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The Local Labor Market Effects of Modern Manufacturing Capital: Evidence from France†

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Many public policies affect the costs of investments in modern manufacturing capital—for example, in automation technologies such as numerically controlled machine tools, automatic conveyor systems, industrial robots, and so forth. To date, the employment effects of these investments remain highly debated.

There are growing concerns about technological unemployment that may be brought about by modern technologies like robots (e.g., Brynjolfsson and McAfee 2014; Acemoglu and Restrepo 2018). However, others have pointed out that robots are a small fraction of total investment (Benmelech and Zator 2022). Furthermore, there are paradigmatic cases of technologies substituting for workers that in fact raise labor demand. For example, Bessen (2015) documents that automated teller machines (ATMs) 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.

Going beyond case studies of specific technologies, we present new evidence estimating the impact of typical modern manufacturing capital investments on labor demand. To do so, in Aghion et al. (2022), we develop two research designs—event studies and a shift-share methodology—that we apply to comprehensive French micro data on the population of firms in the manufacturing sector. While our initial study focused on firm- and industry-level estimates, in this companion paper we use the same data and an event study methodology to present additional evidence on the local labor market effects of modern manufacturing capital. We find that increased modern manufacturing capital leads to positive employment effects at the local labor market level.

In what follows, we first present a simple conceptual framework motivating our analysis, using canonical economic models. The following sections present in turn the data, the event study research design, and the results. The final section concludes.

I. Conceptual Framework

Economic theory shows that the effects of investments in modern manufacturing capital on employment are ambiguous.

Let us first consider the canonical model of factor-augmenting technological change. If modern manufacturing capital is modeled as capital-augmenting technological change with standard production function elasticities, then it should lead to an increase in both labor demand (and wages) and the labor share.

However, in the task model (Acemoglu and Restrepo 2018), automation may reduce the demand for labor and wages, because it assigns to capital tasks that used to be performed by labor; this would lead to a decline in the labor share. Several counteracting forces could nonetheless lead to an increase in labor demand—for example, a productivity effect of automation at the intensive margin (sometimes called "automation deepening").

Thus, from both a modeling and a policy perspective, it is important to assess whether the effects of typical investments in modern manufacturing capital are consistent with the predictions

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of the canonical model of factor-augmenting technological change or rather with those of the task model. While Aghion et al. (2022) address this question by analyzing firm- and industry-level labor demand, in this companion paper we provide complementary evidence at the local labor market.

II. Data

Following Aghion et al. (2022), we analyze comprehensive micro data on the population of firms in the French manufacturing sector between 2003 and 2016. We obtain detailed information on workers and firms from French administrative datasets: the linked employer-employee (DADS)[1] and the balance sheet (BIC-RN)[2] databases. We then build two measures of modern manufacturing capital.

Our first measure is the balance sheet value of industrial machines, which we observe at the firm level in administrative data and subsequently aggregate to the level of commuting zones (CZ). This measure encompasses all machines used for extraction, processing, shaping, and packages of materials or supplies. We can thus isolate changes in the stock of industrial machines from changes in other components of capital (e.g., land, buildings, information technology, office equipment, and so forth). While this measure has the benefit of being available for all manufacturing firms, a limitation is that there is no explicit list describing all machines that are accounted for.

As a complement to the first measure, we use the automation measure of Acemoglu and Restrepo (2022, 25), defined as "a range of technologies for industrial automation." This measure is based on imported intermediate goods, defined as products with a six-digit Harmonized System code in the following list: industrial robots, dedicated machinery, numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, other dedicated textile machinery, automatic conveyors, and regulating and control instruments. This measure is only available for importing firms, which we observe in the French customs data.

While our measures of investment in modern manufacturing capital and industrial automation are initially observed at the firm level, we allocate them across CZ based on the initial distribution of firm employment across CZs.

III. Event Study Research Design

Our event study methodology is identical to Aghion et al. (2022), although we now implement it at the CZ level rather than the firm and industry levels.

Specifically, we analyze large investment events in modern manufacturing capital across CZs. We build two investment events, using either of our two measures of modern manufacturing capital.

An investment event for a CZ is defined as a yearly change in the balance sheet value of industrial equipment or in imports of automation machines above a prespecified threshold, in the distribution of all possible changes across CZs. We take the median as the relevant threshold for our analysis below. The results are similar when using the seventy-fifth and ninetieth percentiles as thresholds, although these results are not reported due to space constraints. When a CZ experiences a change in investment past the threshold more than once during our sample period, we take the largest change as our unique investment event. Thus, each CZ is treated at most once.

The spatial distribution of the investment events is shown below for industrial equipment (Figure 1) and industrial automation (Figure 2). The distributions differ: investments in industrial equipment are more common in the southwest of the country, while industrial automation is more frequent in the northeast.

Indexing CZs by i and years by t, our event study specification is

$$\Delta \log(Y_{it}) = \sum_{k=-5}^{5} \delta_k E_{i,t-k} + \mu_i + \lambda_{st} + \epsilon_{it}, \tag{1}$$

[1] DADS refers to the "All employees databases—job position data" dataset provided by the National Institute of Statistics and Economic Studies: https://doi.org/10.34724/CASD.21.3038.V2.

[2] BIC-RN refers to the "Industrial and commercial profits–normal scheme" dataset provided by the French Ministry of Finance: https://doi.org/10.34724/CASD.259.2469.V1.

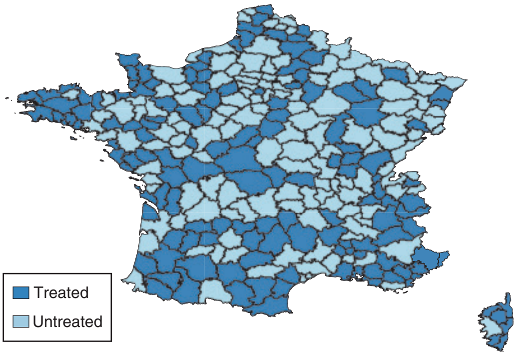

Figure 1. CZ-Level Investment Events for Industrial Equipment

Notes: This figure shows the distribution of CZ-level investments in industrial equipment. Treated CZs experience a change in the balance sheet value of industrial equipment above median at least once between 2003 and 2016.

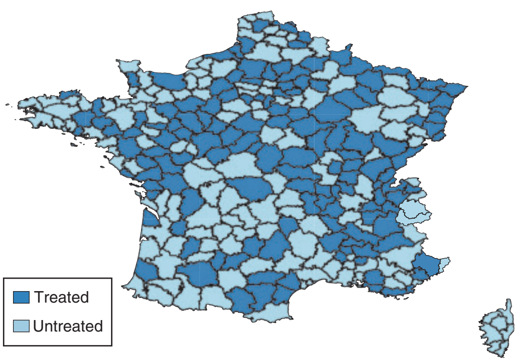

Figure 2. CZ-Level Investment Events for Industrial Automation

Notes: This figure shows the distribution of CZ-level investments in industrial automation. Treated CZs experience a change in imports of industrial automation machines above median at least once between 2003 and 2016.

where $\Delta\log(Y_{it})$ denotes the change in CZ-level employment, $E_{i,\,t-k}$ the investment event indicator, μ_i CZ fixed effects, and λ_{st} "region-by-year" fixed effects.

This event study specification allows for an analysis of pretrends. A lack of pretrends is reassuring and restricts the potential set of confounders to contemporaneous demand or supply shocks.

In Aghion et al. (2022), we validate the event study methodology at the firm level

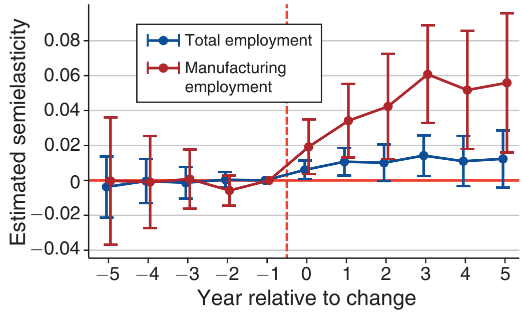

Figure 3. The Response of CZ Employment to Investment in Industrial Equipment

Notes: This figure documents the response of CZ-level total and manufacturing employment to investments in industrial equipment, using specification (1). Standard errors are clustered by CZs.

and the industry level with a complementary research design, a shift-share instrument variable (SSIV) approach. This approach leverages predetermined supply linkages and productivity shocks across foreign suppliers of manufacturing capital. The firm- and industry-level SSIV estimates are similar in magnitudes to the event study estimates, rejecting the hypothesis that the results are driven by contemporaneous shocks. These results motivate our assumption that there are also no contemporaneous shocks confounding the CZ-level event studies.

IV. Results

Using the CZ-level event study approach, we consistently find that investments in modern manufacturing capital lead to an increase in labor demand.

Figure 3 reports the patterns with our first measure, investment in industrial equipment. There are no signs of pretrends, and employment increases after the investment event. The figure shows that both manufacturing employment and total employment increase, but the effect is much stronger for manufacturing employment, with a semielasticity of about 0.05 after 5 years.

Next, we repeat the analysis using our second measure, imports of machines relating to industrial automation as in Acemoglu and Restrepo (2022). Figure 4 shows that the patterns are very similar to our first measure: there are no pretrends, and we observe an increase in CZ employment after the investment event, which

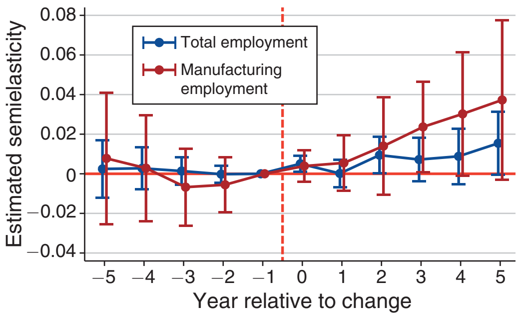

Figure 4. The Response of CZ Employment to Investment in Industrial Automation

Notes: This figure documents the response of CZ-level total and manufacturing employment to imports of automation technologies in the sense of Acemoglu and Restrepo (2022), using specification (1). Standard errors are clustered by CZs.

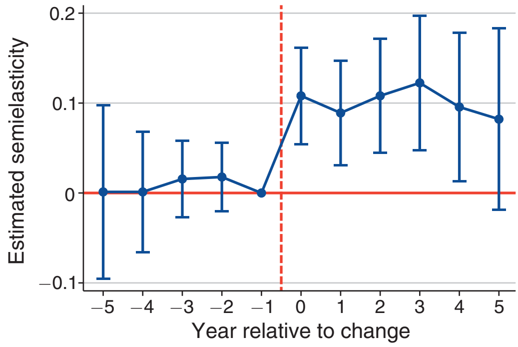

Figure 5. The Response of CZ Manufacturing Sales to Investment in Industrial Equipment

Notes: This figure documents the response of CZ-level manufacturing sales to investments in industrial equipment, using specification (1). Standard errors are clustered by CZs.

is driven by manufacturing employment, with a semielasticity of 0.04 after 5 years.

To understand the channel at play, we analyze the response of manufacturing sales. Figure 5 shows a strong increase in manufacturing sales right after the investment event. The semielasticity is 0.1 from the first year after the event and remains stable thereafter. This finding is consistent with a productivity channel of modern manufacturing capital: firms invest to reduce their production costs, then can reduce consumer prices, expand their sales, and thus have higher labor demand.

Finally, Figure 6 documents an increase in CZ wages after the investment event, with a semielasticity of 0.01 after 5 years. Thus, the CZ-level increase in labor demand brought about by modern manufacturing capital results in both higher employment and higher wages, which is consistent with the fact that labor mobility across CZs is limited. In contrast, at the firm level, Aghion et al. (2022) find that the increase in labor demand from modern manufacturing capital goes entirely through changes in employment, with no change in wages. Indeed, worker mobility is much higher across firms than across CZs.

V. Conclusion

In Aghion et al. (2022), we find that investments in modern manufacturing capital—including automation technologies in the sense of Acemoglu and Restrepo (2022)—lead to an

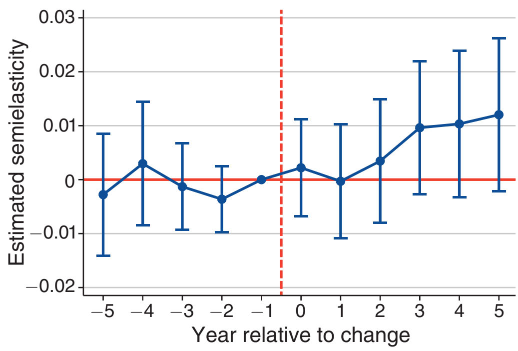

Figure 6. The Response of CZ Wages to Investment in Industrial Equipment

Notes: This figure documents the response of CZ-level wages to investment in industrial equipment, using specification (1). Standard errors are clustered by CZs.

increase in employment at the firm and industry levels. In this paper, we showed that the same conclusion carries over to the local labor market level. Aghion et al. (2022) also document a fall in the labor share at the firm level, which is consistent with the task-based framework since the canonical framework cannot rationalize the observed fall in the labor share.

Overall, our finding of a positive employment response at all levels of analysis implies that the relevant model is a task-based framework where the productivity effect dominates the displacement effect.

Our results are consistent with a growing literature using event studies to estimate the firm-level employment effects of automation and robotization. Indeed, most studies document a positive employment response (e.g., Acemoglu, Lelarge, and Restrepo 2020; Dixon, Hong, and Wu 2019; Domini et al. 2021; Humlum 2021; Koch, Manuylov, Smolka 2021), with a few studies estimating a negative effect (Bessen et al. 2020; Bonfiglioli et al. 2020).

REFERENCES

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with Robots: Firm-Level Evidence from France." *AEA Papers and Proceedings* 110: 383–88.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6): 1488–542.

Acemoglu, Daron, and Pascual Restrepo. 2022. "Demographics and Automation." *Review of Economic Studies* 89 (1): 1–44.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel. 2022. "Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France." Unpublished.

Benmelech, Efraim, and Michal Zator. 2022. "Robots and Firm Investment." NBER Working Paper 29676.

Bessen, James. 2015. *Learning by Doing*. New Haven, CT: Yale University Press.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge. 2020. "Firm-Level Automation: Evidence from the Netherlands." *AEA Papers and Proceedings* 110: 389–93.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia. 2020. "Robot Imports and Firm-Level Outcomes." CESifo Working Paper 8741.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: WW Norton & Company.

Dixon, Jay, Bryan Hong, and Lynn Wu. 2019. "The Employment Consequences of Robots: Firm-Level Evidence." Unpublished.

Domini, Giacomo, Marco Grazzi, Daniele Moschella, and Tania Treibich. 2021. "Threats and Opportunities in the Digital Era: Automation Spikes and Employment Dynamics." *Research Policy* 50 (7): 104137.

Humlum, Anders. 2021. "Robot Adoption and Labor Market Dynamics." Unpublished.

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2021. "Robots and Firms." *Economic Journal* 131 (638): 2553–84.