2 The Effects of Automation on Labor Demand

A Survey of the Recent Literature

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1. Introduction

Should we fear or welcome automation? On the one hand, fear may prevail if we believe that human workers will be replaced by machines which perform their tasks, thereby increasing unemployment and reducing the labor share. On the other hand, we may welcome automation since it spurs growth and prosperity, as illustrated by the big technological revolutions – steam engine in the early 1800s, electricity in the 1920s – none of which generated the mass unemployment anticipated by some.

The fear that machines will destroy human jobs began long ago. Already in 1589, when William Lee invented a machine to knit stockings, the working class was so fearful of the consequences that he was rejected everywhere and even threatened. Then came the first industrial revolution, the "steam engine revolution", and in its wake the so-called Luddite movement. Despite a 1769 law protecting machines from being destroyed, destruction intensified as the weaving loom became widespread, culminating with the Luddite rebellion in 1811–1812.

The second industrial revolution, the "electricity revolution", occurred first in the US in the late 19th century. Thirty years later, economists began to express concern about the unemployment that this revolution would generate. In 1930, Keynes wrote, "We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment."[1] Once again, the prediction of a large-scale increase in unemployment did not materialize.

More recently, the information technologies (IT) and artificial intelligence (AI) revolutions have raised similar fears: by creating further opportunities to automate tasks and jobs, IT and AI may increase unemployment and reduce wages. Consequently, the idea that one should tax robots has become influential in recent years.

In this paper, we discuss the effects of automation on employment, appealing to both the existing literature on AI and automation and our recent empirical work using French data (Aghion et al., 2019, 2020). We first spell out the two contrasting views on the subject. A first view sees automation as primarily destroying jobs, even if this may ultimately result in new job creations taking advantage of the lower equilibrium wage induced by the job destruction. The prediction is that automation should reduce employment, wages, and the aggregate labor share. According to

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this first view, automation may reduce both the aggregate number of jobs and wages, thus reducing the well-being of workers. An alternative viewpoint emphasizes the market size effect of automation: namely, automating firms become more productive, which enables them to lower their quality-adjusted prices and thereby increase the demand for their products; the resulting increase in market size translates into higher employment by these firms. We provide empirical support for the second view, drawing from our empirical work on French firm-level data and a growing literature covering multiple countries.

The chapter is organized as follows. Section 2 presents the debate. Section 3 describes the emerging empirical consensus towards the more optimistic view of automation, with positive direct effects on employment at the firm level. Drawing on our recent empirical work, Section 4 describes the main methodological approaches and the main findings from the literature using data on French plants, firms, and labor markets in recent years. Section 5 concludes.

2. The debate: what are the direct and indirect effects of automation on employment?

In this section we briefly present the two contrasting views of automation and employment.

a. The "negative" view: negative partial equilibrium effects and positive general equilibrium effects of automation on aggregate labor demand

The "negative" view[2] implies that automation reduces demand for labor and pushes wages downward. The "partial equilibrium" (PE) effect is a fall in labor demand through the substitutability between labor and machines at the task level. This effect may then be counteracted in general equilibrium (GE) according to several channels, which are summarized in Table 2.1 and described hereafter.

In Acemoglu and Restrepo (2016) it is counteracted by the fact that automation depresses the equilibrium wage, which in turn encourages the creation of activities that initially employ labor (before being themselves subsequently automated); this in turn increases the demand for labor and therefore limits the wage decline. In Aghion, Jones and Jones (2017), the PE effect on labor demand is counteracted by a "Baumol Cost Disease" GE effect whereby labor becomes increasingly scarce relative to capital over time, which pushes wages upward (due to the complementarity between labor and capital at the aggregate level).

More formally, Acemoglu and Restrepo (2016) assume that final output is produced by combining the services of a unit measure of tasks $X \in [N-1, N]$, according to:

$$\Upsilon = \left(\int_{N-1}^{N} X_i^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$$

Table 2.1 Summary of Theoretical Predictions on the Impact of Automation on Labor Demand

Authors	*PE Effect of Automation*	*GE Effect of Automation*	*Predicted Impact on Employment in Automating Firms*	*Predicted Impact on Wages in Automating Firms*
Acemoglu & Restrepo (2020)	Fall in labor demand through the substitutability between labor and machines at the task level.	Increase in labor demand through a fall in wages and the endogenous creation of new tasks for which labor has a comparative advantage.	Decrease	Decrease
Aghion, Jones & Jones (2017)	Fall in labor demand through the substitutability between labor and machines at the task level.	Increase in labor demand through the complementarity between capital and labor at the aggregate level.	Decrease	Ambiguous
Aghion, Antonin, Bunel & Jaravel (2020)	Increase in labor demand through the increase in productivity and in consumer demand.	Business stealing effects reducing labor demand at non-automating firms.	Increase	Ambiguous

where: (i) tasks X_i with $i > I$ are non-automated, produced with labor alone; (ii) tasks X_i with $i < I$ can be automated, that is, capital and labor are perfect substitutes within tasks, with $\sigma - 1$ denoting the constant elasticity of substitution between tasks; (iii) N indexes the productivity of tasks;[2] (iv)

$$X_i = \alpha(i)K_i + \gamma(i)L_i$$

where: (a) $\alpha(i)$ is an index function with $\alpha(i) = 0$ if $i > I$ and $\alpha(i) = 1$ if $i < I$; (b) $\gamma(i) = e^{A_i}$. $\gamma(i)$ is the productivity of labor in task i. Acemoglu and Restrepo assume that $\gamma(i)$ is strictly – exponentially – increasing, so that labor has a comparative advantage in the production of tasks with a high index.

In the full-fledged Acemoglu-Restrepo model with endogenous technological change, the dynamics of I and N (i.e., the automation of existing tasks and the discovery of new lines) result from endogenous directed technical change. Under reasonable parameter values guaranteeing that innovation is directed towards using the cheaper factor, there exists a unique and (locally) stable Balanced Growth Path (BGP) equilibrium.

Stability of this BGP follows from the fact that an exogenous shock to I or N will trigger forces that bring the economy back to its previous BGP with the same labor share. The basic intuition for this result is the following: if a shock leads to over-automation, then the decline in labor costs will encourage innovation aimed at creating new – more complex – tasks that exploit cheap labor, that is, it will lead to an increase in N. In other words, the negative effect of automation on labor demand in partial equilibrium is mitigated by a general equilibrium effect, whereby the depressing effect of automation on wages encourages entry of new activities that initially take advantage of labor becoming cheaper.

Aghion, Jones, and Jones (2017) point to another counteracting force, namely the "Baumol Cost Disease" effect, which prevents automation from depressing wages too much. There it is the complementarity between existing automated tasks and existing labor-intensive tasks, together with the fact that labor becomes increasingly scarce relative to capital over time, that allows for the possibility that the labor share remains constant over time.

More formally, final output is produced according to:

$$Y_t = A_t\left(\int_0^1 X_{it}^{\rho}di\right)^{\frac{1}{\rho}}$$

where $\rho < 0$ (i.e., tasks are complementary), A is knowledge and grows at constant rate g and, as in Zeira (1998):

$$X_{it} = \begin{cases} L_{it} \text{ if not automated} \\ K_{it} \text{ if automated} \end{cases}$$

Under the assumption that a fraction β_t of tasks is automated by date t, we can re-express the previous aggregate production function as:

$$Y_t = A_t(\beta_t^{1-\rho}\, K_t^{\rho} + (1-\beta_t)^{1-\rho} L^{\rho})^{1/\rho}$$

where K_t denotes the aggregate capital stock and $L_t \equiv L$ denotes the aggregate labor supply.

In equilibrium, the ratio of capital share to labor share at time t is equal to:

$$\frac{\alpha_{K_t}}{\alpha_L} = \left(\frac{\beta_t}{1-\beta_t}\right)^{1-\rho}\left(\frac{K_t}{L_t}\right)^{\rho}$$

Hence an increase in the fraction of automated goods β_t has two offsetting effects on $\frac{\alpha_{K_t}}{\alpha_L}$: (i) first, a positive effect which is captured by the term $\left(\frac{\beta_t}{1-\beta_t}\right)^{1-\rho}$, which we label the partial equilibrium effect of automating tasks (holding the ratio $\frac{K_t}{L_t}$ constant); (ii) second, a negative effect captured by the term $\left(\frac{K_t}{L_t}\right)^{\rho}$, as we recall that $\rho < 0$, which we label the GE effect of automation. This latter effect relates to the well-known Baumol Cost Disease: namely, as $\frac{K_t}{L_t}$ increases due to automation, labor becomes scarcer than capital which, together with the fact that labor-intensive tasks are complementary to automated tasks (indeed we assumed $\rho < 0$), implies that labor will command a sustained share of total income.

While the previous two models emphasize different counteracting forces that limit the wage decline induced by automation, both have in common that the partial equilibrium effect of automation is to destroy employment. In particular, this effect would be observed within firms that automate.

b. The "positive" view: positive partial equilibrium effects and negative general equilibrium effects of automation on labor demand

Recent work suggests a more "positive" view of automation: the direct effect of automation may be to increase employment at the firm level, not to reduce it.[3] The reason is that firms and plants that automate become more productive. This allows them to offer a better quality-adjusted price than their competitors, and therefore to "steal business" away from their competitors, and more generally to expand the size of their markets (domestic and foreign). This in turn increases their demand for labor.[4]

Note that this channel does not exclude the possibility that total labor demand, at the national, industry, regional or commuting zone level may not respond so positively to automation and may even react negatively to it. There may be an overall negative effect if automating firms induce a sufficiently large decline in employment for non-automating firms and cause their exit. But a main difference with the "old view", is that, here, the direct dominant effect of automation is the positive productivity effect, which may then be counteracted by a "creative destruction" or "eviction" effect in general equilibrium. Furthermore, the negative GE effect is partly borne by international competitors, which has implications for the desirability of taxing robots.

c. Implications for the taxation of robots

A growing theoretical literature has examined the reasons that may justify the taxation of robots, notably limiting the potential rise in income inequality that automation might create. Costinot and Werning (2018) examine whether taxation or protectionist trade policies might help to better distribute the economic benefits of AI technologies.[5] Their results indicate that taxing the innovators or developers of the technology is undesirable because it would impede innovation; yet, if robots lead to an increase in inequality, a modest tax on the use of technology (as opposed to innovation *per se*) may be the optimal prescription because of distributional concerns.

Optimal policy depends on the elasticity of employment and inequality to robotization, which highlights the importance of distinguishing empirically between the two aforementioned views. As discussed in Aghion et al. (2020), the second view implies that unilateral taxation of robots by a given country could be counterproductive for industrial employment in that country, because of business stealing effects across countries. According to that view, the positive effect of automation will benefit countries that keep automating, while the negative GE effect will be shared across countries, given that competition operates in world markets. Therefore, as explained by Aghion et al. (2020), unilateral taxes on robots or other automation technologies may be detrimental to domestic employment: "without international coordination, in a globalized world attempts to curb domestic automation in an effort to protect domestic employment may be self-defeating because of foreign competition."

In the next section, we confront the two views with recent evidence from the literature, covering many countries and time periods. Research designs using variation across industries or labor markets deliver mixed evidence with regards to the impact of automation on labor demand. Recent firm-level evidence delivers clear causal evidence supporting the "new view", with an increase in labor demand at automating firms.

3. A survey of the empirical evidence from the recent literature

Early analyses hypothesized an increase in technological unemployment (Keynes, 1930; Leontief, 1952; Lucas & Prescott, 1974), however they lacked empirical support. A next generation of studies were able to confront theoretical models with data. Their analyses have been primarily conducted at the national or industry level and have mostly conveyed the idea of automation having a negative impact on aggregate employment and aggregate wages: automation is primarily reducing labor demand. Yet these analyses fall short of describing the process that goes on within firms. It is only over the past few years, thanks to the increasing availability of new firm-level datasets, that analyses of the effects of automation on employment could be performed at a more disaggregated level.

In this section, we provide an overview of the recent empirical literature on automation and employment. As our literature survey illustrates, the profession has evolved from the more "negative" view of automation as primarily destroying jobs, towards the more "positive" view of automation as enhancing productivity, market size, and therefore labor demand and employment.

a. Mixed evidence from research designs using variation across industries and labor markets

How should automation be measured? Until recently, the number of reliable sources on which empirical analyses of automation could be built was limited.[6] But since the 2010s, the International Federation of Robotics (IFR) has provided data on the deployment of robots by country and industry, and machine learning algorithms have made it possible to measure automation using text analysis of patents. Therefore, recent papers notably investigate these new measures of automation, that is, the number of robots (Autor & Dorn, 2013; Acemoglu & Restrepo, 2020; Cheng et al., 2019; Dauth et al., 2021; Graetz & Michaels, 2018), or automation-related patents (Mann and Püttmann, 2017; Webb, 2020).

As regards the first measure based on IFR data, Graetz & Michaels (2018) use the robot aggregate count from IFR data on a panel of seventeen developed countries and find no effect of automation on aggregate employment, despite a reduction of the low-skilled workers' employment share. Meanwhile, they show that robot densification is associated with increases in both total factor productivity and wages, and with decreasing output prices. Using the same measure on a panel of fourteen European countries, Klenert et al. (2020) find that robot use is correlated with an increase in total employment.

However, the empirical findings in Acemoglu and Restrepo (2020) suggest that the job destruction effect of robotization dominates. More precisely, the authors analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US labor markets. Using variation in robot adoption between commuting zones they estimate the labor market effects of robots by regressing the local change in employment and wages on the local exposure to robots.[7] The authors find that one more robot per thousand workers reduces the employment to population ratio by about 0.2 percentage point and wage growth by 0.42%, while productivity increases and labor share decreases. According to their estimates, each robot installed in the US replaces six workers. The Acemoglu-Restrepo methodology has been applied to several other countries. Chiacchio et al. (2018) find a displacement effect between three and four workers per robot in six European countries, but do not point to robust and significant results for wage evolution. Aghion et al. (2019) find a displacement effect of ten workers per robot using French administrative data. However, using German data, Dauth et al. (2021) report a null effect of exposure to robots on aggregate employment. For low- and mid-skilled workers, they report lower wages.

Attractive as it may be, this methodology based on aggregate robot count has some shortcomings. First, a robot is a specific type of automation that is precisely designed to replace human work, whereas broader measures of automation may encompass machines that only partially substitute for human work. Another concern stems from the fact that IFR data are available only at the country level. Computing a local measure of exposure to robots – a Bartik measure – requires making the strong hypothesis that the number of robots installed by a given industry, divided by the importance of the industry in the commuting zone, is the same across commuting zones. Yet, robotization by a given industry may be more intense in commuting zone A than in commuting zone B even if the shares of that industry are the same in both regions. Furthermore, the IFR data is only available for 13 industries within manufacturing, making it difficult to add a large set of industry-level controls without overfitting and thus raising the possibility that variation in automation rates across industries may be correlated with industry-level unobservables affecting labor demand (e.g., initial skill composition may vary across industries with differing rates of automation). A final potential concern is that variations in the robots exposure index across commuting zones are mostly related to the spatial distribution of automotive activities over the US territory in 1990, since industrial robots are predominant in the automotive industry – automotive robots account for more than one-third of total robots.

Another privileged measure of automation, based on text analysis of patents, also yields mixed results. For instance, Webb (2020) uses a measure of automation that relies on the overlap between patent texts and workers' tasks.[8] This measure is applied to two historical case studies, software and industrial robots. Webb highlights the displacement effect: jobs that were highly exposed to previous automation technologies saw declines in employment and wages over the relevant periods. However, the results of Mann and Püttmann (2017), who also measure automation using patent texts, paint a different picture.[9] Linking automation patents to industries and local labor markets, they find a positive effect of automation on employment.

Whether it be the robot count or the patent measure, the aggregate measures of automation/robotization at the country or industry level provide inconclusive evidence. Cross-country or industry-level research designs make it difficult to isolate a clear causal link between automation and employment. Firm-level research, that has grown recently, sheds new light on this issue.

b. Firm-level research designs provide causal evidence supporting the "new view"

A number of recent studies using firm-level data supports the prediction a direct positive effect of automation on employment in automating firms: in France (Acemoglu et al., 2020, Aghion et al., 2020), in the Netherlands (Bessen et al., 2019), in the United Kingdom (Chandler and Webb, 2019), in Canada (Dixon et al., 2019), in Denmark (Humlum, 2019), and in Spain (Koch et al., 2021). Table 2.2 reports the order of magnitude of employment (and wage) elasticities to automation at the firm-level from these recent papers.

This positive effect may reflect either a net creation of jobs by automating firms or lower separation rates by these firms. Several of these studies provide quasi-experimental evidence to establish that automation *causes* an increase in employment at the firm level. In the next section, we describe the methodology in detail, focusing on our own empirical work on automation and employment at the plant and firm levels.

Thus, the "negative" story faces difficulties when confronted by firm-level data. At odds with the predictions of the "pessimistic" story, most of the previously-mentioned studies do not find evidence of a falling equilibrium wage nor of a declining labor share (e.g., Bessen et al., 2019; Dixon et al., 2019; Humlum, 2019; Koch et al., 2021; Aghion et al., 2020).

Babina et al. (2020) bring out a similar result with firm-level investment in AI technology. Firms that invest more in AI experience faster growth in sales and

Table 2.2 Recent Estimates of Effects of Automation on Firm-level Employment and Wages

Authors	*Country and Time Period*	*Measure of Automation*	*Method*	*Impact on Firm-Level Employment*	*Impact on Firm-Level Wages*
Acemoglu, Lelarge, and Restrepo (2020)	France 2010–2015	Robot adoption by firms (versus non robot adoption)	OLS	Increase in hours worked for robot adopters between + 5.4 % (employment weighted estimates) and 10.9 % (unweighted estimates)	+0.9 % (unweighted estimates), non significant (employment weighted estimates)
Aghion, Antonin, Bunel, & Jaravel (2020)	France 1994–2015	Automation: machines stock	Event study, IV	Elasticity between 0.2 (OLS) and 0.4 (IV)	N/A
Bessen, Goos, Salomons, & van den Berge (2019)	Netherlands, 2000–2016	Automation "spikes" using automation expenditures (all automation technologies)	Event study	Automating firms have 1.8 to 2% higher employment compared to non automating firms	Not significant
Dixon, Hong, and Wu (2019)	Canada, 1996–2017	Robot capital stock (imports of robotics hardware and robot purchases)	Event study	Elasticity of firm employment to robot capital stock in the [0.7–2]% interval	N/A
Koch, Manuylov, and Smolka, (2021)	Spain, 1990–2016	Robot adoption	Event study	4-year elasticity to robot adoption: 10%	Not significant

Source: cited papers.

employment both at the firm- and industry-levels. AI allows the expansion of the most productive firms *ex ante*: they grow larger, gain sales, employment and market share. The authors report a null effect on productivity in the short run, perhaps because of the novelty of AI technologies, which are not fully mastered by workers.

Overall, these studies support the view that automation inside a firm fosters greater labor productivity. It drives quality-adjusted prices down for consumers[10] and increases product demand and market share of the firm, which can result in net job growth. Provided that demand is elastic enough to prices, then growth in demand will offset job losses.[11] The increase in the market share will only last until markets become saturated (Bessen, 2019). As Autor (2015) states it, "journalists and even expert commentators tend to overstate the extent of machine substitution for human labor and ignore the strong complementarities between automation and labor that increase productivity, raise earnings, and augment demand for labor."

Firm-level results are not directly informative about the impact of automation on labor demand at the aggregate level. For example, the productivity effect may contribute to the crowding-out of non-automating firms by automating firms. Since the productivity effect inside the automating firms generates an increase in product demand, the market share of these firms goes up at the expense of its non-automating competitors. Empirically, firms whose competitors adopt robots experience significant declines in value added and employment (Acemoglu, 2020; Aghion et al., 2020; Koch et al., 2021). For example, Koch et al. (2021) find that robot-adopting firms create new jobs and expand the scale of their operations, while non-adopters incur negative output and lose employment because of tougher competition with high technology firms.[12]

Thus, drawing on different measures of automation, different countries, and various time periods, recent micro studies consistently point to the importance of the productivity effect, with positive employment effects within automating firms and potential displacement effects across firms.

c. Which workers benefit or lose from automation?

Separate from the debate about the impact of automation on overall labor demand, there is a debate about the types of jobs that are created or destroyed and the distributional effects of automation. The economics literature has long considered technological change to be labor augmenting and favorable to skilled workers. In the wake of the IT and computer revolution in the 1990s, research has investigated the skill bias of technological progress. This hypothesis indeed supported the idea of complementarity between technology and skilled workers (see Acemoglu & Autor, 2011, for an overview). Technological change would result in the polarization of the job market, i.e., the slower increase in mid-wage occupations compared to both high-wage and low-wage occupations.

In the 2000s, following the critique of Card & DiNardo (2002), and the seminal paper of Autor et al. (2003), the labor-replacing view of automation for routine tasks has become prevalent. According to this idea, automation replaces routine jobs, and creates more demand for non-routine jobs that cannot be performed by machines. Several studies have documented the decline in manufacturing and routine jobs (Autor et al., 2003; Jaimovich & Siu, 2012; Autor & Dorn, 2013; Charnoz & Orand, 2017; Blanas et al., 2019).

Coming back to firm-level studies, some of them highlight a reallocation of workers between occupations (Bessen, 2019; Bonfiglioli et al. 2020; Humlum, 2019; Acemoglu et al., 2020). Humlum (2019) notably reports a shift from low-skilled to high-skilled workers in Denmark: labor demand shifts from production workers toward tech workers, such as skilled technicians, engineers, or researchers. In the same vein, Bonfiglioli et al. (2020) show that robot imports by French firms increase productivity along with the employment share of high-skill professions. Similarly, Bessen (2019) shows that computer automation causes growth in well-paid jobs and decreases in low-paid jobs. Using Canadian data, Dixon et al. (2019) document a polarization effect: investments in robotics are associated with shrinking employment for mid-skilled workers, but with increasing employment for low-skilled and high-skilled workers, notably managerial activities. This shift from low-skilled to high-skilled workers may also contribute to boosting measured productivity (Humlum, 2019; Acemoglu et al., 2020).

Yet, some studies do not find any reallocation effect between different types of workers and occupational categories (Aghion et al., 2020). This could be explained by a reallocation effect within jobs, since automation technologies generally do not replace entire jobs but only a certain number of tasks (Acemoglu and Autor 2011). Some human skills may become more valuable than ever in the presence of machines (Brynjolfsson & McAfee, 2011). Automation may thus lead to a restructuring of the task content of different jobs "within worker" (Aghion et al., 2020), enhancing labor productivity and employment, but without any change in the skill structure of firm's labor force.

This is precisely the issue that Arntz et al. (2017) raise when they question Frey and Osborne's (2017) analysis on the future of AI. Frey and Osborne (2017) tried to forecast the probability of computerization of 702 jobs and concluded that 47% of employment in the US was at risk of automation in the next ten or twenty years, while only 33% of jobs had a low risk of automation. But their analysis disregards the task content of jobs. Arntz et al. (2017) show that, when factoring in the heterogeneity of tasks within occupations, only 9% of all workers in the US face a high risk of automation.

4. Recent empirical evidence from France

We illustrate the main points from the preceding literature review using French data, drawing from our recent work (Aghion et al., 2019, 2020). We first show that labor market level analysis using IFR data provides mixed support in favor of the negative view. Second, we show that firm level and plant level analyses using alternative measures of automation provide quasi-experimental evidence supporting the second view. We present the methodology and main results from our existing work, as well as novel complementary specifications.

a. Labor market level analysis using IFR data

Aghion et al. (2019) reproduce the method developed by Acemoglu and Restrepo (2017, hereafter AR) using French data over the 1994–2014 period, analyzing the impact of increased robotization on employment at the aggregate employment zone level.[13]

To measure exposure to robots at the labor market – defined as commuting zone – level, AR built a local exposure index, which combines two elements: (i) the number of robots per worker in each of industry on the one hand and (ii) the pre-existing share of employment in industry i for a given commuting zone c. Thus, this local exposure index exploits the initial heterogeneity in industry employment structures across commuting zones to distribute cross-industry variation in the stocks of robots in the various industries, observed nationwide during the sample period. More formally, the increases in robot exposure at the commuting zone level is defined as:

$$\textit{US robot exposure}\ 1993-2007_c = \sum_{i\in I} l_{ci}^{1990}\left(\frac{R_{i,2007}^{US}}{L_{i,1990}^{US}} - \frac{R_{i,1993}^{US}}{L_{i,1990}^{US}}\right)$$

where the sum is over all the 19 industries i in the IFR data; l_{ci}^{1990} stands for the 1990 share of employment in industry i for a given commuting zone c; R_i and L_i stand for the stock of robots and the number of people employed in a particular industry i.

Keeping with AR, Aghion et al. (2019) measure the increase in robot exposure in a French employment zone[14] between 1994 and 2014 as:

$$\textit{Robot exposure}\ 1994-2014_c = \sum_{i\in I} \frac{L_{ic,1994}}{L_{c,1994}}\left(\frac{R_{i,2014}}{L_{i,1994}} - \frac{R_{i,1994}}{L_{i,1994}}\right)$$

where $L_{ic,1994}$ refers to employment in the employment zone c in industry i in 1994, $L_{c,1994}$ refers to employment in employment zone c in 1994, and $L_{i,1994}$ refers to employment in industry i in 1994. $R_{i,1994}$ and $R_{i,2014}$ respectively stand for the total number of robots in industry i in 1994 and 2014. This index reflects the exposure to robots per worker between 1994 and 2014. The outcome variable of interest is the evolution of the employment-to-population ratio between 1990 and 2014.

In the baseline OLS specification, we study the impact of exposure to robots on the evolution of employment-to-population ratio. Then we add controls such as an exposure index for information and communication technologies (ICT) $TICExp_r$, built in a similar way as the exposure to robots index and an international trade exposure index *TradeExp* to China and Eastern Europe. In some regressions, we also add a vector X_c of control for the employment zone c: demographic characteristics, manufacturing shares, broad industry shares, broad region dummies, and specific industry shares within manufacturing. The identification assumption is that, conditional on this set of controls, industries that are exposed to an increase in the rate of automation are not simultaneously affected by unobserved shocks to labor demand or labor supply.[15] We can write:

$$\Delta \frac{L_{c,1994}}{Pop_{c,1994}} = \alpha + \beta_1 RobotsExp_c + \beta_2 TradeExp_c + \beta_3 TICExp_c + \gamma X_c + \epsilon_c$$

To measure the impact of exposure to robots on local labor markets, the strategy adopted is similar to the one initiated by Autor et al. (2013): the observed change in robot exposure in U.S. industries is instrumented with changes in robot exposure in the same industries in other developed economies. This approach helps address U.S.-specific threats to identification affecting the OLS approach: one may imagine a shock, which we do not capture in our controls, but which may impact both the installation of robots and local labor markets dynamics. Following AR, the stocks of robots in industries from other developed countries (Germany, Denmark, Spain, Italy, Finland, Norway, Sweden, and the United Kingdom) are used to build other indexes of exposure to robots. These new indexes are then used to instrument the exposure index built on the French stock of robots.

In this shift-share IV research design, identification arises from the heterogeneity in robotization shocks across industries, which is projected to the regional level. Identification stems from the robotization shocks $\frac{R^{US}_{i,2007}}{L^{US}_{i,1990}} - \frac{R^{US}_{i,1993}}{L^{US}_{i,1990}}$ and $\frac{R_{i,2014}}{L_{i,1994}} - \frac{R_{i,1994}}{L_{i,1994}}$. Indeed, as described in Borusyak et al. (2021), the employment shares l^{1990}_{ci} are not tailored to exposure to robotization: they are "generic", in that they could conceivably measure an observation's exposure to multiple shocks, both observed and unobserved. Accordingly, it is important to control for industry-level characteristics that may contaminate the industry-level identifying variation, such as whether an industry belongs to manufacturing. Absent such controls, we would conflate the potential effects of robotization with broad sectoral trends.[16]

Table 2.3 displays the results of the OLS estimation. This table shows a negative correlation between exposure to robots and change in employment-to-population ratio. However, we observe that the level of significance decreases as more controls are added. Significance is lost in column (5) once a control for the local manufacturing industry share is included and the point estimate falls substantially, indicating that broad sector trends play an important role. The correlation is marginally significant in column (6) and non-significant in columns 7 through (10), where we add several types of controls simultaneous or exclude the commuting zones with the highest exposure to robots.

In the instrumental variable regression shown in Table 2.4, the coefficients of robot exposure are significant when we consider broad controls from columns

Table 2.3 Effect of Robot Exposure on Employment-to-Population Ratio, 1990–2014, OLS Estimates

	Dependent Variable: Change in Employment-to-Population Ratio 1990–2014 (in %-age Points)									
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Robots Exposure$_{1994–2014}$	–1.090***	–0.749***	–0.594**	–0.515**	–0.169	–0.549*	–0.398	–0.430	–1.074	–1.035
	(0.253)	(0.263)	(0.239)	(0.243)	(0.239)	(0.294)	(0.244)	(0.324)	(0.768)	(0.783)
TIC Exposure$_{1994–2014}$		–3.099*	–2.397	–2.495*		–0.304	–0.165	–0.154	1.519	1.493
		(1.586)	(1.594)	(1.455)		(1.620)	(1.576)	(1.588)	(1.641)	(1.648)
Trade Exposure$_{1994–2014}$		–0.743***	–0.690***	–0.825***		0.0857	–0.123	–0.124	0.200	0.201
		(0.247)	(0.215)	(0.239)		(0.243)	(0.278)	(0.280)	(0.335)	(0.337)
Demographics			Yes				Yes	Yes	Yes	Yes
Region dummies				Yes			Yes	Yes	Yes	Yes
Manufacturing industry share					Yes	Yes	Yes	Yes	Yes	Yes
Other broad industry shares						Yes	Yes	Yes		
Specific manufacturing industry shares									Yes	Yes
Remove highly exposed areas								Yes		Yes
Observations	297	297	297	297	297	297	297	295	297	295
R-squared	0.058	0.090	0.198	0.205	0.174	0.249	0.407	0.406	0.409	0.408

Source: Data from Aghion et al. (2019).

Notes: Demographics control variables are population share by level of education and population share between 25 and 64 years old. Other broad industry shares cover the share of workers in agriculture, construction, retail, and the share of women in manufacturing in 1994. Specific manufacturing industry shares cover the share of workers in automotive, rubber, food, and the share of women in manufacturing in 1994. Broad region dummies refer to the 13 metropolitan regions of France. Highly exposed areas are Poissy and Belfort-Montbéliard-Héricourt. Robust standard errors in parentheses. Levels of significance: *** p < \$0.01, ** p < \$0.05, * p < \$0.1. Sources: IFR, COMTRADE, EUKLEMS, DADS, Census data.

Table 2.4 Effect of Robot Exposure on Employment-to-Population Ratio, 1990–2014, IV Estimates

	Dependent Variable: Change in Employment-to-Population Ratio 1990–2014 (in %-age Points)									
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Robots Exposure$_{1994–2014}$	–1.317***	–1.010***	–0.974***	–0.737**	–0.389	–0.790***	–0.686***	–0.986***	–1.305	–1.221
	(0.325)	(0.322)	(0.271)	(0.296)	(0.248)	(0.300)	(0.241)	(0.351)	(0.799)	(0.812)
TIC Exposure$_{1994–2014}$		–2.569	–1.699	–2.094		–0.176	–0.0323	0.101	1.590	1.547
		(1.618)	(1.578)	(1.444)		(1.590)	(1.518)	(1.538)	(1.601)	(1.609)
Trade Exposure$_{1994–2014}$		–0.670***	–0.589***	–0.773***		0.110	–0.0922	–0.0882	0.198	0.199
		(0.242)	(0.211)	(0.230)		(0.240)	(0.276)	(0.279)	(0.322)	(0.323)
Demographics			Yes				Yes	Yes	Yes	Yes
Region dummies				Yes			Yes	Yes	Yes	Yes
Manufacturing industry share					Yes	Yes	Yes	Yes	Yes	Yes
Other broad industry shares						Yes	Yes	Yes		
Specific manufacturing industry shares									Yes	Yes
Remove highly exposed areas								Yes		Yes
Observations	297	297	297	297	297	297	297	295	297	295
First-stage F-statistic	57.2	42.6	45.8	46.0	32.6	28.7	35.1	18.9	16.5	16.3
R-squared	0.055	0.087	0.193	0.203	0.172	0.248	0.405	0.400	0.409	0.408

Source: Data from Aghion et al. (2019).

Notes: Demographics control variables are population share by level of education and population share between 25 and 64 years old. Other broad industry shares cover the share of workers in agriculture, construction, retail, and the share of women in manufacturing in 1994. Specific manufacturing industry shares cover the share of workers in automotive, rubber, food, and the share of women in manufacturing in 1994. Broad region dummies refer to the 13 metropolitan regions of France. Highly exposed areas are Poissy and Belfort-Montbéliard-Héricourt. Robust standard errors in parentheses. Levels of significance: *** p$ < $0.01, ** p$ < $0.05, * p$ < $0.1. Sources: IFR, COMTRADE, EUKLEMS, DADS, Census data.

(1) to (4). Column (1) begins with a regression without any control and finds a negative effect: one more robot per 1000 workers leads to a drop in the employment-to-population ratio of 1.317 percentage point. Column (2) adds controls for ICT and imports exposures and the magnitude remains the same. Then, columns (3) and (4) successively test the impact of demographic characteristics and broad region dummies, leaving the results almost unaffected. In column (5), adding a control for the manufacturing share alone is sufficient to lose significance and substantially reduce the point estimate. The result highlights again the importance of controlling for broad industry trends, as emphasized by Borusyak et al. (2021).

Combining different sets of controls, the specifications in columns (6) through (8) deliver negative and statistically significant IV estimates. In columns (9) and (10), we replace broad industry shares controls by controls for specific industry shares within manufacturing at the commuting zone level. Specifically, we control for the three 2-digit industries that have the highest number of robots at the end of the period and that account for 74% of the total number of robots in 2014: automotive, rubber, and food industries. These are key industries relative to the construction of the index. The coefficients remain large and negative; they become non-significant as these controls lead to larger standard errors.

Thus, the OLS and IV evidence from IFR data at the industry level suggest that there is a negative impact of robots on labor demand, although the results are sensitive to the choice of controls due to the small number of industries that are used as the source of identifying variation. Furthermore, the finding of a negative or non-significant effect of robotization on employment at the aggregate employment zone level could be consistent with either the "new view" or "old view" on automation and employment. Indeed, this result could reflect either the fact that robotizing firms destroy jobs and that this direct effect is not fully offset by the counteracting general equilibrium effect working through wage reduction and the resulting entry of new activities; or the fact that the positive market size effect of automation at the firm level is more than offset by the job destruction in the non-automating firms that are partly or fully driven out of the market by the automating firms. To alleviate the limitations of the research design and find out more about which of these two stories applies, we need to move to a more disaggregated analysis of the effect of automation on employment.

b. Firm-level and plant-level analyses

In Aghion, Antonin, Bunel, and Jaravel (2020), henceforth AABJ, we use three complementary measures as proxies for automation at the firm level and plant level. At the firm level, we use the balance sheet value of *industrial equipment and machines* in euros, which is available for all French firms between 1995 and 2017. This type of capital is defined as "the equipment and machines used for the extraction, processing, shaping and packaging of materials and supplies or for carrying out a service" (industrial machines) and "instruments or tools that are added to an existing machine in order to specialize it in a specific task" (industrial equipment). Within the manufacturing sector, this type of capital accounts for 59% of total capital. Our second measure of automation follows the Encyclopaedia Britannica (2015), which defines automation technology as a "class of electromechanical equipment that is relatively autonomous once it is set in motion on the basis of predetermined instructions or procedures".[17] For the manufacturing sector, the French statistical office (Insee) records electricity consumption for motors directly used in the production chain (motive power) since 1983. It distinguishes motive power from other potential uses of electricity such as thermic/thermodynamic or electrolysis. Thus, we are able to proxy automation by motive power, which excludes heating, cooling, or servers uses. Our third measure, also available at the firm level, uses the annual imports of industrial machines by all French firms between 1995 and 2017. Following the spirit of the previous definition of *industrial equipment and machines*, we track all the HS6-products that belong to this definition. It includes 489 different types of machines that relate to the manufacturing industry and automation. In particular, it excludes computers and IT capital, printers, elevators, etc.

In AABJ, we perform two types of event studies: (i) "extensive margin" event studies at the firm level, exploiting the timing of the large investment in industrial equipment and machines for each firm as an automation event, and (ii) distributed lead-lag analysis at the firm and plant level that allows for delayed responses to changes in automation and takes into account continuous changes in the stock of machines.

Our main finding from the event studies is that the impact of automation on employment is positive, and in fact increases over time: namely, a 1% increase in automation in a plant today increases employment by 0.2% immediately and by 0.4% after ten years. Results are similar at the firm level. In other words, conditional on surviving, automation leads to a net increase in employment by automating firms and plants. The event studies also show that automation also translates into an increase in a firm's total sales in the years following automation. The effect remains stable from year of investment in automation to eight years after.

A potential concern is the endogeneity of firm choices of automation. For instance, automation could be the result of a corporate growth strategy following a demand shock. However, the event studies show no sign of pre-trend: conditional on the controls included in the specification, plants that automate more at time t were on a comparable employment path in prior years and start diverging afterwards. This restricts the potential set of confounders that could explain the increase in employment – confounding shocks need to occur simultaneously to the increase in automation. To further alleviate the endogeneity concern, we examine the stability of the estimates when including more stringent time-varying controls, notably 5-digit-industry by year fixed effects and firm-year fixed effects. The specification with firm-year fixed effects only exploits variation in automation across plants within the same firm, controlling for all time-varying demand and supply shocks at the firm level. We find that the estimates remain stable, which further restricts the set of confounders (which must operate across plants within the same firm in the same year).

All these findings speak to a "productivity" effect of automation, in line with the "positive view" spelled out in the previous section: namely, firms that automate more become more productive. This enables them to obtain larger market shares because their products offer consumers better value for money than their competitors. The resulting gain in market share prompts those firms that automate to produce at a larger scale, and therefore to hire more employees.

In AABJ, we also consider the effect of automation on wages inequality within firms. More specifically, we study its effect on the evolution of the ratio between low-skilled workers' mean hourly wage and high-skilled workers' mean hourly wage. Figure 2.1 reports the results: we observe no differences in terms of evolution between these two types of workers.

Note however that the event study research design does not fully address potential correlated demand and supply shocks that could occur exactly at the same time as the increase in automation. Thus, in order to estimate the causal effects of automation on employment, sales, wages, and the labor share across firms, we use a shift-share design.

In fact, the ideal design would randomly assign purchasing prices for machines across firms. In AABJ, our idea is to approximate this hypothetical experiment using a shift-share instrument, which leverages two components: (i) the time variation in the implicit cost of imported machines over time across international

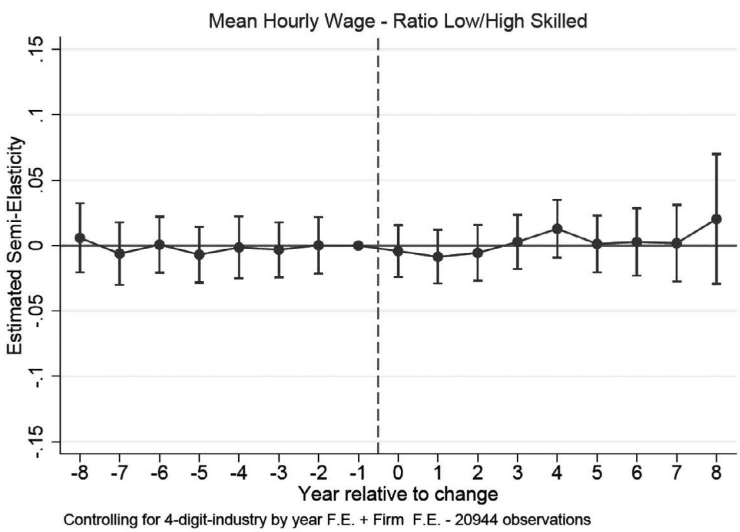

Figure 2.1 Firm-Level Event Study of Automation on Hourly Wage Ratio between Low- and High-Skilled Workers.

Source: reproduced using AABJ data.

trading partners (the "shift" component); and (ii) the heterogeneity in pre-existing supplier relationships across French firms (the "exposure shares" component). The ideal "shock" variable would be the expected quality-adjusted price of imported machines by French manufacturing firms. However, we cannot directly observe these prices; that is why, instead, we infer changes in quality-adjusted price from changes in export flows of these foreign machines.

The intuition behind the shift-share instrument is that firms will be differentially exposed to these changes in quality-adjusted price of machines from different trading partners due to their sticky pre-existing relationships. For instance, if two French firms A and B import respectively 80% and 20% of their machines from Italy, and machines produced in Italy suddenly have a better quality-adjusted price, firm A will have more incentives to automate than firm B due to its strong established relationship with Italian suppliers of machines.

The estimates of the impact of automation on employment using the shift-share instrument are in line with the previous findings from the event studies. The elasticity of firm employment to automation that we find ranges between 0.397 and 0.444 on a five-year horizon (Table 3A of AABJ), significant at the 5% or 1% level depending on the set of controls, and the first stage F-statistic remains close to 10 in all specifications.

Next, we conduct the same exercise with sales and the labor share at firm level. We find that sales increase in response to increased automation, with elasticities ranging from 0.395 to 0.512 (Table 3B of AABJ) across specifications. Using the same specifications, we cannot reject the hypothesis that there is no impact of automation on the labor share, which in turn suggests that the productivity effect may offset the task substitution channel in a way that leaves the labor share unchanged at the firm level.

One can also look separately at specific industries. Particularly interesting is the automobile industry, which accounts for the vast majority of industrial robots. We still find a positive effect of automation on employment at the firm level, considering as treated the top 25% of firms in terms of biggest investment in industrial machines (Figure 2.2). Thus, even in an industry for which industrial robots are a non-negligible share of machines, the relation between automation and employment remains positive.

What happens when we move from firm or plant level to industry level? Using a shift-share design, AABJ find a positive effect of automation on employment also at the industry level, with point estimates ranging from 0.558 to 0.620 across specifications. This again speaks to the importance of the productivity effect: manufacturing industries are integrated into international trade. Therefore French firms that automate expand their export market at the expense of foreign firms. This in turn explains why the productivity effect is the dominant effect even at the industry level, as it is mostly foreign firms in foreign markets that suffer from the resulting business stealing. In a closed economy, domestic non-automating firms would suffer from the business-stealing by the automating firms; the increase in employment in automating domestic firms would be more likely to be counteracted by job destruction in non-automating domestic firms.

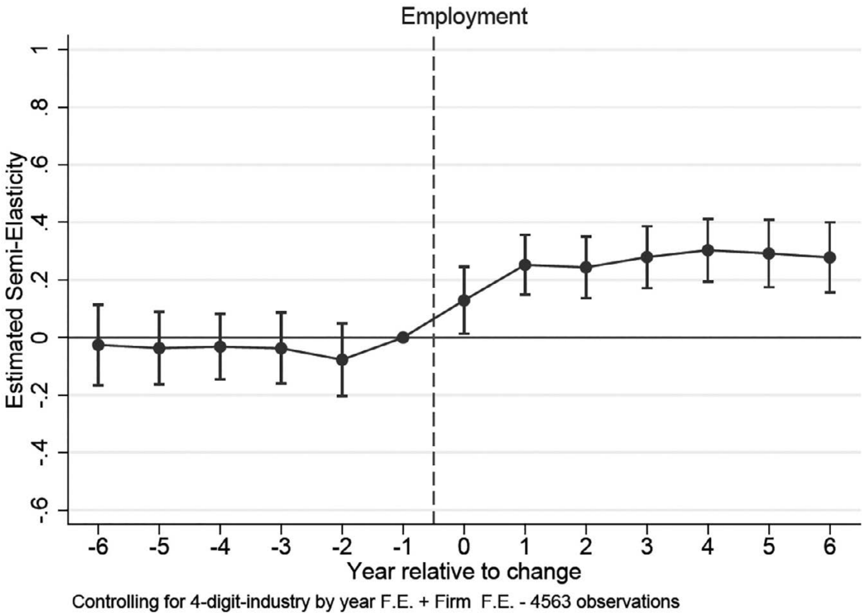

Figure 2.2 Firm-Level Event Study of Automation on Employment in the Automotive Industry

Source: Data from AABJ data.

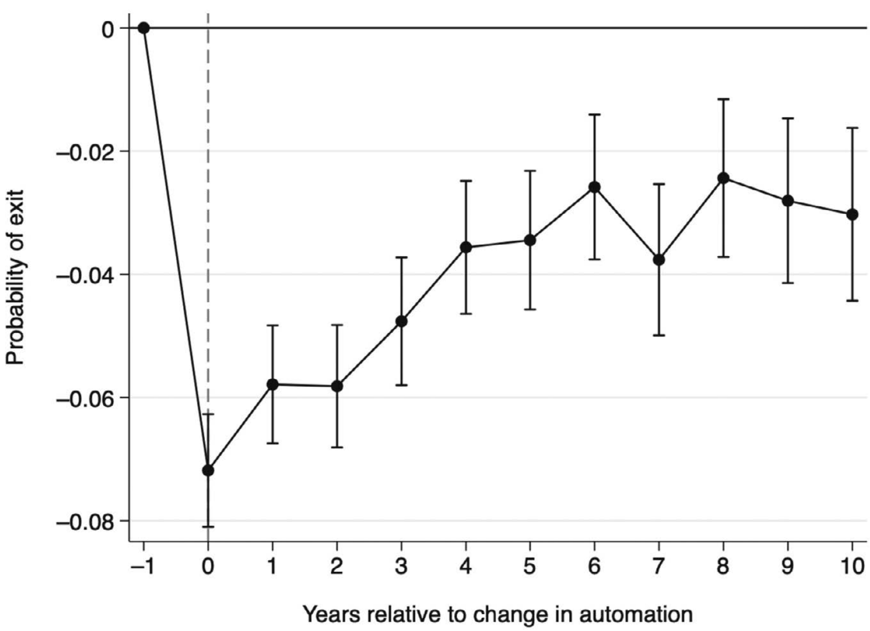

Figure 2.3 Effect of a Substantial Investment in Industrial Equipment on Probability of Firm Exit.

Source: Data from AABJ (2020).

Figure 2.3, which is a novel result using data from AABJ, illustrates this business-stealing – or eviction – effect: firms that invest significantly in new industrial equipment substantially lower their likelihood of going out of business over the following ten years compared to firms that do not make such an investment.

5. Conclusion

In this chapter, we relied on both the existing literature and our own empirical work to discuss the effects of automation on employment. We pointed to two contrasting views on the subject. A first view sees automation as primarily destroying jobs, even if this may ultimately result in new job creations taking advantage of the lower equilibrium wage induced by the job destruction. A second view emphasizes the productivity effect of automation as the main direct effect: namely, automating firms become more productive, which enables them to lower their quality-adjusted prices and therefore to increase the demand for their products; the resulting increase in market size translates into higher employment by these firms. We provided direct empirical evidence supporting the second view in the case of France, and we showed that the empirical literature on automation and employment was also leaning in that direction in a broad set of countries.

Overall, automation is thus not in itself an enemy of employment. By modernizing the production process, automation makes firms more competitive, which enables them to win new markets and therefore to hire more employees in a globalized world.

We can think of several avenues for further empirical research on automation and the labor market. One would be to explore how automation interacts with outsourcing and international trade. Another avenue would be to distinguish between different types of sectors and industries. A third avenue would be to introduce the distinction between routine and non-routine jobs. A fourth avenue would be to refine the empirical analyses of the impact of automation on the distribution of wages at the firm level, industry level, and by skill groups. These and other extensions of the analyses surveyed in this chapter are promising directions for future research.

Notes

1 Keynes, "Economic Possibilities for Our Grandchildren."

2 In this model, a new (more complex) task replaces or upgrades the lowest-index task. The fact that the limits of integration run between $N - 1$ and N imposes that the measure of tasks used in production always remains at 1. Thus, an increase in N represents the upgrading of the quality (productivity) of the unit measure of tasks.

3 See Acemoglu et al. (2020), and Aghion et al. (2020).

4 We can draw a parallel between the productivity-enhancing effect of technological progress and the productivity-enhancing effect of offshoring highlighted by Grossman and Rossi-Hansberg (2008). In the offshoring process, when some

tasks can more readily be performed abroad, firms that use this type of labor intensively augment their profitability and expand at the expense of their competitors that rely on other types of labor. This is turn leads to an increase in their labor demand.

5 Based on a general static framework with a continuum of worker types, Costinot and Werning derive optimal tax formulas that depend on a small set of sufficient statistics that require relatively few structural assumptions.

6 Earlier studies used the measure of computers or IT as a proxy (Krueger, 1993; Autor et al., 1998; Bresnahan et al., 2002; Beaudry, Doms and Lewis, 2010; Michaels, Natraj and Van Reenen, 2014).

7 The local exposure to robots is an indirect measure of robot penetration at the local level – a Bartik measure – which is based on the rise in the number of robots per worker in each national industry on the one hand and on the local distribution of labor between different industries on the other hand.

8 Webb's measure relies on the following pattern: the text of patents contains information about what technologies do, and the text of job descriptions contains information about the tasks workers do in their jobs. These two text sequences are compared in order to quantify how much patenting in a particular technology has been directed at the tasks of a given occupation. A score is attributed to each task, and the task-level scores are aggregated at the occupation level in order to construct an automation exposure score for each occupation.

9 Mann and Püttmann classify patents as automation patents if their texts describe a device that carries out a process independently of human intervention. They match patents to the industries where they are likely to be used according to the patents' technology class and derive a measure of newly available automation technology at a detailed industry and commuting-zone level.

10 Aghion et al. (2020) provide direct empirical evidence on the response of consumer prices. Bonfiglioli et al. (2020) suggest that productivity gains from automation may not be entirely passed on to consumers in the form of lower prices.

11 For a discussion on the type of workers who benefit or lose from automation, see Section 3.c.

12 Koch et al. (2021) first focus on the adoption decisions of firms. They show positive selection, that is, firms that adopt robots in their production process are larger and more productive than non-adopters before adopting robots. They also show that, conditional on productivity, more skill-intensive firms are less likely to adopt robots, and that exporters are more likely to adopt robots than non-exporters.

13 AR analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US local labor markets. They find that one more robot per thousand workers reduces the employment to population ratio by about 0.37 percentage points and wage growth by 0.73 percent.

14 According to the official definition provided by Insee, an employment zone is a geographical area within which most of the labor force lives and works. It provides a breakdown of the territory adapted to local studies on employment.

15 The source of identifying variation is at the industry level and outcomes are measured at the level of local labor markets, as discussed in the recent Bartik identification literature (e.g., Adão et al., 2019 and Borusyak et al., 2021).

16 Note that this research design only speaks to the effects of automation on employment across local labor markets, using industry shocks as the source of variation. It cannot speak to the overall (country-level) macroeconomic effect of automation, which requires a model to account for reallocation of employment across industries and labor markets (e.g., Ngai and Pissarides 2007) or a source of variation at the country level.

17 Definition from Encyclopaedia Britannica (2015), "Automation".

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