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

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Abstract

We use comprehensive micro data in the French manufacturing sector between 1995 and 2017 to document the effects of a fall in the cost of investments in modern manufacturing capital, including modern automation technologies, on employment, wages, sales, prices, and business stealing. Causal effects are estimated with event studies and a shift-share IV design leveraging pre-determined supply linkages and productivity shocks across foreign suppliers of manufacturing capital. At all levels of analysis — plant, firm, and industry — the estimated impact of capital investments on employment is positive, even for unskilled industrial workers. Furthermore, we find that capital investments lead to higher sales and exports, higher profits, and lower consumer prices, while wages and wage inequality remain unchanged. We estimate a positive industry-level employment response to manufacturing capital investments only in industries that are exposed to import competition, due to business-stealing across countries. Thus, typical investments in modern manufacturing capital lead to an increase in domestic labor demand and promote competitiveness in international markets.

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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. (2019)). 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 or plant-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 or plant levels, 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 and plants in the French

[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 Puttmann (2018) and Klenert et al. (2020) 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.

manufacturing 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 — across plants, 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 evidence on the population of firms and plants 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 equipment 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 or across plants in the same 5-digit industry. We find that firm-level and plant-level employment increases after investments in modern manufacturing capital, including for unskilled industrial workers. The elasticity of employment to capital investments increases with the time horizon. In line with the hypothesized productivity effect, we find that sales and exports increase when firms invest, while export prices and competitors' employment fall. We thus provide direct empirical evidence for business-stealing effects. We find no evidence that modern manufacturing capital investments have an impact on firm-level wage inequality, although they lead to a fall in the share of labor in value-added and to 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]

[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. (2021)) 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.

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 or plant-level labor demand. However, potential unobserved shocks may confound the observed relationships. The event studies show no sign of pre-trends, which is reassuring and restricts the potential set of confounders that could explain the increase in employment. Confounding shocks would need to occur exactly at the same time as the increase in capital investment. Nonetheless, absent a quasi-experiment potential concerns over omitted factors cannot be fully 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 validate the causal interpretation of the event study results by developing 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 HS6-level shocks 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.

The results with the shift-share design are in line with the event study results. Firms whose international suppliers of machines become more productive increase their usage of automation technologies (in the sense of Acemoglu and Restrepo (2022)), and in turn their sales and their labor force. The baseline specification with 4-digit product-by-year and 2-digit industry-by-year fixed effects yields an elasticity of firm employment to automation of 0.37 (s.e. 0.126). The point

estimates remain comparable in magnitudes with alternative sets of controls. We find that sales increase substantially in response to increased automation, with elasticities around 0.37 across specifications. In addition, we cannot reject that there is no impact of automation on wages or on inequality across workers, while we estimate a fall in the labor share in value-added.

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 may paint a misleading picture because 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 first use 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 and plants. 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.[4]

To address potential confounding factors in the industry-level event studies, we use 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 exact same productivity shocks across foreign suppliers of machines as in 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 similar to the firm-level responses described previously. The elasticity of industry-level employment to industry-level automation is positive at 0.932 (s.e. 0.173),[5] compared with 0.981 (s.e. 0.285) 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 and wage inequality remain unchanged, while profits increase.

The finding that the employment response to modern manufacturing capital investments, including automation, remains positive at the industry level may appear surprising given the potential

[4]Given our focus on horizons from 5 to 10 years, our findings are instructive for the transitional dynamics of wage inequality at the firm and industry levels. In the long run, given labor mobility, inequality should be studied across groups of workers in a structural model accounting for the reallocation of workers, which is beyond the scope of this paper.

[5]When restricting attention to incumbent firms only, i.e. without accounting for entry and exit, the point estimate is reduced to 0.588 (s.e. 0.262).

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 response 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 effect 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 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 response of 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 the elasticities for the response of sales and consumer prices to manufacturing capital investments, 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 relationship between capital investments and employment can remain positive even at the industry level, because the response 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 Puttmann (2018), Acemoglu and Restrepo (2019), Aghion et al. (2019), Cheng et al. (2019), Webb (2019), Adachi et al. (2020), Klenert et al. (2020)). A more recent line of work, parallel to ours, uses event studies to estimate the firm-level employment effects of robotization and documents a positive reponse (e.g., Acemoglu et al. (2020b), Bessen et al. (2020), Bonfiglioli et al. (2020), Dixon et al. (2019), Domini et al. (2019), Humlum (2019), Koch et al. (2019)).[6] Furthermore, our analysis 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 (2018), Houthakker (1955)) and capital-skill complementarities (e.g., Goldin and Katz (1998), Doms et al. (1997), Baqaee and Farhi (2019), Curtis et al. (2021)).[7]

We contribute to this literature in four ways. First, we introduce a quasi-experimental shift-share design to provide causal estimates of modern manufacturing capital investments, including automation using Acemoglu and Restrepo (2022)'s measure. In contrast, existing firm-level event study approaches focus on very specific technologies including for a small fraction of modern manufacturing capital investments (e.g., robots), and they cannot rule out potential unobserved confounding shocks. Second, we extend our analysis to product market outcomes, including sales, prices, and firm profits, while the existing literature has focused on labor market impacts. Third, we study industry-level, firm-level and plant-level responses in a unified setting, which helps isolate the relevant mechanisms.[8] The shift-share IV design implemented at the industry-level allows us to quantify the impact of automation on domestic employment accounting for business-stealing

[6]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 IT on the middle class.

[7]The paper closest to ours is perhaps the subsequent work by Curtis et al. (2021), which 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. (2021) 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 unemployment and earnings. Thus, a consistent empirical picture emerges: capital investments lead to an increase in labor demand.

[8]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)).

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. Fourth, we examine the role of exports and we document heterogeneity in the industry-level effects automation, depending on exposure to international competition. The heterogeneity we uncover depending on trade exposure can help reconcile some of the diverging industry-level estimates in prior work.[9]

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. (2019), Jaimovich et al. (2021)) or to prescribe optimal technological regulations (e.g., Costinot and Werning (forthcoming) and Guerreiro et al. (2022)). Our results provide a set of identified moments at various levels of aggregation (industry, firm and plant) for a large set of manufacturing capital investments, which the 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 stylized facts and estimates from event studies, at the firm and plant levels. Section V reports the causal estimates from the shift-share design at the firm level. Finally, Section VI implements the industry-level analyses. The Online Appendix reports additional results as well as the 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, 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. Online Appendix A provides a more comprehensive survey of theoretical predictions, including the role of reallocation effects.

[9]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. (2020), including France.

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 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,[10] 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.

[10] 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)).

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 nonautomated 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 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.[11]

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.[12]

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

[11] We test this prediction below: see Figures 7 and A12. Empirically, we 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.

[12] 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.

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 (2021) 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.[13]

Thus, instead of focusing on a particular technology that may *a priori* be viewed as automation, in this paper we aim to 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 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)).

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 causal firm-level and industry-level effects of investments in modern manufacturing capital on labor demand and inequality. 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. (2021)).

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

[13]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.

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.[14] From a policy perspective, our approach is informative about the effects of policies that reduce the costs of investment in 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.

To achieve these goals, we conduct the empirical analysis both at the firm and industry levels, using a unified shift-share research designed described in Sections V and VI. As we show next, we find that investments in manufacturing capital lead to an increase in labor demand translating into an increase in employment, at both the firm and industry level. We also observe a fall in the share of labor in value-added, which can be explained by the task-based framework but not by the canonical model under standard parametrizations. We also assess empirically the importance of business-stealing effects.

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.

[14] In this way, we can assess the extent to which investment 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.

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 plants and 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. At the plant level, we observe the composition of the workforce, notably the number of hours worked, total compensation and occupation codes for each worker.[15]

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,[16] 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."[17]

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

[15] Measures of worker skills are obtained from Charnoz and Orand (2017).

[16] More specifically, the general accounting plan (*Plan Général Comptable*).

[17] 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 %).

hand-operated machine tools and "not numerically controlled" machine tools. This measure also excludes household machines (for cooking, washing, cleaning etc.), agricultural machinery, and IT machines.[18] 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.[19]

As a second proxy for automation, we use only 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 (2019), and Dauth et al. (2021). This proxy may include robots that are not pure substitutes for labor and instead complement labor,[20] at least at some level of aggregation of the production function (e.g., at the firm level rather than at the task level).[21]

Our third proxy for automation is based on 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 electromotive 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. With this motivation in mind,

[18] For example, the measure excludes dish washing machines, lifts and escalators, printers and copying machines, calculating machines, microphones, headphones and hearphones, and telephone sets.

[19] 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"). As discussed below, we repeat our analysis with the original proxy of Acemoglu and Restrepo (2022) in robustness checks, i.e. including only textile machines as the relevant sectoral machines for automation.

[20] 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, either to help them perform a task or as a guide. 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). Viewed through the lens of the task model of Acemoglu and Restrepo (2018c), robots adoption may consist of a mixture of "extensive margin automation" and "intensive margin automation deepening" (see Appendix A for a complete discussion).

[21] As discussed further in Section VI.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 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.

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.

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 a battery of fixed effects. As discussed in greater detail in Sections IV, V and VI, we use panel data to describe how employment or other outcomes change after a plant or firm increases its investments in manufacturing capital (as measured by our proxies), including time-by-industry fixed effects to control for potential time-by-industry changes in efficiency.[22]

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

[22]In particular, because of variation in energy efficiency over time, there could be a non-monotonic relationship between our motive power measure and investments in manufacturing capital. By investing in new machines that are more energy efficient, a firm may increase its effective reliance on machines while at the same time decreasing its energy consumption for motive power. Although possible in principle, we find that this case is not relevant in practice: when examining the empirical relationship between the firm-level balance sheet and the motive power measures, we find that firms that increase their investments in industrial equipment also experience an increase in electric energy used for motive power.

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 used in Section V, as well as to isolate the role of specific machines or robots, 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 Section VI. 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, Table 2 and Figure 1 report the main summary statistics.

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. While this table reports the patterns in changes over the course of our sample, Online Appendix Table A1 reports them in levels. The analysis is conducted with plants and firms that operate continuously from 1995 to 2017 in 255 manufacturing industries.[23] The table shows that there is significant heterogeneity across plants,

[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.C). When we conduct the analysis at the industry level, entry and exit dynamics are accounted for (see Section VI).

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.

Next, Figure 1 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 secotral 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 A1 provides examples of machines using eletcric motive power (pasta machines, conveyors, chemical mixers, etc.). Finally, 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 2 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.

Summary statistics on expenditure shares across income groups are also instructive to learn about the household groups that are most likely to be affected by manufacturing capital. Appendix Figure A2 documents that the average (sales-weighted) income of consumers is *lower* in industries that rely more intensively on manufacturing capital. This pattern indicates that lower-income households are likely to benefit relatively more from potential price declines brought about by manufacturing capital and increased productivity.[24] We estimate the extent to which productivity gains from manufacturing capital are passed through to consumers in the following section, using direct price measures or by inferring consumer price changes from changes in sales.

IV Firm-level Stylized Facts and Event Studies

This section provides evidence from stylized facts and event studies at the firm level on the relationship between investments in modern manufacturing capital, employment, sales, prices, wages,

[24]For small shocks, the envelope theorem (Roy's identity) implies that price changes affect each type of consumer in proportion to their spending share across products indexed, regardless of the demand system (see, e.g, Borusyak and Jaravel (2021)). The first-order effect comes from the expenses the agent saves by paying lower prices, holding spending shares constant.

and the labor share. We find 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.

IV.A Research Design

When a firm relies more extensively on modern manufacturing capital, what happens to sales, employment, demand for worker skills, and the labor share? In this section, we investigate this question in the population of firms and plants. We first report stylized facts on the relationship between these variables in Subsection IV.B, then we provide semi-elasticity estimates from event studies in Subsection IV.C.

The event study design alleviates some of the potential threats to identification (e.g., correlated shocks) thanks to the inclusion of a battery of fixed effects and time-varying controls. Nonetheless, absent a quasi-experiment, potential concerns over omitted factors cannot fully be addressed. For example, increased demand or increased competition both have a direct impact on employment and may also lead a firm to invest more heavily in modern manufacturing capital. It is therefore difficult to sign the potential bias of the estimates of the employment response to capital investment: the estimate could be biased upward because of increased demand or biased downward because of increased competition.

After presenting correlational evidence for the population of plants and firms in this section, we validate the causal interpretation of the estimates using a quasi-experimental research design for a subset of firms. Section V develops a shift-share research design that can be applied to the subset of firms for which exogenous variation in the price of modern manufacturing capital is available from trade patterns.

IV.B Firm-level Stylized Facts

We first 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 plants below and above median. All outcomes are normalized to one in the first year of the sample.

Figure 2 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.

Panels B, C and D show that plants 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. In the remainder of the paper, we refine this analysis to provide causal evidence.

IV.C Event Studies

IV.C.1 Specifications and Identification

To address some of the potential correlated demand or supply shocks that may confound the stylized facts, we introduce an event study design, which can control for time-invariant unobservables as well as industry-year or, when the analysis is carried out a the plant level, firm-year fixed effects.

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 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.

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

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

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}.

This specification allows for delayed responses of employment to changes in capital investments. 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.

Identification. A causal interpretation of the estimates requires the identification condition:

$$E[E_{i,t-k} \cdot \epsilon_{it} | \mu_i, \lambda_{st}] = 0 \ \forall \ (t,k). \tag{2}$$

The estimated coefficients for the "leads" (i.e., $\widehat{\delta_k}$ with $k < 0$) can be used as a standard pre-trend falsification test. If the identification condition (2) holds, we expect the leads to be statistically insignificant and the point estimates to be close to zero. Standard errors are clustered at the firm level.

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. To alleviate this potential concern, we examine the stability of the estimates when including more stringent time-varying controls λ_{st} in robustness checks, before turning to the shift-share IV design in the following section.

IV.C.2 Results

Impact on firm-level employment. Figure 3 reports the results of the firm-level event studies. 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 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] The response of employment is then amplified over time, with a semi-elasticity of +0.4 after ten years. The point estimates are precise; the 95% confidence interval rejects an employment elasticity below +0.20 or above +0.50 after ten years. Panels B and C show similar results using alternative thresholds to define the investment event (p75 and p50, respectively), with slightly smaller semi-elasticities.[26]

There is no sign of pre-trends: conditional on the controls included in our statistical model, firms that invest more at a given time were on a comparable employment path in years prior to the event and started diverging only afterwards. This finding restricts the potential set of confounders that could explain the increase in employment — namely, confounding shocks need to occur simultaneously to the increase in investments.

Figure 4 examines the robustness of these findings when using our three proxies for automation. In Panel A, we use Acemoglu and Restrepo (2022)'s proxy for automation based on imports of industrial automating machines. The patterns are very similar with alternative thresholds to define the investment events (p90 and p75), with no sign of pre-trend. Panel B documents similar patterns using the measure of robots. Finally, Panel C reports the elasticity of employment to motive power, which is also positive at +0.30 after 10 years.[27] Thus, we consistently find a positive response of

[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] 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 exactly once above the specified thresholds (Online Appendix Figure A3).

[27] 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-

employment to investments in automation technologies.

The Online Appendix reports additional robustness checks. In Online Appendix Figure A4, 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.[28] 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. Furthermore, Appendix Figure A5 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. Finally, Appendix Figure A6 shows that the estimates remain similar when we balance the panel over different time horizons.

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. Online Appendix Figure A7 shows that the results are similar when using peak motive power.

Impact on employment by skill groups. Figure 5 documents heterogeneity across skill groups, using the specification with 5-digit-industry-by-year fixed effects. The three panels show a comparable positive response for high-skill, medium-skill and low-skill workers. As previously, the employment semi-elasticity to investment is about +0.2 on impact and increases to about +0.4 after ten years. The paths of the point estimates for the three skill groups are statistically indistinguishable.

These results indicate that investments in modern manufacturing capital do not have different effects across broad skill groups within the firm and leave relative labor demand unchanged. Online

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)).

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

Appendix Figure A8 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.[29]

Impact on wages, within-firm inequality, and labor productivity. Figure 6 reports the impact of investments in modern manufacturing capital on within-firm wage inequality. Panel (i) show that the average hourly wage remains flat after the investment event, with no sign of pre-trends.[30] Panels (ii) and (iii) show that the average hourly wage remains similarly flat for low-skill workers and medium-skill workers. In Panel (iv), we see that the average wage for high-skill workers stays relatively flat, but tends to increase after four years, with a semi-elasticity of 0.02. Thus, none of the broad skill groups suffers from a fall in wages.

Panels (v) through (vii) complement these findings with several measures of within-firm inequality. In Panel (v), we use the ratio of the 90th to the 10th percentile of wages within the firm as our dependent variable. We find that this ratio remains unresponsive to the investment event, i.e. within-firm inequality remains unchanged. Panel (vi) document 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, in Panel (vii) we document the response of 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 stronger reponse in the year immediately following the event. Overall, these patterns indicate that modern manufacturing capital helps increase labor productivity, leading to an increase in labor demand benefitting all skill groups.

The patterns so far 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 responses so far are in line with the canonical model: modern manufacturing capital leads to an increase in both labor demand and labor productivity.[31] In contrast, the patterns are not consistent with parametrizations of the task model in

[29] 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. (2021)). Furthermore, our estimates 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)).

[30] Online Appendix Figure A9 show that the estimated wage reponse is also null when using Acemoglu and Restrepo (2022)'s measure of automation technologies.

[31] In the canonical model with perfect competition and production that uses homogenous labor and capital, all

which the overall effect on labor demand is negative. Next, we turn to displacement effects, where the task model makes distinctive predictions.

Displacement effects. To document whether typical investments in modern manufacturing capital have displacement effects, panel (viii) of Figure 6 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 negative response in the short run that is muted after 8 years.[32] 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.[33]

The Online Appendix report several additional patterns on the labor share for completeness. First, Online Appendix Figure A10 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. Second, Appendix Figure A11 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.

To further characterize the displacement effects, Figure 7 focuses on the rates of job creation and destruction within the firm. Using the balance sheet value of industrial machines as our proxy for industrial equipment, Panels A(i) and A(ii) show that investment events lead to an increase in both job creation and job destruction. Although there is more job creation than job destruction,

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.

[32]Given that wages do not change (panel (i) of Figure 6), 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. $dlog(s_L) = -dlog(VA/L) + dlog(w)$, where the second term is estimated to be zero empirically.

[33]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 indicates that the productivity effect is strong and results in an overal increase in labor demand.

these patterns indicate that investment events lead to many instances of job reallocations. In Panel A(iii), we compute a within-firm job dissimilarity index, using the shares of workers by occupation across consecutive years.[34] 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. Online Appendix Figure A12 provides additional evidence for the change in the production function: investments in modern manfacturing capital are associated with a fall in expenses for temporary workers, while they remain unchanged for investments in real estate.

These estimated displacement effects are consistent with the view that investments in modern manufacturing capital can be conceptualized as automation, in that they induced a fall in the labor share in value added as well as a change in the production process inducing a reallocation of occupations within the firms, which is not observed for alternative investments like real estate. Overall, the patterns in Figures 6, 7 and A12 indicate 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 (e.g., temporary or permanent workers), but there is no evidence that they lead to important changes in within-firm inequality.

Market dynamics. Figure 8 documents the impact of the investment event on market dynamics. Panel A 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 B reports that export sales also increase. Finally, Panel C uses competitor employment as the outcome, showing a negative impact. The semi-elasticity of competitors' employment (defined as domestic firms in the same 5-digit industry) is negative, at about -0.001.[35]

Together, these patterns highlight the importance of the scale effect brought about by the increase in productivity due to investment in modern industrial capital, but also the potential for business-stealing effects negatively affecting employment in firms that do not invest. These findings

[34] 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.

[35] 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 event studies at the industry level in Section VI.

motivate our analysis at the industry level in Section VI, which account for these equilibrium effects at the industry level.

Exports prices. Next, 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 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 9. 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 VI.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 9, 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 Appendix Figure A13, 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.

Limitations. Despite the robustness of the firm-level relationships documented above, two potential concerns remain. First, because so far we do not have an explicit quasi-experimental source of variation, it could be that some unobserved factors explain these relationships. We address this limitation in Section V with a shift-share design approximating the experimental ideal of a fall in the cost of investment in modern manufacturing capital. Second, the positive firm-level relationship between investments in manufacturing capital and employment, along with the negative relationship between investments in manufacturing capital and prices, may be misleading because of business-stealing effects and reallocation across firms, which could affect the industry-level relationships. In Section VI, we conduct a similar analysis at the industry level to directly account for these reallocation effects.

V Firm-Level Shift-Share IV

In this section, we introduce a quasi-experimental shift-share design to estimate the causal effects of investment in modern manufacturing capital on employment, sales, wages, and the labor share across firms. The results validate the findings from Section IV: firm-level employment and sales increase, while the average wage remain stable, and the labor share falls.

V.A 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.[36] We use Acemoglu and Restrepo (2022)'s measure of imported automation technologies, which cover 185 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 t.

To obtain an instrument plausibly exogenous to the choices made by French firms, we study

[36]The Hamonized System (HS) nomenclature, which was developed by the World Customs Organisation (WCO), is an internationally recognized nomenclature of standardized product classification used in over 200 countries. It encompasses over 5,000 commodity groups, every group being labeled with a 6-digit code.

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:

$$g_{nt} = \frac{ImportMachines_{n,t+1,t+5} - ImportMachines_{n,t-4,t}}{ImportMachines_{n,t+1,t+5} + ImportMachines_{n,t-4,t}}, \tag{3}$$

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 oucnitres other than France. In the baseline specification, we measure the shocks g_{nt} across 149 trading partners in 185 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 (3).[37]

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 n in firm i's total imports of machines and robots 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. Because 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

[37] 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.

$t = 2005$ and $t = 2010$. The endogenous variable is the log change in the balance sheet value of industrial equipment, denoted ΔM_{it},[38] across firms indexed by i. Denoting by ΔL_{it} log changes in employment, we estimate by 2SLS the following specification:

$$\begin{cases} \Delta L_{it} = \beta Z_{it} + \gamma X_{it} + \varepsilon_{it}, \\ \Delta M_{it} = \alpha Z_{it} + \widetilde{\gamma} X_{it} + \widetilde{\varepsilon}_{it}, \end{cases} \tag{4}$$

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

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

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 specification we use HS4-by-period fixed effects (i.e., all variation arises within HS4 product categories within each 5-year period) as well as 2-digit-industry-by-period fixed effects and trading-partner-by-period fixed effects. In this way, we compare French firms in the same 2-digit industry that source their inputs from different suppliers, within narrowly defined HS4 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 apply (see for example Borusyak et al. (2022)). First, a relevance condition must hold such that the instrument has power, i.e. $E[\Delta M_{it} \cdot Z_{it} | X_{it}] \neq 0$. This can be checked directly in the data by computing the first-stage F statistic, accounting to the correlation of shocks. 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, Online Appendix Figure A14 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

[38] 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.

expressed equivalently at the firm level or in space of productivity shocks (across foreign suppliers of different machines):

$$\left(\frac{1}{I}\sum_i Z_i\varepsilon_i \xrightarrow{p} 0\right) \Longleftrightarrow \left(\sum_n \hat{s}_{0n} g_n \bar{\varepsilon}_n \xrightarrow{p} 0\right), \tag{5}$$

with $\bar{\varepsilon}_n = (\sum_i s_{i0n}\varepsilon_i)/\sum_i s_{i0n}$ 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.[39] 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 ($E\left(\sum_{n=1}^{N}(\hat{s}_{0n})^2\right) \to 0$) may not be met. In practice, we compute that the inverse HHI of the weights $\hat{s}_{0n}$ is 268, indicating that the effective sample size is large.[40]

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 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. As mentioned above our baseline specification uses three types of fixed effects: HS4-by-period fixed effects, 2-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 HS6-by-period fixed effects and 5-digit-industry-by-period fixed effects, then HS4-by-period fixed effects without industry-period fixed effects. In addition, we run a second falsification test using the lagged outcome variable, providing evidence on the correlation between the instrument and

[39] In contrast, Goldsmith-Pinkham et al. (2020) propose an identification framework where the shares are the identifying source of variation.

[40] Equation (5) follows from Proposition 1 in Borusyak et al. (2022). Following their recommendations, when we 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. See Borusyak et al. (2022) for a complete discussion.

potential lagged demand shocks. 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 trading partner by period fixed effects, 4-digit product period fixed effects, and 2-digit industry-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 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 explained in the discussion of identification in shift-share IV designs of Borusyak et al. (2022).

V.B Results

The results and falsification tests are reported in Tables 3 and 4, using the change in the firm-level balance sheet value of industrial machines as our endogenous variable.[41]

OLS. We start by reporting the OLS relationship between investment in modern manufacturing capital and employment at the firm level in Table 3. We only keep the set of firms that import

[41]The source of variation in the SSIV is trade shocks for imports of industrial automating machines, following Acemoglu and Restrepo (2022). Online Appendix Table A2 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. These results suggest that investments in modern manufacturing capital can be thought of primarily as corresponding to automation technologies in the sense of Acemoglu and Restrepo (2022).

machines so that the results can be compared with the shift-share IV design. Panel A focuses on employment growth. Column (1) includes year fixed effects interacted with trading partners, HS4 categories and 2-digit industries. We obtain an elasticity of employment to modern manufacturing capital investments of +0.406 (s.e. 0.0210), which is similar to the event study design from Section 3 over a comparable time horizon. The other columns show that this elasticity remains similar in magnitude as we vary the set of controls: the point estimates hover between 0.413 and 0.410 across specifications. Panels B of Table 3 shows that the OLS relationships with sales are positive, with elasticities around 0.30. Panel C reports the relationship with hourly wages, with a small, statistically insignificant point estimate around -0.013 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 E shows a positive correlation with profits, with an elasticity close to 0.32 across specifications. Finally, Panel F reports that manufacturing capital investments are associated with a decline in competitors' employment within the same 5-digit industry. To assess whether these OLS estimates are biased, we next turn to the shift-share IV design.

Shift-share IV. Panel A of Table 4 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 +0.368 (s.e. 0.126). The point estimate is statistically significant at the 1% level and the first stage F statistic of 16.90 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 vary between 0.360 and 0.374, are all significant at the 1% level, and are statistically indistinguishable from one another. The first stage F statistic remains above 16 in all specifications.

These results support the conclusion from Section IV: increases in manufacturing capital investments lead to higher employment at the firm level. Relative to these SSIV results, the OLS estimates from Table 3 are statistically indistinguishable and thus do not appear to be biased either upward or downward. Offsetting effects may explain why OLS estimates appear to be unbiased: while some firms automate in response to increased competition, which could have a direct negative effect on employment (downward bias), other firms automate in response to increase demand, which could have a direct positive effect on employment (upward bias), such that the net bias in OLS estimates is close to zero.

Next, Panel B of Table 4 takes sales as the outcome. We find that sales increase in response to increased automation, with elasticities ranging from 0.365 to 0.388 across specifications. The estimates are significant at the 5% level in specifications (4) and (5), which include the largest number of controls; they are statistically indistinguishable across all columns. 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 4 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 4 presents estimates of the impact of automation on the labor share in value-added. The point estimates are consistently negative, although they are relatively imprecisely estimated and significant only at the 10% level in most specifications. 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: we estimate an increase in labor productivity, with point estimates aroud 0.20, statistically significant at the 10% level. For completeness, Online Appendix Table A3 reports additional evidence on the firm-level response of the labor share, showing that there is no change in the labor share in total sales and that there is an increase in the ratio of value-added to sales. 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 4 shows a positive impact of automation on firm profits, with point estimates ranging from 0.809 to 1.072 across specifications. Turning to business-stealing effects, Panel G of Table 4 reports a negative impact of automation on competitors' employment (within the same 2-digit industry).[42] The point estimates are negative and statistically significant at the 5% level in Columns (2) through (4), with point estimates close to -0.0101.

Finally, Panel H and I of Table 4 report the results of pre-trend falsification tests, using the exact same shift-share IV specification, but using lagged employment and sales as the outcomes. Conceptually, these lagged outcomes can serve as a proxy for the unobserved error terms ε_{it} in equation (4). 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.

[42]The results are similar when considering competitors' employment within the same 5-digit industry, as reported in Appendix Table A4.

V.C Robustness

We implement several robustness checks. First, using the specification from Column (1) of Table 4, Figure 10 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 figure depicts relationships that appear to be robust graphically, with conditional expectation functions close to linear.

Second, we obtain very similar results when using a more stringent set of fixed effects. In Appendix Table A4, we use HS6-by-period fixed effects along with 5-digit-industry-by-period fixed effects and trading partner by period fixed effects. All results are statistically indistinguishable from those of our baseline specification in Table 4. Appendix Figure A15 reports the binned scatter plots for the first stage, reduced-form relationships and falsification tests corresponding to Column (1) of Table A4.

Third, in Appendix Table A5, we conduct the analysis with less stringent fixed effects, using HS4-by-period fixed effects and trading partner by period fixed effects, without industry fixed effects. The results remain statistically indistinguishable and are depicted graphically in Appendix Figure A16 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.

Fourth, we repeat our analysis with the original proxy of Acemoglu and Restrepo (2022) in robustness checks, i.e. including only textile machines as the relevant sectoral machines for automation. The estimates are similar and are reported in Table A6.

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

Finally, 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 and test whether the "local" average treatment effect in the shift-share

sample is different from the average treatment effect in the population, we carry out the event study analysis from Section IV.C 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 A17) or Acemoglu and Restrepo (2022)'s proxy for automation (Appendix Figure A18). The effects are also similar when we only consider firms that purchase for the firm time from a foreign trading partner supplying automation technologies, using Acemoglu and Restrepo (2022)'s proxy (Appendix Figure A19). 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. Furthermore, the shift-share analysis estimated a fall in the labor share of value-added, which in Acemoglu and Restrepo (2018c)'s framework 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 shift-share IV analysis is primarily driven by intensive margin capital deepening.

VI 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 VI.A, then the industry-level shift-share IV design in Section VI.B., and we assess the role of international business stealing effects and the demand reallocation channel in Section VI.C.

VI.A Industry-level Event Studies

The positive plant-level and 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 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.

The results are reported in Figure 11. Panel (i) shows that industry-level employment increases

after the investment event, with a semi-elasticity of about 0.10 on impact, increasing to about 0.20 over 5 years. These patterns indicate that the employment response remains positive at the industry level. Panel (ii) to (iv) are also similar to the firm-level estimates, showing no impact on inequality: Panel (ii) shows that there is no impact on relative labor demand between high- and low-skill workers at the industry level; Panel (iii) documents that average hourly wages remain unaffected; Panel (iv) reports that the wage ratio between high skill and low skill employees remains constant. Panel (v) shows that we cannot reject that the labor share in value added remains constant, in contrast with the firm-level results. Finally, Panel (vi) reports the response of sales, with a semi-elasticity of about 0.2 on impact, similar to the firm-level pattern.

The Online 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 A20, 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.

VI.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 V.A with specification (4), 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 (3). We can thus examine the response of employment and sales in industries that source their

machines from increasingly productive foreign suppliers.[43]

In this design, all outcomes are measured at the level of 5-digit industries, which are narrow and include, for example, "manufacture of plastics plates, sheets, tubes and profiles" or "manufacture of metal structures." The exposure share s_{i0n} is computed as the share of trading partner 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 185 HS6 categories, with 149 trading partners in the 257 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 638, indicating that the effective sample size is large. To address potential correlated demand shocks, we use HS4-by-period fixed effects as well as partner-period fixed effects.

Results. The results and falsification tests are reported in Tables 5 and 6. 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.

Table 5 reports the OLS relationships. 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 positive 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).

Panel A of Table 6 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 +0.932 (s.e. 0.173). The point estimate is statistically significant at the 1% level and the first stage F statistic of 14.04. The point estimates remain comparable in magnitudes in columns (2) through (4) as we change the set of controls, with similar F statistics. The point estimates vary between 0.921 and 0.934, are all significant at the 1% level, and are statistically indistinguishable from one another. These results support the findings from the previous subsection: increases in automation

[43] 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.

lead to higher employment at the level of the industry. Given the magnitudes of the standard errors, we cannot reject that the elasticity at the industry level is of the same magnitude as at the firm level. 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 0.55 in Panel B when focusing on incumbent firms that exist in all periods.

Panel C of Table 6 documents the response of sales. We find that sales increase after increased automation, with elasticities ranging from 0.795 to 0.981 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 automation allows the industry as a whole to expand its sales and scale, which requires hiring additional workers for production. By assuming a given industry-level demand elasticity of substitution, we can infer the impact on the industry-level price index, which we investigate further in the next subsection. Panels A and B of Figure 12 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.

Next, Panels D and E of Table 6 present the estimates for the impact of automation on wages and the labor share in value added. In all four specifications, we cannot reject that there is no impact of automation on hourly wages, similar to the firm-level analysis. The point estimates for the labor share are negative but imprecisely estimated, such that we can reject neither a null effect nor an effect of the same magnitude as the firm-level SSIV estimates from Table 3.[44] Similarly, Panel F shows that the effect on labor productivity is positive, although the point estimates are not statistically significant.

Finally, Panel G documents a positive elasticity of industry profits to automation. The elasticity is large in magnitude at about 1.7–1.9 but is imprecisely estimated, with standard errors of about 1.0, such that the results are statistically indistinguishable from the firm-level estimates in Table 4.

Table 6 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 can 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

[44]For completeness, Online Appendix Table A8 reports the industry-level reponse of the labor share in total sales, which remains flat. This table reports a positive point estimate for the reponse of the industry-level share of value-added in total sales; altough it is not statistically significant, it is similar to the firm-level results in Table A3.

Figure 12 reports the reduced-form relationships with lagged employment and lagged sales. These results lend credibility to a causal interpretation of the industry-level estimates.

In Online Appendix Table A7, for robutness we implement the industry SSIV with a less stringent set of fixed effects, using partner-by-period fixed effects and HS4 fixed effects. The F statistics are now above 23 in all specifications and the point estimates remain similar, hovering between 1.005 and 1.016 across specifications for total employment, between 0.497 and 0.530 for incumbents' employment, and between 1.092 and 1.225 for sales. For completeness, Online Appendix Table A8 reports additional evidence on the industry-level response of the labor share, showing that there is no change in the labor share in total sales and no change in the ratio of value-added to sales.

VI.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 elasticity of substitution of consumer demand 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 is smaller at the industry level than at the firm level.[45]

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 relatively substitutable goods (e.g., Broda and Weinstein (2006)). To assess the role of international trade, in Table 7 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.[46]

Heterogeneous impacts by exposure to international competition. In Table 7, we document that the positive industry-level relationship between modern manufacturing capital investments and employment or sales 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. The results for employment and sales with this specifica-

[45] We also expect to find larger employment effects when consumers' demand elasticity of substitution is larger because consumers reallocate their spending toward firms or sectors where productivity increases and prices fall.

[46] This measure is available at the level of 255 industries defined by the national accounts.

tion for all industries, reported in Column (1), are in line with the industry-level estimates from Section VI.B.

With higher exposure to international competition, the point estimate for employment in Column (2) is 0.404 (s.e. 0.055) and is similar to firm-level employment elasticities. In contrast, with lower exposure to international competition in Column (3), the point estimate loses statistical significance and falls in magnitude to 0.171 (s.e. 0.133). 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 (2) is 0.510 (s.e. 0.084) with higher exposure to international competition, while is becomes smaller and statistically insignificant at 0.188 (s.e. 0.121) with lower exposure in Column (3).

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 Table 8 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 7 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 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.

The demand reallocation channel. We now 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 A9 reports a negative relationship between man-

ufacturing capital investments and the industry-level producer price index, with point estimates ranging from -0.113 (s.e. 0.0573) to -0.199 (s.e. 0.0698) across specifications. The magnitudes are very similar to the firm-level price response documented in Figure 9.

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, $p_k \cdot q_k$:

$$\Delta \log(p_k) = -\frac{1}{\sigma - 1} \Delta \log\left(p_k \cdot q_k\right) + \Omega. \tag{6}$$

In response to a 1% increase in manufacturing capital investment, according to Column (4) of Table 6 the sales response is $\widehat{\Delta \log\left(p_k \cdot q_k\right)} = 0.934$; according to Column (4) of Appendix Table A9 the price response is $\widehat{\Delta \log(p_k)} = -0.178$. To satisfy equation (6), these estimates imply the following demand elasticity of substitution: $\widehat{\sigma} = 1 - \frac{\widehat{\Delta \log(p_k \cdot q_k)}}{\widehat{\Delta \log(p_k)}} = 6.25$.[47]

Is the magnitude of $\widehat{\sigma}$ in line with existing estimates? A demand elasticity of substitution of 6.25 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). This result indicates that the consumer demand substitution channel is plausible in an open economy facing international competition.

[47] 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 4 we obtain $\widehat{\Delta \log\left(p_k \cdot q_k\right)} = 0.346$ and Figure 9 yields $\widehat{\Delta \log(p_k)} = -0.10$, implying $\widehat{\sigma} = 4.46$.

In contrast, estimated consumer demand elasticities between domestic industries are much smaller and closer to one (e.g., Costinot and Rodríguez-Clare (2014)). It would be 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. Competition with international suppliers providing close substitutes can explain why the relationship between modern manufacturing capital investments and employment can remain positive even at the industry level, because the response of consumer demand can be large.[48]

This observation may also 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. (2020) estimate a positive relationship in a sample of European countries, including France, which are more exposed to international competition.

The analysis presented above is based on the industry-level OLS results on prices reported in Appendix Table A9, because we lacked power to estimate price effects directly in the industry-level shift-share IV design. If we know the demand elasticity of substitution σ, equation (6) can be used to infer price changes from our SSIV estimates for the change in sales. The industry-level SSIV yields an elasticity of sales to investment of 0.795 in Column (4) of Table 6. We can plug this estimate of $\Delta \log (p_k \cdot q_k)$ into equation (6) 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), while Simonovska and Waugh (2014) obtain an elasticity of 4.2.

Depending on the choice of σ, the implied price elasticity to modern manufacturing capital investment, $\Delta \log(p_k)$, ranges from -0.25 $(= -\frac{1}{4.2-1} \cdot 0.795)$ to-0.12 $(= -\frac{1}{7.5-1} \cdot 0.795)$. This range of implied price elasticities is close to the estimates obtained with the event study at the firm level,

[48] 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.

with a price elasticity of -0.20 in Appendix Figure A13, as well as with the OLS analysis at the industry level, with a price elasticity of -0.113 in Column (1) of Appendix Table A9. This confirms that the demand reallocation channel can account for the estimates collected in this paper.[49]

VII Conclusion

In this paper, we have leveraged new micro data on plants, 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 on employment, wages, prices, sales, profits, and business stealing between 1995 and 2017.

At all levels of analysis — plant, firm and industry — the relationship between manufacturing capital investment (including automation) and employment is positive, indicating that in practice the productivity effect tends to outweigh the displacement effects. There is also an increase in sales, a fall in consumer prices, an increase in firm profits. The estimated fall in the firm-level 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 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)). At the industry-level, we find that the relationship between employment and manufacturing capital investments remains positive on average, but that the effect is heterogeneous depending on exposure to international trade, with a significant employment response only in industries that face international competition.

Thus, 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

[49] 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 the next generation of models of optimal technology regulation.

foreign competitors. Due to international business-stealing, 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.

Taken together, the results suggest that modern manufacturing capital investments can increase labor demand and generate productivity gains that are broadly shared across workers, consumers and firm owners. Because the observed distributional effects of capital investments are nuanced, training programs targeting specific groups of workers that may be negatively affected by modern manufacturing capital like automation (e.g., older workers specializing in routine tasks) may be more appropriate than broader tax instruments (e.g., taxing robots or capital, or increasing redistribution through the income tax system). Developing and testing such policies is therefore a promising direction for research and policy going forward.

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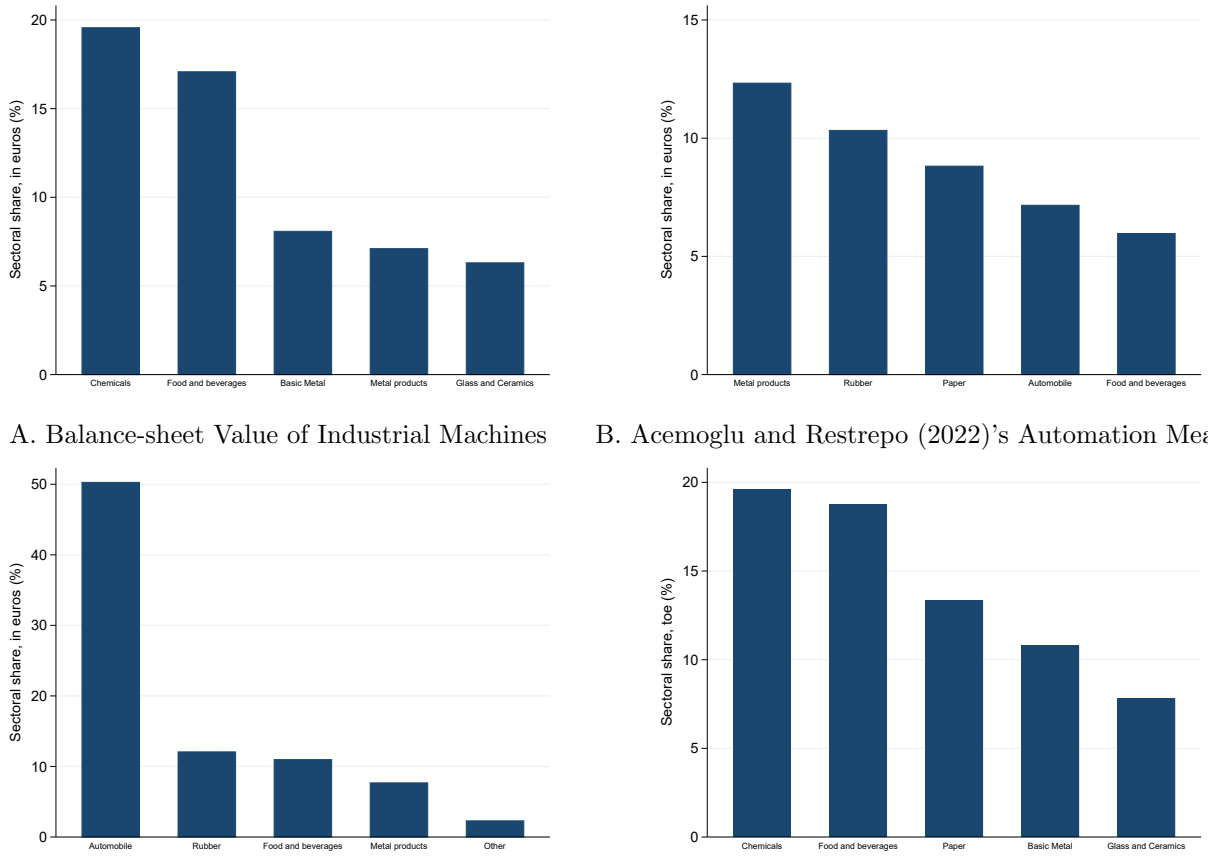
Figure 1: Distribution of Modern Manufacturing Capital across Industries



A. Balance-sheet Value of Industrial Machines

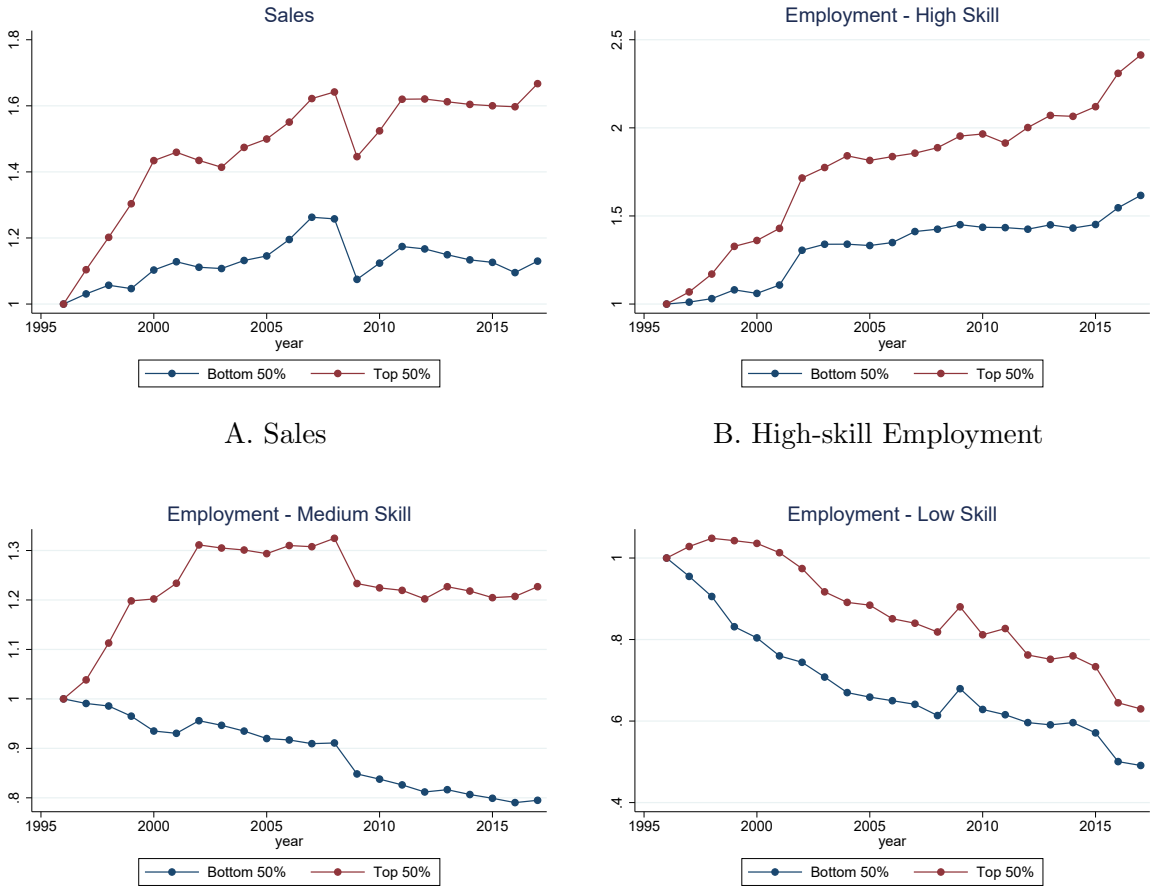
B. Acemoglu and Restrepo (2022)'s Automation Measure

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 2: Firm-level Stylized Facts by Use of Industrial Machines



A. Sales

B. High-skill Employment

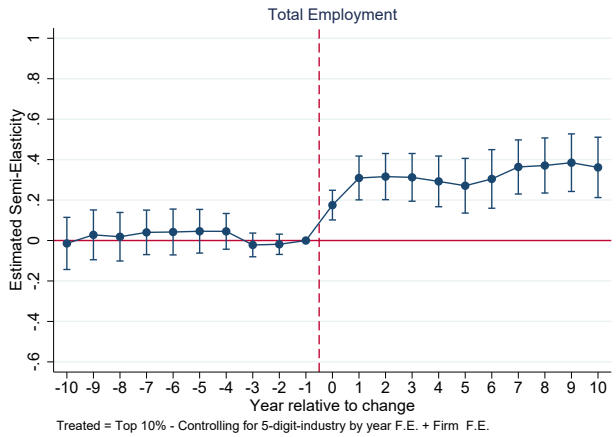
C. Medium-skill Employment

D. Low-skill Employment

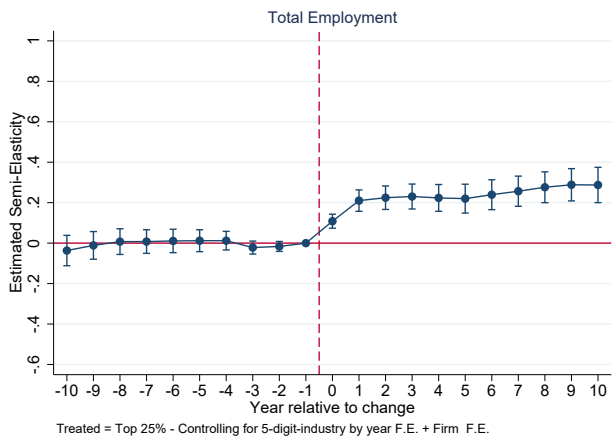
Notes: This figure describes the means of firm-level outcomes for firms with a change in industrial machines above or below median from 1996 to 1999. All outcomes are normalized to one in 1996. The figure plots in turn the path of sales in panel A, and employment by skill group in panels B, C, and D.

Figure 3: Firm-Level Event Studies for Employment

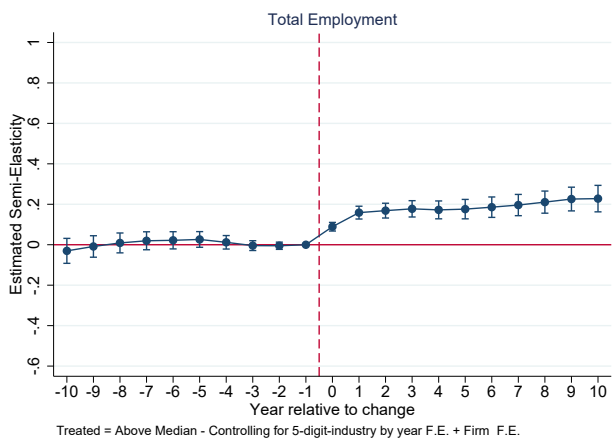
A. 90th percentile of investment in industrial equipment



B. 75th percentile of investment in industrial equipment



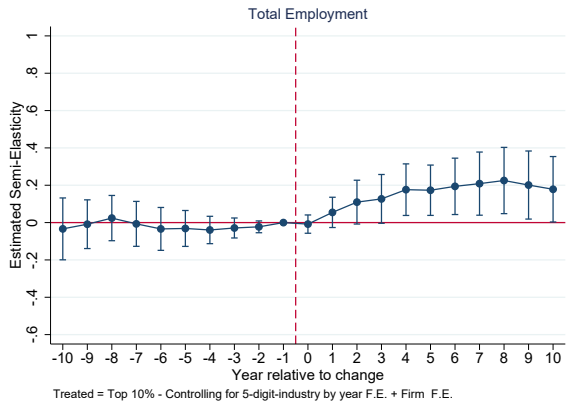
C. 50th percentile of investment in industrial equipment



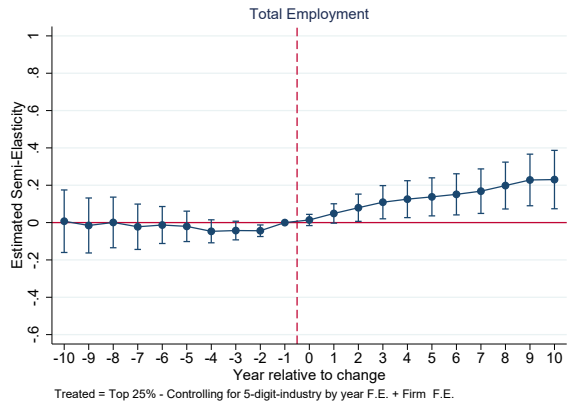
Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome. In Panel A, the investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. Panel B uses the 75th percentile as the event thresholds, 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.

Figure 4: Robustness of Firm-level Employment Effect across Measures of Manufacturing Capital

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

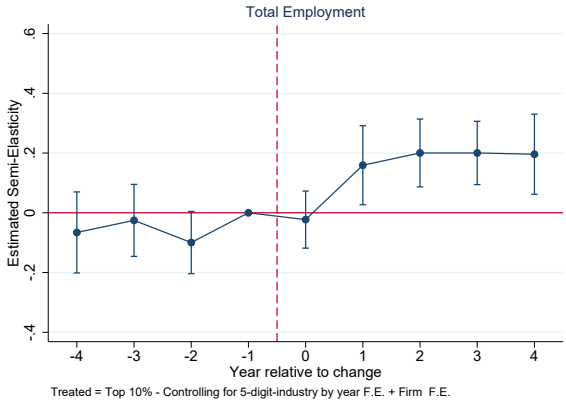


(i) 90th percentile

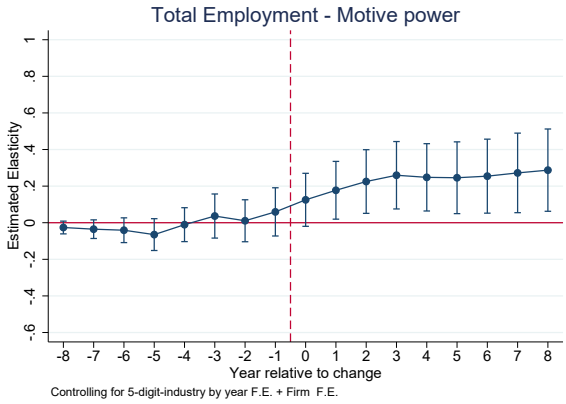


(ii) 75th percentile

B: Robots



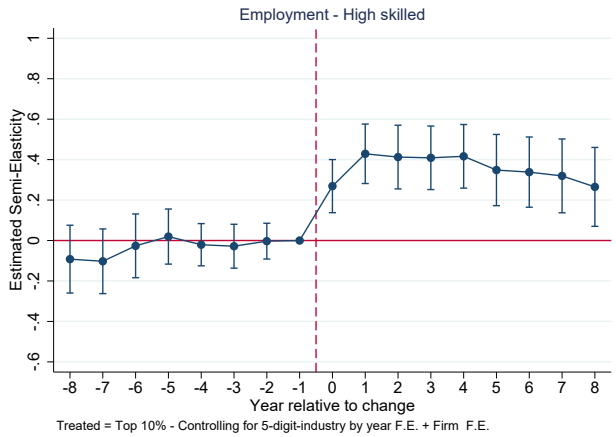
C: Electric Motive Power (Distributed Lag)



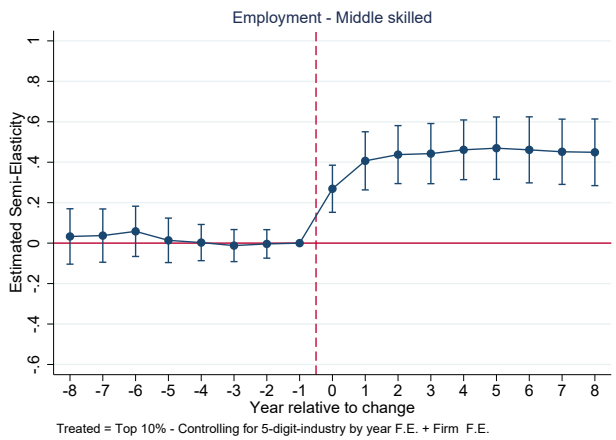
Notes: This figure analyzes the firm-level employment response to various measures of investments in modern manufacturing capital, using in turn Acemoglu and Restrepo (2022)'s automation measure (panel A), imports of industrial robots (panel B), and electric motive power (panel C). Panels A and B use event studies, while Panel C uses a distributed lead-lag model. All specifications include 5-digit industry by year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level.

Figure 5: Heterogeneity across Skill Groups

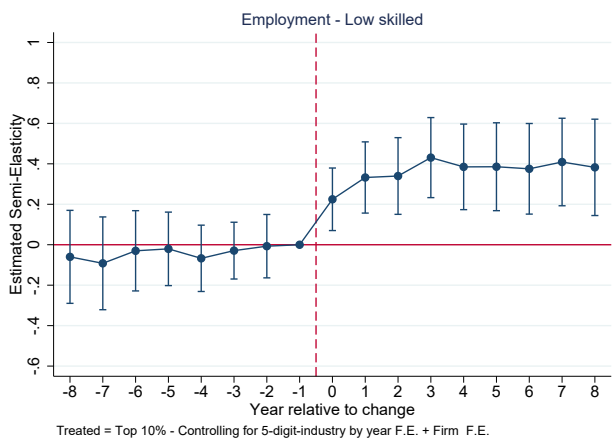
A. High-Skill Employment



B. Medium-Skill Employment



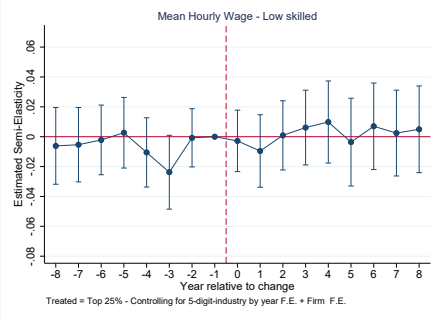
C. Low-Skill Employment



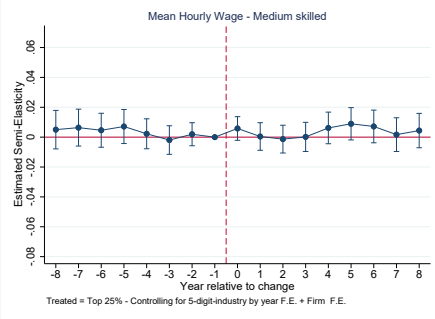
Notes: This figure reports the firm-level event study results for employment by skill groups. The investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. High, medium and low skill groups are taken from Charnoz and Orand (2017). All specifications include 5-digit industry by year fixed effects along with firm fixed effects. Standard errors are clustered at the firm level.

Figure 6: Firm-Level Event Studies for Wages and Within-Firm Inequality

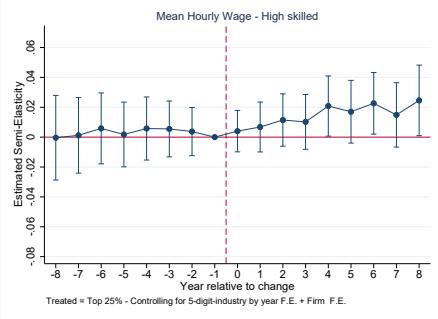
(i) Mean Hourly Wage, All



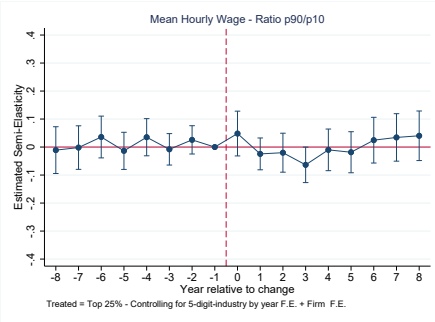
(ii) Mean Hourly Wage, Low Skill



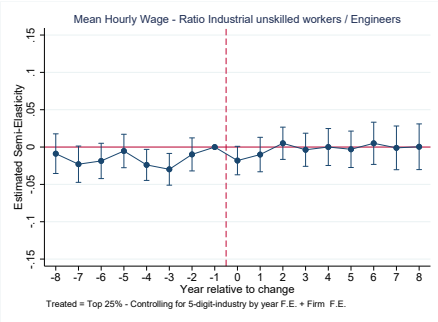
(iii) Mean Hourly Wage, Medium Skill



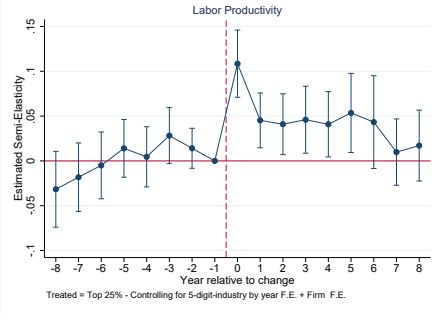
(iv) Mean Hourly Wage, High Skill



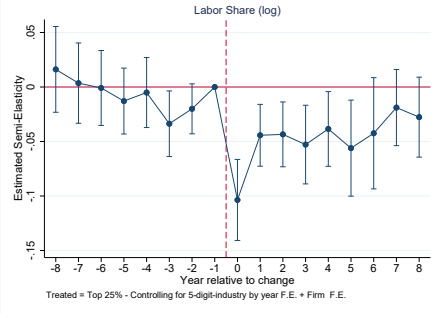
(v) P90/P10 of Wage Distribution



(vi) Wage Ratio Unskilled Workers / Engineers



(vii) Labor Productivity

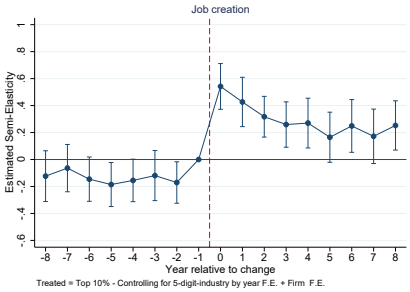


(viii) Labor Share in Value Added

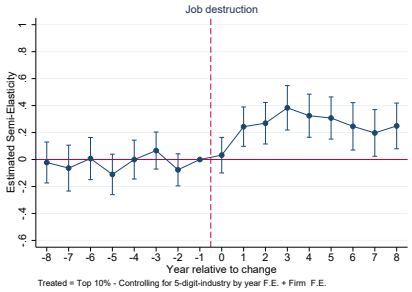
Notes: This figure reports the result of firm-level event studies for eight outcomes characterizing the reponse of wages and within-firm inequality to investments in modern manufacturing capital. In all panels, the investment event is defined as a logarithmic change beyond the 75th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. All panels use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

Figure 7: Firm-Level Event Studies for Job Creation/Destruction

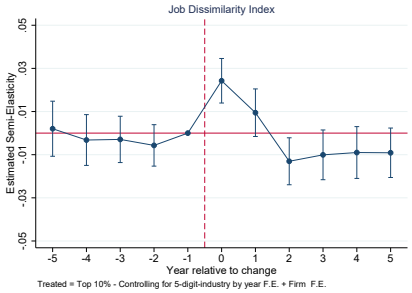
A: Main Result with Investments in Industrial Equipment



(i) Job Creation

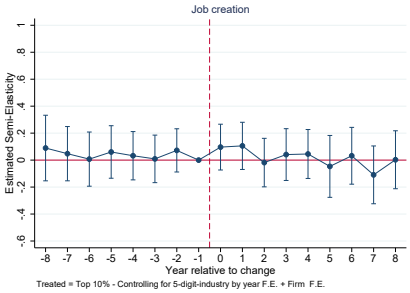


(ii) Job Destruction

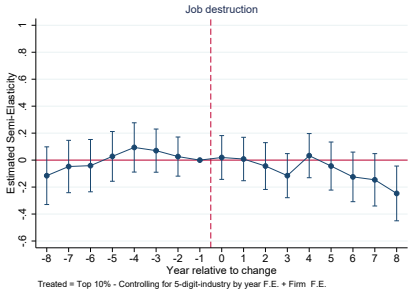


(iii) Job Dissimilarity Index

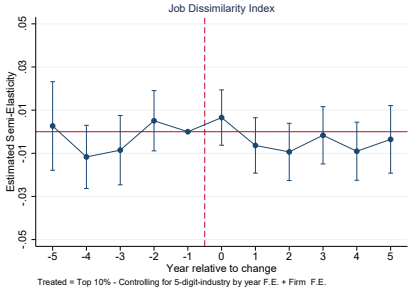
B: Placebo Test with Investments in Real Estate



(i) Job Creation



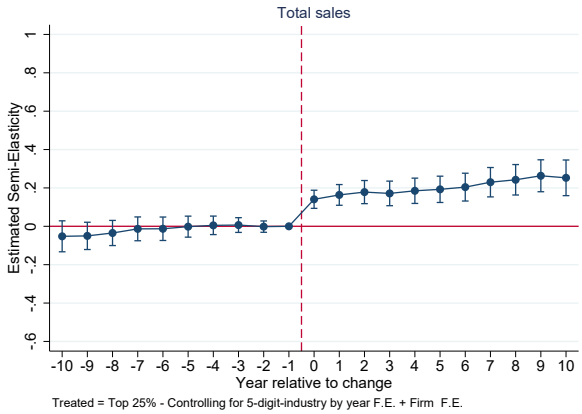
(ii) Job Destruction



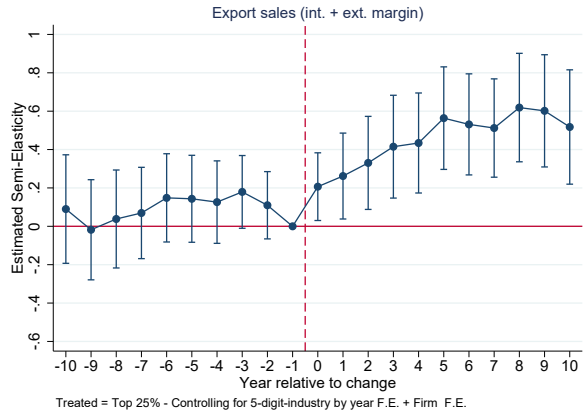
(iii) Job Dissimilarity Index

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.

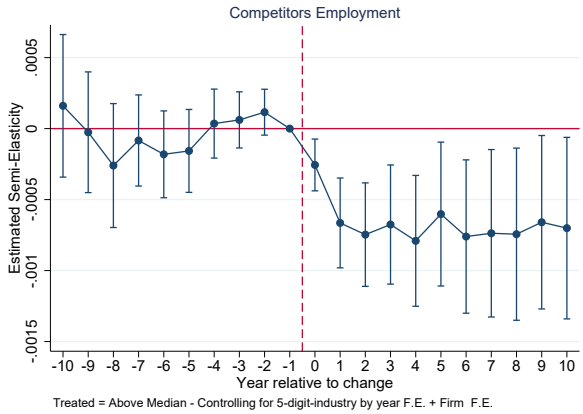
Figure 8: Firm-Level Event Studies for Market Dynamics



A. Sales



B. Log(1+Export Sales)

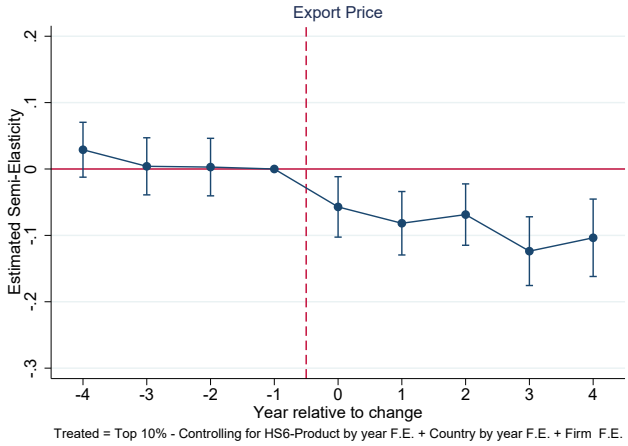


C. Business Stealing across Firms

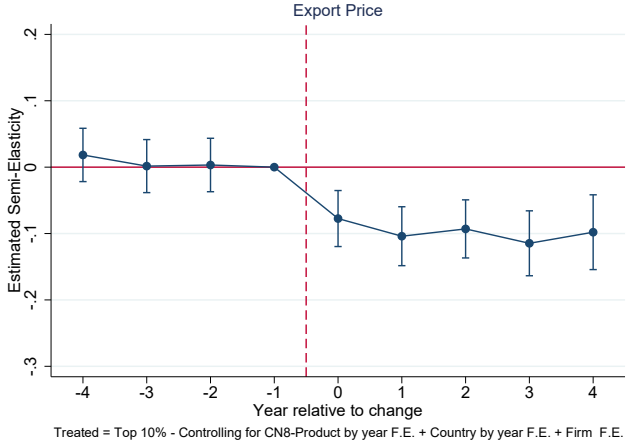
Notes: This figure reports the event study results with sales, exports, and competitors' employment as outcomes. For competitors' employment, we study employment dynamics at firms that belong to the same 5-digit industry as the focal firm that invests in industrial equipment. All panels use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level.

Figure 9: Firm-Level Event Studies for Prices

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



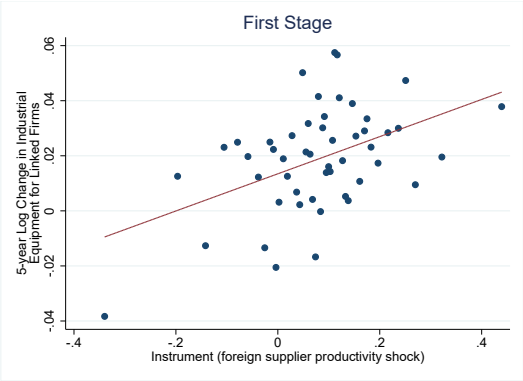
B. 90th percentile of investment for industry equipment, NC8 product level



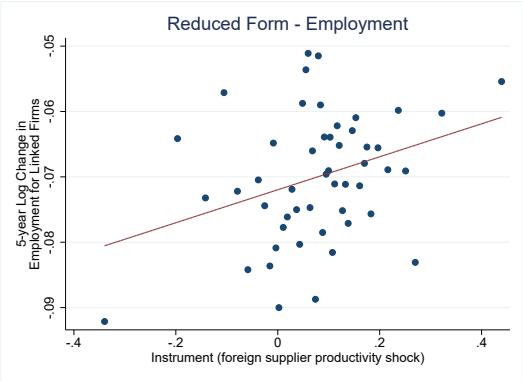
Notes: This figure reports the event study results with export prices as outcomes. Panel A conducts the analysis at the level of HS6 product categories, with HS6-by-year fixed effects, partner country by year fixed effects, and firm fixed effects. Panel B uses an identical specification using NC8 product 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 10: Firm-level Shift-Share IV Design

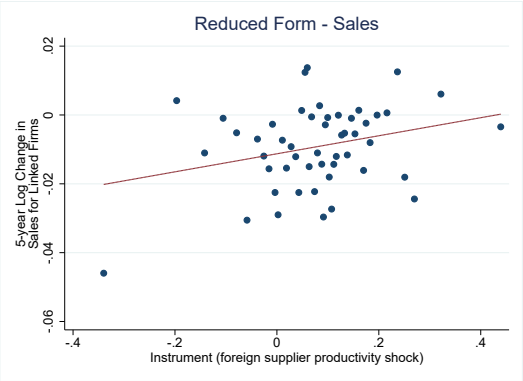
A. First stage



B. Reduced-form

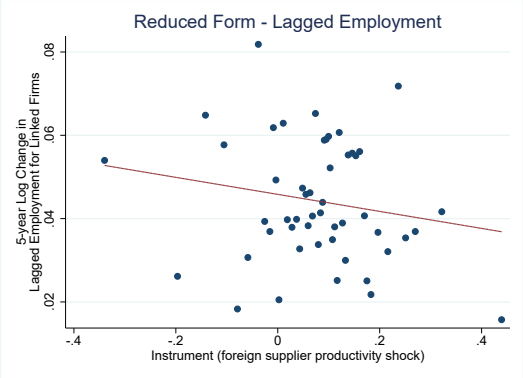


(i) Employment

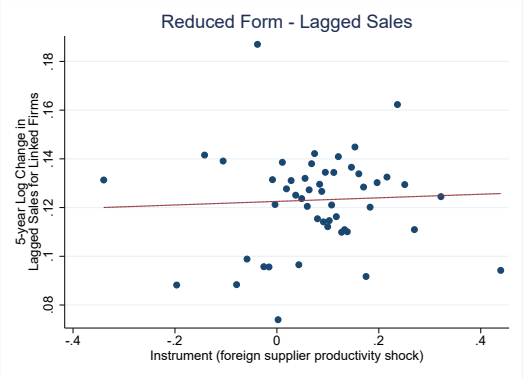


(ii) Sales

C. Falsification tests



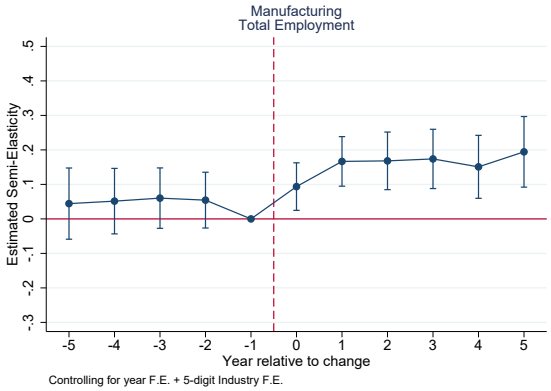
(i) Lagged Employment



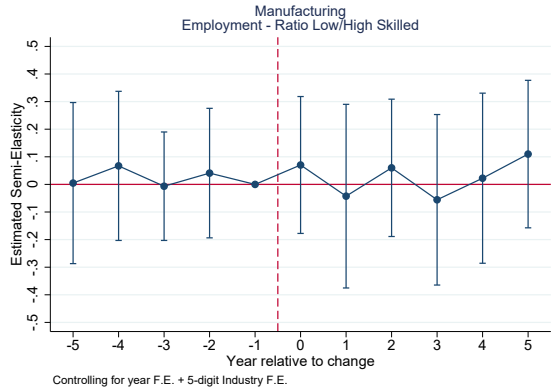
(ii) Lagged Sales

Notes: The binned scatter plots in this figure depict the relationships underlying the firm-level SSIV research design described by specification (4), 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.

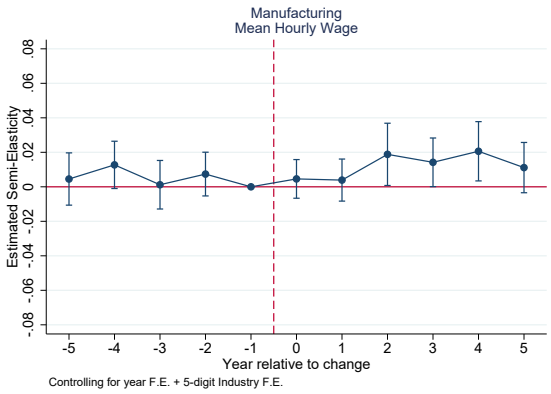
Figure 11: Industry-Level Event Studies



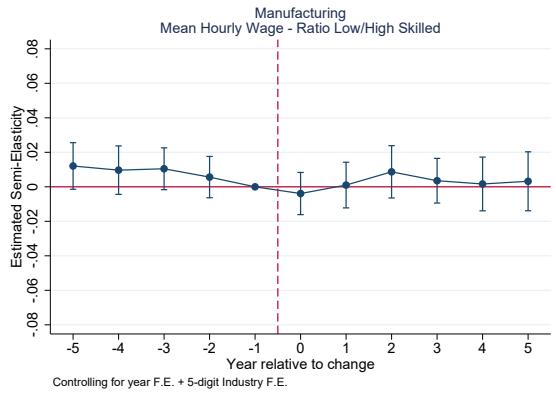
(i) Employment



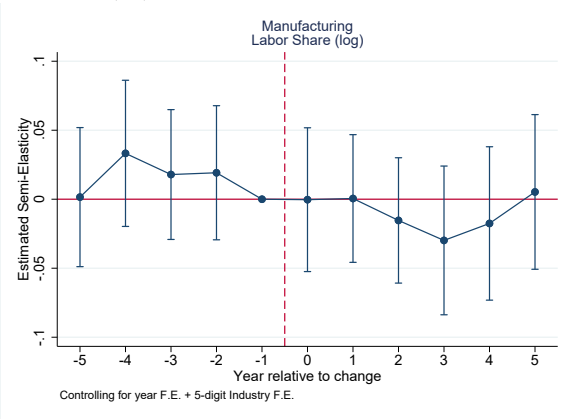
(ii) Employment Ratio, High- vs. Low-Skill



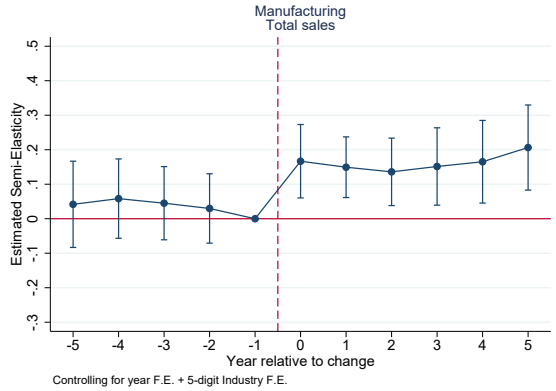
(iii) Mean Hourly Wage, All



(iv) Hourly Wage Ratio, High- vs. Low-Skill



(v) Labor Share in Value Added

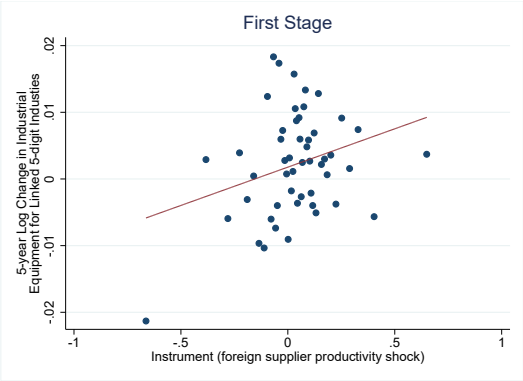


(vi) Sales

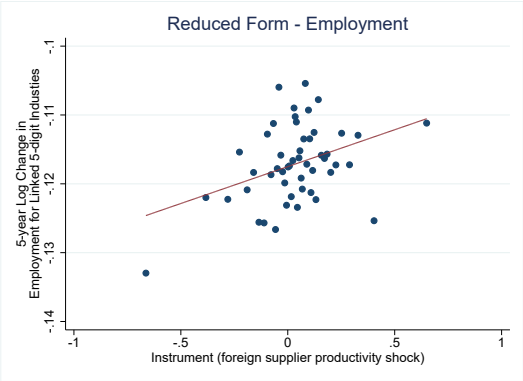
Notes: This figure reports the results of industry-level event studies for several outcomes. The investment event is defined as a logarithmic change beyond the 50th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. All panels include 5-digit industry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

Figure 12: Industry-level Shift-Share IV Design

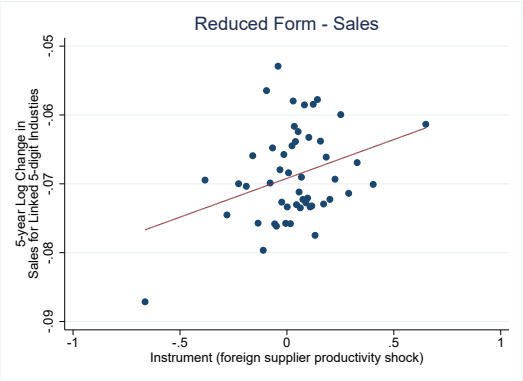
A. First stage



B. Reduced-form

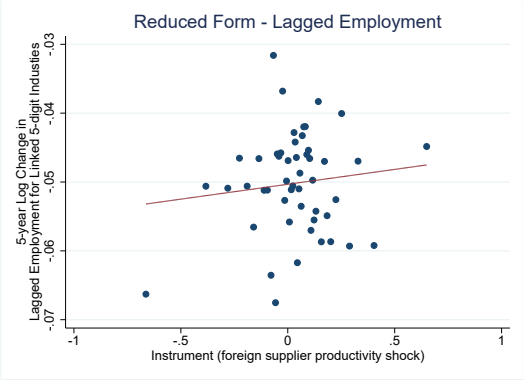


(i) Employment

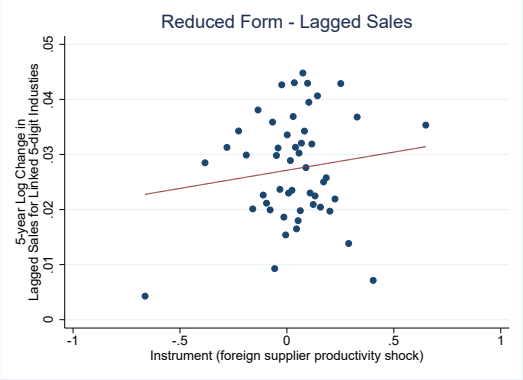


(ii) Sales

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 (4), 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 industries importing from the corresponding foreign supplier in the relevant HS6 product category.

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	2,773	39,647	-2	48	-46	-1	41
Modern manufacturing capital – motive force (toe)	2,773	39,647	-1	1,175	-309	1	295
Panel B: Firm level							
Employment	1,599	31,980	0	33	-7	0	8
Sales (thousands of euros)	1,599	31,980	228	19,796	-2,041	14	3,079
Modern manufacturing capital:							
Industrial machines (thousands of euros)	1,599	31,980	142	6,008	-116	1	557
Acemoglu and Restrepo (2022)'s imports of machines (thousands of euros)	1,599	31,980	3	619	-28	0	32
Imports of robots (thousands of euros)	1,599	33,579	0	62	0	0	0
Motive force (toe)	485	7,161	2	1,325	-369	2	369
Panel C: Industry level							
Employment	255	5,610	-95	1,124	-1,148	-38	876
Sales (millions of euros)	255	5,610	22	2,018	-421	4	521
Modern manufacturing capital:							
Industrial machines (millions of euros)	255	5,610	16	620	-67	4	121
Acemoglu and Restrepo (2022)'s imports of machines (thousands of euros)	255	5,610	0	9	-7	0	8
Imports of robots (millions of euros)	255	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. Online Appendix Table A1 reports the same statistics in levels.

Table 2: Imported Industrial Automating Machines following Acemoglu and Restrepo (2022)

A. Randomly-Drawn Subset of 10 Machines

Name	Import Value, $
Apparatus for dry-etching patterns on semiconductor materials	430,688
Bending, folding, straightening or flattening machines	675,899
Letterpress printing machinery, reel fed (excl. flexographic printing machinery)	122,370
Machine tools for working any material by removal of material, operated by electro-discharge processes	129,927
Machines for butt welding of metals	28,319
Machines for preparing textile fibres (excl. carding, combing, drawing or roving machines)	134,543
Machines for processing reactive resins	30,259
Machining centres for working metal (excl. horizontal machining centres)	2,194,883
Parts of machinery and apparatus for soldering, brazing, welding or surface tempering	197,589
Printing machinery for use in the production of semiconductors	5,056

B. Top 10 Machines by Value of Imports

Name	Import Value, $
Machines, apparatus and mechanical appliances	5,640,191
Parts of machines and mechanical appliances having individual functions (excl. of cast iron or cast steel)	2,860,606
Parts of machinery for working rubber or plastics	2,811,272
Machines, apparatus and mechanical appliances	2,739,767
Parts of machinery for sorting, screening, separating, washing, crushing of modulding mineral susbtances	2,359,772
Parts of machinery for the industrial preparation or manufacture of food or drinks	2,203,525
Machining centres for working metal (excl. horizontal machining centres)	2,194,883
Parts of machines and mechanical appliances having individual functions	2,087,921
Industrial robots	2,021,562
Parts and accessories for machine tools for working metal without removing material	2,009,490

Notes: This table provides examples of our proxy for automation based on the taxonomy for machines in the customs data, following 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 3: Firm-level OLS Relationships with Modern Manufacturing Capital Investments

	(1)	(2)	(3)	(4)	(5)
Panel A: $\Delta_5 Employment$					
$\Delta_5 Machines$	0.406***	0.413***	0.412***	0.412***	0.410***
	(0.0210)	(0.0200)	(0.0200)	(0.0199)	(0.0198)
Panel B: $\Delta_5 Sales$					
$\Delta_5 Machines$	0.315***	0.328***	0.326***	0.325***	0.315***
	(0.0254)	(0.0257)	(0.0257)	(0.0260)	(0.0251)
Panel C: $\Delta_5 Hourly\ Wages$					
$\Delta_5 Machines$	-0.0139	-0.0121	-0.0127	-0.0129	-0.0135
	(0.00859)	(0.00809)	(0.00845)	(0.00860)	(0.00847)
Panel D: $\Delta_5 Labor\ Share$					
$\Delta_5 Machines$	0.00182	-0.000635	0.00783	0.00891	0.0137
	(0.0213)	(0.0213)	(0.0218)	(0.0221)	(0.0224)
Panel E: $\Delta_5 Labor\ Productivity$					
$\Delta_5 Machines$	-0.0157	-0.0115	-0.0205	-0.0219	-0.0272
	(0.0203)	(0.0195)	(0.0200)	(0.0207)	(0.0210)
Panel F: $\Delta_5 Profits$					
$\Delta_5 Machines$	0.321***	0.335***	0.332***	0.330***	0.314***
	(0.0586)	(0.0553)	(0.0550)	(0.0546)	(0.0542)
Panel G: $\Delta_5 Competitors'\ Employment$					
$\Delta_5 Machines$	-0.00459***	-0.00507***	-0.00510***	-0.00510***	-0.00514***
	(0.000772)	(0.000709)	(0.000714)	(0.000707)	(0.000712)
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
2-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)	4,016	4,016	4,016	4,016	4,016

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 4: Firm-level Effects with Shift-Share IV

	(1)	(2)	(3)	(4)	(5)
Panel A: $\Delta_5 Employment$					
$\Delta_5 Machines$	0.368***	0.360***	0.361***	0.373***	0.374***
	(0.126)	(0.139)	(0.138)	(0.134)	(0.135)
Panel B: $\Delta_5 Sales$					
$\Delta_5 Machines$	0.365*	0.367*	0.367*	0.385**	0.388**
	(0.203)	(0.199)	(0.200)	(0.191)	(0.186)
Panel C: $\Delta_5 Hourly\ Wages$					
$\Delta_5 Machines$	-0.0266	-0.0133	-0.0133	-0.0146	-0.0145
	(0.0530)	(0.0512)	(0.0512)	(0.0507)	(0.0507)
Panel D: $\Delta_5 Labor\ Share$					
$\Delta_5 Machines$	-0.285**	-0.221*	-0.222*	-0.228*	-0.228*
	(0.124)	(0.120)	(0.120)	(0.118)	(0.117)
Panel E: $\Delta_5 Labor\ Productivity$					
$\Delta_5 Machines$	0.258*	0.208*	0.208*	0.213*	0.214*
	(0.143)	(0.126)	(0.126)	(0.122)	(0.120)
Panel F: $\Delta_5 Profits$					
$\Delta_5 Machines$	1.072**	0.809**	0.809**	0.856**	0.861**
	(0.450)	(0.391)	(0.389)	(0.369)	(0.362)
Panel G: $\Delta_5 Competitors'\ Employment$					
$\Delta_5 Machines$	-0.00541	-0.0101**	-0.0101**	-0.0101**	-0.0100**
	(0.00480)	(0.00466)	(0.00465)	(0.00468)	(0.00465)
Panel H: $Lagged\ \Delta_5 Employment$					
$\Delta_5 Machines$	-0.307	-0.290	-0.289	-0.302	-0.303
	(0.291)	(0.283)	(0.289)	(0.281)	(0.281)
Panel I: $Lagged\ \Delta_5 Sales$					
$\Delta_5 Machines$	-0.0384	0.142	0.143	0.110	0.109
	(0.263)	(0.266)	(0.273)	(0.268)	(0.266)
First-Stage F	16.90	16.66	16.69	16.11	17.63
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
2-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)	4,016	4,016	4,016	4,016	4,016

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (4). 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 5: Industry-level OLS Relationships with Modern Manufacturing Capital Investments

	(1)	(2)	(3)	(4)
Panel A: $\Delta_5 Employment$				
$\Delta_5 Machines$	0.651***	0.651***	0.656***	0.656***
	(0.00955)	(0.00933)	(0.00968)	(0.00962)
Panel B: $\Delta_5 Incumbents' \ Employment$				
$\Delta_5 Machines$	0.330***	0.328***	0.332***	0.332***
	(0.0242)	(0.0219)	(0.0213)	(0.0213)
Panel C: $\Delta_5 Sales$				
$\Delta_5 Machines$	0.744***	0.744***	0.727***	0.728***
	(0.0152)	(0.0151)	(0.0130)	(0.0116)
Panel D: $\Delta_5 Hourly \ Wages$				
$\Delta_5 Machines$	0.0179***	0.0177***	0.0122***	0.0123***
	(0.00305)	(0.00290)	(0.00261)	(0.00246)
Panel E: $\Delta_5 Labor \ Share$				
$\Delta_5 Machines$	-0.0481***	-0.0460***	-0.0486***	-0.0488***
	(0.0105)	(0.00995)	(0.00942)	(0.00912)
Panel F: $\Delta_5 Labor \ Productivity$				
$\Delta_5 Machines$	0.0660***	0.0637***	0.0608***	0.0610***
	(0.0120)	(0.0112)	(0.0107)	(0.0102)
Panel G: $\Delta_5 Profit$				
$\Delta_5 Machines$	0.939***	0.930***	0.952***	0.953***
	(0.0633)	(0.0583)	(0.0569)	(0.0512)
Partner-period F.E.	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	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)	6,894	6,894	6,894	6,894

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 6: Industry-level Effects with Shift-Share IV

	(1)	(2)	(3)	(4)
Panel A: $\Delta_5 Employment$				
$\Delta_5 Machines$	0.932***	0.927***	0.921***	0.934***
	(0.173)	(0.171)	(0.174)	(0.182)
Panel B: $\Delta_5 Incumbents' \ Employment$				
$\Delta_5 Machines$	0.588**	0.530**	0.552**	0.558**
	(0.262)	(0.213)	(0.226)	(0.229)
Panel C: $\Delta_5 Sales$				
$\Delta_5 Machines$	0.981***	0.977***	0.868***	0.795***
	(0.285)	(0.286)	(0.302)	(0.278)
Panel D: $\Delta_5 Hourly\ Wages$				
$\Delta_5 Machines$	0.0218	0.0161	0.00101	-0.0193
	(0.0628)	(0.0637)	(0.0713)	(0.0793)
Panel E: $\Delta_5 Labor\ Share$				
$\Delta_5 Machines$	-0.163	-0.118	-0.151	-0.109
	(0.184)	(0.171)	(0.178)	(0.173)
Panel F: $\Delta_5 Labor\ Productivity$				
$\Delta_5 Machines$	0.185	0.134	0.152	0.0900
	(0.161)	(0.144)	(0.148)	(0.143)
Panel G: $\Delta_5 Profit$				
$\Delta_5 Machines$	1.912*	1.743*	1.970*	1.785*
	(1.026)	(0.984)	(1.045)	(0.975)
Panel H: $Lagged\ \Delta_5 Employment$				
$\Delta_5 Machines$	0.376	0.408	0.453	0.481
	(0.334)	(0.327)	(0.339)	(0.333)
Panel I: $Lagged\ \Delta_5 Sales$				
$\Delta_5 Machines$	0.573	0.548	0.570	0.611
	(0.364)	(0.363)	(0.385)	(0.386)
First-Stage F	14.04	14.42	12.05	11.61
Partner-period F.E.	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	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)	6,894	6,894	6,894	6,894

Notes: This table reports industry-level SSIV estimates, implementing the research design described by specification (4) at the industry level with 4-digit product-period fixed effects and partner-period fixed effects. 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 7: The Role of International Business-Stealing Effects, Industry Level

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)
Δ Machines 1996-2017	0.345***	0.404***	0.171
	(0.059)	(0.055)	(0.133)
Δ Other types of capital 1996-2017	✓	✓	✓
N	255	121	134

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)
Δ Machines 1996-2007	0.427***	0.510***	0.188
	(0.066)	(0.084)	(0.121)
Δ Other types of capital 1996-2017	✓	✓	✓
N	255	121	134

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, column (1) uses the full sample of industries while column (2) considers only industries with a level of import competition above median (as measured by domestic absorption in the national accounts tables), and column (3) analyzes those below median. All specifications include controls for contemporaneous changes in others types of capital. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: The Role of International Business-Stealing Effects, Falsification Tests at the Firm Level

A. Modern Manufacturing Capital, Employment, and International Competition

	Δ Employment 1996-2017		
		Exposure to Import Competition	
	All industries	Above Median	Below Median
	(1)	(2)	(3)
Δ Machines 1996-2017	0.323***	0.316***	0.327***
	(0.010)	(0.017)	(0.012)
5-digit industry F.E.	✓	✓	✓
Δ Other types of capital 1996-2017	✓	✓	✓
N	5,375	1,921	3,454

B. Modern Manufacturing Capital, Sales, and International Competition

	Δ Sales 1996-2017		
		Exposure to Import Competition	
	All industries	Above Median	Below Median
	(1)	(2)	(3)
Δ Machines 1996-2007	0.344***	0.287***	0.377***
	(0.011)	(0.019)	(0.014)
5-digit industry F.E.	✓	✓	✓
Δ Other types of capital 1996-2017	✓	✓	✓
N	5,375	1,921	3,454

Notes: This table reports the results of firm-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, column (1) uses the full sample of industries while column (2) considers only industries with a level of import competition above median (as measured by domestic absorption in the national accounts tables), and column (3) analyzes those below median. All specifications include 5-digit industry-year fixed effects and controls for contemporaneous changes in others types of capital. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

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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: $W = A_L F_L$.[50]

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

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

[50] 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.

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

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

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.[51]

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

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

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.

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

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,[52] 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).[53]

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:

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

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

[53] 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.

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:

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

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,[54] 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:

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

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, 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 7 and A12). Overall,

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

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 Online Appendix Figures and Tables

Figure A1: Examples of Technologies using Electric Motive Power

A. Chemicals

B. Rubber

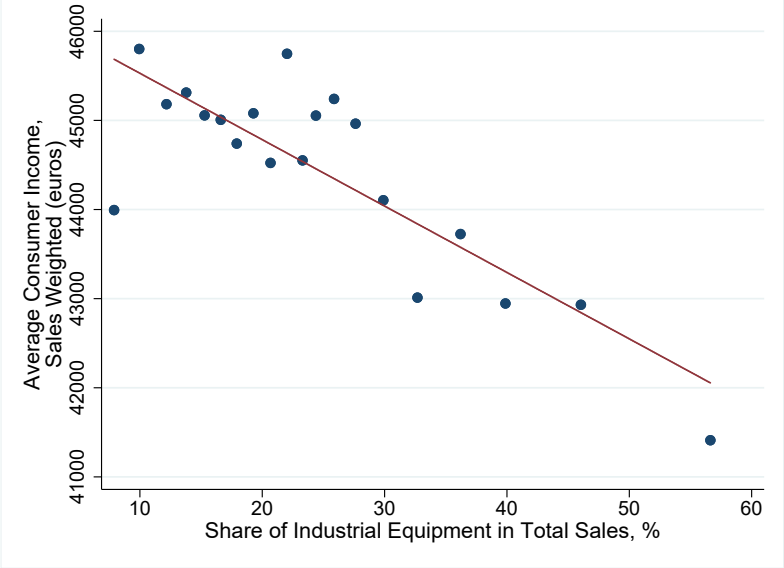
C. Paper

D. Glass and Ceramics

E. Food

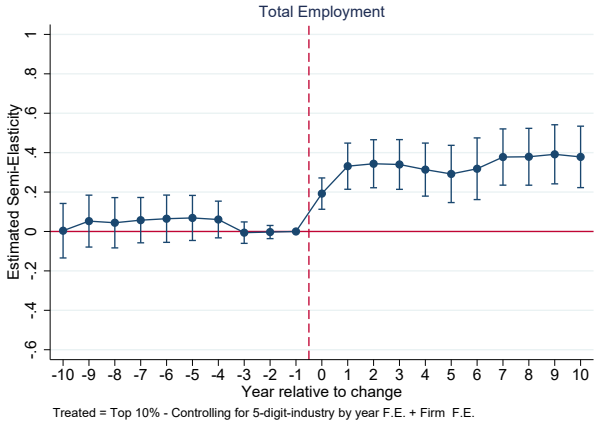
Notes: This figure gives examples of machines for five industries with high usage of motive force. It thus illustrates the breadth of technologies that are encompassed in our measure of electric motive power.

Figure A2: Consumer Income and Intensity of Modern Manufacturing Capital



Notes: This figure reports the relationship between the average income of consumers an industry sells to and the value of industrial equipment as a share of total sales for this industry. The average consumer income is computed using sales weights. Similar patterns hold when using average total household expenditures as the outcome, as a proxy for households' permanent incomes.

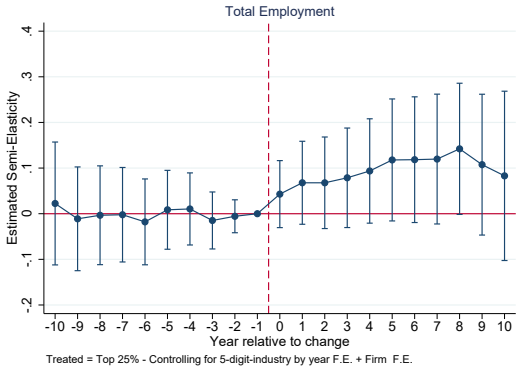
Figure A3: Firm-level Event Studies across Measures of Modern Manufacturing Capital



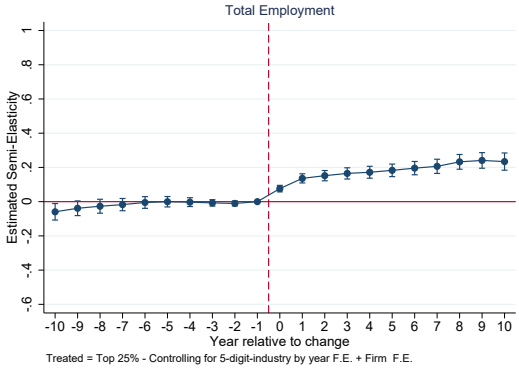
Notes: This figure reports the results of firm-level event studies with total employment as the outcome. The investment event is defined as a logarithmic change beyond the 90th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment. We exclude all firms 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 A4: Firm-level Event Studies across Measures of Modern Manufacturing Capital

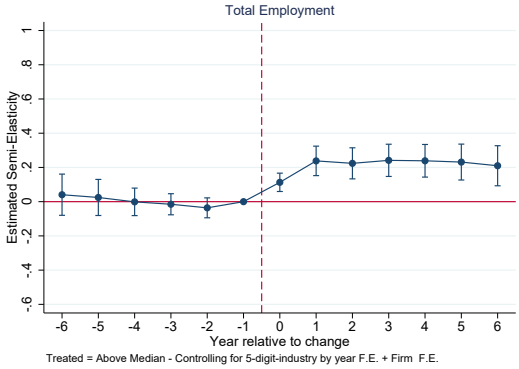
A: Results with Acemoglu and Restrepo (2022)'s Baseline Automation Measure



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



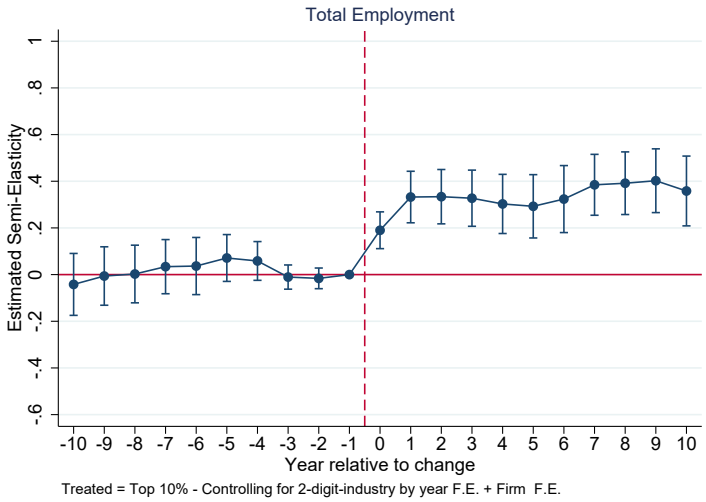
C: Investments in Industrial Equipment for the Automobile Industry



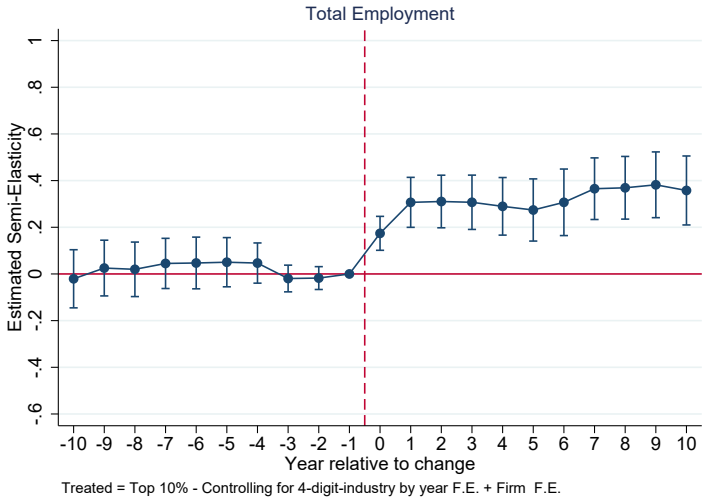
Notes: This figure reports the results of firm-level event studies with total employment as the outcome, considering alternative measures of investment in modern manufacturing capital. Panel A uses Acemoglu and Restrepo (2022)'s baseline automation measure, Panel B measures the balance sheet value of 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 A5: Robustness of Firm-level Event Study with Alternative Fixed Effects

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



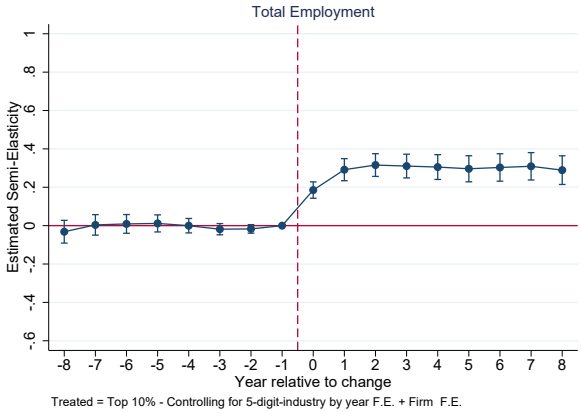
B: With 4-digit-by-year Fixed Effects



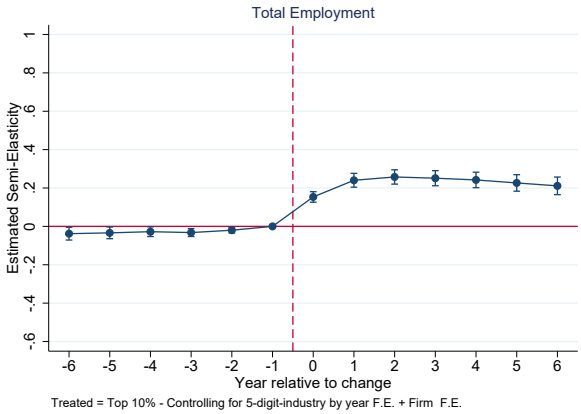
Notes: The figure reports the results of firm-level event studies with employment as the outcome. The specification is given by equation (1) in the main text, with 2-digit by year (panel A) or 4-digit by year (panel B) fixed effects. The investment event is defined as a logarithmic change beyond the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

Figure A6: Robustness of Firm-level Event Study across Balanced Samples

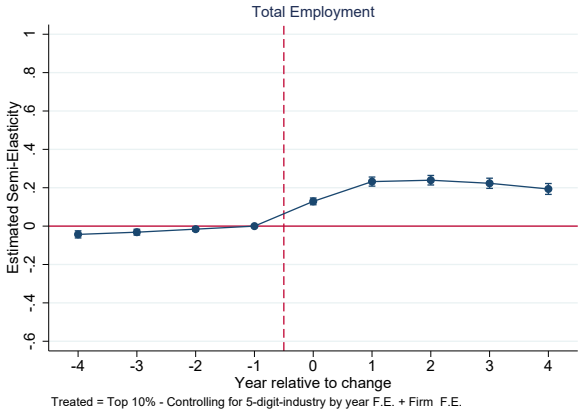
A: 8-Year Horizon



B: 6-Year Horizon

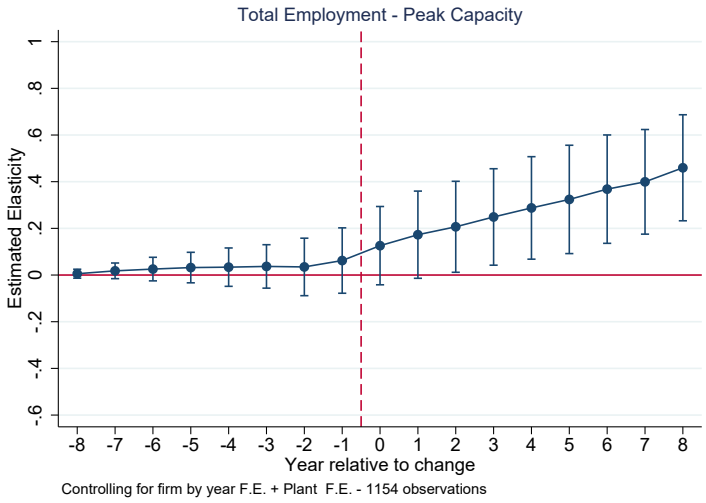


C: 4-Year Horizon



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.

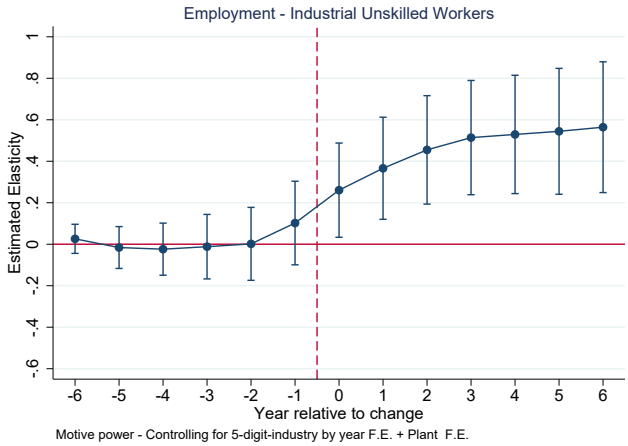
Figure A7: Effects on Plant-level Employment with Distributed Lag Model using Peak Capacity for Motive Power



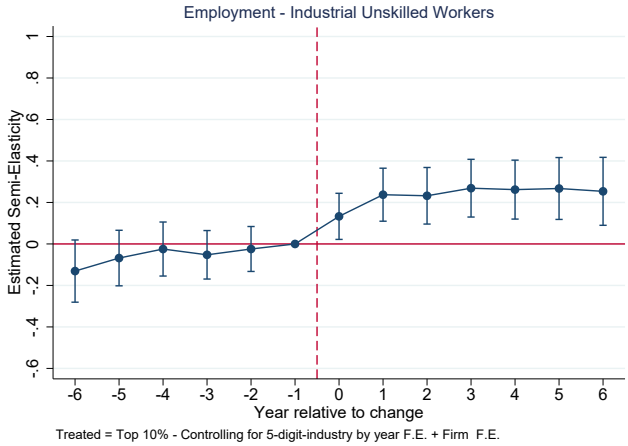
Notes: This figure reports the estimates of the distributed lead-lag model, with plant-level employment as the outcome. The specification is the same as in footnote 27 and Panel C of Figure 4, except that we use peak capacity for motive power instead of actual electricity consumption for motive power. Firm-by-year fixed effects and plant fixed effects are used.

Figure A8: The Employment Response for Unskilled Industrial Workers

A: Plant level (Distributed Lag)

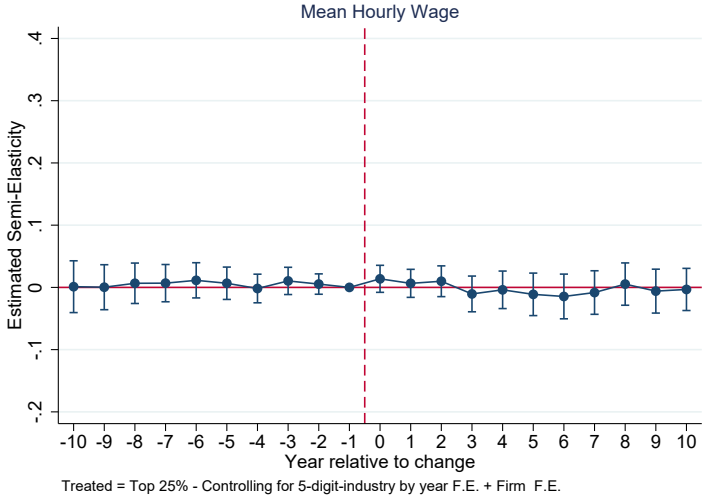


B: Firm level (Event Study)



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 27 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.

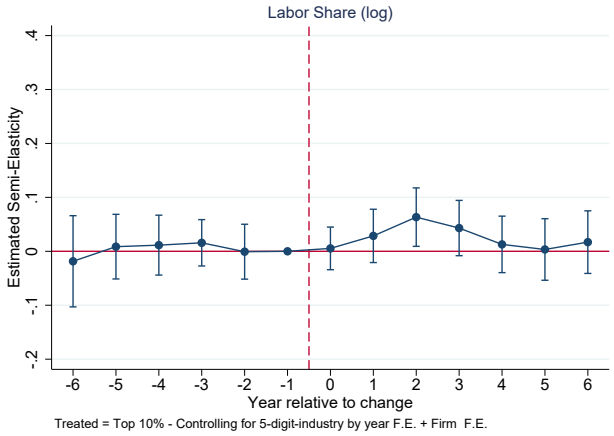
Figure A9: The Response of Wages using Acemoglu and Restrepo (2022)'s Automation Measure



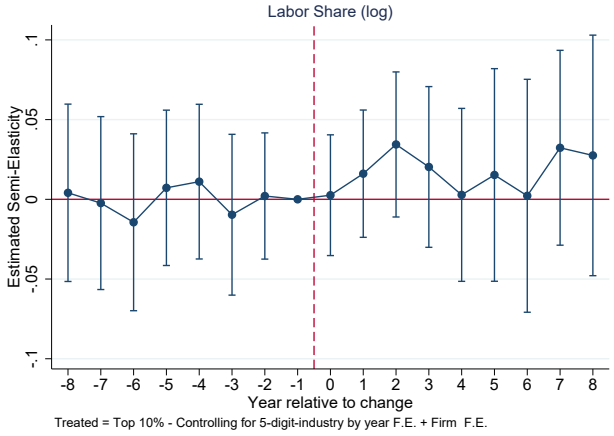
Notes: This figure reports the results of the firm-level event study for wage, using Acemoglu and Restrepo (2022)'s measure of automation. In all panels, the investment event is defined as a logarithmic change beyond the 75th percentile of the distribution of logarithmic changes in the balance-sheet 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 A10: Firm-level Event Studies for the Labor Share in Value Added, using

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



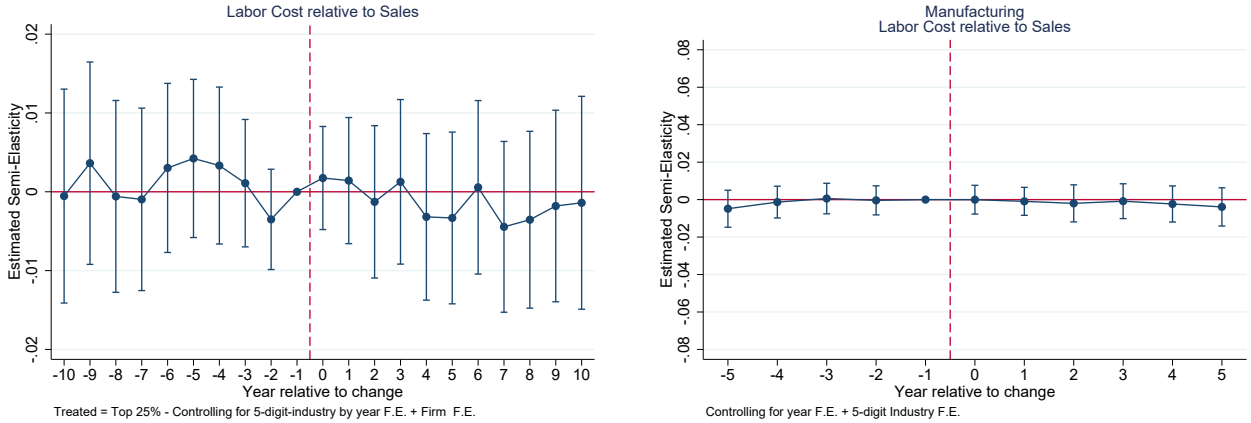
B. Real Estate Investments



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.

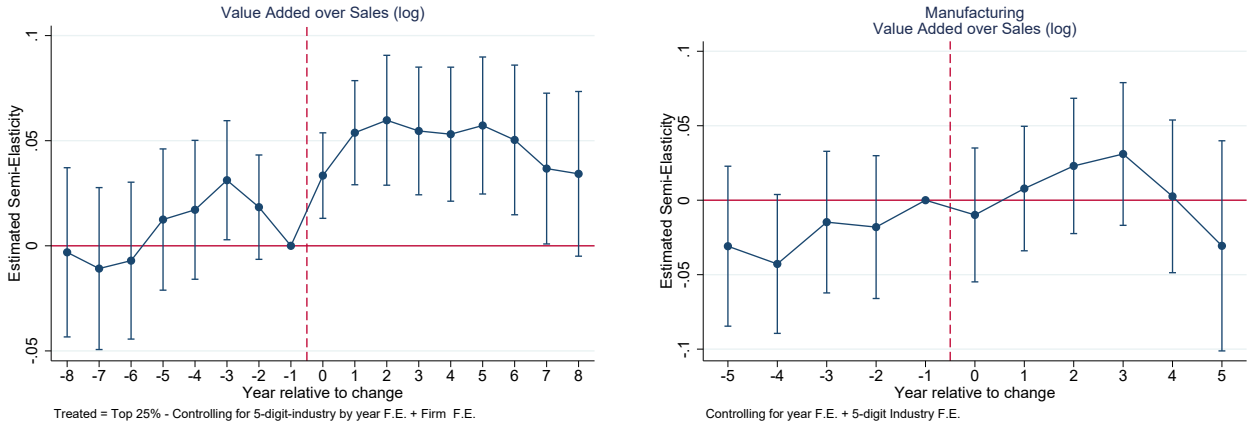
Figure A11: Additional Evidence on the Labor Share, Event Studies

A: Share of Labor in Total Sales



(i) Firm level (ii) Industry level

B: Share of Value-Added in Total Sales

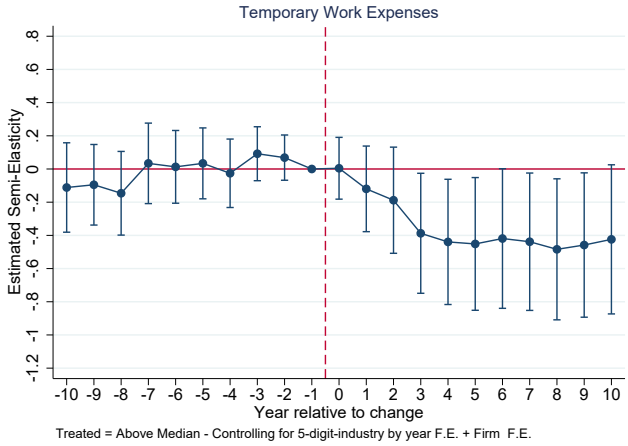


(i) Firm level (ii) Industry level

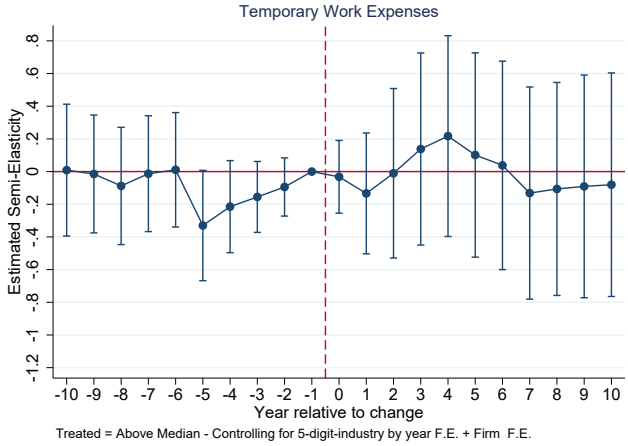
Notes: This figure reports the results of event studies with the labor share in total sales (panel A) and the share of value-added in total sales (panel B) as outcomes. In each panel, we report two specifications, conducting in turn the analysis at the firm level and the industry level to complement 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 A12: Firm-Level Event Studies for Temporary Work Expenses

A: Main Result with Investments in Industrial Equipment



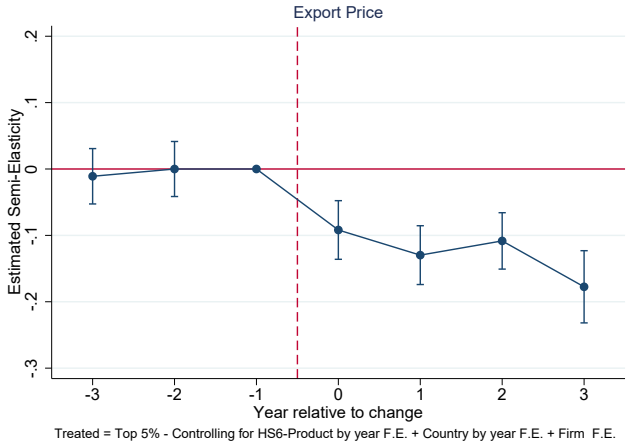
B: Placebo Test with Investments in Real Estate



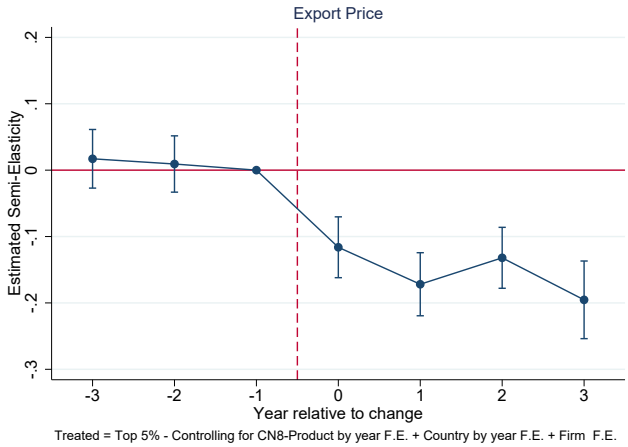
Notes: This figure reports the event study results with expenses for temporary workers as the outcome. We consider in turn investments in industrial equipment (panel A) and investments in real estate (panel B). The investment event is defined as a logarithmic change beyond the 50th percentile of the distribution of logarithmic changes in the balance-sheet value of industrial equipment or real estate. All panels use 5-digit industry by year fixed effects and firm fixed effects, with standard errors clustered at the firm level. The panel illustrate a change in the production function for investments in industrial equipment, as temporary work expenses are reduced, which we do not observe for investments in real estate capital.

Figure A13: Firm-Level Event Studies for Prices, Robustness with p95 Investment Threshold

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

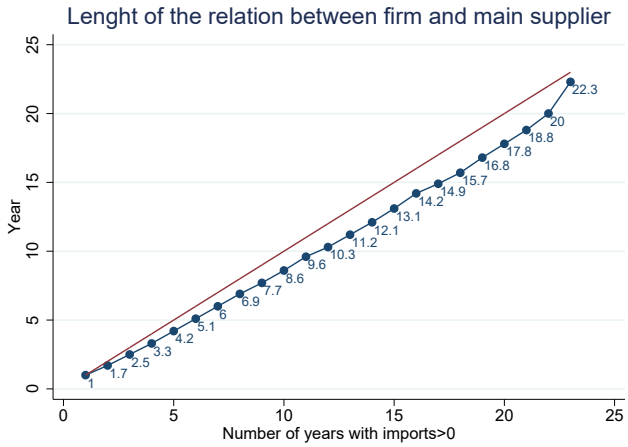


B. 95th percentile of investment for industry equipment, NC8 product level



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.

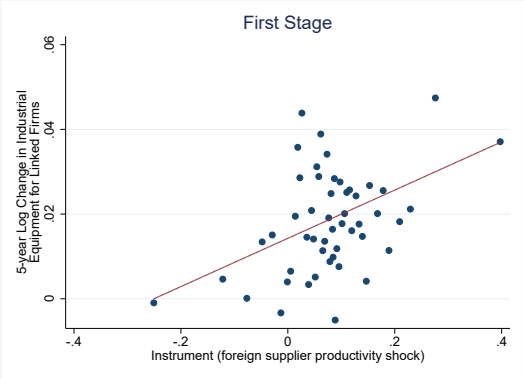
Figure A14: Persistence of Importer-Supplier Relationships



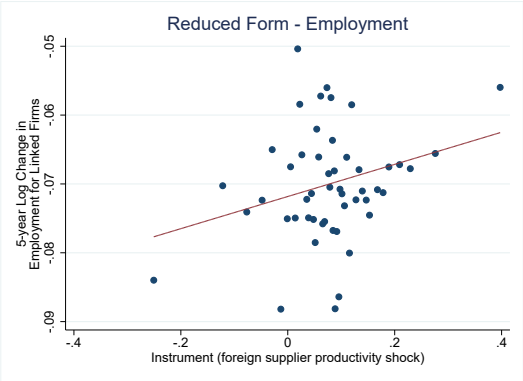
Notes: This figure documents the persistence of the network of international suppliers of machines, plotting the length of the relationships between a French firm and its main international supplier, depending on the number of years during which machines are imported. The set of imported machines is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

Figure A15: Firm-level Shift-Share IV, Robutness with More Stringent Fixed Effects

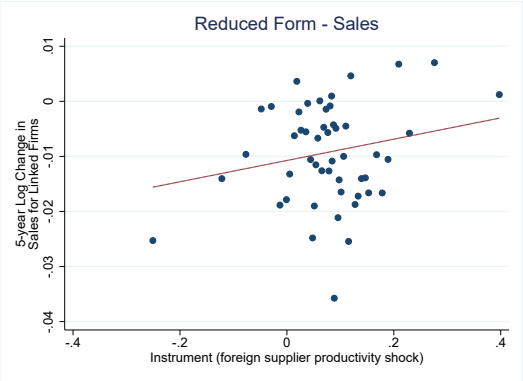
A. First stage



B. Reduced-form

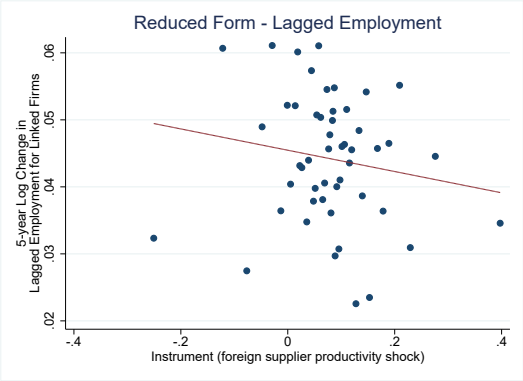


(i) Employment

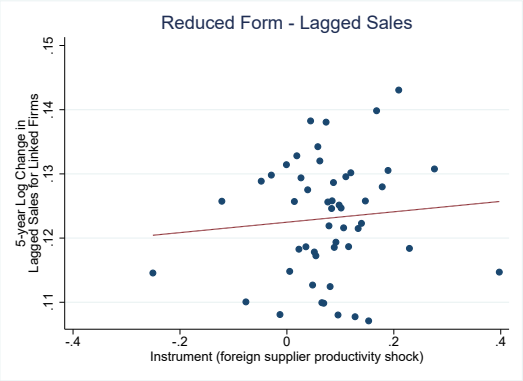


(ii) Sales

C. Falsification tests



(i) Lagged employment

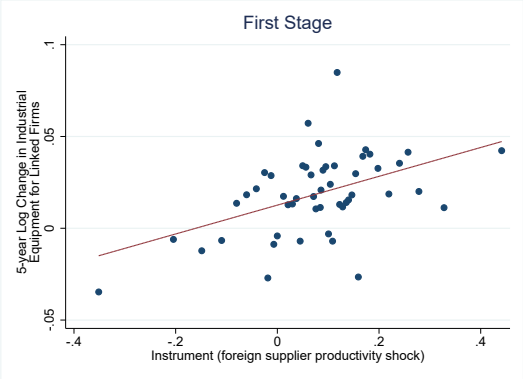


(ii) Lagged sales

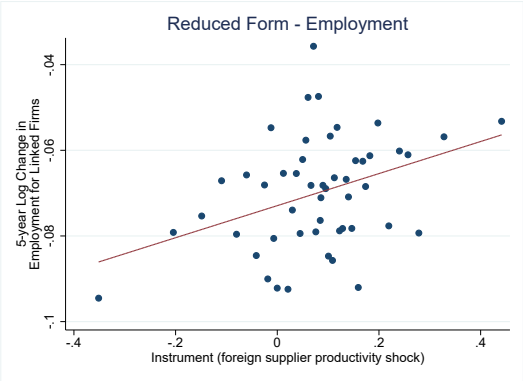
Notes: The binned scatter plots in this figure depict the relationships underlying the firm-level SSIV research design described by specification (4) in the main text, except that a more stringent set of fixed effects is used, with HS6-by-period and 5-digit-industry-by-period fixed effects. The figure 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 A4. 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 A16: Firm-level Shift-Share IV, Robustness with Less Stringent Fixed Effects

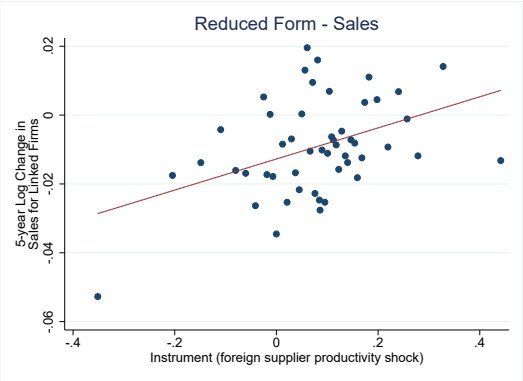
A. First stage



B. Reduced-form

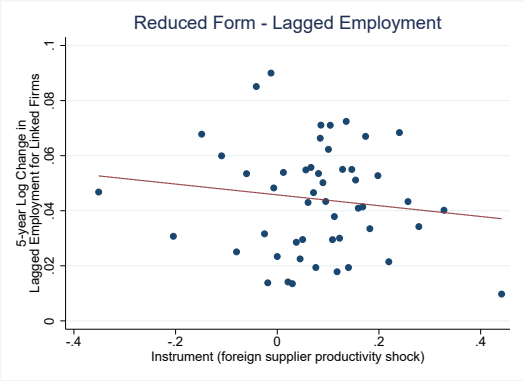


(i) Employment

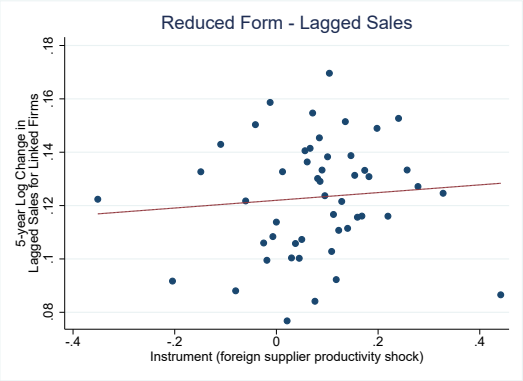


(ii) Sales

C. Falsification test



(i) Employment

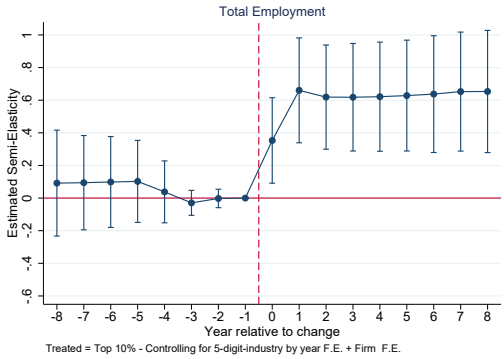


(ii) Sales

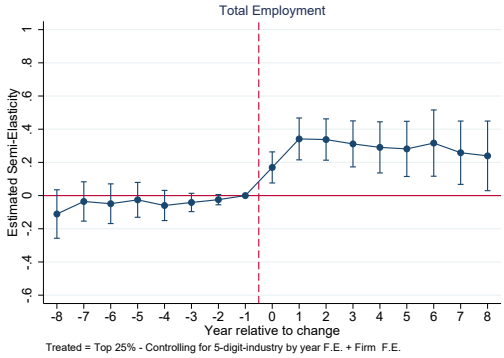
Notes: The binned scatter plots in this figure depict the relationships underlying the firm-level SSIV research design described by specification (4) in the main text, except that a more stringent set of fixed effects is used, with HS6-by-period and 5-digit-industry-by-period fixed effects. The figure 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 A5. 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 A17: Firm-level Event Studies in SSIV Sample Only

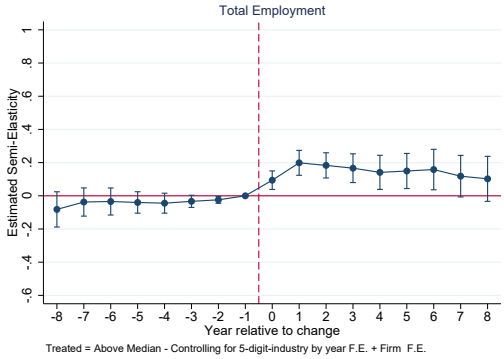
A. 90th percentile of investment in industrial equipment



B. 75th percentile of investment in industrial equipment

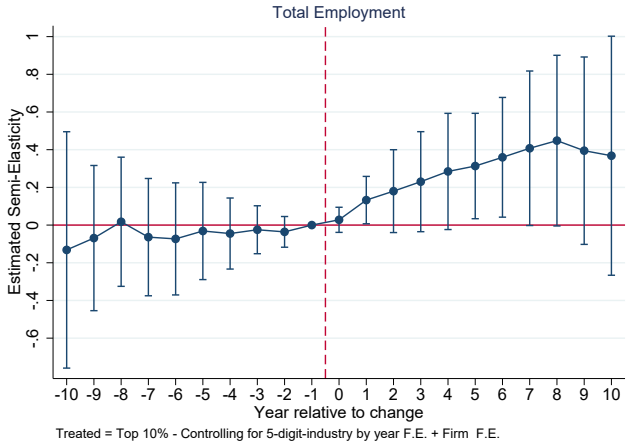


C. 50th percentile of investment in industrial equipment



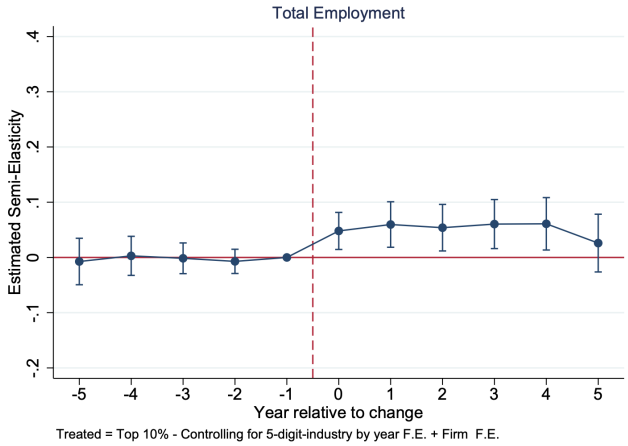
Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome in the sample of firms used in the SSIV analysis, i.e. firms that had positive imports of machines between 1996 and 2000, using the list of machines of Acemoglu and Restrepo (2022). In Panel A, 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 Figure 3 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 A18: 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 A of Figure 4 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).

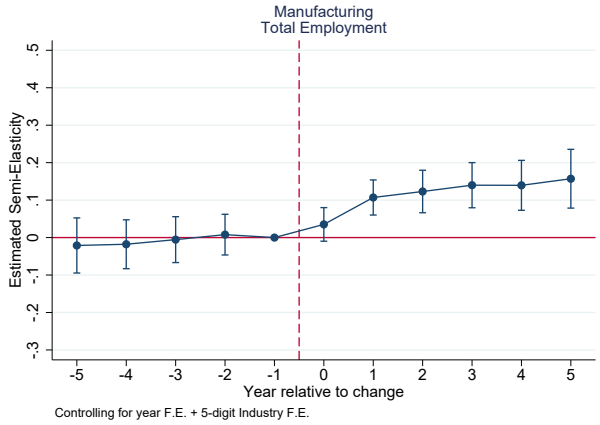
Figure A19: Firm-level Event Studies using Acemoglu and Restrepo (2022)'s Automation Measure for First-Time Purchases Only



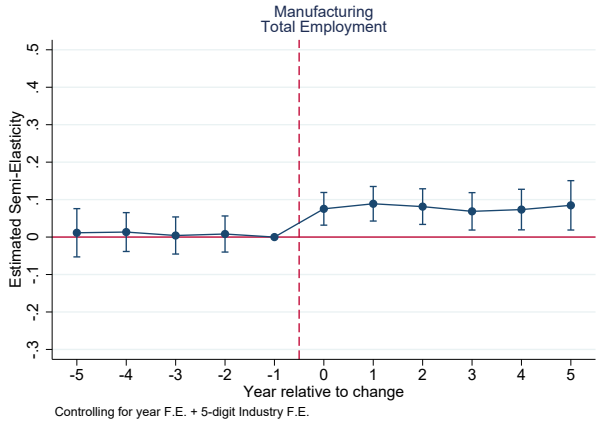
Notes: This figure reports the results of firm-level event studies with firm-level employment as the outcome, considering the full sample of firms. This figure uses Acemoglu and Restrepo (2022)'s automation measure of imported machines to measure investment events, defined as a logarithmic change beyond 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 A17 and A18. The point estimates are very similar to our baseline approach, reported on panel A of Figure 4 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 A20: 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.

Table A1: Summary Statistics, Annuals Levels, 1995–2017

	Units	Units-by-year	Mean	S.D.	p5	p50	p95
Panel A: Plant level							
Employment	2,773	54,755	273	461	24	163	824
Modern manufacturing capital – motive force (toe)	2,773	54,755	1,381	4,943	34	353	5,489
Panel B: Firm level							
Employment	1,599	33,579	55	158	3	15	204
Sales (thousands of euros)	1,599	33,579	18,289	97,344	350	2,404	52,228
Modern manufacturing capital:							
Industrial machines (thousands of euros)	1,599	33,579	7,519	114,066	15	328	12,047
Acemoglu and Restrepo (2022)'s imports of machines (thousands of euros)	1,599	33,579	72	807	0	0	137
Imports of robots (thousands of euros)	1,599	33,579	2	70	0	0	0
Motive force (toe)	485	7,910	2,144	8,506	41	346	7,353
Panel C: Industry level							
Employment	255	5,865	10,868	15,215	491	6,287	34,630
Sales (millions of euros)	255	5,865	3,463	8,887	117	1,764	9,761
Modern manufacturing capital:							
Industrial machines (millions of euros)	255	5,865	988	2,653	21	391	2,881
Acemoglu and Restrepo (2022)'s imports of machines (thousands of euros)	255	5,865	10	21	0	3	45
Imports of robots (millions of euros)	255	5,865	0	1	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 A2: SSIV Analysis of Modern Manufacturing Capital: Automation or Capital Deepening?

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

	$\Delta_5 Machines$				
	(1)	(2)	(3)	(4)	(5)
Shift-share Instrument	0.0722***	0.0668***	0.0668***	0.0673***	0.0675***
	(0.0176)	(0.0164)	(0.0164)	(0.0168)	(0.0161)
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
2-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)	4,016	4,016	4,016	4,016	4,016

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

	$\Delta_5 Machines$				
	(1)	(2)	(3)	(4)	(5)
Shift-share Instrument	-0.0252	-0.0403	-0.0402	-0.0458	-0.0495
	(0.0483)	(0.0429)	(0.0434)	(0.0438)	(0.0432)
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
2-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)	1,080	1,080	1,080	1,080	1,080

Notes: These tables report first-stage estimates for the shift-share research designed described in Section V and specification (4) 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 A3: Additional Evidence on the Labor Share, Firm-level SSIV

	(1)	(2)	(3)	(4)	(5)
Panel A: Δ_5*Labor Cost Over Sales*					
$\Delta_5 Machines$	0.00796	0.00736	0.00733	0.00553	0.00495
	(0.0311)	(0.0331)	(0.0332)	(0.0319)	(0.0301)
Panel B: Δ_5*Value Added Over Sales*					
$\Delta_5 Machines$	0.261**	0.202	0.202	0.202	0.199*
	(0.127)	(0.125)	(0.125)	(0.123)	(0.117)
First-Stage F	16.90	16.66	16.69	16.11	17.63
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	Yes	Yes	Yes	Yes	Yes
2-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)	4,016	4,016	4,016	4,016	4,016

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (4). This table is identical to Table 4 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 A4: Firm-level Shift-Share IV, Robustness with More Stringent Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Panel A: $\Delta_5 Employment$					
$\Delta_5 Machines$	0.417***	0.398***	0.411***	0.413***	0.410***
	(0.132)	(0.129)	(0.134)	(0.137)	(0.143)
Panel B: $\Delta_5 Sales$					
$\Delta_5 Machines$	0.429**	0.346**	0.345**	0.346**	0.339**
	(0.168)	(0.150)	(0.156)	(0.156)	(0.147)
Panel C: $\Delta_5 Hourly\ Wages$					
$\Delta_5 Machines$	-0.0693	-0.0811**	-0.0892**	-0.0898**	-0.0903**
	(0.0436)	(0.0413)	(0.0408)	(0.0445)	(0.0447)
Panel D: $\Delta_5 Labor\ Share$					
$\Delta_5 Machines$	-0.226	-0.139	-0.137	-0.140	-0.139
	(0.144)	(0.126)	(0.133)	(0.130)	(0.131)
Panel E: $\Delta_5 Labor\ Productivity$					
$\Delta_5 Machines$	0.156	0.0576	0.0483	0.0507	0.0491
	(0.144)	(0.117)	(0.128)	(0.123)	(0.123)
Panel F: $\Delta_5 Profits$					
$\Delta_5 Machines$	0.156	-0.0377	-0.0649	-0.0510	-0.0678
	(0.635)	(0.593)	(0.640)	(0.622)	(0.626)
Panel G: $\Delta_5 Competitors'\ Employment$					
$\Delta_5 Machines$	-0.0668***	-0.0497***	-0.0512***	-0.0516***	-0.0512***
	(0.0224)	(0.0165)	(0.0179)	(0.0180)	(0.0183)
Panel H: $Lagged\ \Delta_5 Employment$					
$\Delta_5 Machines$	-0.311	-0.234	-0.274	-0.278	-0.279
	(0.312)	(0.239)	(0.269)	(0.266)	(0.265)
Panel I: $Lagged\ \Delta_5 Sales$					
$\Delta_5 Machines$	0.0458	0.181	0.148	0.144	0.142
	(0.326)	(0.300)	(0.326)	(0.325)	(0.327)
First-Stage F	8.11	11.18	11.03	11.05	11.52
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
6-digit Product-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)	4,016	4,016	4,016	4,016	4,016

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (4). This table is identical to Table 4 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. Standard errors and the first-stage F-statistics are clustered at the partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Firm-level Shift-Share IV, Robustness with Less Stringent Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Panel A: $\Delta_5 Employment$					
$\Delta_5 Machines$	0.459***	0.471***	0.472***	0.479***	0.477***
	(0.100)	(0.112)	(0.112)	(0.113)	(0.116)
Panel B: $\Delta_5 Sales$					
$\Delta_5 Machines$	0.526***	0.597***	0.598***	0.598***	0.575***
	(0.186)	(0.186)	(0.185)	(0.183)	(0.184)
Panel C: $\Delta_5 Hourly\,Wages$					
$\Delta_5 Machines$	-0.0190	-0.000675	-0.000622	-0.00119	-0.00250
	(0.0483)	(0.0479)	(0.0478)	(0.0485)	(0.0495)
Panel D: $\Delta_5 Labor\ Share$					
$\Delta_5 Machines$	-0.266***	-0.280***	-0.281***	-0.273***	-0.268***
	(0.0807)	(0.0891)	(0.0881)	(0.0881)	(0.0901)
Panel E: $\Delta_5 Labor\ Productivity$					
$\Delta_5 Machines$	0.247**	0.280***	0.280***	0.271***	0.265***
	(0.102)	(0.0914)	(0.0901)	(0.0895)	(0.0918)
Panel F: $\Delta_5 Profits$					
$\Delta_5 Machines$	1.404***	1.422***	1.422***	1.380***	1.349***
	(0.402)	(0.311)	(0.311)	(0.309)	(0.318)
Panel G: $Lagged\ \Delta_5 Employment$					
$\Delta_5 Machines$	-0.228	-0.260	-0.259	-0.261	-0.250
	(0.295)	(0.304)	(0.305)	(0.300)	(0.308)
Panel H: $Lagged\ \Delta_5 Sales$					
$\Delta_5 Machines$	0.110	0.183	0.185	0.173	0.184
	(0.309)	(0.284)	(0.288)	(0.287)	(0.293)
First-Stage F	17.61	22.06	23.01	23.64	24.30
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-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)	4,016	4,016	4,016	4,016	4,016

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (4). This table is identical to Table 4 in the main text, except that a less stringent set of fixed effects is used, with HS4-by-period fixed effect 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 A6: Firm-level Effects with Shift-Share IV, Robustness with Acemoglu and Restrepo (2022)'s Original Automation Measure

	(1)	(2)	(3)	(4)	(5)
Panel A: $\Delta_5 Employment$					
$\Delta_5 Machines$	0.741***	0.740***	0.744***	0.745***	0.746***
	(0.282)	(0.239)	(0.246)	(0.241)	(0.242)
Panel B: $\Delta_5 Sales$					
$\Delta_5 Machines$	0.660***	0.694***	0.696***	0.717***	0.705***
	(0.188)	(0.180)	(0.188)	(0.204)	(0.193)
Panel C: $\Delta_5 Hourly\ Wages$					
$\Delta_5 Machines$	-0.0952	-0.0910*	-0.0936*	-0.0949*	-0.0963*
	(0.0674)	(0.0512)	(0.0527)	(0.0544)	(0.0565)
Panel D: $\Delta_5 Labor\ Share$					
$\Delta_5 Machines$	-0.301***	-0.304**	-0.304**	-0.329**	-0.327**
	(0.113)	(0.136)	(0.140)	(0.144)	(0.146)
Panel E: $\Delta_5 Labor\ Productivity$					
$\Delta_5 Machines$	0.206*	0.213	0.210	0.234*	0.231*
	(0.119)	(0.130)	(0.132)	(0.129)	(0.133)
Panel F: $\Delta_5 Profits$					
$\Delta_5 Machines$	1.333**	1.239**	1.239*	1.231*	1.211*
	(0.581)	(0.621)	(0.635)	(0.670)	(0.656)
Panel G: $Lagged\ \Delta_5 Employment$					
$\Delta_5 Machines$	-0.397	-0.419	-0.436	-0.453	-0.445
	(0.398)	(0.347)	(0.349)	(0.367)	(0.357)
Panel H: $Lagged\ \Delta_5 Sales$					
$\Delta_5 Machines$	-0.442	-0.381	-0.419*	-0.401	-0.405
	(0.358)	(0.259)	(0.248)	(0.264)	(0.272)
First-Stage F	7.13	8.96	8.67	9.62	8.96
Partner-period F.E.	Yes	Yes	Yes	Yes	Yes
4-digit Product-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)	1,491	1,491	1,491	1,491	1,491

Notes: This table reports firm-level SSIV estimates, implementing the research design described by specification (4). This table is identical to Table 4 in the main text, except that we use Acemoglu and Restrepo (2022)'s original automation measure, which includes textile machines only in the set of sectoral automating technologies. Standard errors and the first-stage F-statistics are clustered at the partner level. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Industry-level Shift-Share IV, Robustness with Less Stringent Fixed Effects

	(1)	(2)	(3)	(4)
Panel A: $\Delta_5 Employment$				
$\Delta_5 Machines$	1.009***	1.007***	1.005***	1.016***
	(0.149)	(0.148)	(0.149)	(0.154)
Panel B: $\Delta_5 Incumbents' \ Employment$				
$\Delta_5 Machines$	0.530***	0.497***	0.514***	0.517***
	(0.181)	(0.149)	(0.157)	(0.157)
Panel C: $\Delta_5 Sales$				
$\Delta_5 Machines$	1.225***	1.225***	1.145***	1.092***
	(0.253)	(0.251)	(0.257)	(0.245)
Panel D: *Lagged* $\Delta_5 Employment$				
$\Delta_5 Machines$	0.230	0.247	0.276	0.295
	(0.250)	(0.251)	(0.262)	(0.259)
Panel E: *Lagged* $\Delta_5 Sales$				
$\Delta_5 Machines$	0.214	0.197	0.195	0.221
	(0.281)	(0.276)	(0.292)	(0.291)
First-Stage F	27.94	28.11	24.10	23.13
Partner-period F.E.	Yes	Yes	Yes	Yes
4-digit Product 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)	6,894	6,894	6,894	6,894

Notes: This table reports industry-level SSIV estimates, implementing the research design described by specification (4) at the industry level. This table is identical to Table 6 in the main text, except that we use a less stringent set of fixed effects, i.e. 4-digit product fixed effects instead of interacted 4-digit-product-by-period fixed effects 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 A8: Additional Evidence on the Labor Share, Industry-level SSIV

	(1)	(2)	(3)	(4)
Panel A: $\Delta_5 Labor\ Cost\ Over\ Sales$				
$\Delta_5 Machines$	-0.0238	-0.0252	-0.0166	-0.00645
	(0.0404)	(0.0414)	(0.0435)	(0.0401)
Panel B: $\Delta_5 Value\ Added\ Over\ Sales$				
$\Delta_5 Machines$	0.136	0.0831	0.205	0.229
	(0.204)	(0.172)	(0.200)	(0.205)
First-Stage F	14.04	14.42	12.05	11.61
Partner-period F.E.	Yes	Yes	Yes	Yes
4-digit Product-period F.E.	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)	6,894	6,894	6,894	6,894

Notes: This table reports industry-level SSIV estimates, implementing the research design described by specification (4) 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 A9: Industry-level OLS Relationships between Manufacturing Capital and Producer Prices

	$\Delta_5 Producer\ Price\ Index$			
	(1)	(2)	(3)	(4)
$\Delta_5 Machines$	-0.113**	-0.199***	-0.194***	-0.178**
	(0.0573)	(0.0698)	(0.0699)	(0.0750)
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 by Period)	183	183	183	183

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. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.