main proxy follows Acemoglu and Restrepo (2022), who draw a list of "technologies that relate to industrial automation" using trade data. Using customs data for the universe of French firms, this measure is available for the subset of firms that import machines from abroad. The list consists of imported intermediate goods belonging to the following HS code categories: industrial robots, dedicated machinery, numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, dedicated textile machines, automatic conveyors, and regulating and control instruments. As Acemoglu and Restrepo (2022) do, we explicitly exclude hand-operated machine tools and machines tools that are "not numerically controlled." This measure also excludes household machines (for cooking, washing, cleaning etc.), agricultural machinery, and IT machines. Our proxy is thus identical to Acemoglu and Restrepo (2022), except that we also include industrial machines in sectors other than the textile industry to obtain a larger coverage of industries.[20]

As a second proxy for automation, we focus on imported industrial robots, which we also measure in the French customs data. The International Federation of Robots (IFR) defines industrial robots as "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes". We thus follow a broad literature studying industrial robots, including Graetz and Michaels (2018), Acemoglu and Restrepo (2019), Humlum (2021), and Dauth et al. (2021). This proxy may include robots that are not pure substitutes for labor and instead complement labor,[21] at least at some level of aggregation of the production function (e.g., at the firm level rather than at the task level).[22]

[19] For each firm, we observe the balance sheet value of "industrial equipment and machines" in euros. This subset of capital accounts for a large share (55 %) of total capital in manufacturing, more than the three other categories, namely "land" (1 %),"building" (12 %) and "others" (32 %).

[20] While Acemoglu and Restrepo (2022) only include dedicated machines for the textile industry (e.g., within the HS4 category "knitting machines, stitch-bonding machines and machines for making gimped yarn, tulle, lace, embroidery, trimmings, braid or net"), we expand coverage by also including dedicated machines for other industries (for example, we include the HS4 category "machines for assembling electric or electronic lamps, tubes or valves or flashbulbs").

[21] This feature is common to all proxies for automation. For example, the robots measure includes so-called "cobots", collaborative robots that assist workers in some way. Unlike autonomous robots which operate alone and without supervision, cobots are programmed and designed to respond to human instructions and actions. "These collaborative robots are not replacing human work, but are increasing the productivity of human workers, whilst simultaneously reducing the risk of workplace injury-for example due to repetitive heavy lifting" (IFR, 2017).

[22] As discussed further in Section V.C, our empirical results show that such complementarity is not the main force at work explaining the increase in employment. If the complementarity between capital and labor was the driving

Our third proxy for automation is based on plant-level electric motive power, motivated by the Encyclopaedia Britannica (2015)'s definition of automation as "the class of electro-mechanical devices that are relatively self-operating after they have been set in motion based on predetermined instructions or procedures." In manufacturing, common automation technologies are typically based on electro-motive force, i.e. the machines used in the production process are set in motion using electric motors. For example, conveyors in the food industry, robotic arms in the automobile industry, or autosamplers in the chemical industry all fall under this definition. Appendix B provides a description of this measure, which we use for robustness.

Potential limitations. A first limitation of our measures of manufacturing capital investments is that they all suffer from the drawback that it is difficult to assess the "efficiency" of machines. For example, machines or robots may be more expensive or require more motive power in a given industry while still being less efficient than in another industry. To address this potential drawback, we leverage the panel dimension of the data and conduct our analyses in changes with time-by-industry fixed effects to control for potential time-by-industry changes in efficiency.

Another feature of our approach which may appear at first glance to be a limitation is that our proxies for automation cannot isolate "extensive margin" automation (i.e., the first instance of adoption of an automation technology by a firm) as they also take into account "intensive margin" automation (i.e., increased reliance on automation technologies that the firm started using at an earlier time). This seeming limitation applies to all prior studies using imported automation technologies or robots as proxies for automation. Given our focus, this feature should not be viewed as a limitation: from a policy perspective, we must take into account both types of automation. Indeed, tax incentives (e.g., a tax on robots) or subsidies (e.g., through accelerated depreciation) affect automation both at the extensive and intensive margins; we aim to estimate the overall effect of lowering the cost of modern manufacturing capital, inlcuding automation technologies, on a range of outcomes including labor demand, prices, etc.

Trade. The trade dataset is available from customs records and covers the population of French firms in manufacturing, keeping track of all imports and exports for all firms. We use the trade data to build the shift-share instrument, as well as to isolate the role of specific machines or robots,

force, (i) we would find an increase in the labor share, while we find that the labor share remains stable; (ii) we would find a positive response of industry-level employment in all industries, whereas we observe a positive response only in sectors that are open to international trade.

focusing on the subset of French firms that import, as discussed previously. The trade data also provide export prices, measured as unit values, which we use to measure the effects of modern manufacturing capital investments on prices.

Prices and expenditures. For all detailed industries in our sample, we obtain producer price indices from INSEE, which we use to characterize the industry-level impact of capital investments on prices. In complementary analyses, we match these data to consumption spending patterns by income groups, also from INSEE, to describe the distributional effects of capital investments via changes in purchasing power. Using these datasets, we can describe the extent to which the benefits from modern manufactuing capital investments accrue to firm owners via increased profits or to consumers via lower (quality-adjusted) prices.

III.B Summary Statistics

Table 1: Summary Statistics, Year-to-year Changes, 1995-2017

	Units	Units-by-year	Mean	S.D.	p5	p50	p95
Panel A: Plant level							
Employment	2,372	39,647	-2	47	-48	-1	41
Modern Manufacturing Capital - Motive force (toe)	2,372	39,647	4	1,112	-263	2	289
Panel B: Firm level							
Employment	4,296	31,980	-0	53	-6	0	7
Sales (thousands of euros)	4,296	31,980	-116	72,828	-1,918	11	3,080
Modern manufacturing capital:							
Industrial machines (thousands of euros)	4,296	31,980	183	23,644	-120	1	592
Acemoglu and Restrepo (2022)'s imports of machines (thousands of euros)	4,296	31,980	1	559	-23	0	24
Imports of robots (thousands of euros)	4,296	33,579	-0	43	0	0	0
Motive force (toe)	1,008	7,161	6	1,149	-288	2	303
Panel C: Industry level							
Employment	256	5,610	-92	950	-1,217	-35	973
Sales (millions of euros)	256	5,610	22	1,038	-433	2	521
Modern manufacturing capital:							
Industrial machines (millions of euros)	256	5,610	17	197	-71	4	126
Acemoglu and Restrepo (2022)'s imports of machines (millions of euros)	256	5,610	2	24	-7	0	13
Imports of robots (millions of euros)	256	5,610	0	1	-0	0	0

Notes: This table reports the distribution of the main outcome variables – employment and sales – and of the four measures of modern manufacturing capital – the balance sheet value of industrial equipment, Acemoglu and Restrepo (2022)'s imports of industrial machines, robots, and motive power. The statistics are reported at three levels of aggregation: plant-level, firm-level, and industry-level. All variable are reported in year-to-year changes, from 1995 to 2017.

Table 1 reports the distribution of our main outcome variables, sales and employment, and of investments in manufacturing capital – the balance sheet value of industrial equipment, Acemoglu and Restrepo (2022)'s imports of industrial machines, robots, and motive power – at various levels of aggregation, i.e. plant level, firm level and industry level. The analysis is conducted with plants and firms that operate continuously from 1995 to 2017 in 256 manufacturing industries.[23]

The table shows that there is significant heterogeneity across plants, firms and industries in terms of employment, investment in modern manufacturing capital, and sales. The following sections characterize the relationships between these variables using several complementary research designs. In Appendix C.A, we discuss several additional summary statistics for completeness (see Figure E1 as well as Tables E1 and E2).

IV Firm-level Estimates

In this section, we show that firms that use more manufacturing capital, including automation technologies, increase their sales and total employment, without affecting relative labor demand across skill groups. We also observe an increase in labor productivity and a fall in the labor share in value added, a displacement effect in line with task-based models of automation. We first provide descriptive evidence using event studies (Subsection IV.A), and then introduce a quasi-experimental shift-share design to estimate causal effects (Subsection IV.B).

IV.A Event Studies

When a firm relies more extensively on modern manufacturing capital, what happens to sales, employment, demand for worker skills, and the labor share? We now investigate this question in the population of firms with an event study design.[24]

IV.A.1 Event Study Specification

To describe employment dynamics as a firm or plant invests in modern manufacturing capital, we use a standard "extensive margin" event study that isolates investment events. Since most firms and plants adjust every year their investment in manufacturing capital – regardless of the measure we use –, we define discrete investment thresholds isolating large changes in manufacturing capital

[23]We focus the analysis on the set of firms that operate continuously, but our main results are similar when using an unbalanced panel of firms (unreported) or a balanced panel over shorter horizons (see Section IV.A). When we conduct the analysis at the industry level, entry and exit dynamics are accounted for (see Section V).

[24]Appendix C.B discusses stylized facts on the relationship between modern manufacturing capital, sales, employment, demand for worker skills, and the labor share.

investments. In the baseline approach, an investment event for a firm corresponds to a change in its balance sheet value of industrial equipment above a pre-specified threshold, in the distribution of all possible changes across firms. We then consider alternative thresholds and variables, defining the investment event based on different percentiles of the distribution and using our three other proxies for investments in modern manufacturing capital.

In our baseline specification, we study investment event thresholds defined alternatively by percentiles p90, p75 or p50 of the change in the balance sheet value of industrial machines. In robustness checks, we analyze our three proxies for automation – the value of imported automating machines as in Acemoglu and Restrepo (2022), the value of imported robots, and electric motive power.

Indexing firms by i and years by t, our event study is specified as

$$\log(Y_{it}) = \sum_{k=-10}^{10} \delta_k E_{i,t-k} + \mu_i + \lambda_{st} + \epsilon_{it}, \tag{1}$$

with Y_{it} the outcome of interest, the investment event $E_{i,t-k}$, firm fixed effects μ_i, and industry-by-year fixed effects λ_{st}. The lead-lag coefficient δ_k gives the cumulative dynamic response of the outcome Y_{it} at time $t+k$ to the investment event at time t. We consider a variety of outcomes at the firm level, including employment, sales, wage, the labor share, and measures of within-firm wage inequality.

A causal interpretation of the estimates requires the identification condition $\mathrm{E}[E_{i,t-k} \cdot \epsilon_{it} | \mu_i, \lambda_{st}] = 0 \;\forall\, (t,k)$. If this holds, we expect the leads (i.e., $\widehat{\delta_k}$ with $k < 0$) to be statistically insignificant and the point estimates to be close to zero. Although the lack of pre-trends is a necessary condition, it may not be sufficient to guarantee the validity of the identification condition. Indeed, correlated demand and supply shocks may occur exactly at the same time as the firm or plant investments in modern manufacturing capital. For example, increased demand or increased competition could lead to new investments, with a simultaneous direct impact on employment. The shift-share IV design in the following section addresses this concern.

IV.A.2 Event Study Results

Labor demand. We find that employment increases in firms that invest more, using the change in the balance sheet value of industrial equipment as a proxy. Panel A of Figure 1 implements the event study with 5-digit industry by year fixed effects, defining the investment event as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. The semi-elasticity of firm employment to the investment event is +0.2 on impact,[25] with no signs of pre-trends. The semi-elasticity is then amplified over time, reaching +0.35 after ten years. The point estimates are precise; the 95% confidence interval rejects an employment elasticity below +0.15 or above +0.50 after ten years.

Panels B through D of Figure 1 examine the employment response when using our three proxies for automation. In Panel B, we use Acemoglu and Restrepo (2022)'s proxy for automation based on imports of industrial automating machines: the patterns are very similar. Panel C also documents similar patterns using the measure of robots. Finally, Panel D reports the elasticity of employment to motive power, which is also positive at +0.30 after 10 years.[26] Thus, we consistently find a positive response of employment to investments in automation technologies. These patterns are very robust, as discussed in Appendix C.C: see Figures E2 to E8.

Heterogeneity by skill group. Panels E through G of Figure 1 documents heterogeneity across skill groups. The three panels show a comparable employment change for high-skill, medium-skill and low-skill workers. As previously, the semi-elasticity is about +0.2 on impact and increases in subsequent years. The paths of the point estimates for the three skill groups are statistically indistinguishable. These results suggest that investments in modern manufacturing capital do not have different effects across broad skill groups within the firm and leave relative labor demand unchanged. Appendix Figure E9 focuses on the subset of unskilled industrial workers, who are more likely to perform routine tasks that may be taken over by automated technologies. We find that the employment elasticity remains positive and comparable in magnitude for industrial unskilled workers, both at the firm level and plant level.[27]

Next, Figure 2 presents complementary evidence examining changes in wages, within-firm inequality, labor productivity, the labor share, displacement effects, and market dynamics.

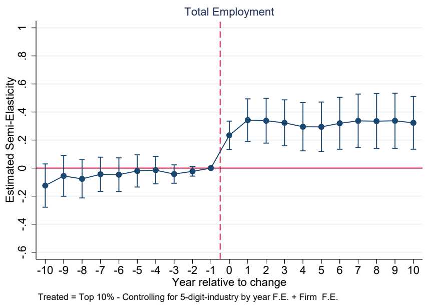
[25] Empirically, the average log change in the balance sheet value of industrial machines after the event (defined at the 90th percentile threshold) is close to one, such that the semi-elasticities can also be interpreted as elasticities.

[26] When using motive power, which is only available for the representative sample of plants surveyed by INSEE, to maximize power we leverage the entire variation available in the data by specifying a standard distributed lead-lag model (e.g., Stock and Watson (2015)). The specification is similar to equation (1). Indexing plants or firms by i and years by t, our baseline distributed lead-lag model is specified as $Y_{it} = \sum_{k=-10}^{9} \delta_k \Delta M_{i,t-k} + \delta_{10} M_{i,t-10} + \mu_i + \lambda_{st} + \epsilon_{it}$,with the outcome Y_{it}, the change in peak capacity for electric motive power $\Delta M_{i,t}$, plant fixed effects μ_i, and industry-by-year fixed effects λ_{st}. δ_k is the cumulative impact of investments on the outcome after k periods (see Stock and Watson (2015), equation (15.7)).

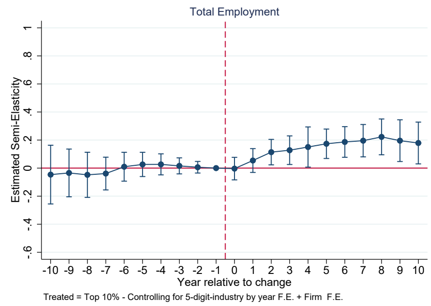
[27] While these results differ from the estimates of seminal structural models of capital-skill complementarity (e.g., Krusell et al. (2000)), they are in line with other causal estimates of the effects of capital investments on relative labor demand (e.g., Curtis et al. (2022)). Furthermore, our findings are similar in spirit to the literature on offshoring documenting that distributional effects are concentrated within skill groups, rather than across (Hummels et al. (2014)).

Figure 1: Firm-Level Event Studies, Main Results

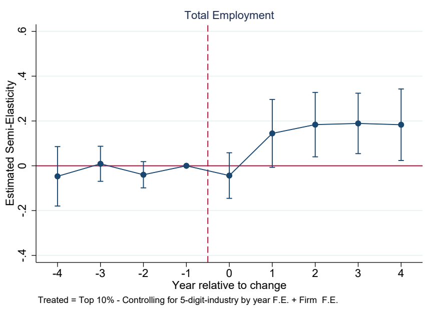
A. Investment in industrial equipment



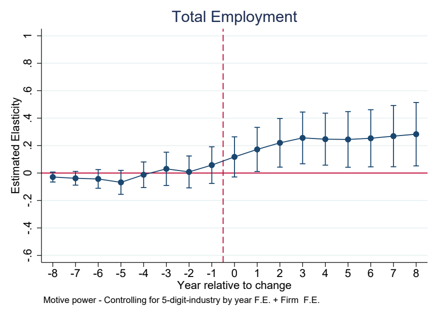
B. Acemoglu and Restrepo (2022)'s automation measure



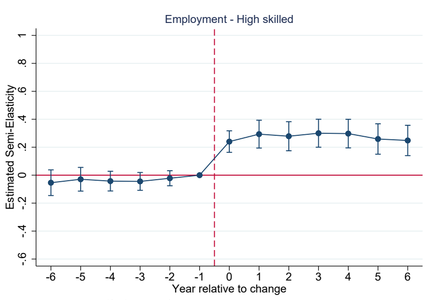
C. Robots



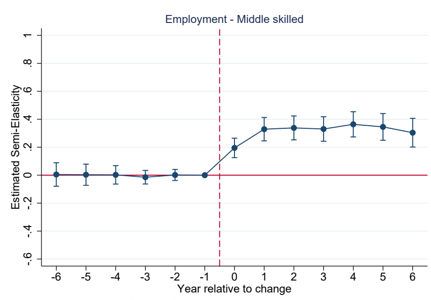
D. Electric motive power



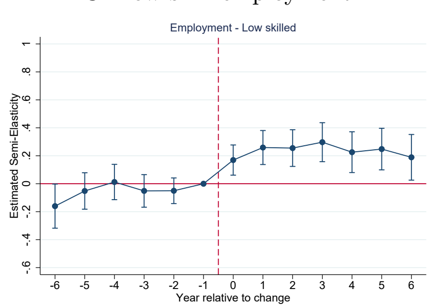
E. High-skill employment



F. Medium-skill employment



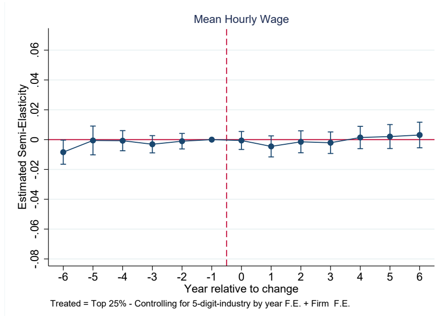
G. Low-skill employment



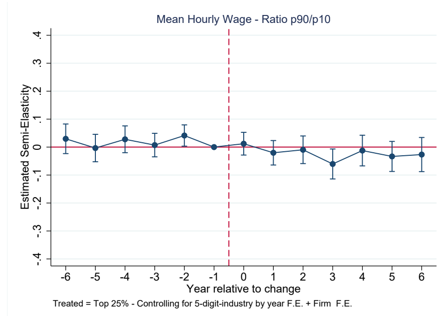
Notes: This figure reports the result of firm-level event studies, with the exception of panel (iv), where we use a distributed lead-lag model. To define the investment event, we use in turn changes in the balance-sheet value of industrial equipment (panel A), Acemoglu and Restrepo (2022)'s automation measure (panel B), imports of industrial robots (panel C), and electric motive power (panel D). Panels E through G analyze employment by skill groups, using changes in the balance-sheet value of industrial equipment. All specifications include 5-digit industry by year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level.

Figure 2: Firm-Level Event Studies, Additional Results

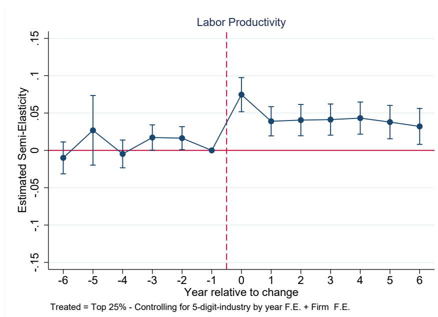
A. Mean hourly wage



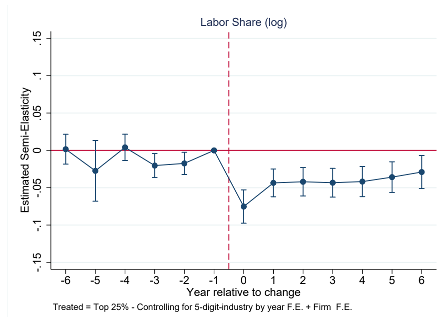
B. p90/p10 of wage distribution



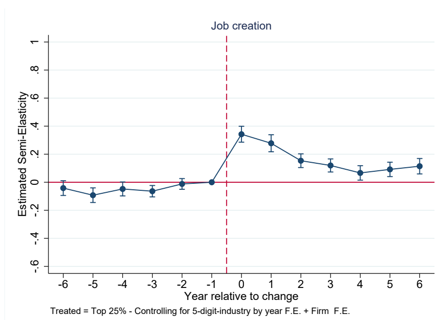
C. Labor productivity



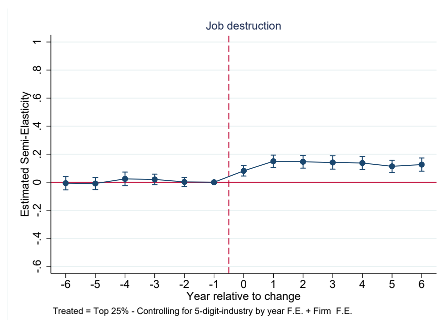
D. Labor share in value added



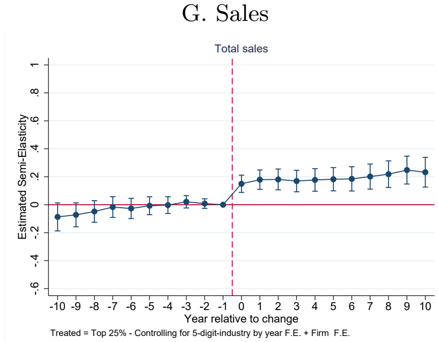
E. Job creation



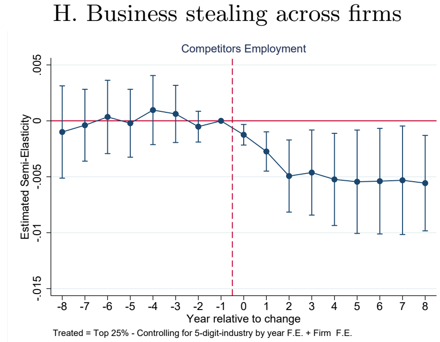
F. Job destruction



G. Sales



H. Business stealing across firms



Notes: This figure reports the result of firm-level event studies for eight outcomes after investments in modern manufacturing capital, measured as changes in the balance sheet value of industrial equipment. All panels use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

Panel A of Figure 2 shows that the average hourly wage remains flat after the investment event, with no sign of pre-trends.[28] Figure E11 shows that the average hourly wage remains similarly flat for low-skill, medium-skill, and high-skill workers, i.e. none of the broad skill groups suffers from a fall in wages. Panel B of Figure 2 shows that within-firm wage inequality remains unchanged, using the ratio of the 90th to the 10th percentile of wages within the firm as our dependent variable. Figure E11 documents a similar pattern by studying two specific occupations, unskilled industrial workers and engineers. We find that the wage ratio of unskilled industrial workers to engineers remains unchanged after the investment event. Finally, Panel C of Figure 2 studies labor productivity, defined as value added per worker. We find that labor productivity increases right after the investment event, with a semi-elasticity of 0.05 after 5 years and a spike in the year immediately following the event.

These patterns suggest that workers from all skill groups may benefit from modern manufacturing capital investments, on average, as employment increases and wages remain stable, with no impact on within-firm inequality. The estimated elasticities are in line with the canonical model, where capital investments lead to an increase in both labor demand and labor productivity.[29] These patterns are also consistent with parametrizations of the task model in which the overall effect on labor demand is positive. Next, we turn to displacement effects, where the task model makes distinctive predictions.

Displacement. To document whether typical investments in modern manufacturing capital have displacement effects, panel D of Figure 2 examines the response of the labor share in value added. We find a fall of the labor share after the investment event, with a large fall in the short run that is muted after 8 years.[30] As discussed in Section II and Appendix A, under standard parametrizations it is difficult for the canonical model to account for a fall in the labor share in value-added, while the task model can through reallocation of tasks across factors of production.[31] Appendix C.D

[28] Figure E10 show that the estimated wage reponse is also null when using Acemoglu and Restrepo (2022)'s measure of automation technologies.

[29] In the canonical model with perfect competition and production that uses homogenous labor and capital, all firms (or industries) face the same wage regardless of their labor demand. Thus, when a firm (or industry) increases labor demand, it continues to pay the same wage as everyone else. From that perspective, the fact that wages remain flat while output per worker increases should not be viewed as a puzzle.

[30] Given that wages do not change (panel (i) of Figure E11), the fall in the labor share in value added is just the mirror image of the increase in labor productivity (value added per worker), since the labor share is $s_L \equiv wL/VA$, i.e. $d\log(s_L) = -d\log(VA/L) + d\log(w)$, where the second term is estimated to be zero empirically.

[31] Through the lens of the task model in Appendix A, the fall in the labor share of value added indicates that typical investments in modern manufacturing capital encompass "automation at the extensive margin", which creates displacement effects affecting the labor share. Our earlier finding of an increase in firm-level employment suggests that the productivity effect is strong enough and results in an overall increase in labor demand.

discusses several additional patterns on the labor share, showing that firms that invest in modern manufacturing capital are able to rely less intensively on intermediate inputs through higher capital intensity of value-added (Figures E12 and E13).

To further characterize the displacement effects, panels E and F of Figure 2 focus on the rates of job creation and destruction within the firm. These panels show that there is an increase in both job creation and job destruction after the investment event. The rate of job reallocations goes up, with more job creation than job destruction. Appendix C.E discusses additional evidence, with a placebo test using investments in real estate (Figure E14).

These displacement effects suggest that typical investments in modern manufacturing capital can be conceptualized as automation, given the observed fall in the labor share in value added as well as the observed change in the production process inducing a reallocation of occupations within the firms, which is not observed for alternative investments like real estate. Overall, our results suggest that investments in modern manufacturing capital have subtle distributional effects in the labor market. Indeed, distributional effects may occur within each skill group, depending on the set of tasks performed across detailed occupations or employment status, but there is no evidence that they lead to important changes in within-firm inequality.

Market dynamics. Finally, we turn to market dynamics in the last two panels of Figure 2. Panel G shows the response of the firm's total sales, which increase markedly after the event, with a semi-elasticity of 0.2 on impact that increases slightly over time. Panel H uses competitors' employment (defined as domestic firms employment in the same 5-digit industry) as the outcome. The semi-elasticity of competitors' employment is negative, at about -0.001.[32]

Together, these patterns point to the importance of a scale effect brought about by the increase in productivity from investments in modern industrial capital, but also the potential for business-stealing effects negatively affecting employment in firms that do not invest. These findings motivate our analysis at the industry level in Section V, which accounts for these equilibrium effects at this level of aggregation. Appendix C.F discusses addtional evidence on market dynamics, including the response of export prices (Figures E24 to E26).

[32]In unreported robustness checks, we document that the estimated fall in competitors' employment (measured at the 5-digit industry level) continues to hold when we use 4-digit industry-by-year fixed effects and firm fixed effects. To fully account for business stealing effects, including entry and exit, we carry out the analysis at the industry level in Section V.

IV.B Causal Estimates from Firm-Level Shift-Share IV

Because so far we do not have an explicit quasi-experimental source of variation, it could be that unobserved factors explain some of the relationships documented above. We now address this limitation with a shift-share design.

IV.B.1 Research Design

To estimate the causal effect of modern manufacturing capital investment on labor demand, sales and other outcomes, the ideal experiment would randomly assign purchasing prices for modern manufacturing capital investments across firms. We approximate this ideal experiment using a shift-share IV design, which leverages two components: shocks and pre-determined exposure shares.

The shocks are obtained from variation in the cost of imported machines over time from international trading partners across detailed HS6 product categories. We use Acemoglu and Restrepo (2022)'s measure of imported automation technologies, which cover 167 HS6 product categories. Shocks are observed across "trading partners by HS6 product" cells indexed by n (for example, imports of machines from the Netherlands for the production of semi-conductors). The shocks g_{nt} are measured as the aggregate changes in import flows of industrial machines from each trading partner for each HS6 product category between 5-year periods centered around year t.

To obtain an instrument plausibly exogenous to the choices made by French firms, we study trade flows in countries similar to France. Specifically, we use HS6-level trade shocks measured in EU countries (except France) and Switzerland as instruments for the adoption of machines in France. Considering trade flows in these countries, we compute the following symmetric percentage change over time:

$$g_{nt} = \frac{ImportMachines_{n,t+1,t+5} - ImportMachines_{n,t-4,t}}{ImportMachines_{n,t+1,t+5} + ImportMachines_{n,t-4,t}}, \tag{2}$$

where n is a "trading partner by HS6 product" cell and $ImportMachines_{n,t+1,t+5}$ is the total value of imports of machines (using Acemoglu and Restrepo (2022)'s list of imported automation technologies) between years $t+1$ and $t+5$ in Switzerland and EU countries other than France. In the baseline specification, we measure the shocks g_{nt} across 98 trading partners in 167 HS6 product categories. We conduct the analysis around years $t = 2005$ and $t = 2010$, i.e. we leverage variation across consecutive five-year periods from 2001 to 2015, measuring the shocks using equation (2).[33]

[33] To be clear, the five-year periods centered about $t = 2005$ are 2001-2005 and 2006-2010, while those centered around and $t = 2010$ are 2006-2010 and 2011-2015.

Using changes in the market shares of international suppliers over time is helpful because changes in the quality-adjusted prices of machines are not directly observed. The customs dataset only provides unit values, which are difficult to adjust for quality. But changes in import flows can be used to infer changes in quality adjusted prices. Indeed, we can infer that countries with rising market shares become more productive at supplying industrial equipment in specific sectors in specific periods: standard consumer optimization yields that the quality adjusted price must go down when market shares go up. For example, for machines imported by French car manufacturers, the share of German suppliers increases in the 2000s; for food products, Dutch suppliers do particularly well in the 2010s.

The shift-share design combines this set of shocks with variation in the pre-existing network of international supplier relationships across French firms. The exposure share s_{i0n} is computed as the share of "trading partner by HS6 product" cell n in firm i's total imports of automation technologies in the reference period 0, which we set to be 1996-2000. Intuitively, because of switching costs, a French firm may benefit more from its trading partners' productivity shocks if it has a pre-existing importing relationship with them. Since contemporaneous shares are liable to reverse causality, we use initial shares, measured from 1996 to 2000, and conduct the analysis from 2000 onward, with the trade shocks measured using trade data excluding France.

The shift-share instrument is built by combining the shocks and exposure shares. The outcomes and endogenous variable are log changes across consecutive five year periods, centered around $t = 2005$ and $t = 2010$. The endogenous variable is the log change in the balance sheet value of industrial equipment, denoted ΔM_{it},[34] across firms indexed by i. Denoting by ΔL_{it} log changes in employment, we estimate by 2SLS the following specification:

$$\begin{cases} \Delta M_{it} = \alpha Z_{it} + \widetilde{\gamma} X_{it} + \widetilde{\varepsilon}_{it}, \\ \Delta L_{it} = \beta \Delta M_{it} + \gamma X_{it} + \varepsilon_{it}, \end{cases} \tag{3}$$

where Z_{it} is the shift-share instrument constructed from shocks g_{nt} and exposure shares $s_{i0n} \geq 0$,

$$Z_{it} = \sum_{n=1}^{N} s_{i0n} g_{nt},$$

with $\sum_{n=1}^{N} s_{i0n} = 1 \quad \forall i$. We study the sensitivity of the estimates to changes in the set of time-varying controls X_{it}. We use a battery of period-specific fixed effects. Specifically, in our baseline

[34] In our baseline specification, we do not use the Acemoglu and Restrepo (2022)'s measure of automation based on imports as our endogenous variable because it is measured as a flow rather than a stock.

specification we use HS6-by-period fixed effects, 4-digit industry by period fixed effects, and trading partner by period fixed effects. In this way, we compare French firms in the same 4-digit industry that source their inputs from different suppliers, within narrowly defined HS6 product categories. Fixed effects for industries and product categories are allowed to be period-specific so that they can flexibly absorb potential time-varying demand shocks.

Identification. The standard shift-share IV identification assumptions from shocks apply (see Borusyak et al. (2022)). First, a relevance condition must hold such that the instrument has power, i.e. $\mathrm{E}[\Delta M_{it} \cdot Z_{it} | X_{it}] \neq 0$. This can be checked directly in the data by computing the first-stage F statistic, accounting for the correlation of shocks (Adao et al. (2019)). The plausibility of the source of variation can also be assessed more directly by checking that the network of international suppliers is relatively sticky. To do so, Appendix Figure E15 reports the length of the relationships between a French firm and its main international supplier, depending on the number of years during which machines are imported. The figure shows that importer-supplier relationships are sticky. For example, firms that import machines for 15 years have the same main supplier for 13.2 years on average.

The exclusion restriction underlying this research design is that firms linked to increasingly productive suppliers should not feature unobservable characteristics that affect the outcomes of interest. Formally, omitting the period subscripts for brevity, the exclusion restriction can be expressed equivalently at the firm level or in space of productivity shocks (across foreign suppliers of different machines):

$$\left(\frac{1}{I}\sum_i Z_i \varepsilon_i \xrightarrow{p} 0\right) \Longleftrightarrow \left(\sum_n \hat{s}_{0n} g_n \bar{\varepsilon}_n \xrightarrow{p} 0\right), \tag{4}$$

with $\bar{\varepsilon}_n = \left(\sum_i s_{i0n}\varepsilon_i\right) / \sum_i s_{i0n}$ and $\hat{s}_{0n} = \frac{1}{I}\sum_i s_{i0n}$. As discussed in Borusyak et al. (2022), the expression for the exclusion restriction on the right-hand side is helpful because it highlights that identification "comes from" the shocks, rather than from exposure shares.[35] The effective number of shocks leveraged by this research design can be gauged by estimating the inverse of the Herfindahl index (HHI) of the weights $\hat{s}_{0n}$. Intuitively, if a few trading partners have most of the market shares, the effective sample size is small and the condition for consistency ($E\left[\sum_{n=1}^{N} \left(\hat{s}_{0n}\right)^2\right] \rightarrow 0$) may not be met. In practice, we compute that the inverse HHI of the weights $\hat{s}_{0n}$ is 341, indicating that the effective sample size is large.[36]

[35] In contrast, Goldsmith-Pinkham et al. (2020) develop an identification framework where the shares are the identifying source of variation. With the approach we take, shares can be endogenous.

[36] Equation (4) follows from Proposition 1 in Borusyak et al. (2022). Following their recommendations, when we

Falsification tests. The intuition underlying our shift-share IV reseach design is that we can isolate supply shocks by analyzing international trade data and trace out their consequences across French firms with different levels of shock exposure. The main threat to identification is that, rather than stemming from supply shocks only, changes in trade flows abroad could reflect correlated demand shocks across importing firms in France and abroad who share the same foreign suppliers. Such unobserved shocks could reflect consumer demand and have a direct effect on the outcomes of interest, including employment and sales, inducing a bias in our estimates.

To address this potential concern, we implement two falsification tests. First, as mentioned above our baseline specification uses three types of fixed effects: HS6-by-period fixed effects, 4-digit-industry-by-period fixed effects, and trading-partner-by-period fixed effects. If demand patterns confounded our results, we would expect the results to be very sensitive to the included set of fixed effects. To test this hypothesis, we repeat the analysis with more or less granular fixed effects, considering first 5-digit-industry-by-period fixed effects, and then a specification with 2-digit industry-period fixed effects. Second, we run a falsification test using the lagged outcome variable, providing evidence on the correlation between the instrument and potential lagged confounders. As described below, the point estimates remain similar regardless of the set of fixed effects and we find no correlation with lagged outcomes, alleviating concerns about correlated demand shocks.

Inference. In a shift-share IV design, observations cannot be treated as i.i.d. because regression residuals are likely to be correlated across firms with similar import shares. We follow Adao et al. (2019) and Borusyak et al. (2022) to correct standard errors and the first-stage F-statistic appropriately. All results are clustered by trading partner, which allows for correlated shocks within a trading partner over time and across industries. For example, China may experience positive productivity shocks throughout our period of study in a large number of industries.

Specifications. We report the results of the shift-share IV design for five specifications with alternative sets of controls X_{it}. The first specification only includes HS6-by-period fixed effects, 4-digit-industry-by-period fixed effects, and trading-partner-by-period fixed effects. The second specification adds a set of pre-determined firm controls including lagged turnover, total asset, employment, and the share of industrial workers in total employment. The third specification

plot the first-stage and reduced-form specifications below, we use scatter plots in the space of shocks across "trading partner by product by period" cells, rather than across firm-periods. This approach helps visualize the true source of identifying variation in this research design. The estimate retains its interpretation as a firm-level causal effect.

controls for the lagged balance sheet value of industrial equipment, and the fourth specification controls for other types of capital (land, buildings, and other types of capital). Finally, because trade flows play a central role for identification, the final specification adds controls for contemporaneous exports to ensure that potential correlated export shocks do not confound the results. The stability of coefficients across specifications can be viewed as a further test of the exclusion restriction, as discussed in Borusyak et al. (2022).

IV.B.2 SSIV Results

The results and falsification tests are reported in Table 2, using the change in the firm-level balance sheet value of industrial machines as our endogenous variable.[37] For completeness, we discuss OLS relationships in Appendix C.G (Table E4).

Panel A of Table 2 reports the estimates of the impact of automation (in the sense of Acemoglu and Restrepo (2022)) on employment using the shift-share instrument. The baseline specification in Column (1) yields an elasticity of firm employment to automation of +0.179 (s.e. 0.0710). The point estimate is statistically significant at the 5% level and the first stage F statistic of 27.22 indicates that the shift-share instrument is strong. The point estimates remain comparable in magnitudes in columns (2) through (5) as we change the set of controls. The point estimates are all close to 0.2, and significant at the 1% level. The first stage F statistic ranges between 23 and 26 in these alternative specifications.

Relative to these SSIV results, the OLS estimates from Table E4 are smaller, with elasticities around 0.14. Although the OLS point estimates are smaller, they are statistically indistinguishable from the SSIV estimates at the 5% level. The lower point estimate we obtain with OLS may be explained by the fact that some firms may automate in response to increased competition, which could have a direct negative effect on employment, hence a downward bias.

[37] The source of identifying variation in the SSIV is trade shocks for imports of industrial automating machines, following Acemoglu and Restrepo (2022). As a result, in the remainder of this section we interpret our results as the causal effects of reducing the costs of such automation technologies. Appendix Table E3 reports that the first stage is significant only when using Acemoglu and Restrepo (2022)'s automation measure as the instrument, and insignificant with Acemoglu and Restrepo (2022)'s alternative measure of capital deepening.

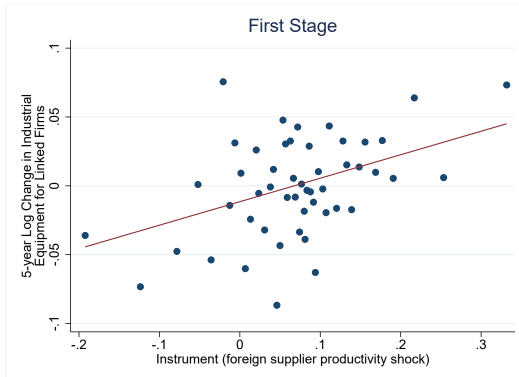
Table 2: Firm-level Effects with Shift-Share IV

	(1)	(2)	(3)	(4)	(5)
Panel A: Δ_5 *Employment*					
$\Delta_5 Machines$	0.179**	0.204***	0.210***	0.190***	0.195***
	(0.0710)	(0.0654)	(0.0694)	(0.0670)	(0.0638)
Panel B: Δ_5 *Sales*					
$\Delta_5 Machines$	0.329**	0.317**	0.322**	0.310**	0.319**
	(0.141)	(0.145)	(0.153)	(0.153)	(0.148)
Panel C: Δ_5 *Hourly Wages*					
$\Delta_5 Machines$	-0.0144	-0.0158	-0.0165	-0.0137	-0.0136
	(0.0423)	(0.0429)	(0.0427)	(0.0432)	(0.0430)
Panel D: Δ_5 *Labor Share*					
$\Delta_5 Machines$	-0.174**	-0.153**	-0.156**	-0.163**	-0.163**
	(0.0724)	(0.0710)	(0.0677)	(0.0689)	(0.0688)
Panel E: Δ_5 *Labor Productivity*					
$\Delta_5 Machines$	0.219***	0.193***	0.196***	0.209***	0.209***
	(0.0698)	(0.0669)	(0.0670)	(0.0706)	(0.0704)
Panel F: Δ_5 *Profits*					
$\Delta_5 Machines$	0.630	0.557	0.574	0.599	0.592
	(0.435)	(0.460)	(0.462)	(0.465)	(0.465)
Panel G: Δ_5 *Competitors' Employment*					
$\Delta_5 Machines$	-0.0462**	-0.0476*	-0.0492*	-0.0491*	-0.0487*
	(0.0226)	(0.0245)	(0.0249)	(0.0253)	(0.0253)
Panel H: *Lagged* Δ_5 *Employment*					
$\Delta_5 Machines$	0.0379	0.0518	0.0467	0.0383	0.0386
	(0.155)	(0.159)	(0.163)	(0.165)	(0.165)
Panel I: *Lagged* Δ_5 *Sales*					
$\Delta_5 Machines$	-0.0825	-0.00682	-0.00261	0.00593	0.00517
	(0.199)	(0.194)	(0.201)	(0.206)	(0.204)
First-Stage F	27.22	25.67	24.15	23.44	25.33
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	3,608	3,608	3,608	3,608	3,608

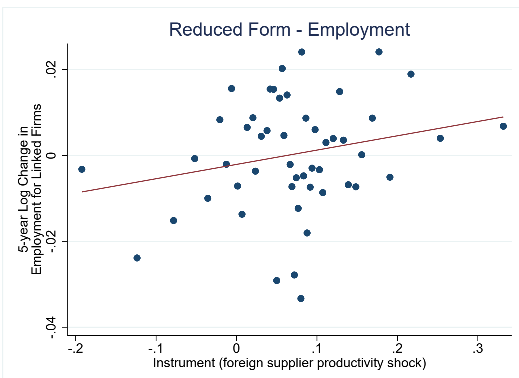
Notes: This table reports industry-level SSIV estimates. Standard errors and the first-stage F-statistic are clustered at the trading partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3: Firm-level Shift-Share IV Design

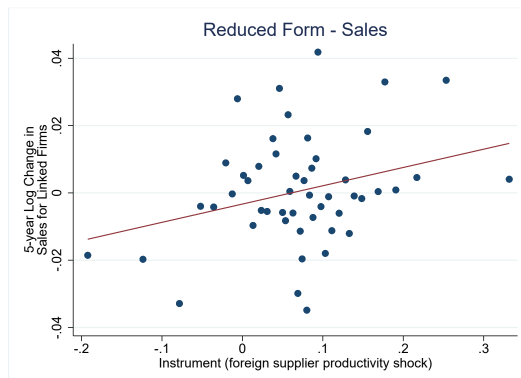
A. First stage



B. Reduced-form

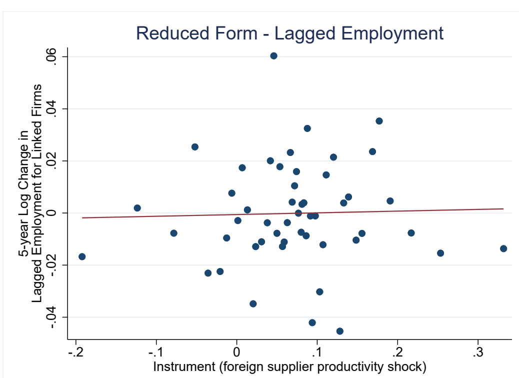


(i) Employment

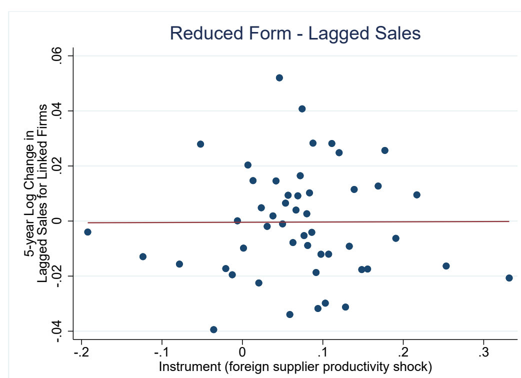


(ii) Sales

C. Falsification tests



(i) Lagged Employment



(ii) Lagged Sales

Notes: The binned scatter plots in this figure depict the relationships underlying the firm-level SSIV research design described by specification (3), considering in turn the first stage (panel A), the reduced-form relationships for employment and sales (panel B), and falsification tests with lagged outcomes (panel C). Each dot represents 2% of the data. HS6-product-by-foreign-supplier shocks measured in EU countries (except France) and Switzerland are used as the source of identifying variation. Shock size is shown on the x-axis for each foreign supplier by HS6 product category. The y-axis plots the average outcome for all firms importing from the corresponding foreign supplier in the relevant HS6 product category.

Next, Panel B of Table 2 takes sales as the outcome. We find that sales increase in response to increased automation, with elasticities close to 0.32 in all specifications, all statistically significant at the 5% level. This finding is consistent with the role of the productivity effect of automation. Increased automation allows the firm to expand its sales and scale, which requires hiring additional workers for production.

Panel C of Table 2 presents estimates of the impact of automation on average hourly wages in the firm. Consistent with the results from Section IV, we find no impact on wages. Next, Panel D of Table 2 presents estimates of the impact of automation on the labor share in value-added. The point estimates are consistently negative, around -0.16, and significant at the 5% level. Given that wages remain flat, the change in labor productivity, reported in Panel E, is the mirror image of the change in the labor share: the estimates for labor productivity are positive, around 0.20, and significant at the 1% level. For completeness, Appendix Table E5 reports additional evidence on the firm-level response of the labor share. All of these results are similar to those of the event studies reported in Section IV.

Next, we use the shift-share IV design to study market dynamics. Panel F of Table 2 shows no detectable impacts on firm profits, with positive but noisy point estimate. Turning to business-stealing effects, Panel G of Table 2 reports a negative impact of automation on competitors' employment within the same 2-digit industry.[38] The point estimates are negative, around -0.05, and statistically significant at the 5% or 10% levels across specifications.

Finally, Panel H and I of Table 2 report the results of pre-trend falsification tests, using the exact same shift-share IV specification, but using lagged employment and sales as outcomes. Conceptually, these lagged outcomes serve as a proxy for the unobserved error terms ε_{it} in equation (3). Across all five specifications, we cannot reject that there is no relationship between the shocks and lagged employment growth or lagged sales growth. These results lend credibility to a causal interpretation of the SSIV estimates.

To conclude this subsection, we present graphical evidence for the main results discussed above. Using the specification from Column (1) of Table 2, Figure 3 shows the first-stage (panel A) and reduced-form relationships underlying the shift-share IV design (panels B(i) and B(ii)), as well as the falsification tests (panels C(i) and C(ii)). Supplier shocks are depicted as the unit of observation since they are the source of identifying variation, as recommended by Borusyak et al. (2022). This

[38] The results are similar when considering competitors' employment within the same 5-digit industry, as reported in Appendix Table E6.

figure depicts relationships that appear to be robust graphically, with conditional expectation functions close to linear.

IV.B.3 SSIV Robustness

We now conduct several robustness checks. First, we obtain very similar results when using a more stringent set of fixed effects. In Appendix Table E6, we use HS6-by-period fixed effects and trading-partner-by-period fixed effects with 5-digit-industry-by-period fixed effects, instead of 4-digit industry-by-period fixed effects in our baseline specification. All results are statistically indistinguishable from those of our baseline specification in Table 2. Appendix Figure E16 reports the binned scatter plots for the first stage, reduced-form relationships and falsification tests corresponding to Column (1) of Table E6.

Second, in Appendix Table E7, we conduct the analysis with less stringent fixed effects, using HS6-by-period fixed effects and trading-partner-by-period fixed effects with 2-digit-industry-by-period fixed effects. The results remain statistically indistinguishable and are depicted graphically in Appendix Figure E17 for the specification of Column (1). As discussed previously, given the stability of the results when we vary the set of fixed effects, it appears unlikely that our SSIV estimates would be driven by unobserved correlated demand shocks.

Third, we also obtain similar results when repeating the analysis with an alternative set of shocks, using French customs data to focus on more detailed item categories called NC8 product categories (not reported).

IV.B.4 Extensive Margin Automation

In the framework of Acemoglu and Restrepo (2018c), automation on the intensive and extensive margins can have different effects on labor demand. Our shift-share research design focuses on a subsample of firms with pre-existing suppliers of machines and automation technologies, raising the potential concern that our sample may be biased in favor of firms that engage in "automation deepening", i.e. on the intensive rather than on the extensive margin.

To address this concern, we implement an alternative shift-share design. The idea is to focus on the effect of extensive margin automation at the firm level, i.e. the adoption of machines that are "new to the firm". To implement this research design, we build an "extensive margin automation" variable $\Delta M_{\text{Extensive},it}$, defined as the ratio between the sum of imports of automation technologies that are new to the firm - i.e. not imported by the firm in the past - divided by the stock of imported machines.[39] We also build an "intensive margin automation" variable $\Delta M_{\text{Intensive},it}$ as the ratio between the sum of imports of automation technologies that are not new to the firm - i.e. already imported by the firm in the past - divided by the stock of imported machines. We build these variables using the finest level of disagregation available in the French customs data, called NC8, which is more detailed than HS6 codes.

As previously, we define exposure shares s_{i0n} as the share of "trading partner by HS6 product" cell n in firm i's total imports of automation technologies in the reference period 0 (1996-2000). We use the same HS6-level trade shocks as previously, measured in EU countries (except France) and Switzerland as defined in equation (2). Thus, our shift-share instrument is unchanged. However, we now run a specification with extensive margin automation $\Delta M_{\text{Extensive},it}$ as the outcome – rather than using the change in the balance sheet value of industrial machines, which captures both intensive and extensive margin automation – and we control for contemporaneous intensive margin automation $\Delta M_{\text{Intensive},it}$.

To illustrate how this research design isolates extensive margin automation, consider an example: a French firm importing certain textile machines from Italy. There are different types of textile machines, corresponding to different NC8 categories, which are all part of the same HS6 codes. Because of predetermined linkages with Italian suppliers, after a positive supply shock for textile machines in Italy the French firm may be more likely to purchase more textile machines it already used in the past but also certain new types of machines – i.e., from a NC8 category it never bought in the past, which will be captured by $\Delta M_{\text{Extensive},it}$.

The results are reported in Table 3. The first-stage F statistic indicates that the instrument is strong. The results are in line with our main SSIV design, with an increase in employment and sales in Panels A and B; there is still no detectable change in wages in Panel C; the labor share falls in Panel D and productivity increases in Panel E; the point estimate for profits is positive but noisy in Panel F; and there is a negative response of competitors' employment in Panel G. Panels H and I report the falsification test, showing no signs of pre-trends. These results suggest that isolating extensive margin automation yields similar conclusions to our main analysis using to full set of investments.

[39] We measure the stock of imported machine as follows: first, we calculate the annual total value of imports of machines (using Acemoglu and Restrepo (2022)'s list of imported automation technologies),$\text{Imports}_{i,t}$. Then, following the French accounting standards, i.e. assuming a linear depreciation of 8 years for machines, we compute the stock of imported machines as $M_{it} = \sum_{k=0}^{7}(1 - \frac{k}{8})\text{Imports}_{i,t}$.

Table 3: Firm-level Effects with Shift-Share IV, Extensive Margin Automation

	(1)	(2)	(3)	(4)
Panel A: Δ_5 *Employment*				
$\Delta_5 Machines_{ext}$	0.727**	0.725**	0.681**	0.617**
	(0.306)	(0.316)	(0.296)	(0.294)
Panel B: Δ_5 *Sales*				
$\Delta_5 Machines_{ext}$	0.982**	0.980**	0.956**	0.844**
	(0.418)	(0.422)	(0.415)	(0.400)
Panel C: Δ_5 *Hourly Wages*				
$\Delta_5 Machines_{ext}$	0.0781	0.0763	0.0848	0.0889
	(0.174)	(0.172)	(0.171)	(0.172)
Panel D: Δ_5 *Labor Share*				
$\Delta_5 Machines_{ext}$	-0.660*	-0.658*	-0.665*	-0.638*
	(0.375)	(0.367)	(0.364)	(0.363)
Panel E: Δ_5 *Labor Productivity*				
$\Delta_5 Machines_{ext}$	0.845*	0.839*	0.863*	0.835*
	(0.472)	(0.473)	(0.468)	(0.463)
Panel F: Δ_5 *Profits*				
$\Delta_5 Machines_{ext}$	2.073	2.069	2.099	1.884
	(1.720)	(1.702)	(1.700)	(1.658)
Panel G: Δ_5 *Competitors' Employment*				
$\Delta_5 Machines_{ext}$	-0.0998*	-0.0996*	-0.100*	-0.0958
	(0.0566)	(0.0585)	(0.0585)	(0.0581)
Panel H: *Lagged* Δ_5 *Employment*				
$\Delta_5 Machines_{ext}$	-0.171	-0.170	-0.194	-0.219
	(0.610)	(0.612)	(0.606)	(0.620)
Panel I: *Lagged* Δ_5 *Sales*				
$\Delta_5 Machines_{ext}$	0.0967	0.104	0.125	0.0798
	(0.652)	(0.661)	(0.661)	(0.667)
First-Stage F	16.17	16.17	16.16	16.02
6-digit Product-period F.E.	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes
4-digit Industry-period F.E.	Yes	Yes	Yes	Yes
Lagged Firm Controls	Yes	Yes	Yes	Yes
Contemporaneous Intensive Margin Automation	Yes	Yes	Yes	Yes
Lagged Machines		Yes	Yes	Yes
Lagged Other Capital			Yes	Yes
Contemporaneous Exports				Yes
N (Trading partner - Product - Period)	4,328	4,328	4,328	4,328

Notes: This table reports industry-level SSIV estimates, with extensive margin automation as the endogenous variable and controlling for contemporaneous intensive margin automation. Standard errors and the first-stage F-statistic are clustered at the trading partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Moreover, the firm-level shift-share analysis in our main sample provided evidence of a fall in the labor share in value-added. In Acemoglu and Restrepo (2018c)'s framework, a fall in the labor share can only occur in the presence of "extensive margin" automation. Through the lens of their framework, we can thus reject that the positive labor demand response estimated in our main shift-share IV analysis is primarily driven by intensive margin capital deepening.

Finally, as an additional test to assess whether the local average treatment effect in our main shift-share sample is different from the average treatment effect in the population, we carry out the event study analysis from Section IV.A on several subsamples. We find that the event study results in the subsample used for the shift-share analysis are similar to those of the event studies in the full sample, both when using the balance sheet value of industrial equipment (Appendix Figure E18) or Acemoglu and Restrepo (2022)'s proxy for automation (Appendix Figure E19). The effects are also similar when we only consider firms that purchase for the first time from a foreign trading partner supplying automation technologies, using Acemoglu and Restrepo (2022)'s proxy (Appendix Figure E20). Together, these results show that there is no evidence supporting the idea that our SSIV sample leads to a bias in the estimated treatment effect.

V Industry-level Estimates

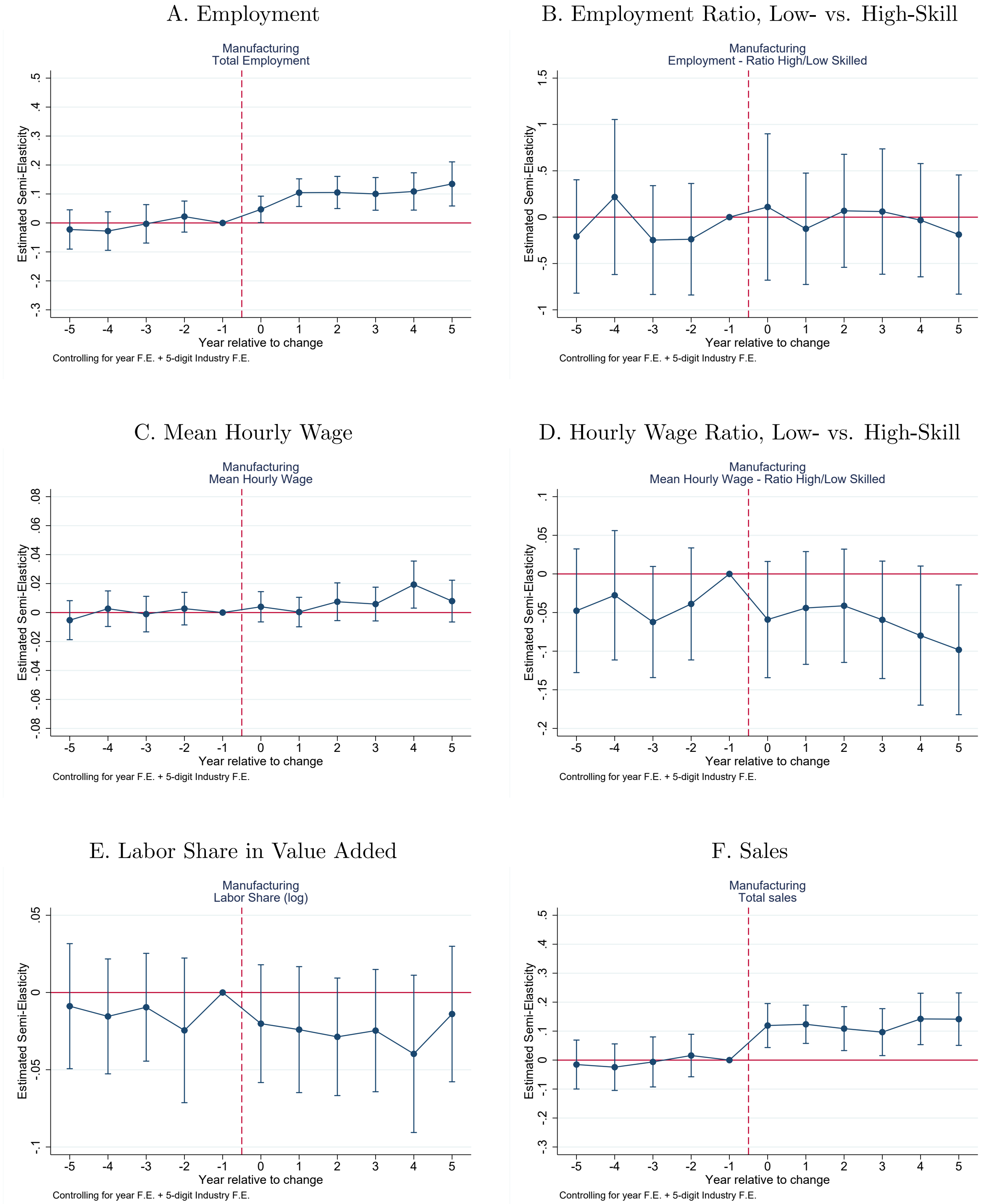
In this section, we study the relationship between modern manufacturing capital investments, employment, prices, and profits at the level of industries. We first present event studies in Section V.A, then the industry-level shift-share IV design in Section V.B, and we assess the role of international business stealing effects and the demand reallocation channel in Section V.C.

V.A Industry-level Event Studies

The positive firm-level relationships between employment and manufacturing capital investments could in principle be overturned at the industry level, because firms that invest less may be displaced by firm that invest more. To examine how such business stealing effects may add up, we examine the industry-level relationship between manufacturing capital investments and employment.

We start by implementing the same event study methodology as in Section IV at the 5-digit industry level, with year fixed effects and 5-digit-industry fixed effects. In the baseline specification, we use the 50th percentile of relative changes in the balance-sheet value of industrial machines as our event threshold. Our measure of employment includes all firms, i.e. we account for entry and exit at the industry level.

Figure 4: Industry-Level Event Studies



Notes: This figure reports the results of industry-level event studies for several outcomes. The investment event is defined as a logarithmic change beyond the 50th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. All panels include 5-digit industry and year fixed effects, with standard errors clustered at the industry level.

The results are reported in Figure 4. Panel A shows that industry-level employment increases after the investment event, with a semi-elasticity of about 0.10 on impact, with a slight increase afterwards. These patterns indicate that the employment response remains positive at the industry level. Panel B to D are also similar to the firm-level estimates, showing no impact on inequality: Panel B shows that there is no clear impact on relative labor demand between high- and low-skill workers at the industry level; Panel C documents that average hourly wages remain unaffected; Panel D reports no clear impact on the wage ratio between high skill and low skill employees.

Next, Panel E shows that we cannot reject that the labor share in value added remains constant, in contrast with the firm-level results. Finally, Panel F reports the response of sales, with a semi-elasticity of about 0.1 on impact, a bit lower than the firm-level pattern.

The Appendix reports robustness checks with alternative definitions of industry-level capital investments. While our baseline measure considers the log change in the industry-level balance sheet value of industrial equipment, we repeat the analysis with two alternative measures in Appendix Figure E21, considering in turn (i) investments as a fraction of the initial balance sheet value of industrial equipment, and (ii) the log change in the industry-level balance sheet value of industrial equipment for firms that operate continuously during our sample. The results remain similar.

Overall, these findings indicate that, despite the potential for business stealing effects, the overall effect of manufacturing capital investments on labor demand and employment remains positive at the industry level through a scale effect, with a large increase in sales. However, like previously, the event study remains liable to correlated demand or supply shocks, which we address next by developing an industry-level SSIV design.

V.B Causal Estimates from Industry-Level Shift-Share IV

To assess whether a causal interpretation of the industry-level event study estimates is warranted, we implement an industry-level shift-share IV design.

Research design. The research design is identical to the shift-share IV presented in Section IV.B.1 with specification (3), except for that i now indexes 5-digit industries rather than firms. We use the same trade shocks, measured across detailed HS6 product categories in the EU (excluding France) and Switzerland. We use the same set of imported inputs as previously, following Acemoglu and Restrepo (2022), and compute the symmetric percentage change over 5-year periods as in equation (2). We can thus examine the response of employment and sales in industries that source their machines from increasingly productive foreign suppliers.[40]

In this design, all outcomes are measured at the level of 5-digit industries, which are narrow and include, for example, "manufacture of plastic plates, sheets, tubes and profiles" or "manufacture of metal structures." The exposure share s_{i0n} is computed as the share of "trading partner by HS6 product" cell n in industry i's total imports of machines. As previously, we use initial shares measured from 1996 to 2000. In the baseline specification, we measure the shocks across 167 HS6 categories, with 125 trading partners in the 256 5-digit industries during consecutive 5-years periods centered about $t = 2005$ and $t = 2010$. The inverse HHI of the relevant weights $\hat{s}_{0n}$ is 425. To address potential correlated demand shocks, we use HS4-by-period fixed effects as HS2-by-trading-partner-by-period fixed effects.

Results. The results and falsification tests are reported in Table 4. In line with the firm-level analysis in the previous section, we use the change in the industry-level balance sheet value of industrial machines as our endogenous variable and we measure productivity shocks across foreign suppliers through trade flows using Acemoglu and Restrepo (2022)'s definition of imported automation technologies. Appendix C.H discusses the industry-level OLS relationships (Table E8).

Panel A of Table 4 reports the estimates of the impact of automation (in the sense of Acemoglu and Restrepo (2022)) on employment and other outcomes using the industry-level shift-share IV design. The baseline specification yields an elasticity of firm employment to automation of +0.41 (s.e. 0.112). The point estimate is statistically significant at the 1% level and the first stage F statistic of 10.55. The point estimates are close in magnitudes, around 0.4, as we change the set of controls in columns (2) through (4), with F statistics around 10.

These results support the findings from the previous subsection: increases in automation lead to higher employment at the level of the industry. While Panel A accounts for the impact of entry and exit on employment, the point estimates for the industry-level employment elasticities are reduced to about 0.2 in Panel B when focusing on incumbent firms that exist in all periods (similar to the firm-level SSIV estimates in Table 2).

Panel C of Table 4 documents the response of sales. We find that sales increase, with elasticities around 0.47 across specifications. The relationship is significant at the 1% level in all specifications. This finding is consistent with the role of the productivity effect of automation. Increased automa-

[40] To the best of our knowledge, this paper is the first to develop a unified shift-share design using the same shocks to estimate causal effets at different levels of aggregation, a methodology which could be applied in future work to study other topics (e.g., the firm-level and industry-level effects of immigration). In particular, this methodology provides a reduced-form approach to assess the role of business-stealing effects.

tion allows the industry as a whole to expand its sales and scale, which requires hiring additional workers for production. Panels A and B of Figure 5 shows the first-stage and reduced-form relationships underlying the industry-level shift-share IV design for employment and sales, depicting graphically the robustness of the findings.

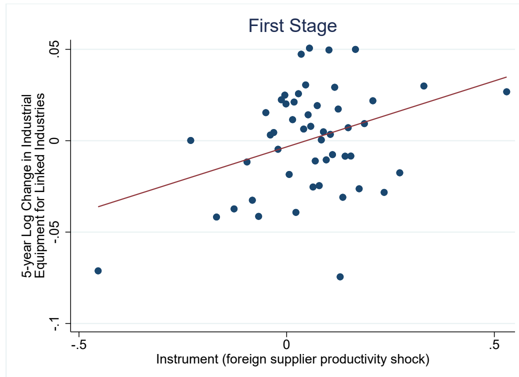
Table 4: Industry-level Effects with Shift-Share IV

	(1)	(2)	(3)	(4)
Panel A: Δ_5 *Employment*				
$\Delta_5 Machines$	0.412***	0.404***	0.409***	0.409***
	(0.112)	(0.111)	(0.104)	(0.106)
Panel B: Δ_5 *Incumbents' Employment*				
$\Delta_5 Machines$	0.219*	0.223**	0.218**	0.219**
	(0.114)	(0.107)	(0.102)	(0.102)
Panel C: Δ_5 *Sales*				
$\Delta_5 Machines$	0.481***	0.464***	0.460***	0.468***
	(0.153)	(0.149)	(0.145)	(0.152)
Panel D: Δ_5 *Hourly Wages*				
$\Delta_5 Machines$	-0.0367	-0.0295	-0.0241	-0.0210
	(0.0419)	(0.0420)	(0.0370)	(0.0364)
Panel E: Δ_5 *Labor Share*				
$\Delta_5 Machines$	-0.305*	-0.311**	-0.298**	-0.310**
	(0.158)	(0.152)	(0.147)	(0.127)
Panel F: Δ_5 *Labor Productivity*				
$\Delta_5 Machines$	0.210	0.210*	0.197	0.222**
	(0.137)	(0.125)	(0.119)	(0.0970)
Panel G: Δ_5 *Profits*				
$\Delta_5 Machines$	2.180***	2.123***	2.066***	2.113***
	(0.698)	(0.717)	(0.693)	(0.574)
Panel H: *Lagged* Δ_5 *Employment*				
$\Delta_5 Machines$	0.105	0.0896	0.0893	0.0849
	(0.188)	(0.192)	(0.184)	(0.182)
Panel I: *Lagged* Δ_5 *Sales*				
$\Delta_5 Machines$	0.110	0.106	0.0853	0.0769
	(0.282)	(0.275)	(0.259)	(0.250)
First-Stage F	10.55	9.91	10.90	11.79
4-digit Product-period F.E.	Yes	Yes	Yes	Yes
2-digit Product-Partner-period F.E.	Yes	Yes	Yes	Yes
Lagged Industry Controls	Yes	Yes	Yes	Yes
Lagged Machines		Yes	Yes	Yes
Lagged Other Capital			Yes	Yes
Contemporaneous Exports				Yes
N (Trading partner - Product - Period)	7,138	7,138	7,138	7,138

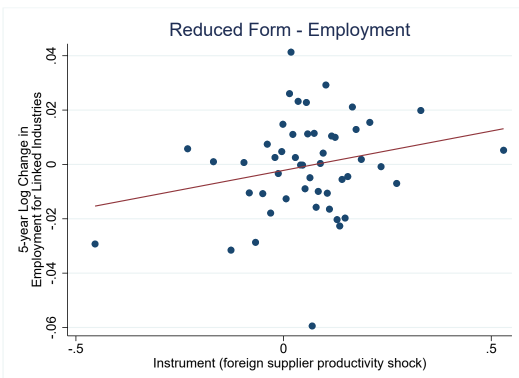
Notes: This table reports industry-level SSIV estimates. Standard errors and the first-stage F-statistic are clustered at the trading partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5: Industry-level Shift-Share IV Design

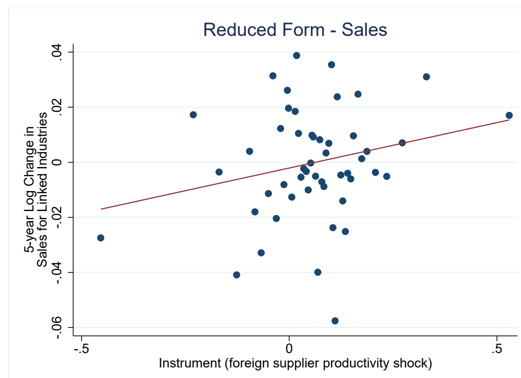
A. First stage



B. Reduced-form

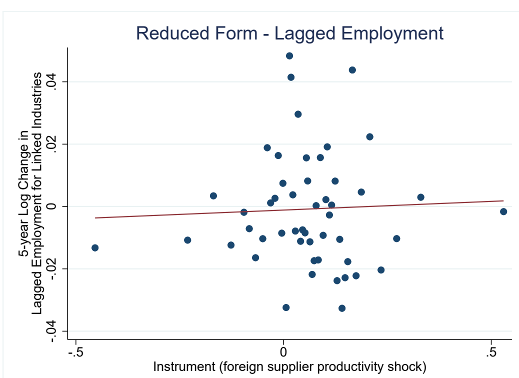


(i) Employment

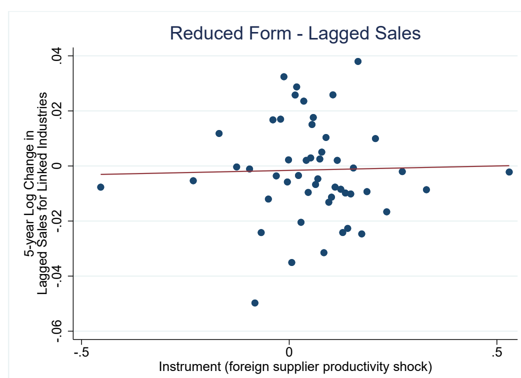


(ii) Sales

C. Falsification Tests



(i) Lagged Employment



(ii) Lgged Sales

Notes: The binned scatter plots in this figure depict the relationships underlying the industry-level SSIV research design described by specification (3), considering in turn the first stage (panel A), the reduced-form relationships for employment and sales (panel B), and falsification tests with lagged outcomes (panel C). Each dot represents 2% of the data. HS4-product-by-foreign-supplier shocks measured in EU countries (except France) and Switzerland are used as the source of identifying variation. Shock size is shown on the x-axis for each foreign supplier by HS4 product category. The y-axis plots the average outcome for all industries importing from the corresponding foreign supplier in the relevant HS4 product category.

Next, Panel D of Table 4 present the estimates for the impact of automation on wages. In all four specifications, we cannot reject that there is no impact of automation on hourly wages, similar to the firm-level analysis. In Panel E, the point estimates for the change in the labor share in value added are negative, close to -0.3 in all specifications. [41] Conversely, Panel F shows that the effect on labor productivity is positive, with elasticities close to 0.2, although the estimate is statistically significant only in Column (4).

Finally, Panel G documents a positive elasticity of industry profits to automation. The elasticity is large in magnitude at about 2–2.2 but is imprecisely estimated, with standard errors of about 0.7, such that the results are statistically indistinguishable from the firm-level estimates in Table 2.

Table 4 also reports the results of pre-trend falsification tests, implementing the shift-share IV design taking as outcome the lagged changes in industry employment in Panel H and lagged changes in industry sales in Panel I. As previously, these lagged outcomes serve as a proxy for the unobserved error terms ε_{it}, now at the industry level. Across all four specifications, we cannot reject that there is no relationship between the shocks and lagged employment growth. Panel C of Figure 5 reports the reduced-form relationships with lagged employment and lagged sales. These results lend credibility to a causal interpretation of the industry-level estimates.

Finally, in Appendix Table E9, we repeat the analysis with an alternative, less stringent set of fixed effects. Using partner by period fixed effects instead of 2-digit product by partner by period fixed effects yields very similar results.

V.C International Business Stealing and the Demand Reallocation Channel

Our finding that the elasticity of industry-level employment to modern manufacturing capital investments is quantitatively similar to the firm-level employment elasticity may seem surprising. Indeed, the demand elasticity of substitution is larger between firms within the same industry than between industries. Therefore, in a closed economy we would expect the industry-level employment elasticity to modern manufacturing capital investments to be smaller than at the firm level, because demand reallocation should be smaller at the industry level than at the firm level.

However, in an open economy, the industry-level elasticity of substitution of consumer demand may remain high, because domestic producers compete with foreign suppliers and produce substitutable goods (e.g., Broda and Weinstein (2006)). To assess the role of international trade, in Table

[41] For completeness, Appendix Table E10 reports the industry-level reponse of the labor share in value added and accounting only for wages as labor costs (e.g., not taking into account retirement contributions).

5 we repeat the analysis for subsets of industries with trade exposure above or below median. We use the share of imports in final consumption, obtained from national accounts, to measure exposure to international competition. This measure is available at the level of 253 industries defined by the French national accounts.

Heterogeneous impacts by exposure to international competition. In Table 5, we document that the positive industry-level relationship between modern manufacturing capital investments and employment (panel A) or sales (panel B) is driven by industries that face a higher degree of international competition. To reduce noise in this subsample analysis, we implement OLS specifications with long differences between 1996 and 2017. Both panels of this table document industry-level relationships in columns (1), (3), and (5); we also report firm-level relationships in columns (2), (4), and (6), which we use as falsification tests and discuss below.

The results for employment and sales for all industries, reported in Column (1) of each panel, are in line with the industry-level estimates from the preceding subsections. With higher exposure to international competition, the point estimate for employment in Column (3) of panel A is 0.402 (s.e. 0.056) and is similar to firm-level employment elasticities. In contrast, with lower exposure to international competition in Column (5) of panel A, the point estimate loses statistical significance and falls in magnitude to 0.183 (s.e. 0.136). When exposure to international competition is low, the positive relationship between employment and modern manufacturing capital investments disappears, but it is instructive to note that it does not turn negative. Likewise, the response of sales in Column (3) of panel B is 0.523 (s.e. 0.079) with higher exposure to international competition, while is becomes smaller and statistically insignificant at 0.169 (s.e. 0.124) with lower exposure in Column (5) of panel B.

The heterogeneity by exposure to international competition is thus consistent with the role of international business stealing. The demand reallocation channel predicts that heterogeneity should be visible only for industry-level outcomes, since at the firm level business stealing will operate regardless of exposure to international trade. With this motivation in mind, in columns (2), (4), and (6) of Table 5, we implement a falsification test by running the firm-level analysis in the same subsamples of exposure to international competition. Consistent with the role of international business stealing, at the firm-level there is no heterogeneity and the employment and sales responses remain positive and similar in magnitudes regardless of the degree of exposure to international competition.

Furthermore, the findings in Table 5 confirm that the positive impact of modern manufacturing capital investments on employment, which we found at both the firm and industry levels, cannot be explained by a standard model with factor augmenting technological change and complementarity between labor and some machines. In such a model, we should have found a positive correlation between capital investments and employment at the industry level even in industries that are not exposed to international competition.

Table 5: The Role of International Business-Stealing Effects

A. Modern Manufacturing Capital Investments, Employment, and International Competition

	Δ Employment 1996-2017					
			Exposure to Import Competition			
	All industries		Above Median		Below Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Machines 1996-2017	0.351***	0.315***	0.402***	0.309***	0.183	0.320***
	(0.061)	(0.010)	(0.056)	(0.017)	(0.136)	(0.013)
Δ Other types of capital 1996-2017	✓	✓	✓	✓	✓	✓
5-digit industry F.E.		✓		✓		✓
Industry-level regression	✓		✓		✓	
Firm-level regression		✓		✓		✓
N	253	5,112	120	1,906	133	3,206

B. Modern Manufacturing Capital Investments, Sales, and International Competition

	Δ Sales 1996-2017					
			Exposure to Import Competition			
	All industries		Above Median		Below Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Machines 1996-2007	0.424***	0.334***	0.523***	0.277***	0.169	0.370***
	(0.065)	(0.012)	(0.079)	(0.019)	(0.124)	(0.015)
Δ Other types of capital 1996-2017	✓	✓	✓	✓	✓	✓
5-digit industry F.E.		✓		✓		✓
Industry-level regression	✓		✓		✓	
Firm-level regression		✓		✓		✓
N	253	5,112	120	1,906	133	3,206

Notes: This table reports the results of industry-level OLS regressions using long differences between 1996 and 2017, considering changes in employment as the outcome in panel A and changes in sales in panel B. The independent variable is the change in the balance sheet value of industrial equipment. In both panel, columns (1) and (2) use the full sample of industries while columns (3) and (4) consider only industries with a level of import competition above median (as measured by domestic absorption in the national accounts tables), and columns (5) and (6) analyze those below median. All specifications include controls for contemporaneous changes in others types of capital. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The demand reallocation channel. In Appendix D, we present a simple calibration in a CES framework to assess whether the estimated industry-level increase in employment and sales can be accounted for by the observed price changes following investments in modern manufacturing capital. We find that standard estimates of consumers' demand elasticities between international suppliers operating in the same industry can indeed rationalize the positive employment and sales effects together with the negative price effects we observe in the data.

Specifically, competition between international suppliers providing close substitutes explains why the relationship between modern manufacturing capital investments and employment can remain positive even at the industry level, because the response of consumer demand to price changes is large.[42] In contrast, the industry-level results on sales and employment is difficult to rationalize in a closed economy, because demand reallocation would need to operate between domestic industries (rather than between products produced either by domestic firms or by international competitors within the same industry); given the smaller demand elasticity governing industry-level substitution, this would require large price changes that we do not observe in the data.

These observations may help reconcile some of the diverging industry-level estimates in the literature, depending on the degree of import competition in a country. For example, Acemoglu and Restrepo (2019) report a negative relationship between robots and employment in the United States, where domestic firms have a larger domestic market and are less exposed to international competition (i.e., business stealing effects operate primarily between domestic firms rather than internationally). By contrast, Klenert et al. (2023) estimate a positive relationship in a sample of European countries, including France, which are more exposed to international competition.

VI Conclusion

In this paper, we have leveraged new micro data on firms and industries in the French manufacturing sector to provide a unified analysis of the effects of a fall in the cost of investments in modern manufacturing capital, including automation technologies, on employment, wages, prices, sales, profits, and business stealing between 1995 and 2017.

At both the firm at the industry levels, we find an increase in employment, indicating that the productivity effect tends to outweigh the displacement effects. There is also an increase in sales, a fall in the labor share, and a fall in consumer prices. The estimated fall in the share of labor in value added is in line with task-based frameworks of automation but difficult to account for in the canonical model of factor-augmenting technological change. This finding highlights that Acemoglu

[42] We focus on the impact of investments on domestic labor demand and our results do not speak to the impact on overall labor demand across multiple countries, which we view as an important topic for future research left outside the scope of this paper. Our results are not inconsistent with the idea that investments in modern manufacturing capital, including automation, leads to structural change and labor reallocation across sectors (e.g., Ngai and Pissarides (2007)); rather, they highlight that, perhaps surprisingly, domestic manufacturing employment is better preserved in countries that invest more, including in automation technologies (as in Germany, for example), due to a productivity effect and international business-stealing.

and Restrepo (2018c)'s task-based modeling framework of automation is relevant to understand a broad class of modern manufacturing capital, beyond the specific examples that have been studied empirically in work prior to ours (e.g., studies of robots including Graetz and Michaels (2018) and Acemoglu and Restrepo (2019)). Our empirical findings thus point to a task-based framework where the productivity effect dominates the displacement effect. At the industry-level, we find that the employment elasticity remains positive on average, but that the effect is heterogeneous depending on exposure to international trade.

Our estimates highlight the importance of business-stealing effects (e.g., as in Acemoglu and Guerrieri (2008) and Baqaee and Farhi (2019)), at both the firm level and the industry level. After productivity-enhancing investments, firm owners increase their profits but pass through some of the productivity gains to consumers, inducing reallocation of expenditures across firms or industries and thus scale effects. Modern manufacturing capital, including automation, can thus lead to higher firm profits, lower consumer prices, increased consumer demand, and in turn to increased firm and industry scale, higher labor demand and higher domestic employment at the expense of foreign competitors. Absent international policy coordination, unilateral attempts to curb domestic automation or capital investments in an effort to protect domestic employment may be self-defeating because of foreign competition and international business-stealing.

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Online Appendix to "Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France"

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In this appendix, we first present a survey of the theoretical predictions from models of factor-augmenting technological change and task-based automation (Appendix A). We discuss our plant-level records of electro-motive force (Appendix B). We then provide a discussion of a series of additional empirical results (Appendix C), and we present a simple calibration of the demand reallocation channel (Appendix D). Additional figures and tables are reported in Appendix E.

A A Survey of Theoretical Predictions: Factor-Augmenting Technological Change vs. Task-Based Automation

In this appendix, we relate our empirical analysis to state-of-the-art theoretical analyses of automation and capital-labor substitution. We discuss in turn models of factor-augmenting technological change, including the role of reallocation effects, and models of task-based automation.

A.A Factor-Augmenting Technological Change

Canonical macroeconomic models formalize technological change either as "factor augmenting", i.e. technological progress increases the effective units of one of the factors of production, or as Hicks neutral, which leads to a proportionate increase in the output obtained from any input combination. Consider an aggregate production function where aggregate output is given by the constant returns to scale production function $Y = F(A_K K, A_L L)$, with K capital, L labor, A_K and A_L capital-augmenting and labor-augmenting technological change. The production function is concave in each input. With competitive labor markets, wages are equal to the marginal product of labor: $W = A_L F_L$.[43]

[43] A proportional increase in both A_K and A_L corresponds to Hicks-neutral technological change, leaving relative factor prices and the labor share unchanged. As productivity increases, labor demand and the equilibrium wage increase.

Capital-augmenting technological change. Consider a change in A_K. We have:

$$\frac{dW}{dA_K} = A_L K F_{LK} = -A_L L F_{LL} > 0, \tag{A1}$$

where the second equality follows from the fact that, given constant returns to scale, by Euler's theorem we have $K \cdot F_K + L \cdot F_L = F$, implying $K \cdot F_{KL} + L \cdot F_{LL} = 0$. Thus, capital-augmenting technology always increases labor demand and the equilibrium wage. Intuitively, in this model, any increase in the productivity of capital leads to an increase in the marginal product of labor, hence labor demand and wages must increase.

Denoting by ε_{KL} the elasticity of substitution between capital and labor, by $s_L \equiv \frac{WL}{Y}$ the labor share, and by $s_K \equiv 1 - \frac{WL}{Y}$ the capital share, Acemoglu and Restrepo (2018b) show that the effect of capital-augmenting technological change on the labor share is given by

$$\frac{d\ln(s_L)}{d\ln(A_K)} = s_K \left(\frac{1}{\varepsilon_{KL}} - 1 \right),$$

which is negative if and only if $\varepsilon_{KL} > 1$. Most available estimates of the elasticity of substitution between capital and labor are below 1 (e.g., Oberfield and Raval (2021)), therefore capital-augmenting technological change should lead to an increase in the labor share.[44]

Thus, if modern manufacturing capital primarily consisted in capital-augmenting technological change, then it should result in an increase in the equilibrium wage and the labor share.

Labor-augmenting technological change. Next, consider a change in A_L. Acemoglu and Restrepo (2018b) show that the effect of labor-augmenting technological change on the wage is

$$\frac{dW}{dA_L} = \left(1 - \frac{s_K}{\varepsilon_{KL}} \right) F_L,$$

which is positive if $\frac{s_K}{\varepsilon_{KL}} < 1$, a condition statisfied with standard parameter values for s_K and ε_{KL}. Indeed, most estimates of the capital share are about 0.3–0.4 (e.g., Karabarbounis and Neiman (2014)), while leading estimates of the capital-labor elasticity of susbtitution are about 0.5–0.7 (e.g., Oberfield and Raval (2021)). Labor-augmenting technological change should therefore increase labor demand and wages. Furthermore, Acemoglu and Restrepo (2018b) show that the response of the labor share is given by

$$\frac{d\ln(s_L)}{d\ln(A_L)} = s_K \left(1 - \frac{1}{\varepsilon_{KL}} \right),$$

[44] There are a few exceptions to the consensus estimates below one; for example, Karabarbounis and Neiman (2014) estimate an elasticity above one using cross-country data.

which is negative if and only if $\varepsilon_{KL} < 1$. Thus, if modern manufacturing capital primarily consisted in labor-augmenting technological change, it should increase the wage and reduce the labor share.

The role of aggregation and reallocation. Baqaee and Farhi (2019) analyze aggregation production functions as reduced-form relationships that emerge endogenously from input–output interactions between heterogeneous producers and factors in general equilibrium. They highlight that capital-augmenting technological change at the microeconomic level (e.g., firm level) could lead to a decline in both the labor share of income and the wage at the macroeconomic level. They thus show that technical change that is capital augmenting at the microeconomic level (as in equation (A1)) may lead to very different predictions at the macroeconomic level, in particular due to reallocation effets — which could alternatively be called "business stealing effects".

In Baqaee and Farhi (2019)'s framework with heterogeneous producers,[45] capital-augmenting technological change leads households to reallocate their expenditure toward producers or goods that are more intensive in tasks performed by capital, which increases the overall expenditure on capital in the aggregate. Furthermore, labor is reallocated to tasks that use labor less intensively, which reduces the marginal product of labor and hence the wage. As shown by equation (A1), these patterns cannot be generated with an aggregate production function with capital-augmenting technical change, since such a shock should always increase the marginal product of labor and the wage.

These theoretical results demonstrate the importance of reallocation effects and thus motivate our analysis of both firm-level and industry-level outcomes in a unified shift-share IV framework.

A.B Task-Based Automation

In this section, we briefly present the benchmark model of automation in a task-based framework, following Acemoglu and Restrepo (2018a), which provides a simplified version of the task-based framework introduced in Acemoglu and Restrepo (2018c).[46]

[45]See Section 6.4 of Baqaee and Farhi (2019).

[46]Acemoglu and Restrepo (2018c) built on Zeira (1998), Acemoglu and Zilibotti (2001) and Acemoglu and Autor (2011). Aghion et al. (2018) model A.I. as a new form of automation, allowing for the automation of tasks that were previously thought to be out of reach; they highlight that, through a "cost disease" in sectors with lower exposure to A.I., one can obtain overall balanced growth with a constant capital share well below 100%, even with nearly complete automation of all tasks in the economy. Hémous and Olsen (2022) build an endogenous growth model with automation, in which the share of automation innovations endogenously increases through an increase in low-skill wages. To analyze retraining and redistribution policies that could address the adverse consequences of automation, Jaimovich et al. (2021) develop a heterogeneous agent macroeconomic model with investment in automation capital, labor force participation and occupational choice, and a rich tax-transfer system.

Aggregate output is produced by combining the services of a unit measure of tasks $x \in [N–1, N]$ with a Cobb-Douglas (unit elastic) aggregator:

$$\ln(Y) = \int_{N-1}^{N} \ln(y)dx,$$

where Y denotes aggregate output and $y(x)$ is the output of task x. Depending on whether it has been automated or not, each task could be produced by human labor, $\ell(x)$, or by machines, $m(x)$. Tasks $x \in [N–1, I]$ are automated and can be produced by either labor or machines, while other tasks are not technologically automated and can only be produced with labor:

$$y(x) = \begin{cases} \gamma_L(x)\ell(x) + \gamma_M(x)m(x) & if \;\; x \in [N-1, I] \\ \gamma_L(x)\ell(x) & if \;\; x \in (I, N] \end{cases}$$

The threshold I can thus be interpreted as the frontier of automation possibilities.

Using this framework, it is possible to distinguish formally between different types of technological changes: labor-augmenting technological change corresponds to an increase in $\gamma_L(x)$; automation "at the extensive margin" corresponds to an expansion of the set of tasks that are technologically automated, governed by the parameter I; automation "at the intensive margin" (or "automation deepening") corresponds to an increase in the parameter $\gamma_M(x)$ for tasks $x \leq I$. Finally, the creation of new tasks is captured by an increase in N.

Using this setting and assuming fixed labor supply L and supply of machines K, Acemoglu and Restrepo (2018a) show that the equilibrium wage rate, denoted W, is given by:

$$W = (N - I)\frac{Y}{L}.$$

This equation illustrates that automation "at the extensive margin" creates a displacement effect, reducing labor demand, but is also counteracted by a productivity effect raising labor demand:

$$\begin{aligned} \frac{d\ln(W)}{dI} &= \frac{d\ln(N-I)}{dI} + \frac{d\ln(Y/L)}{dI} \\ &= \underbrace{-\frac{1}{N-I}}_{\text{displacement effect} < 0} \quad \underbrace{+\ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right)}_{\text{productivity effect} > 0}, \end{aligned}$$

where R is the equilibrium rental rate of capital.

Acemoglu and Restrepo (2018a) highlight that the displacement effect of automation dominates the productivity effect and thus reduce labor demand (and wages) when $\frac{\gamma_L(I)}{W} \approx \frac{\gamma_M(I)}{R}$, a case they call "so-so new technologies", i.e. new automated technological are only marginally more productive than labor when performing the newly-automated tasks.

The wage equation also illustrates that the effects of standard labor-augmenting technological change, i.e. a shock to $\gamma_L(x)$, may be different from those of automation. Indeed, from the wage equation, a change in $\gamma_L(x)$ leads to an increase in average output per worker Y/L and a proportionate increase in the equilibrium wage W, and there is no impact on the labor share.

This framework also highlights several forces counteracting the displacement effect. First, capital accumulation strengthens the productivity effect. Indeed, in this model automation corresponds to an increase in the capital intensity of production. Capital accumulation then raises the demand for labor, as in the standard analysis of factor-augmenting technological change. Acemoglu and Restrepo (2018a) highlight that, if capital accumulation leaves the rental rate fixed at a constant level,[47] the productivity effect will always dominate the displacement effect. Even in that case, automation continues to reduce the labor share.

A second force counteracting the displacement effect from automation comes from the "deepening of automation", i.e. "automation at the intensive margin", for example because of improvements in the performance of already-existing automation technologies. An increase in the parameter $\gamma_M(x)$ for tasks $x \leq I$ leads to an increase labor demand and wages, further counteracting the displacement effect above.

The third force counteracting the displacement effect is the creation of new tasks, which increases labor demand and equilibrium wages:

$$\begin{aligned}\frac{d\ln(W)}{dN} &= \frac{1}{N-I} + \frac{d\ln(Y/L)}{dN} \\ &= \underbrace{\frac{1}{N-I}}_{\text{reinstatement effect} > 0} + \underbrace{\ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right)}_{\text{productivity effect} > 0}.\end{aligned}$$

Furthermore, Acemoglu and Restrepo (2018a) show that new tasks increase the labor share. In their model, for the labor share to remain stable, the extensive margin of automation, I, must grow at the same rate as the range of new tasks, N. Thus, automation does not rule out the possibility of a stable or increasing labor share.

Comparison with our empirical analysis of modern manufacturing capital. Our empirical analysis can be interpreted as showing the effects of advances in modern manufacturing capital in France in recent years. View through the lens of Acemoglu and Restrepo (2018c)'s framework,

[47] This is the case, for example, when we have a representative household with exponential discounting and time-separable preferences.

changes in modern manufacturing capital correspond to a combination of "intensive margin automation deepening" and "extensive margin automation" shocks. Our results show that modern manufacturing capital leads to an increase in labor demand and in output per worker, with a fall in the labor share in value added. Displacement effects can explain the fall in the labor share in value added as well as the reallocation of tasks we observe empirically (see Figures E14). Overall, our findings highlight that Acemoglu and Restrepo (2018c)'s task-based modelling framework of automation is relevant to understand a broad class of modern manufacturing capital, beyond the specific examples that have been studied empirically in work prior to ours (e.g., studies of robots including Graetz and Michaels (2018) and Acemoglu and Restrepo (2019)). Our empirical results also show the importance of business stealing effects (e.g., Acemoglu and Guerrieri (2008), Baqaee and Farhi (2019)).

B Plant-Level Records of Electromotive Force

In this appendix, we describe the plant-level records of electricity consumption we use in robustness checks.

We build a proxy for automation using plant-level records of electricity consumption for motors directly used in the production chain. These records have been assembled by the French statistical institute INSEE since 1983 in the Annual survey on industrial energy consumption, covering a large representative sample of plants. The records distinguish between different uses of electricity: motive power, thermic/thermodynamic, and other uses such as electrolysis. We focus on the motive power measure, which excludes electricity used for heating and cooling as well as for servers (because servers are not considered to be directly part of the production chain). Furthermore, the motive power measure only takes into account electric motors that are constantly plugged-in when the production process is ongoing; it therefore excludes machines powered by electric batteries such as an electric forklift or electric car. The measure is expressed in tons of oil equivalent (toe), a common energy metric.

In comparison with the firm-level balance sheet measure, the plant-level motive power measure has the advantage of isolating a more specific set of automation technologies, at the cost of being available only for a sample of plants rather than the full population.

C Discussion of Additional Empirical Results

In this appendix, we discuss several additional empirical results.

C.A Additional Summary Statistics

We now report four types of additional summary statistics.

First, Figure E1 describes the distribution of manufacturing capital across industries. Panel A focuses on the balance-sheet measure of manufacturing capital, panel B depicts the imports of automation technologies defined by Acemoglu and Restrepo (2022), panel C reports the count of robots, and panel D the use of electric motive power across industries. Each panel reports the sectoral share of the top five industries, ranked their share in aggregate modern manufacturing capital. This figure illustrates the breadth of our measures, which cover many industries including chemicals, glass and ceramics, food and beverages, metals, etc. Panel C shows that industrial robots are concentrated in the automobile industry, which accounts for 50% of imports of robots. As a complement to panel D, Appendix Figure E22 provides examples of machines using electric motive power (pasta machines, conveyors, chemical mixers, etc.).

Second, to better describe the types of machines included in the import categories that we selected in the trade data following Acemoglu and Restrepo (2022), Table E1 provides a series of examples. The table shows that this measure encompasses machines for the production of semiconductors, for metal working, for bending, folding, straightening or flattening, etc.

Finally, for completness, Appendix Table E2 reports summary statistics in levels, while Table 1 in the main text reported the same summary statistics in changes over the course of our sample.

C.B Firm-Level Stylized Facts

In this section, we compare the path of sales and employment for firms that invest in modern manufacturing capital more or less over time. Considering all firms that operate between 1995 and 2017, we rank them by the change in the balance sheet value of industrial equipment observed at the beginning of the sample, between 1996 and 1999. We then compare the path of outcomes for firms below and above median. All outcomes are normalized to one in the first year of the sample.

Figure E23 presents the results. Panel A shows that firms that invest more at the beginning of the sample experience a larger increase in sales over the full sample. By 2017, total (nominal) sales have increased by 70% for firms with investment above median and by only about 15% for those below median.[48]

Panels B, C and D show that firms that invest more expand employment relative to those that invest less. Panel B reports this pattern for high-skill workers. By 2017, the number of high-skill workers increases by about 140% at firms above median, compared with 60% for those below median. In panel C, the number of medium-skill workers increases for firms with investment above median, while it decreases for those below median. Panel D shows that the number of low-skill workers decreases in both groups, but more steeply for firms with investment below median. For firms that invest more at the beginning of the sample, low skill employment falls by about 33% by 2017, while the fall is more pronounced and reaches about 45% for firms with investment below median.

Consistent with the observed increase in sales, the potential productivity effect from modern manufacturing capital may more than offset the potential displacement effect on workers, resulting in a positive effect on labor demand employment. We obtain similar results when repeating this analysis with thresholds other than the median, when using the plant or the industry (rather than the firm) as the level of analysis, and with our other measures of manufacturing capital investments.

C.C Further Analyses of the Employment Response in Firm-Level Event Studies

We conduct several robustness tests about the overall employment response observed in firm-level event studies.

First, we analyze the results when using alternative threshold to define the investment event based on the change in the balance sheet value of industrial machines. Appendix Figure E2 shows the results using alternative thresholds to define the investment event (p75 and p50), with slightly smaller semi-elasticities than in the main text (with p90). Similarly, Appendix Figure E3 reports the results with Acemoglu and Restrepo (2022)'s proxy for automation, using the 75th percentile to define the investment event (rather than p90 in the main text); the results are again similar.

Second, considering the change in the balance sheet value of industrial equipment, we note that among the firms that are above the threshold at least once, ten percent invest above the specified threshold more than once over the course of our sample. In such cases, we define the event for the firm to be the largest investment. The results are similar when we only work with firms that invest

[48] 30% of this increase is contemporaneous to the initial period. After 2000, the rise in sales for firms that invest in modern manufacturing capital more is still positive, explaining around one half of the overall increase between 1996 and 2017.

exactly once above the specified thresholds (Appendix Figure E4).

Third, in Figure E5, we obtain similar results with alternative measures of investments in modern manufacturing capital. In Panel A, we use Acemoglu and Restrepo (2022)'s original proxy for automation, which does not include sectoral machines outside of the textile industry. In Panel B, we use investments in industrial equipment expressed as a fraction of the initial balance-sheet value of the stock of machines.[49] In Panel C, we keep the balance sheet value of industrial machines but restrict attention to firms in the automobile industry, where industrial robots are prevalent. In all panels, the patterns are very similar.

Fourth, Figure E6 shows that the results remain stable in alternative specifications with other sets of interacted industry fixed effects, i.e. 2-digit industry by year fixed effects or 4-digit industry by year fixed effects; the point estimates are nearly unchanged, with no pre-trends.

Fifth, Figure E7 shows that the estimates remain similar when we balance the panel over different time horizons.

Finally, a potential concern about the proxy based on motive power is that electricity is a variable input. Changes in motive power could simply correspond to a change in the utilization rate of machines, for example because of changes in demand that require adjusting variable inputs. To address this concern, instead of relying on the actual electricity consumption for motive power, we use the plant's peak capacity for electric motive power, which is provided by INSEE in the same survey. After major investments in machines, the plant should adjust its peak capacity for motive power, while there is no such change when the plant simply varies its factor utilization rate. Figure E8 shows that the results are similar when using peak motive power.

C.D Further Analyses of the Labor Share Response in Firm-Level Event Studies

We conduct further analyses of the labor share response in firm-level event studies.

First, Figure E12 analyzes the reponse of the labor share in value-added with alternative measures of investment, defining the event using in turn Acemoglu and Restrepo (2022)'s proxy for capital deepening and investments in real estate capital. With both measures, we find no change in the labor share in value added, in contrast with the estimated fall in the labor share when using all investments in modern manufacturing capital. Thus, the displacement effects are not observed with measures that focus on more traditional capital investments.

[49] This alternative measure is not sensitive to depreciation.

Second, Figure E13 show that the labor share in total sales, as in Autor et al. (2020), remains constant after the investment event, and that the decline in the labor share of value-added is driven by an increase in the share of value added in total sales following the investment event. These patterns indicate that firms that invest in modern manufacturing capital are able to rely less intensively on intermediate inputs through higher capital intensity of value-added.

C.E Further Analyses of Displacement Effects in Firm-Level Event Studies

We conduct further analyses of the displacement effects after investments in modern manufacturing capital.

In panel A of Figure E14, we compute a within-firm job dissimilarity index, using the shares of workers by occupation across consecutive years.[50] We find that there is an increase in the dissimiliarity index exactly at the time of the investment, which induces a reallocation of occupations within the firm. Panel B reports a placebo test, using investments in real estate: in this case, the event is not related to patterns of job creation and destruction, and the job dissimilarity index remains flat.

Overall, the patterns in Figures 2 and E14 indicate that investments in modern manufacturing capital have subtle distributional effects in the labor market, depending on the set of tasks performed across detailed occupations, with no evidence that they lead to important changes in within-firm inequality.

C.F Further Analyses of Market Dynamics and Price Changes in Firm-Level Event Studies

We now discuss additional evidence on market dynamics in firm-level event studies, including evidence on export prices.

First, Figure E24 reports that export sales increase after investment in industrial machines.

Second, we document the relationship between investments in modern manufacturing capital and price changes. We do so using export prices, which are readily available for all exporting firms from customs data. Export prices are measured as the unit value of exported products. To account for potential changes in composition over time, we run the specification at the level of detailed product cells identified by the standard product classification for traded goods, namely HS6 codes. Our baseline specification is the same event study as in equation (1), but with a different set of

[50]For each firm, the dissimilarity index is computed as $D_t \equiv \frac{1}{2}\sum_{o=1}^{K} |s_{o,t} - s_{o,t-1}|$, where o indexes occupations and $s_{o,t}$ is the share of workers in occupation o at time t in the firm.

fixed effects: we now control for HS6-by-year fixed effects, trading partner by year fixed effects, and firm fixed effects.

The results of the baseline specification are reported in Panel A of Figure E25. We find that export prices fall after an increase in the firm's industrial equipment, with no sign of pre-trends. The estimated elasticity of prices reaches -0.10 after four years. The observed fall in prices suggests that firms that invest in modern manufacturing capital pass through some of the productivity gains to consumers, leading to higher demand and more employment. We return to this demand reallocation channel in Section V.C.

We conduct additional tests to address the possibility that changes in the composition of products sold by the firm may affect the average unit price of exported goods we observe over time. In Panel B of Figure E25, we implement the same specification using NC8 product category codes rather than HS6 codes. The NC8 product category codes are the most detailed classification used by the French customs. The panel shows that the results are very similar, with a semi-elasticity of -0.10 after 4 years. The finding suggests that composition effects (i.e., unobserved changes in the product mix used to compute the average unit price) do not drive our results, which remain stable across product classifications.

In Figure E26, we document similar results when using the 95th percentile instead of the 90th percentile as the threshold defining the investment event. With this alternative threshold, the semi-elasticity is 0.10 on impact and falls further to -0.20 after 4 years. In unreported robustness checks, we find that the results are similar in a sample restricted to firms that only export products in a single HS6 code.

C.G Firm-level OLS Estimates in Shift-Share IV Sample

We discuss the OLS firm-level estimates obtained in the sample we use for the shift-share IV analysis.We report the OLS relationship between investment in modern manufacturing capital and employment at the firm level in Table E4. We only keep the set of firms that import machines so that the results can be compared with the shift-share IV design.

Panel A focuses on employment growth. We obtain an elasticity of employment to modern manufacturing capital investments of +0.141 (s.e. 0.0141) on the baseline specification. The other columns show that this elasticity remains similar in magnitude as we vary the set of controls: the point estimates remain between 0.140 and 0.148 across specifications.

The other panels of Table E4 study other outcomes. Panel B shows that the OLS relationships with sales are positive, with elasticities around 0.13. Panel C reports the relationship with hourly wages, with a small, statistically insignificant point estimate hovering around -0.005 across specifications. Panel D shows the results for the labor share in value added, which is small and insignificant. In Panel E, we find no significant relationship with labor productivity. Panel F shows a positive correlation with profits, with an elasticity close to 0.15 across specifications. Finally, Panel G reports that manufacturing capital investments are associated with a decline in competitors' employment within the same 5-digit industry.

C.H Industry-level OLS Estimates in Shift-Share IV Sample

We now discuss the OLS industry-level estimates obtained in the sample we use for the shift-share IV analysis, reported in Table E8. The results are similar to the firm-level estimates, with an increase in employment whether we consider total industry employment (including entry and exit) in Panel A or only incumbent firms in Panel B. The correlation with sales is positive in Panel C. There is a small and insignificant correlation with wages (Panel D), a negative correlation with the labor share in value added (Panel E), a positive correlation with labor productivity (Panel E), and a large positive correlation with profits (Panel G).

D The Demand Reallocation Channel

In this appendix, we assess whether the estimated industry-level increase in employment and sales can be accounted for by the observed price changes following investments in modern manufacturing capital. Intuitively, because we found that prices fall in response to manufacturing capital investments, consumers should reallocate their expenditures toward industries that invest more. The magnitude of this reallocation effect is governed by consumers' demand elasticity of substitution. Appendix Table E11 reports a negative relationship between manufacturing capital investments and the industry-level producer price index, with point estimates ranging from -0.096 (s.e. 0.0513) to -0.170 (s.e. 0.0643) across specifications. The magnitudes are very similar to the firm-level price response documented in Appendix Figure E25.

To assess the plausibility of the demand reallocation channel, we present a simple calibration in a CES framework. The goal is to assess whether standard estimates of consumers' demand elasticities can rationalize the positive employment and sales effects together with the negative price effects.

Assume consumers have CES preferences over a set of varieties that may be supplied by domestic or foreign industries and are indexed by $k \in \Omega$. Given our focus on industry-level outcomes, we interpret varieties as industry-specific aggregates, which combine all varieties produced in the same industry by a given country (domestic or foreign). The utility of the representative agent is given by $U = \left(\sum_{k\in\Omega} \omega_k q_k^{1-\sigma}\right)^{1/(1-\sigma)}$,where σ is the elasticity of substitution between varieties, q_k is the quantity index for variety k, and ω_k is a taste parameter reflecting the intensity of the representative agent's preference for variety k. p_k denotes the price index for country-industry variety k.

Consider a perturbation of the equilibrium: domestic firms invest in modern manufacturing capital, which results in changes in consumer prices $\{p_k\}$ and equilibrium quantities $\{q_k\}$. CES preferences yield the standard log-linear relationship between the change in the price index for industry k, p_k, and the change in total sales, $p_k \cdot q_k$:

$$\Delta \log(p_k) = -\frac{1}{\sigma - 1}\Delta \log\left(p_k \cdot q_k\right) + \Omega. \tag{A2}$$

In response to a 1% increase in manufacturing capital investment, according to Column (4) of Table 4 the sales response is $\Delta \widehat{\log\left(p_k \cdot q_k\right)} = 0.409$; according to Column (4) of Appendix Table E11 the price response is $\Delta \widehat{\log(p_k)} = -0.149$. To satisfy equation (A2), these estimates imply the following demand elasticity of substitution: $\widehat{\sigma} = 1 - \frac{\Delta \widehat{\log(p_k \cdot q_k)}}{\Delta \widehat{\log(p_k)}} = 3.7$.[51]

Is the magnitude of $\widehat{\sigma}$ in line with existing estimates? A demand elasticity of substitution of 3.7 is consistent with estimates of elasticities of substitution between varieties produced by different countries for the same industry. For example, Broda and Weinstein (2006) estimate a mean demand elasticity of substitution of 7.5 between internationally traded varieties (within 5-digit SITC industries) and a median elasticity of 2.8. This result indicates that the consumer demand substitution channel is plausible in an open economy facing international competition.

In contrast, estimated consumer demand elasticities between domestic industries are much smaller and closer to one (e.g., Costinot and Rodríguez-Clare (2014)), making it difficult to rationalize the industry-level results on sales and employment in a closed economy, because industry-level substitution would need to operate between industries (rather than between products produced either by domestic firms or by international competitors within the same industry) and would require large price changes that we do not observe in the data.

The analysis presented above is based on the industry-level OLS results on prices reported in Appendix Table E11, because we lacked power to estimate price effects directly in the industry-level

[51]The implied magnitude for $\widehat{\sigma}$ is similar when using the sales and price estimates from the firm-level analysis. From Column (5) of Table 2 we obtain $\Delta \widehat{\log\left(p_k \cdot q_k\right)} = 0.319$ and Figure E25 yields $\Delta \widehat{\log(p_k)} = -0.10$, implying $\widehat{\sigma} = 4.2$.

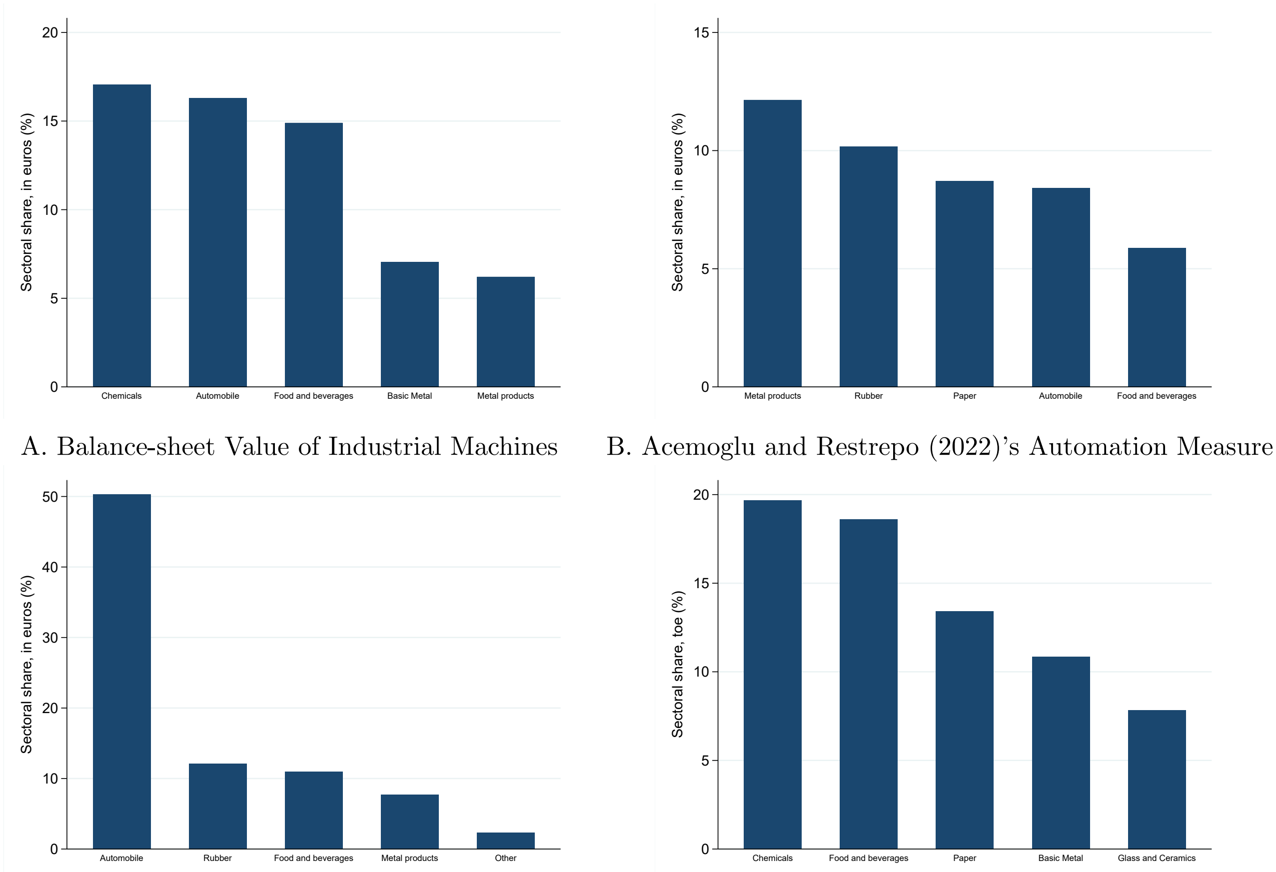
shift-share IV design. If we know the demand elasticity of substitution σ, equation (A2) can be used to infer price changes from our SSIV estimates for the sales response. The industry-level SSIV yields an elasticity of sales to investment of 0.409 in Column (4) of Table 4. We can plug this estimate of $\Delta \log (p_k \cdot q_k)$ into equation (A2) and use a standard range of empirical estimates for σ. For example, Broda and Weinstein (2006) report a mean of 7.5 between internationally traded varieties (within 5-digit SITC industries), with a median of 2.7.

Depending on the choice of σ, the implied price elasticity to modern manufacturing capital investment, $\Delta \log(p_k)$, ranges from -0.24 $(= -\frac{1}{2.7-1} \cdot 0.409)$ to-0.063 $(= -\frac{1}{7.5-1} \cdot 0.409)$. This range of implied price elasticities is close to the estimates obtained with the event study at the firm level, with a price elasticity of -0.20 in Appendix Figure E26, as well as with the OLS analysis at the industry level, with a price elasticity between -0.09 and -0.17 across specifications in Appendix Table E11. This confirms that the demand reallocation channel is broadly consistent with the estimates collected in this paper.

It may be instructive to note that the demand reallocation channel could affect the optimal design of innovation policies. Domestic policymakers may not internalize the effects of domestic innovations on foreign consumer prices, nor their effects on the disruption of foreign labor markets. These channels create a motive for coordinating innovation policies internationally, which would be fruitful to characterize formally in future work.

E Online Appendix Figures and Tables

Figure E1: Distribution of Modern Manufacturing Capital across Industries



A. Balance-sheet Value of Industrial Machines

B. Acemoglu and Restrepo (2022)'s Automation Measure

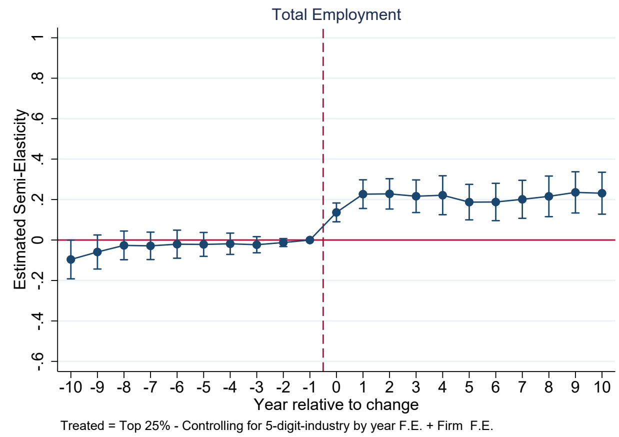
C. Imported Robots

D. Electric Motive Power

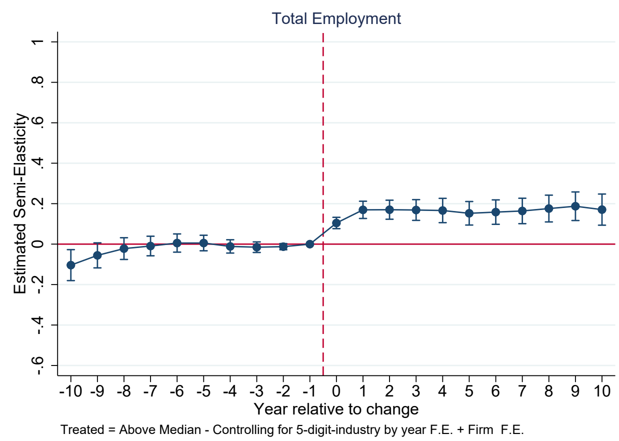
Notes: This figure describes the distribution of modern manufacturing capital across industries, using each of our four measures in turn in the four panels. Each panel reports the share of the top five industries in aggregate modern manufacturing capital. The industry share is measured in value (euros) for industrial machines (panel A), Acemoglu and Restrepo (2022)'s automation measure (panel B), and imported robots (panel C). For electric motive power (panel D), the share corresponds to energy use in tons of oil equivalent.

Figure E2: Firm-Level Event Studies for Employment with Alternative Investment Thresholds

A. 75th percentile of investment in industrial equipment

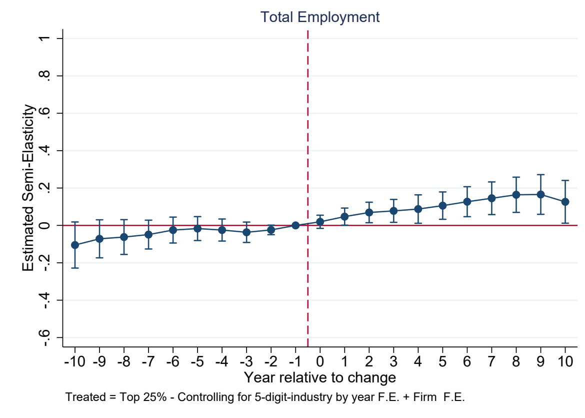


B. 50th percentile of investment in industrial equipment



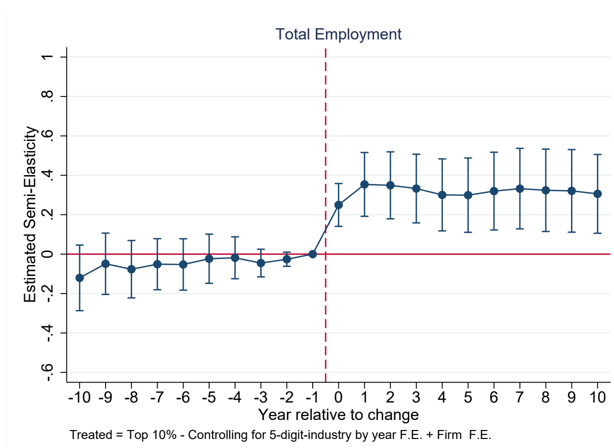
Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome. Panel A uses the 75th percentile as the event thresholds, while Panel B uses the 50th percentile. All specifications include 5-digit industry-by-year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level.

Figure E3: Firm-level Employment Effect with an Alternative Threshold for Acemoglu and Restrepo (2022)'s Automation Measure



Notes: This figure analyzes the firm-level employment response when using Acemoglu and Restrepo (2022)'s automation measure, defining the investment events as imports above the 75th percentile of the firm-level distribution of imports. The specification includes 5-digit industry by year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level.

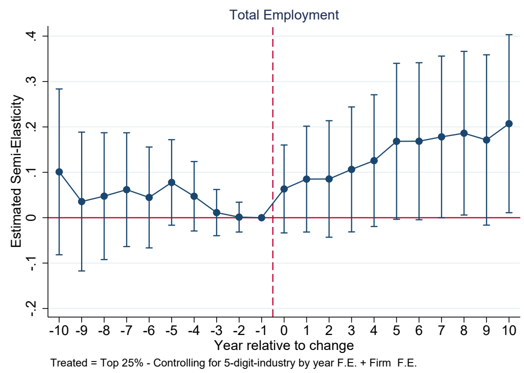
Figure E4: Firm-level Event Studies with Firm Experiencing a Single Investment Event



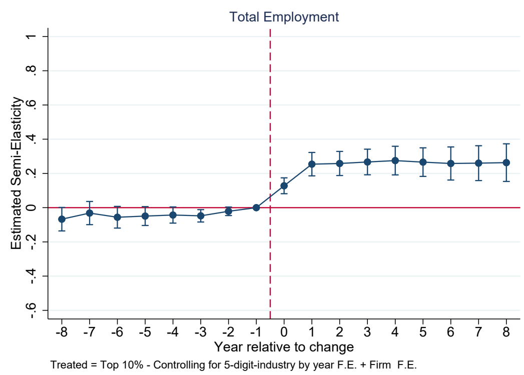
Notes: This figure reports the results of firm-level event studies with total employment as the outcome. The investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. We exclude all firms that invest above this threshold more than once during our sample, i.e. the treatment group is composed of firms that have exactly one investment event. 5-digit industry-by-year fixed effects and firm fixed effects are used.

Figure E5: Firm-level Event Studies across Measures of Modern Manufacturing Capital

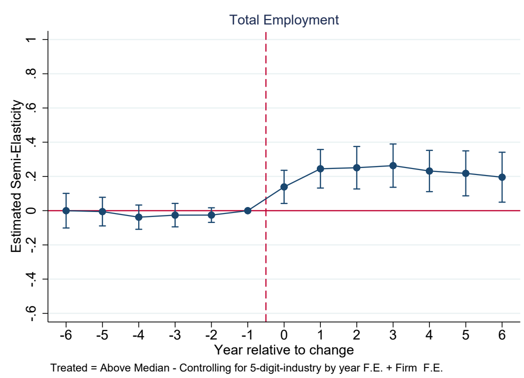
A: Results with Acemoglu and Restrepo (2022)'s Baseline Automation Measure



B: Investments as a Fraction of the Initial Balance Sheet Value



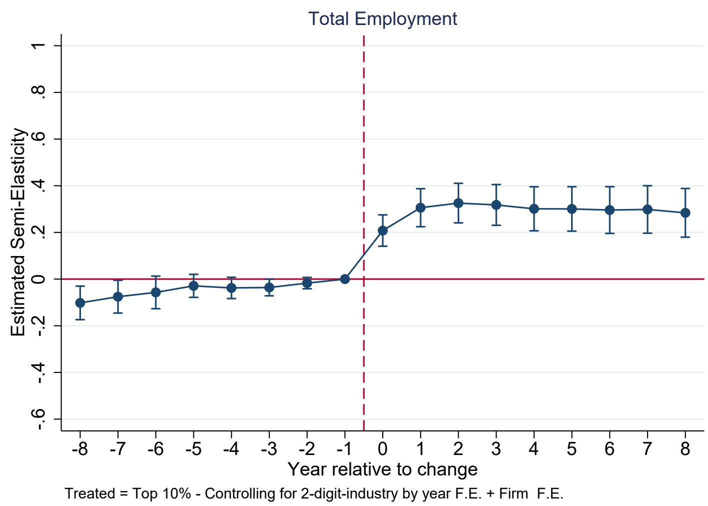
C: Investments in Industrial Equipment for the Automobile Industry



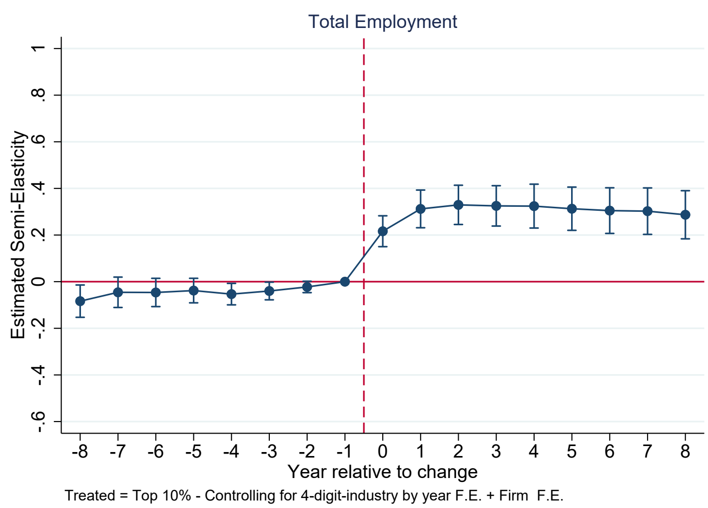
Notes: This figure reports the results of firm-level event studies with total employment as the outcome, considering alternative measures of investment in modern manufacturing capital. Panel A uses Acemoglu and Restrepo (2022)'s baseline automation measure, Panel B measures the balance sheet value of investment as a fraction of the initial balance sheet value of the stock of machines, which does not require assumptions about capital depreciation, and panel C uses investment in industrial equipment in the automobile industry, which primarily consists of industrial robots.

Figure E6: Robustness of Firm-level Event Study with Alternative Fixed Effects

A: With 2-digit-by-year Fixed Effects



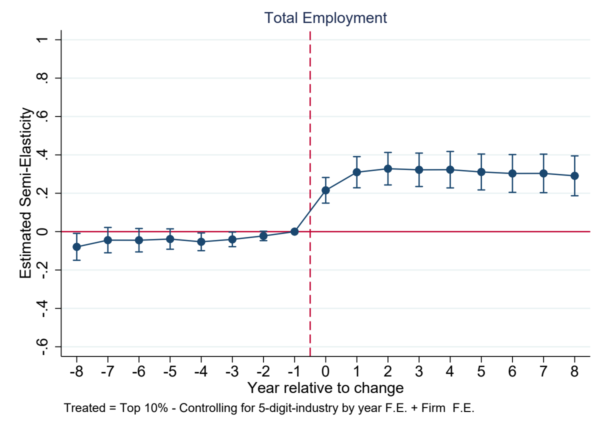
B: With 4-digit-by-year Fixed Effects



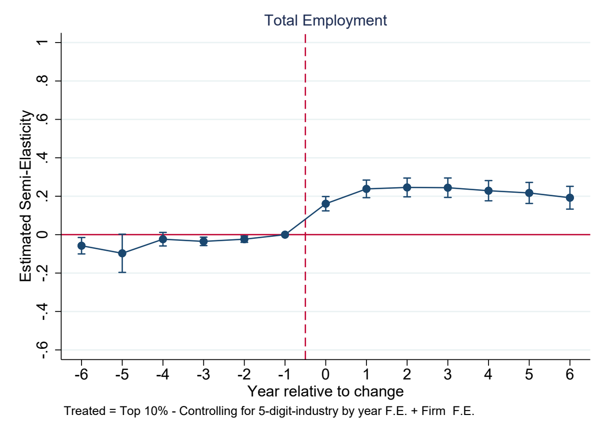
Notes: The figure reports the results of firm-level event studies with employment as the outcome. The specification is given by equation (1) in the main text, with 2-digit by year (panel A) or 4-digit by year (panel B) fixed effects. The investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment.

Figure E7: Robustness of Firm-level Event Study across Balanced Samples

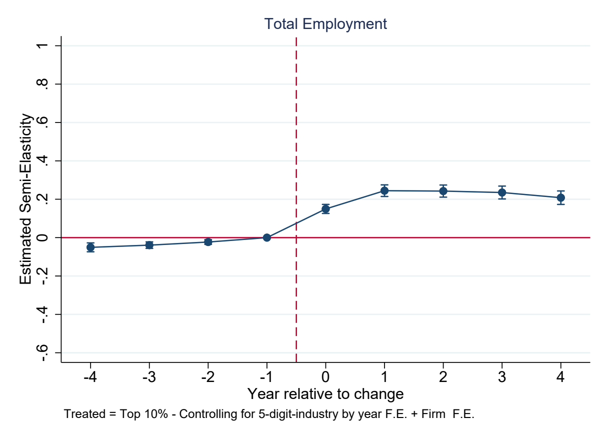
A: 8-Year Horizon



B: 6-Year Horizon

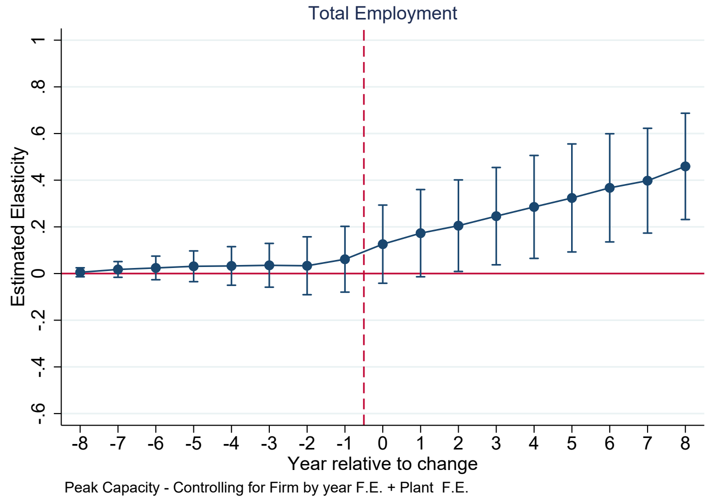


C: 4-Year Horizon



Notes: This figure reports the results of firm-level event studies with employment as outcome. The specification is given by equation (1) in the main text, with 5-digit industry by year fixed effects and firm fixed effects. In each panel, the sample is restricted to firms that remain in the sample throughout the specified time horizon. In each panel, the investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment.

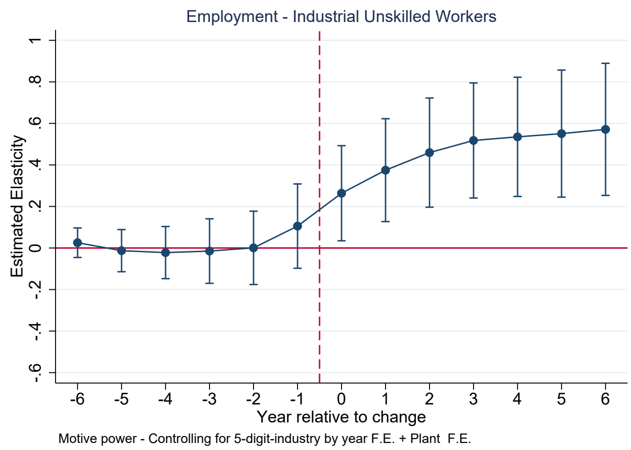
Figure E8: Effects on Plant-level Employment with Distributed Lag Model using Peak Capacity for Motive Power



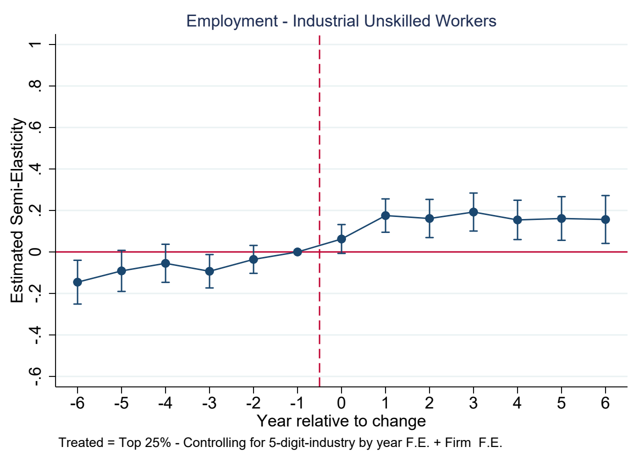
Notes: This figure reports the estimates of the distributed lead-lag model, with plant-level employment as the outcome. The specification is the same as in footnote 26 and Panel C of Figure E3, except that we use peak capacity for motive power instead of actual electricity consumption for motive power. Firm-by-year fixed effects and plant fixed effects are used.

Figure E9: The Employment Response for Unskilled Industrial Workers

A: Plant level (Distributed Lag)

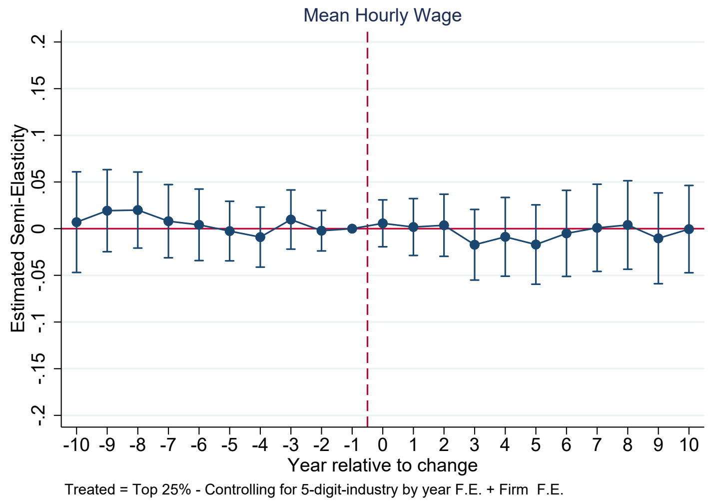


B: Firm level (Event Study)



Notes: This figure reports the estimates of the reponse of employment of unskilled industrial workers at the plant level (panel A) and firm level (panel B). The plant-level analysis uses the distribution lead-lag model with 5-digit industry by year fixed effects and plan fixed effects, clustering standard errors at the plant level (see footnote 26 in the main text). The firm-level analysis uses the event study specification of equation (1) in the main text, with 5-digit industry by year fixed effects and firm fixed effects and standard errors clustered at the firm level.

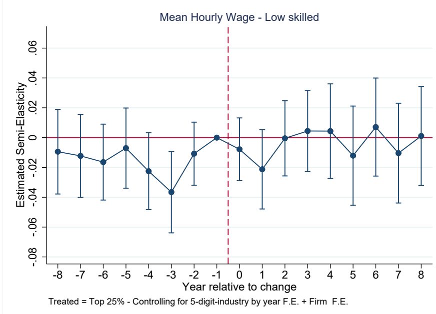
Figure E10: The Response of Wages using Acemoglu and Restrepo (2022)'s Automation Measure



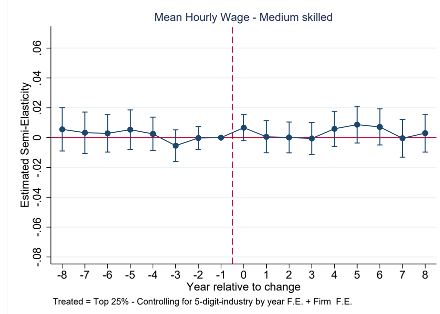
Notes: This figure reports the results of the firm-level event study for wage, using Acemoglu and Restrepo (2022)'s measure of automation. In all panels, the investment event is defined as a logarithmic change beyond the 75th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. The specification uses 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

Figure E11: Additional Firm-Level Event Studies for Wages and Within-Firm Inequality

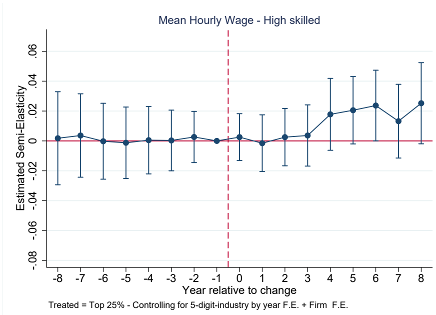
A. Mean Hourly Wage, Low Skill



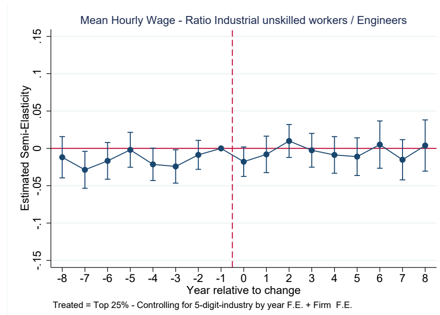
B. Mean Hourly Wage, Medium Skill



C. Mean Hourly Wage, High Skill



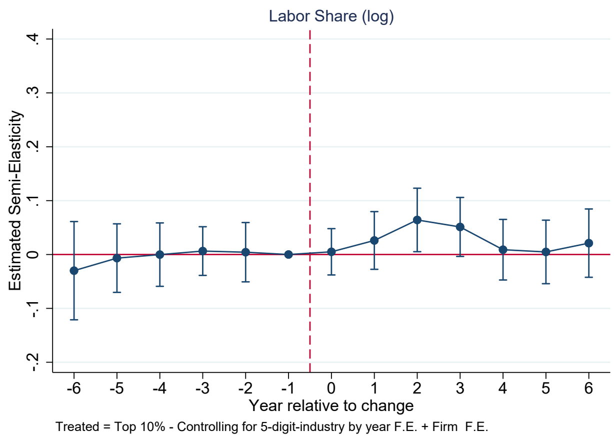
D. Wage Ratio Unskilled Workers / Engineers



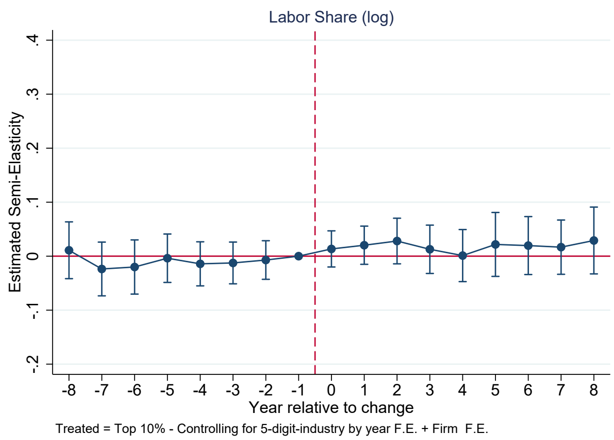
Notes: This figure reports the result of firm-level event studies for four outcomes characterizing the changes in wages and within-firm inequality after investments in modern manufacturing capital, measured as changed in the balance-sheet value of industrial equipment. All panels use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

Figure E12: Firm-level Event Studies for the Labor Share in Value Added, using...

A. Acemoglu and Restrepo (2022)'s Capital Deepening Measure



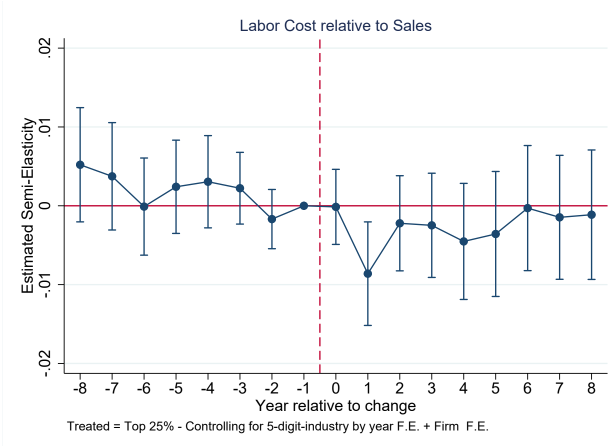
B. Real Estate Investments



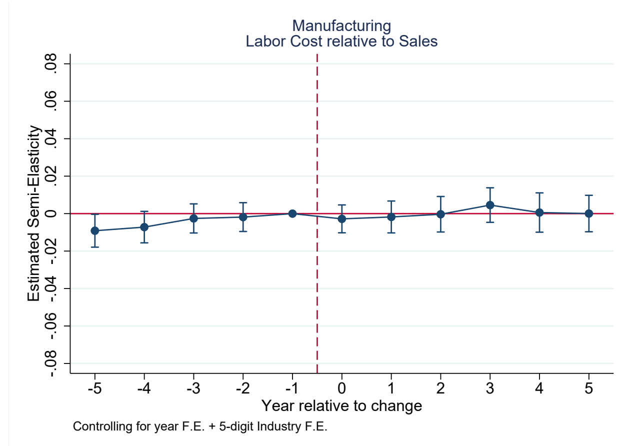
Notes: This figure repeats the event study analysis for the labor share in value added using alternative measures of investments. Panel A uses Acemoglu and Restrepo (2022)'s proxy for capital deepening (namely, imports of machines classified as capital deepening technologies), while Panel B uses the balance sheet value of real-estate investments. In each panel, the investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the investment measures. 5-digit-industry by year fixed effects and firm fixed effects are used. Standard errors are clustered at the firm level.

Figure E13: Additional Evidence on the Labor Share, Event Studies

A: Share of Labor in Total Sales

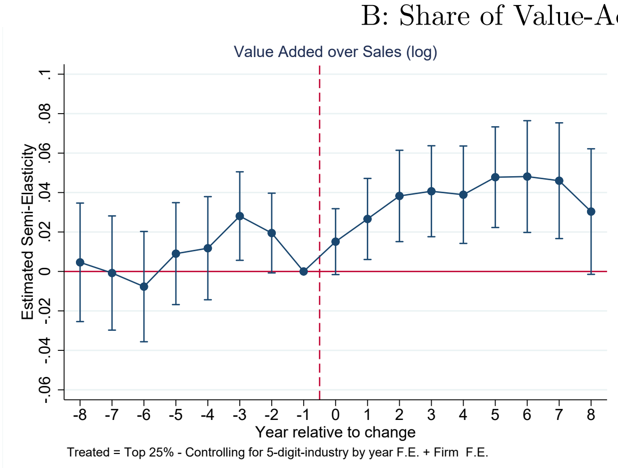


(i) Firm level

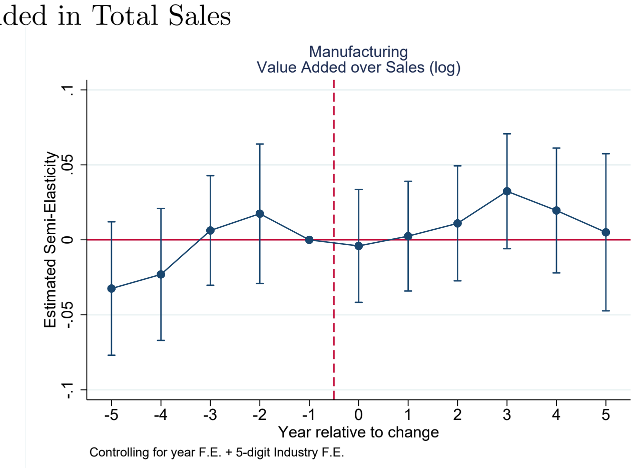


(ii) Industry level

B: Share of Value-Added in Total Sales



(i) Firm level

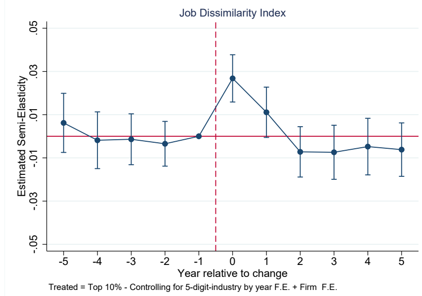


(ii) Industry level

Notes: This figure reports the results of event studies with the labor share in total sales (panel A) and the share of value-added in total sales (panel B) as outcomes. In each panel, we report two specifications, conducting in turn the analysis at the firm level and the industry level to complement the results of both Section on firms and Section on industries. The investment event is defined as a logarithmic change beyond the 75th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. Panel A shows that the labor share in total sales remain flat after the investment event, at both the firm level (panel A(i)) and the industry level (panel A(ii)). Panel B shows that there is an increase in the share of value-added in sales at the firm level (panel B(i)) but not at the industry level (panel B(ii)). In all panels, 5-digit-industry by year fixed effects and firm fixed effects are used. Standard errors are clustered at the firm level.

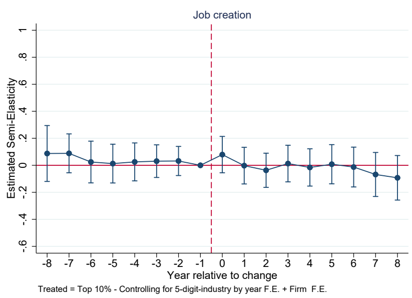
Figure E14: Firm-Level Event Studies for Job Creation/Destruction

A: Main Result with Investments in Industrial Equipment

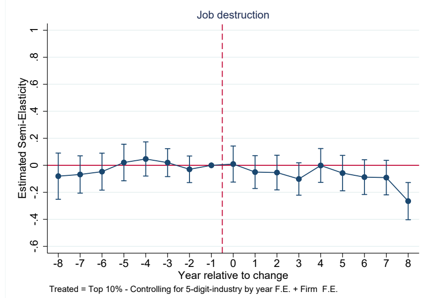


(i) Job Dissimilarity Index

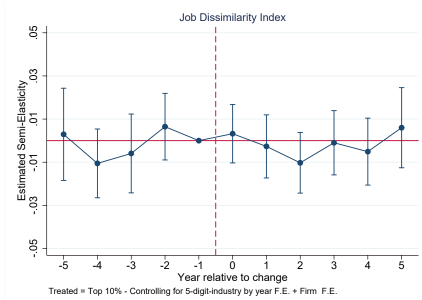
B: Placebo Test with Investments in Real Estate



(i) Job Creation



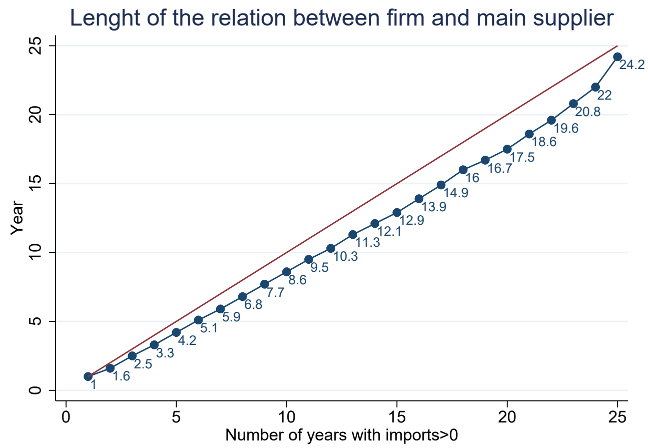
(ii) Job Destruction



(iii) Job Dissimilarity Index

Notes: This figure reports the event study results with job creation, job destruction and the job dissimilarity index as outcomes. We consider in turn investments in industrial equipment (panel A) and investments in real estate (panel B). In all panels, the investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. All panels use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

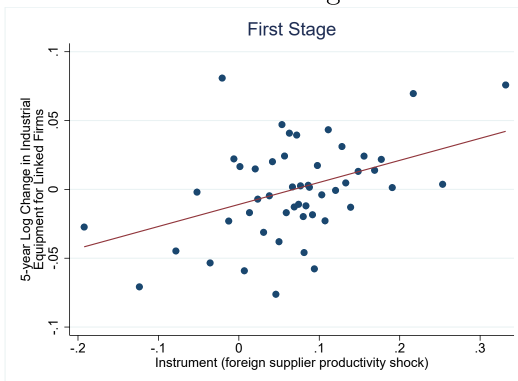
Figure E15: Persistence of Importer-Supplier Relationships



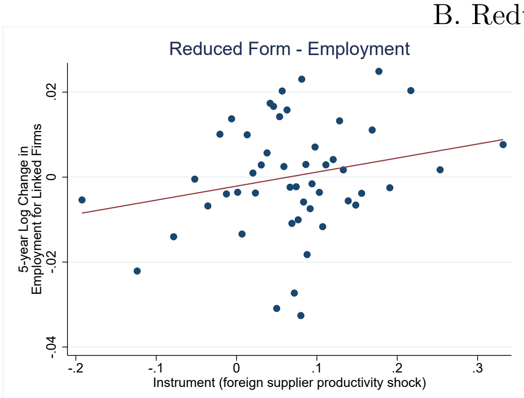
Notes: This figure documents the persistence of the network of international suppliers of machines, plotting the length of the relationships between a French firm and its main international supplier, depending on the number of years during which machines are imported. The set of imported machines is the list of automation technologies drawn by Acemoglu and Restrepo (2022).

Figure E16: Firm-level Shift-Share IV, Robustness with More Stringent Fixed Effects

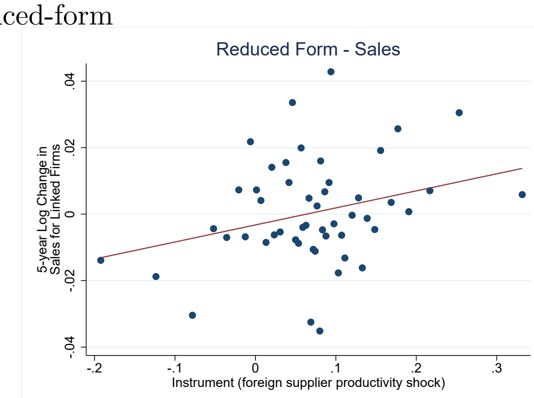
A. First stage



B. Reduced-form

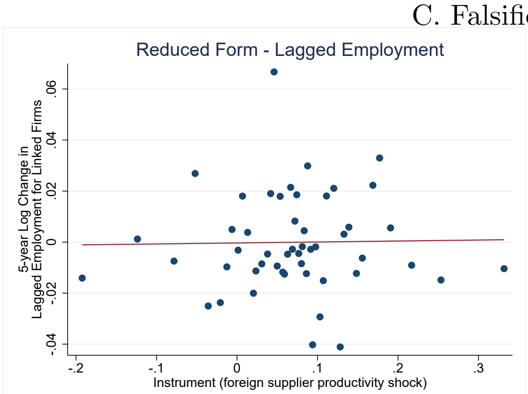


(i) Employment

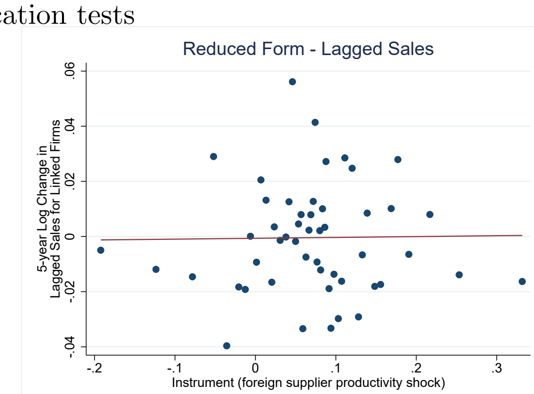


(ii) Sales

C. Falsification tests



(i) Lagged employment

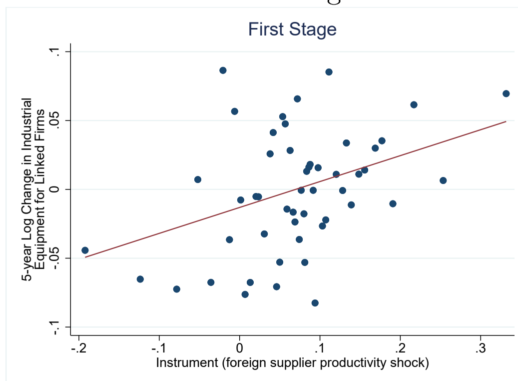


(ii) Lagged sales

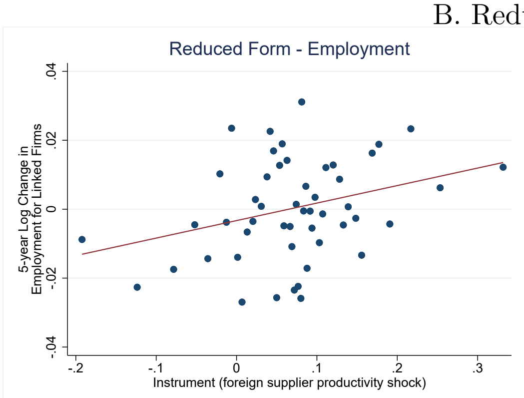
Notes: The binned scatter plots in this figure depict the relationships underlying the firm-level SSIV research design described by specification (3) in the main text, except that a more stringent set of fixed effects is used, with HS6-by-period and 5-digit-industry-by-period fixed effects. The figure reports the first stage (panel A), the reduced-form relationships for employment and sales (panel B), and the falsification tests with lagged outcomes (panel C) corresponding to Column (1) of Appendix Table E6. Each dot represents 2% of the data. HS6-product-by-foreign-supplier shocks measured in EU countries (except France) and Switzerland are used as the source of identifying variation. Shock size is shown on the x-axis for each foreign supplier by by HS product category. The y-axis plots the average outcome for all firms importing from the corresponding foreign supplier in the relevant HS6 product category.

Figure E17: Firm-level Shift-Share IV, Robustness with Less Stringent Fixed Effects

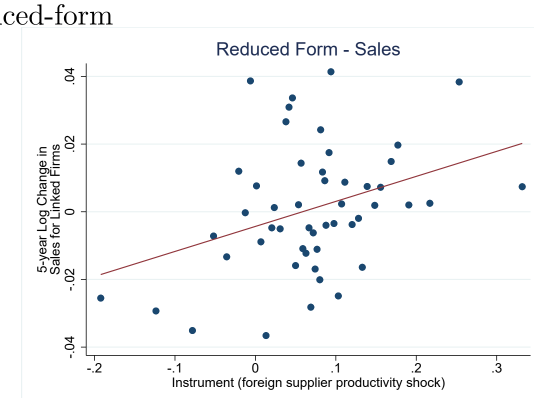
A. First stage



B. Reduced-form

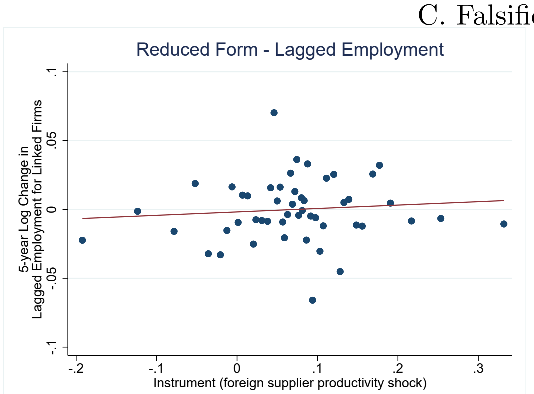


(i) Employment

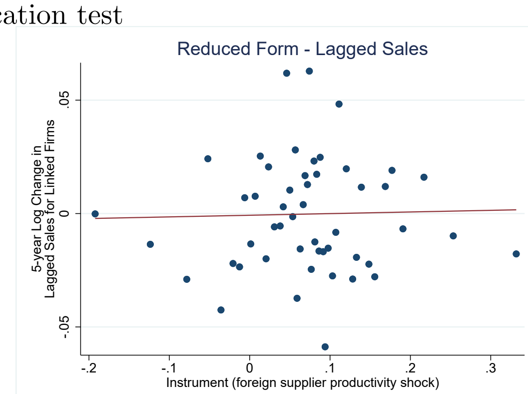


(ii) Sales

C. Falsification test



(i) Employment

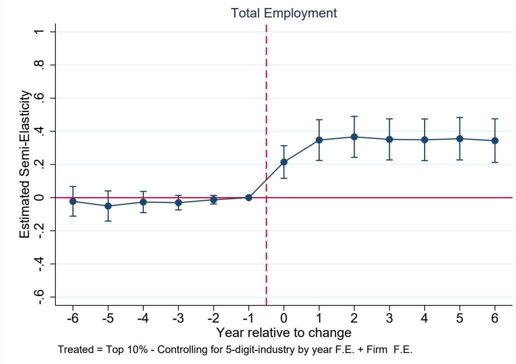


(ii) Sales

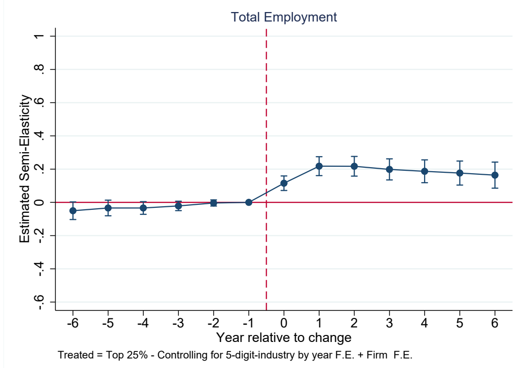
Notes: The binned scatter plots in this figure depict the relationships underlying the firm-level SSIV research design described by specification (3) in the main text, except that a more stringent set of fixed effects is used, with HS6-by-period and 5-digit-industry-by-period fixed effects. The figure reports the first stage (panel A), the reduced-form relationships for employment and sales (panel B), and the falsification tests with lagged outcomes (panel C) corresponding to Column (1) of Appendix Table E7. Each dot represents 2% of the data. HS6-product-by-foreign-supplier shocks measured in EU countries (except France) and Switzerland are used as the source of identifying variation. Shock size is shown on the x-axis for each foreign supplier by by HS product category. The y-axis plots the average outcome for all firms importing from the corresponding foreign supplier in the relevant HS6 product category.

Figure E18: Firm-level Event Studies in SSIV Sample Only

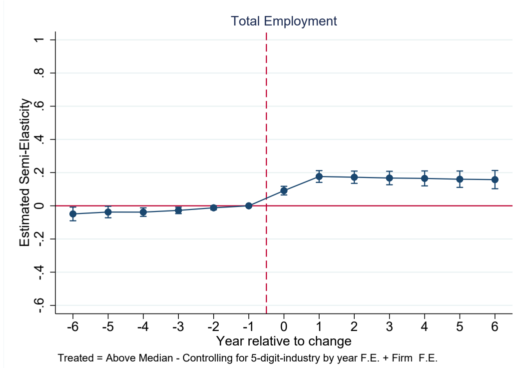
A. 90th percentile of investment in industrial equipment



B. 75th percentile of investment in industrial equipment

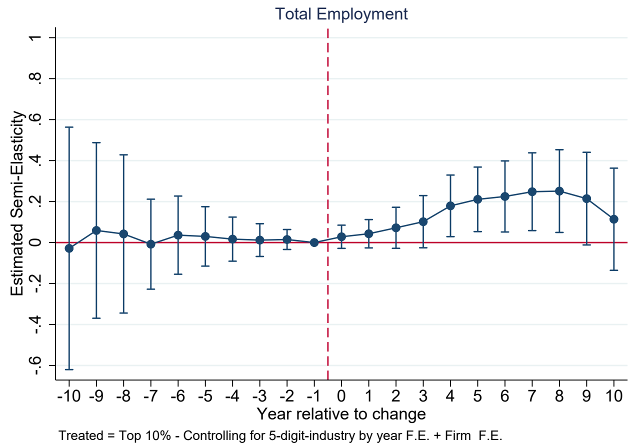


C. 50th percentile of investment in industrial equipment



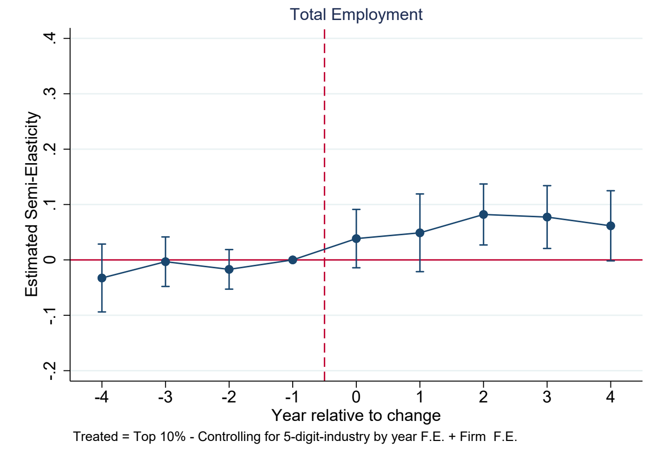
Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome in the sample of firms used in the SSIV analysis, i.e. firms that had positive imports of machines between 1996 and 2000, using the list of machines of Acemoglu and Restrepo (2022). In Panel A, the investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. Panel B uses the 75th percentile as the event threshold, while Panel C uses the 50th percentile. All specifications include 5-digit industry by year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level. The results are very similar to the results obtained in the full sample of firms (reported in Panel B of Figure 1 in the main text), indicating that the SSIV research design is unlikely to estimate a local average treatment effect (LATE) that would be significantly different from the population average treatment effect (ATE).

Figure E19: Firm-level Event Studies in SSIV Sample Only, using Acemoglu and Restrepo (2022)'s Automation Measure



Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome in the sample of firms used in the SSIV analysis, i.e. firms that had positive imports of machines between 1996 and 2000, using the list of machines of Acemoglu and Restrepo (2022). This figure uses Acemoglu and Restrepo (2022)'s automation measure of imported machines to measure investment events, defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in imports of machines. All specifications include 5-digit industry by year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level. The results are very similar to the results obtained in the full sample of firms (reported in Panel B of Figure 1 in the main text), indicating that the SSIV research design is unlikely to estimate a local average treatment effect (LATE) that would be significantly different from the population average treatment effect (ATE).

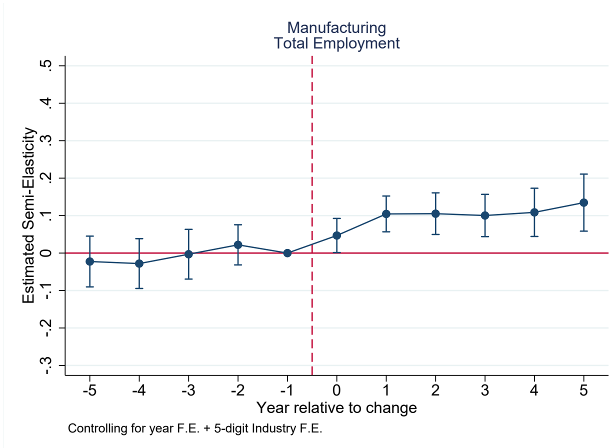
Figure E20: Firm-level Event Studies using Acemoglu and Restrepo (2022)'s Automation Measure for First-Time Purchases Only



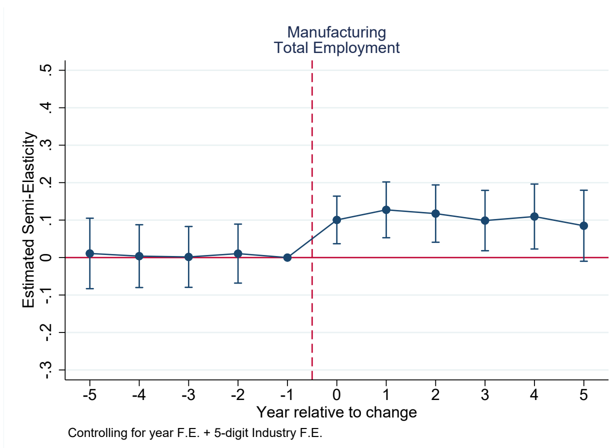
Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome, considering the full sample of firms. This figure uses Acemoglu and Restrepo (2022)'s automation measure of imported machines to measure investment events, defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in imports of machines, considering only instances when the firm imports for the first time from a given foreign supplier-HS6 code. These events are not taken into account in the SSIV analysis, which restricts attention to the set of firms with pre-existing suppliers, as in Appendix Figures E18 and E19. The point estimates are very similar to our baseline approach, reported on panel A of Figure E3 in the main text. This finding suggests that the SSIV sample, which does not take into account firms that import for the first time, is unlikely to estimate a local average treatment effect (LATE) that would be significantly different from the population average treatment effect (ATE).

Figure E21: Industry-level Event Studies across Measures of Modern Manufacturing Capital

A: Industry-level Investments as a Fraction of the Initial Balance Sheet Value



B: Industry-level Change in the Balance Sheet Value of Industrial Equipment for Continuously Operating Firms



Notes: This figure reports the results of industry-level event studies with total employment as the outcome, considering two alternative measures of investment in modern manufacturing capital. Panel A uses the balance sheet value of investment as a fraction of the initial balance sheet value of the stock of machines. Panel B uses the change in the balance sheet value of industrial equipment taking only into account firms that exist throughout our sample. Year fixed effects and 5-digit industry fixed effects are used in both panels.

Figure E22: Examples of Technologies using Electric Motive Power

A. Chemicals

B. Rubber

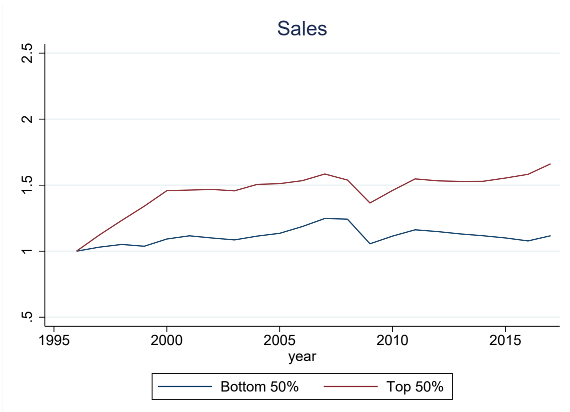
C. Paper

D. Glass and Ceramics

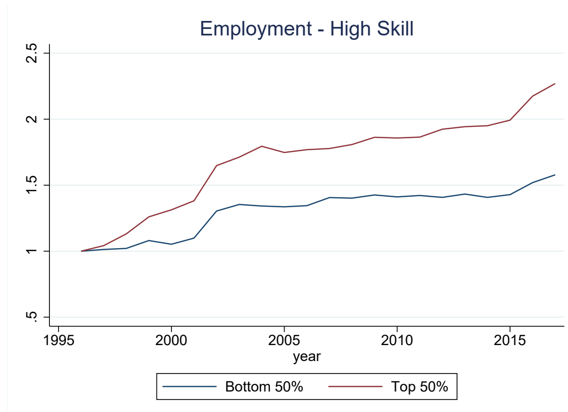
E. Food

Notes: This figure gives examples of machines for five industries with high usage of motive force. It thus illustrates the breadth of technologies that are encompassed in our measure of electric motive power.

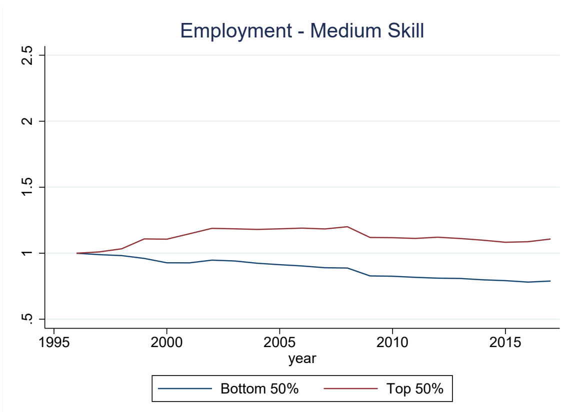
Figure E23: Firm-level Stylized Facts by Use of Industrial Machines



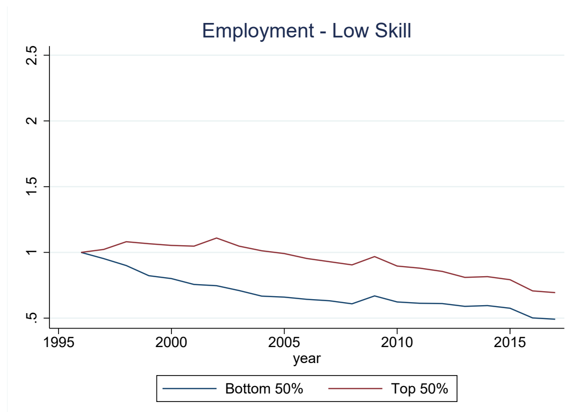
A. Sales



B. High-skill Employment



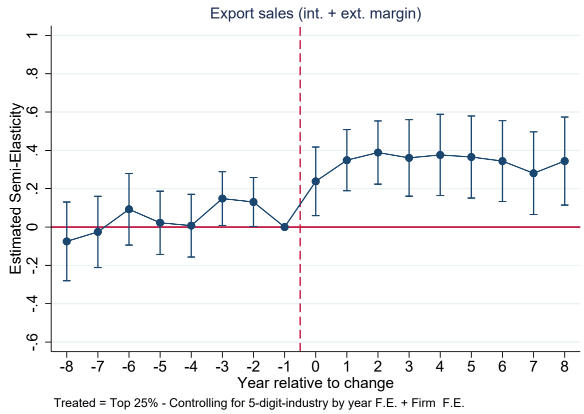
C. Medium-skill Employment



D. Low-skill Employment

Notes: This figure describes the means of firm-level outcomes for firms with a change in industrial machines above or below median from 1996 to 1999. All outcomes are normalized to one in 1996. The figure plots in turn the path of sales in panel A, and employment by skill group in panels B, C, and D.

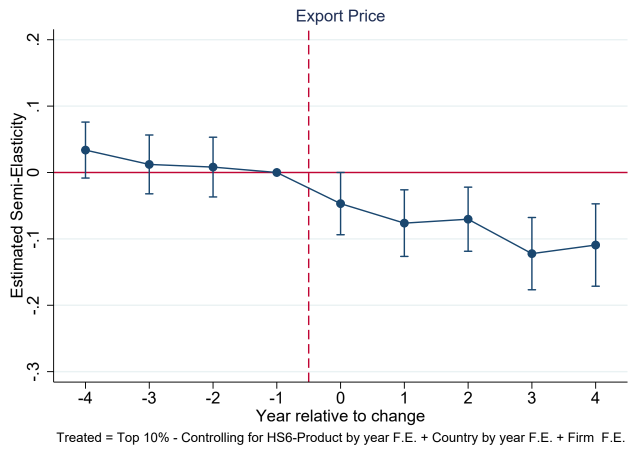
Figure E24: Firm-Level Event Studies for Export Sales



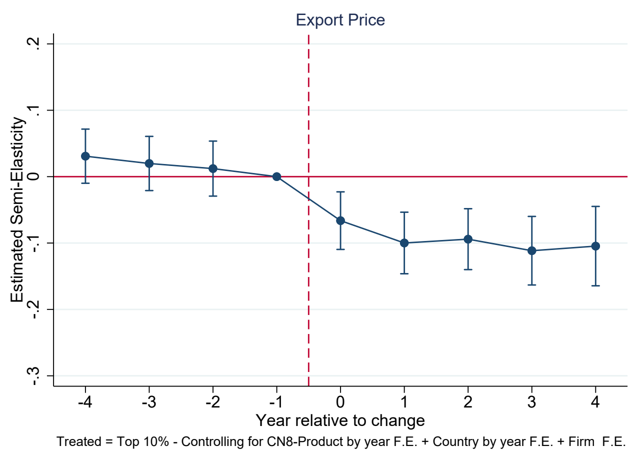
Notes: This figure reports the event study results with the logarithm of "1+exports" as outcomes. We use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

Figure E25: Firm-Level Event Studies for Prices

A. 90th percentile of investment for industry equipment, HS6 product level



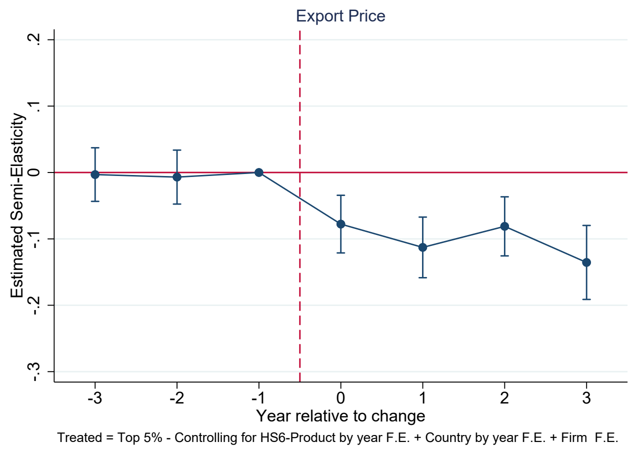
B. 90th percentile of investment for industry equipment, NC8 product level



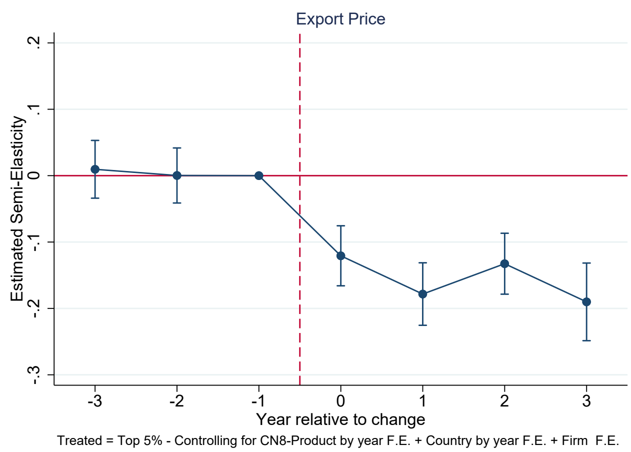
Notes: This figure reports the event study results with export prices as outcomes. Panel A conducts the analysis at the level of HS6 product categories, with HS6-by-year fixed effects, partner country by year fixed effects, and firm fixed effects. Panel B uses an identical specification using NC8 product categories instead, which are more detailed than HS6 codes. The investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. Standard errors are clustered at the firm level in all panels.

Figure E26: Firm-Level Event Studies for Prices, Robustness with p95 Investment Threshold

A. 95th percentile of investment for industry equipment, HS6 product level



B. 95th percentile of investment for industry equipment, NC8 product level



Notes: This figure reports the event study results with export prices as outcomes. Panel A conducts the analysis at the level of HS6 product categories, with HS6-by-year fixed effects, partner country by year fixed effects, and firm fixed effects. Panel B uses an identical specification using NC8 product categories instead, which are more detailed than HS6 codes. The investment event is defined as a logarithmic change beyond the 95th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. Standard errors are clustered at the firm level in all panels.

Table E1: Imported industrial Automating Machines following Acemoglu and Restrepo (2022)

Panel A. Randomly-Drawn Subset of 10 Machines

Name	Import Value, k euros
Brewery machinery (excl. centrifuges and filtering, heating or refrigerating equipment)	1,467
Machines for moulding articles in paper pulp, paper or paperboard (excl. drying equipment)	2,202
Letterpress printing machinery, reel fed (excl. flexographic printing machinery)	112
Flat knitting machines (excl. warp knitting machines, incl. Raschel type)	1,146
Machines for reeling, unreeling, folding, cutting or pinking textile fabrics	7,799
Machine tools for working any material by removal of material, operated by electro-discharge processes, wire-cut, numerically controlled	5,982
Machining centres for working metal (excl. horizontal machining centres)	45,326
Drilling machines for working metal, numerically controlled (excl. way-type unit head machines)	7,411
Parts of machinery and apparatus for soldering, brazing, welding or surface tempering, non-electric, n.e.s.	9,965
Machines for processing reactive resins	2,124

Panel B. Top 10 Machines by Value of Imports

Name	Import Value, k euros
Machines, apparatus and mechanical appliances, n.e.s.	408,861
Parts and accessories for machine tools for working metal without removing material, n.e.s.	137,395
Parts of machinery for working rubber or plastics	128,122
Parts of machinery of heading 8474 (excl. of cast iron or cast steel)	118,092
Parts of machinery for the industrial preparation or manufacture of food or drink, n.e.s.	109,477
Mixing, kneading, crushing, grinding, screening, sifting, homogenising, emulsifying or stirring machines, n.e.s. (excl. industrial robots)	81,128
Industrial robots, n.e.s.	65,579
Machinery for the industrial preparation of meat or poultry	65,309
Parts and accessories of printing machinery used for printing by means of plates, cylinders and other printing components	59,504
Continuous-action conveyors for goods or materials	56,268

Notes: This table provides examples of our proxy for automation based on the taxonomy for machines in the customs data defined by Acemoglu and Restrepo (2022). Panel A reports statistics on the value of imports for a randomly-drawn subset of ten machines, while Panel B repeats the analysis for the ten machines with the largest value in import flows.

Table E2: Summary Statistics, Year-to-year Changes, 1995-2017

	Units	Units-by-year	Mean	S.D.	p5	p50	p95
Panel A: Plant level							
Employment	2,372	54,755	303	478	36	182	889
Modern Manufacturing Capital - Motive force (toe)	2,372	54,755	1,389	4,740	39	355	5,668
Panel B: Firm level							
Employment	4,296	33,579	73	1,081	2	14	204
Sales (thousands of euros)	4,296	33,579	28,141	718,719	312	2,060	59,003
Modern manufacturing capital:							
Industrial machines (thousands of euros)	4,296	33,579	10,581	318,145	13	281	14,744
Acemoglu and Restrepo (2022)'s imports of machines (thousands of euros)	4,296	33,579	67	779	0	0	129
Imports of robots (thousands of euros)	4,296	33,579	1	45	0	0	0
Motive force (toe)	1,008	7,910	1,730	7,380	34	311	6,285
Panel C: Industry level							
Employment	256	5,865	10,440	14,884	410	5,933	33,779
Sales (millions of euros)	256	5,865	3,335	7,514	110	1,706	9,450
Modern manufacturing capital:							
Industrial machines (millions of euros)	256	5,865	991	2,690	20	385	2,908
Acemoglu and Restrepo (2022)'s imports of machines (millions of euros)	256	5,865	38	85	0	10	175
Imports of robots (millions of euros)	256	5,865	0	2	0	0	1

Notes: This table reports the distribution of the main outcome variables – employment and sales – and of the four measures of modern manufacturing capital – the balance sheet value of industrial equipment, Acemoglu and Restrepo (2022)'s imports of industrial machines, robots, and motive power. The statistics are reported at three levels of aggregation: plant-level, firm-level, and industry-level. All variable are reported in annual levels, from 1995 to 2017. Table 1 in the main text reports the same statistics for year-to-year changes.

Table E3: SSIV Analysis of Modern Manufacturing Capital: Automation or Capital Deepening?

Panel A: Fist stage with Acemoglu and Restrepo (2022)'s automation measure

	Δ_5 *Machines*				
	(1)	(2)	(3)	(4)	(5)
Shift-Share Instrument	0.183***	0.176***	0.173***	0.170***	0.171***
	(0.0350)	(0.0347)	(0.0352)	(0.0351)	(0.0339)
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	3,608	3,608	3,608	3,608	3,608

Panel B: First stage with Acemoglu and Restrepo (2022)'s measure of capital deepening

	Δ_5 *Machines*				
	(1)	(2)	(3)	(4)	(5)
Shift-Share Instrument	0.0412	0.0462	0.0545	0.0550	0.0585
	(0.111)	(0.108)	(0.111)	(0.111)	(0.108)
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	935	935	935	935	935

Notes: These tables report first-stage estimates for the shift-share research designed described in Section IV.B and specification (3) in the main text. We report in turn the first-stage OLS estimates, with the change in the balance sheet value of industrial equipment as the endogenous variable, and two versions of the instrument, using alternatively Acemoglu and Restrepo (2022)'s automation measure to define the set of machines for which we compute changes in trade flows (panel A) or Acemoglu and Restrepo (2022)'s alternative measure of capital deepening (panel B). To account for the correlation of residuals due to shock exposure, standard errors and the first-stage F-statistics are clustered at the partner level. $*p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table E4: Firm-level OLS Relationships with Modern Manufacturing Capital Investments

	(1)	(2)	(3)	(4)	(5)
Panel A: Δ_5 *Employment*					
$\Delta_5 Machines$	0.141***	0.140***	0.148***	0.146***	0.144***
	(0.0141)	(0.0142)	(0.0133)	(0.0132)	(0.0128)
Panel B: Δ_5 *Sales*					
$\Delta_5 Machines$	0.133***	0.131***	0.139***	0.137***	0.132***
	(0.0125)	(0.0129)	(0.0132)	(0.0133)	(0.0126)
Panel C: Δ_5 *Hourly Wages*					
$\Delta_5 Machines$	-0.00568	-0.00621	-0.00616	-0.00594	-0.00616
	(0.00416)	(0.00427)	(0.00413)	(0.00415)	(0.00426)
Panel D: Δ_5 *Labor Share*					
$\Delta_5 Machines$	-0.0000793	0.00133	0.00142	0.00115	0.00227
	(0.00792)	(0.00811)	(0.00821)	(0.00822)	(0.00801)
Panel E: Δ_5 *Labor Productivity*					
$\Delta_5 Machines$	-0.00587	-0.00620	-0.00805	-0.00750	-0.00866
	(0.00834)	(0.00866)	(0.00868)	(0.00870)	(0.00864)
Panel F: Δ_5 *Profits*					
$\Delta_5 Machines$	0.149***	0.148***	0.155***	0.156***	0.147***
	(0.0336)	(0.0333)	(0.0333)	(0.0334)	(0.0334)
Panel G: Δ_5 *Competitors' Employment*					
$\Delta_5 Machines$	-0.00699***	-0.00691***	-0.00751***	-0.00743***	-0.00729***
	(0.00129)	(0.00123)	(0.00140)	(0.00141)	(0.00132)
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	3,608	3,608	3,608	3,608	3,608

Notes: This table reports firm-level OLS correlation coefficients between changes in the balance-sheet value of industrial equipment and several outcomes. Each panel considers a different outcome and reports the OLS point estimates and standard errors under five specifications. The sample covers two five-year periods centered about 2005 and 2010 and is restricted to firms that imported machines, covered in the set of automation technologies defined by Acemoglu and Restrepo (2022), between 1996 and 2000. To account for the correlation of residuals due to shock exposure, standard errors are clustered at the trading partner level. $*p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table E5: Additional Evidence on the Labor Share, Firm-level SSIV

	(1)	(2)	(3)	(4)	(5)
Panel A: Δ_5 *Labor Share (alternative definition)*					
$\Delta_5 Machines$	-0.230***	-0.204**	-0.206**	-0.216**	-0.216**
	(0.0779)	(0.0815)	(0.0798)	(0.0830)	(0.0829)
Panel B: Δ_5 *Labor Cost Over Sales*					
$\Delta_5 Machines$	-0.0899	-0.0619	-0.0620	-0.0630	-0.0679
	(0.132)	(0.126)	(0.127)	(0.129)	(0.130)
Panel C: Δ_5 *Value Added Over Sales*					
$\Delta_5 Machines$	0.0915	0.0947	0.0953	0.101	0.100
	(0.0981)	(0.0962)	(0.0966)	(0.0983)	(0.0971)
First-Stage F	27.22	25.67	24.15	23.44	25.33
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	3,608	3,608	3,608	3,608	3,608

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (3). This table is identical to Table 2 in the main text, except that the outcomes are the labor share in total sales and the share of value added in total sales. To account for the correlation of residuals due to shock exposure, standard errors and the first-stage F-statistics are clustered at the partner level. $*p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table E6: Firm-level Shift-Share IV, Robustness with More Stringent Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Panel A: Δ_5 *Employment*					
$\Delta_5 Machines$	0.181**	0.205**	0.219**	0.200**	0.206**
	(0.0812)	(0.0786)	(0.0940)	(0.0931)	(0.0910)
Panel B: Δ_5 *Sales*					
$\Delta_5 Machines$	0.319**	0.303**	0.319*	0.307*	0.320**
	(0.149)	(0.148)	(0.163)	(0.162)	(0.157)
Panel C: Δ_5 *Hourly Wages*					
$\Delta_5 Machines$	-0.0163	-0.0165	-0.0182	-0.0156	-0.0154
	(0.0370)	(0.0379)	(0.0383)	(0.0383)	(0.0379)
Panel D: Δ_5 *Labor Share*					
$\Delta_5 Machines$	-0.199**	-0.176**	-0.184**	-0.189**	-0.191**
	(0.0820)	(0.0790)	(0.0759)	(0.0772)	(0.0762)
Panel E: Δ_5 *Labor Productivity*					
$\Delta_5 Machines$	0.245***	0.217**	0.224**	0.234**	0.234**
	(0.0903)	(0.0838)	(0.0859)	(0.0894)	(0.0888)
Panel F: Δ_5 *Profits*					
$\Delta_5 Machines$	0.640	0.552	0.583	0.605	0.600
	(0.459)	(0.471)	(0.485)	(0.487)	(0.482)
Panel G: Δ_5 *Competitors' Employment*					
$\Delta_5 Machines$	-0.0484*	-0.0503*	-0.0538*	-0.0533*	-0.0529*
	(0.0266)	(0.0285)	(0.0308)	(0.0310)	(0.0308)
Panel H: *Lagged* Δ_5 *Employment*					
$\Delta_5 Machines$	0.0176	0.0337	0.0309	0.0224	0.0239
	(0.169)	(0.172)	(0.181)	(0.182)	(0.180)
Panel I: *Lagged* Δ_5 *Sales*					
$\Delta_5 Machines$	-0.0868	0.00404	0.0111	0.0178	0.0193
	(0.211)	(0.204)	(0.219)	(0.222)	(0.219)
First-Stage F	24.73	22.80	19.21	18.99	20.01
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
5-digit Industry-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	3,608	3,608	3,608	3,608	3,608

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (3). This table is identical to Table 2 in the main text, except that a more stringent set of fixed effects is used, with 4-digit product-partner-period and 4-digit-industry-by-period fixed effects. Standard errors and the first-stage F-statistics are clustered at the partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E7: Firm-level Shift-Share IV, Robustness with Less Stringent Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Panel A: Δ_5 *Employment*					
$\Delta_5 Machines$	0.254***	0.267***	0.289***	0.267***	0.270***
	(0.0650)	(0.0656)	(0.0720)	(0.0704)	(0.0662)
Panel B: Δ_5 *Sales*					
$\Delta_5 Machines$	0.385**	0.370**	0.394**	0.376**	0.393**
	(0.149)	(0.152)	(0.162)	(0.166)	(0.152)
Panel C: Δ_5 *Hourly Wages*					
$\Delta_5 Machines$	-0.0174	-0.0134	-0.0151	-0.0106	-0.0105
	(0.0373)	(0.0370)	(0.0379)	(0.0379)	(0.0374)
Panel D: Δ_5 *Labor Share*					
$\Delta_5 Machines$	-0.129	-0.0997	-0.105	-0.111	-0.112
	(0.0889)	(0.0845)	(0.0871)	(0.0888)	(0.0886)
Panel E: Δ_5 *Labor Productivity*					
$\Delta_5 Machines$	0.164**	0.134**	0.137*	0.152**	0.152**
	(0.0651)	(0.0660)	(0.0689)	(0.0703)	(0.0689)
Panel F: Δ_5 *Profits*					
$\Delta_5 Machines$	0.597	0.493	0.529	0.565	0.572
	(0.533)	(0.546)	(0.567)	(0.574)	(0.561)
Panel G: Δ_5 *Competitors' Employment*					
$\Delta_5 Machines$	-0.0687	-0.0732	-0.0772	-0.0855	-0.0864
	(0.0705)	(0.0728)	(0.0765)	(0.0784)	(0.0772)
Panel H: *Lagged* Δ_5 *Employment*					
$\Delta_5 Machines$	0.129	0.134	0.144	0.133	0.132
	(0.157)	(0.163)	(0.171)	(0.175)	(0.173)
Panel I: *Lagged* Δ_5 *Sales*					
$\Delta_5 Machines$	-0.0249	0.0168	0.0248	0.0372	0.0385
	(0.172)	(0.170)	(0.181)	(0.186)	(0.183)
First-Stage F	21.50	22.17	26.68	25.55	29.02
6-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
Lagged Firm Controls		Yes	Yes	Yes	Yes
Lagged Machines			Yes	Yes	Yes
Lagged Other Capital				Yes	Yes
Contemporaneous Exports					Yes
N (Trading partner - Product - Period)	3,608	3,608	3,608	3,608	3,608

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (3). This table is identical to Table 2 in the main text, except that a less stringent set of fixed effects is used, with 4-digit product-partner-period fixed effects and no industry fixed effects. Standard errors and the first-stage F-statistics are clustered at the partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E8: Industry-level OLS Relationships with Modern Manufacturing Capital Investments

	(1)	(2)	(3)	(4)
Panel A: Δ_5 *Employment*				
$\Delta_5 Machines$	0.389***	0.385***	0.376***	0.376***
	(0.0227)	(0.0221)	(0.0211)	(0.0213)
Panel B: Δ_5 *Incumbents' Employment*				
$\Delta_5 Machines$	0.235***	0.228***	0.225***	0.227***
	(0.0368)	(0.0374)	(0.0367)	(0.0372)
Panel C: Δ_5 *Sales*				
$\Delta_5 Machines$	0.398***	0.400***	0.395***	0.399***
	(0.0250)	(0.0250)	(0.0245)	(0.0251)
Panel D: Δ_5 *Hourly Wages*				
$\Delta_5 Machines$	0.00683	0.00652	0.00558	0.00588
	(0.00636)	(0.00657)	(0.00651)	(0.00706)
Panel E: Δ_5 *Labor Share*				
$\Delta_5 Machines$	-0.0375***	-0.0346***	-0.0308***	-0.0357***
	(0.00701)	(0.00759)	(0.00789)	(0.00896)
Panel F: Δ_5 *Labor Productivity*				
$\Delta_5 Machines$	0.0218*	0.0197	0.0179	0.0238
	(0.0127)	(0.0135)	(0.0131)	(0.0151)
Panel G: Δ_5 *Profits*				
$\Delta_5 Machines$	0.678***	0.669***	0.633***	0.654***
	(0.0539)	(0.0533)	(0.0551)	(0.0602)
4-digit Product-period F.E.	Yes	Yes	Yes	Yes
2-digit Product-Partner-period F.E.	Yes	Yes	Yes	Yes
Lagged Industry Controls	Yes	Yes	Yes	Yes
Lagged Machines		Yes	Yes	Yes
Lagged Other Capital			Yes	Yes
Contemporaneous Exports				Yes
N (Trading partner - Product - Period)	7,138	7,138	7,138	7,138

Notes: This table reports industry-level OLS correlation coefficients between changes in the balance-sheet value of industrial equipment and several outcomes. Each panel considers a different outcome and reports the OLS point estimates and standard errors under five specifications. The sample covers two five-year periods centered about 2005 and 2010. To account for the correlation of residuals due to shock exposure, standard errors are clustered at the trading partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E9: Industry-level SSIV, Robustness with Less Stringent Fixed Effects

	(1)	(2)	(3)	(4)
Panel A: Δ_5 *Employment*				
$\Delta_5 Machines$	0.404***	0.395***	0.401***	0.401***
	(0.113)	(0.112)	(0.104)	(0.106)
Panel B: Δ_5 *Incumbents' Employment*				
$\Delta_5 Machines$	0.224*	0.228**	0.222**	0.224**
	(0.117)	(0.109)	(0.104)	(0.104)
Panel C: Δ_5 *Sales*				
$\Delta_5 Machines$	0.465***	0.448***	0.444***	0.457***
	(0.156)	(0.155)	(0.149)	(0.155)
Panel D: Δ_5 *Hourly Wages*				
$\Delta_5 Machines$	-0.0390	-0.0314	-0.0258	-0.0218
	(0.0446)	(0.0439)	(0.0386)	(0.0375)
Panel E: Δ_5 *Labor Share*				
$\Delta_5 Machines$	-0.305*	-0.311*	-0.298*	-0.314**
	(0.168)	(0.161)	(0.155)	(0.133)
Panel F: Δ_5 *Labor Productivity*				
$\Delta_5 Machines$	0.216	0.215	0.201	0.232**
	(0.149)	(0.136)	(0.128)	(0.105)
Panel G: Δ_5 *Profits*				
$\Delta_5 Machines$	2.243***	2.181***	2.119***	2.184***
	(0.752)	(0.768)	(0.739)	(0.610)
Panel H: *Lagged* Δ_5 *Employment*				
$\Delta_5 Machines$	0.0985	0.0828	0.0826	0.0771
	(0.204)	(0.207)	(0.199)	(0.196)
Panel I: *Lagged* Δ_5 *Sales*				
$\Delta_5 Machines$	0.0789	0.0755	0.0556	0.0447
	(0.292)	(0.284)	(0.268)	(0.257)
First-Stage F	9.08	8.66	9.55	10.29
4-digit Product-period F.E.	Yes	Yes	Yes	Yes
Partner-period F.E.	Yes	Yes	Yes	Yes
Lagged Industry Controls	Yes	Yes	Yes	Yes
Lagged Machines		Yes	Yes	Yes
Lagged Other Capital			Yes	Yes
Contemporaneous Exports				Yes
N (Trading partner - Product - Period)	7,174	7,174	7,174	7,174

Notes: This table reports industry-level SSIV estimates, implementing the research design described by specification (3) at the industry level. This table is identical to Table 4 in the main text, except that we now use partner-period fixed effects, rather than 2-digit Product-Partner-period fixed effects as in the main text. To account for the correlation of residuals due to shock exposure, standard errors and the first-stage F-statistic are clustered at the trading partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E10: Additional Evidence on the Labor Share, Industry-level SSIV

	(1)	(2)	(3)	(4)
Panel A: Δ_5 *Labor Cost Over Sales*				
$\Delta_5 Machines$	-0.157	-0.145	-0.144	-0.164
	(0.117)	(0.112)	(0.107)	(0.110)
Panel B: Δ_5 *Labor Share (Alternative)*				
$\Delta_5 Machines$	-0.245*	-0.246*	-0.228*	-0.243**
	(0.138)	(0.134)	(0.125)	(0.106)
Panel C: Δ_5 *Value Added Over Sales*				
$\Delta_5 Machines$	0.195	0.205	0.190	0.179
	(0.198)	(0.183)	(0.175)	(0.182)
First-Stage F	10.55	9.91	10.90	11.79
4-digit Product-period F.E.	Yes	Yes	Yes	Yes
2-digit Product-Partner-period F.E.	Yes	Yes	Yes	Yes
Lagged Industry Controls	Yes	Yes	Yes	Yes
Lagged Machines		Yes	Yes	Yes
Lagged Other Capital			Yes	Yes
Contemporaneous Exports				Yes
N (Trading partner - Product - Period)	7,138	7,138	7,138	7,138

Notes: This table reports industry-level SSIV estimates, implementing the research design described by specification (3) at the level of industries and studying the labor share in total sales (panel A) and the share of value added in total sales (panel B) as outcomes. To account for the correlation of residuals due to shock exposure, standard errors and the first-stage F-statistic are clustered at the trading partner level. $^*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E11: Industry-level OLS Relationships between Manufacturing Capital and Producer Prices

	Δ_5 *Producer Price Index*			
	(1)	(2)	(3)	(4)
$\Delta_5 Machines$	-0.0956*	-0.170***	-0.167**	-0.149**
	(0.0513)	(0.0643)	(0.0644)	(0.0697)
2-digit Industry-period F.E.	Yes	Yes	Yes	Yes
4-digit Industry F.E.	Yes	Yes	Yes	Yes
Lagged Industry Controls	Yes	Yes	Yes	Yes
Lagged Machines		Yes	Yes	Yes
Lagged Other Capital			Yes	Yes
Contemporaneous Exports				Yes
N (Industry - Period)	174	174	174	174

Notes: This table reports the industry-level OLS relationship between the changes in the producer price index and changes in the balance sheet value of industrial equipment. The level of observation is a 4-digit industry by 5-year period. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.