ARTICLE IN PRESS

Research Policy xxx (xxxx) xxx

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Threats and opportunities in the digital era: Automation spikes and employment dynamics

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ARTICLE INFO

JEL classification:
D25
J23
L25
O33

Keywords:
Automation
Gross worker flows
Skills
Technological change

ABSTRACT

This paper investigates the change in worker flows (i.e. net growth, but also hiring and separation rates) around an investment in automation-intensive goods and, within firms, across occupational categories. Resorting to an integrated dataset encompassing detailed information on firms, their imports, and employer-employee data for French manufacturing employers over the period 2002–2015, we identify 'automation spikes' using imports of capital goods embedding automation technologies. Even after controlling for firms' non-random selection into automation, we find that automation spikes are linked to an increase in firms' contemporaneous net employment growth rate, jointly explained by a higher hiring rate and a lower separation rate. Furthermore, we find that automation spikes are not associated with significant changes in the composition of the workforce (in terms of 1-digit and 2-digit occupational categories, and routine-intensive vs. non routine-intensive jobs).

1. Introduction

Technology is presented in the policy debate either as a major threat to employment – reviving the concept of technological unemployment –, or as the main driver of societal change. Such mix of fear and excitement can be explained by the difficulty to catch-up with a moving target: quoting Schumpeter (1942, pp. 82–83), technological change feeds a process of 'creative destruction', which "incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one". New, 'digital' technological paradigms are currently emerging (such as the Internet of Things, additive manufacturing, and artificial intelligence; see Rindfleisch et al., 2017), and their development is widely regarded as able to bring about a Fourth Industrial Revolution. This, together with the globalisation of exchanges, requires all firms to rethink their production process so as to respond to higher levels of complexity and adaptability (Caliendo and Rossi-Hansberg, 2012).

Assessing how innovation affects employment has long been at the centre of economic debates, both in terms of the effects on the single person, i.e. how the changing working conditions affect the life of people, as well as on employment at a more aggregate level (Ricardo, Marx and Keynes all have discussed technological unemployment; for recent reviews, see Mokyr et al., 2015; Piva and Vivarelli, 2017).[1] Yet the extent and the manners through which digital technologies are expected to impact on work are much broader than in previous waves of innovations.

As a consequence, the type of jobs affected is much more diffused and difficult to identify. Previously, it was mostly manual jobs that were at risk of being replaced by a machine. Currently, all jobs that are rich in routine-intensive, highly codified tasks are exposed to the risk of being replaced (see, for instance, Autor, 2015; Autor et al., 2003; Goos et al., 2014). Moreover, this process is largely orthogonal to the traditional classification in blue versus white collar jobs (among the others, refer to Frey and Osborne, 2017; Furman and Seamans, 2019; Trajtenberg, 2018).[2]

Our work moves from two related hypotheses: i) automation

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[1] We refer to their works in Keynes (1932); Marx (1988); Ricardo (1891).

[2] In this respect, the distinction between codified and tacit knowledge, and its implication, as put forth in a vivid way by Polanyi (1967), has been very relevant in shaping the debate around the so-called skill-biased technical change (see among the many others Autor, 2014; Autor et al., 2003).

https://doi.org/10.1016/j.respol.2020.104137
Received 17 June 2019; Received in revised form 2 October 2020; Accepted 4 October 2020

happens in *spikes*; ii) those spikes may have heterogeneous effects on the different components of gross worker flows (hiring, separation, net growth rates) and across different types of workers. Hypothesis (i) is grounded on the fact that our automation variable shares many of the characteristics of investment in tangible assets. Moreover, even when considering other dimensions of automation, not related to investments, Bessen et al. (2019) have discussed that they share the same characteristics of lumpy investments, i.e. irreversibility and non-convex adjustment costs. Hypothesis (ii) is grounded on the fact that automation may induce a reorganization in the workforce, which could have different implications for separation and hiring rates. Patterns of hiring and separation rates are thus relevant to show the job creation/-destruction dynamics behind the net employment effect at the firm level.

Our work studies the impact of investment in automation on firm-level job creation and destruction and, within firms, across occupational categories. Our analysis focuses on French manufacturing firms over the period 2002–2015, and relies on two exhaustive and detailed data sources, namely DADS (*Déclaration Annuelle de Donnés Sociales*), an employer-employee dataset from the French National Statistical Office (INSEE), and the transaction-level international trade dataset by the French customs office (DGDDI), which we employ to identify imports of automation-intensive capital goods based on the taxonomy employed by Acemoglu and Restrepo (2018). Notice that, given the currently available datasets, this is one of the few possibilities to assess the impact of digital and automation technologies at the firm level. This choice implies that we restrict our analysis to *importing* manufacturing firms (see Section 2.2.3 where we discuss some potential limitations of this approach). The richness of the data in our hand allows a highly detailed analysis, especially on the employment side. In particular, we are able to decompose firm growth into the contributions of hiring and separation; and to study patterns and dynamics for different types of workers.

Our work contributes to two, neighboring fields of literature. *First*, in more general terms, we provide a detailed empirical perspective of the magnitude and characteristics of the advent of the latest wave of innovations (see among the others, Dosi and Galambos, 2012; Roco and Bainbridge, 2003). Our investigation on the statistical properties of imports of goods embedding automation technologies reveals that such products display the same characteristics of capital goods, and most importantly their spiky nature that recalls the archetypal non-convexity of the costs related to capital adjustment (see among the many others Cooper and Haltiwanger, 2006; Doms and Dunne, 1998).[3] Indeed, similar to investment spikes, imports of capital goods embedding automation technologies are rare across and within firms, and each event represents a significantly high share of total investment within firms (Asphjell et al., 2014; Grazzi et al., 2016; Letterie et al., 2004). Our automation spikes therefore represent a significant disruption in the way firms produce, and we characterise their impact on the employment dynamics and structure of firms.

Second, more in detail, we contribute to the literature that investigates the impact of automation or robotisation on employment. To date, most of the evidence on this channel relies either upon indirect measures of occupations that can be impacted upon by technological progress (see, for example, the Routine Task Intensity (RTI) index approach used, among the others, by Autor et al., 2013 and Goos et al., 2014), or on measures of technological adoption related to the ICT services (as in Harrigan et al., 2020). The latter approach is to consider jobs related to STEM fields (Science, Technology, Engineering and Math), or, as identified by Harrigan et al. (2018, 2020), 'techies'. The latter authors show, using data on France, that the advent of techies led to occupational polarization (mostly driven by between firm changes), skill-biased productivity and increases in low-skill employment.

On the contrary, evidence on the direct effect of the most recent wave of automation technologies is scanter. To begin with, the impact of robotisation at an aggregate level is investigated in Dauth et al. (2018), Acemoglu and Restrepo (2020), Michaels et al. (2014), Graetz and Michaels (2018), and Klenert et al. (2020). Dauth et al. (2018) find no overall effect of the adoption of robots on German local labour markets, but highlight a reallocation effect from manufacturing to business services. Acemoglu and Restrepo (2020) find a negative effect of robots adoption on employment across commuting zones in US during the period 1990–2007; whereas in Graetz and Michaels (2018) robots are not found to decrease employment in a sample of countries and industries during the same period, and in Klenert et al. (2020) a positive relation between robot adoption and aggregate employment is found for the European Union in the period 1995–2015.[4]

Other works have instead focused on the impact of automation at the worker level. Using a yearly firm survey on automation costs over the period 2000–2016 in the Netherlands, Bessen et al. (2019) show that automation increases the probability of workers separating from their employers, especially for higher-skilled workers (corresponding to higher wages in their framework). Interestingly, they attribute this last result to workers voluntarily moving out of the firm after an automation event.

Few firm-level works have restricted their attention to the effects of robots. Koch et al. (2019), within a panel of Spanish manufacturing firms, find that robot adoption generates net job creation; Acemoglu et al. (2020), using a small sample of French firms that purchased industrial robots, show that employment increases faster within adopting firms, even if the overall market-level effect may be negative.

Our work, while building on these approaches and resorting to a similar definition of automation technologies as in Acemoglu and Restrepo (2018), moves a step further by focusing on the within-firm job creation and destruction effects of automation. Indeed, while the literature, starting from the seminal work of Davis and Haltiwanger (1990, 1992), has shown the relevance of focusing on gross job flows to study employment dynamics, not much is known about job flows at the firm level,[5] and in particular on the impact of technologies on them.

We start by showing that our chosen proxy to identify investment in automation-intensive capital goods displays analogous properties, especially non-convexity, to the variable that is generally employed to capture investment in capital-embodied technical change at large.

With this in mind, we first study the correlation between such spikes and worker flows before and after they happen, using a fixed-effect regression. Our findings show that firms investing in goods which are intensive in automation technologies do not display a negative trend in employment. On the contrary, automation spikes are positively correlated with preceding and contemporaneous growth in employment, which is mainly due to lower separation rates of investing firms. However, firms' probability to automate may not be random, but conditioned by prior performance and characteristics. Using a propensity score reweighting approach, which accounts for the different dynamics of automating firms before their spike, we show that automation robustly generates a contemporaneous net employment growth premium: the decision to automate therefore has a positive impact on firms' *own* employment. Note that such results are in tune with the evidence on investment in capital goods, irrespective of their technological content (Grazzi et al., 2016). Finally, automation spikes do not seem to affect

[3] Standard theoretical models of investment assumed convex costs of capital adjustments yielding a smooth process of investment over the years. More recent evidence from empirical works (see also Nilsen and Schiantarelli, 2003) have shown that the sequence of zeros and lumps is hardly compatible with a convex cost of capital adjustment. Further, due to irreversibilities in new equipment purchases, also disinvesting is very difficult and seldom observed.

[4] In turn, Michaels et al. (2014) document the job-polarization response to ICT technologies across industries and countries in the period 1980–2004, and show a relative increase of demand for high- versus middle-skills.

[5] But see, for firm level studies, Abowd et al. 1999; Bellon 2016, on France; and Moser et al. 2010, on trade.

shares of different types of workers within firms (1- and 2-digit occupational categories, and routine-intensive vs. non routine-intensive). These results do not change when performing several robustness checks (see Section 4.4).

The paper is structured as follows. Section 2 first presents the data and variables that are used in the following analysis and then shows descriptive statistics on the employment dynamics at the firm level. In Section 3, we provide evidence that imports of capital goods embedding automation technologies behave in a way consistent with an investment variable, and in particular they occur *in spikes*. Section 4 presents the results from the regression analysis of the relationship between automation spikes, and net and gross worker flows. We show findings both on aggregate (i.e. for all workers) and by separate occupational categories. Section 5 concludes.

2. Data and descriptive statistics

2.1. Sources

We employ data concerning French manufacturing firms with employees over the period 2002–2015. To construct our dataset, we merge different sources, using the unique identification number of French firms (SIREN). The starting point is the *Déclaration Annuelle de Donnés Sociales* (DADS), a confidential database provided by the French national statistical office (INSEE) and based on the mandatory forms that all establishments with employees must hand in to the Social Security authorities. In particular, we use the DADS *Postes* dataset, in which the unit of observation is the 'job' (*poste*), defined as a worker-establishment pair (and used with this meaning throughout this section).[6] We restrict our attention to manufacturing firms, identified as those whose reported main activity code (*Activité Principale Exercée*, APE) belongs to divisions 10 to 33 of the NAF rev. 2 classification (corresponding to the European NACE rev. 2).[7] As a firm's APE may vary across years, we assign each firm a permanent 2-digit sector based on the most frequent occurrence.[8]

DADS is then matched to other sources: first, the exhaustive transaction-level international trade dataset by the French customs office (*Direction Générale des Douanes et des Droits Indirects*, DGDDI), containing detailed information on import and export flows, among which trade value, country of origin/destination, and an 8-digit product code, expressed in terms of the European Union's Combined Nomenclature, an extension of the international Harmonized System (HS) trade classification. Then, we retrieve several firm-level variables (notably, physical assets, value added, foundation year) by matching DADS with FICUS and FARE, two confidential datasets, also provided by INSEE, based on the fiscal statements that all French firms must make to the tax authorities, which contain detailed balance-sheet and revenue-account data.[9]

2.2. Definitions

In what follows we explain how we construct the variables used in the analysis, on one side the gross employment flows (net growth, hiring and separation rates) and on the other side the automation variable.

2.2.1. Gross worker flows at the firm level

A major contribution of this study concerns the decomposition, at the firm level, of net employment flows into gross worker flows, in and out of the firm, i.e. *hirings* and *separations*. This is possible thanks to the use of worker-level data from the DADS *Postes* dataset. Each yearly issue of the latter contains information on all workers that are employed in that year (t), or were employed in the previous year (t-1); and, for each variable, it reports information at both t and t-1 (coded as missing in one year if the job is not present in that year). This structure is perfectly suitable for the identification of gross worker flows, defined by Davis and Haltiwanger (1999, p. 2717) as "the number of persons who change place of employment or employment status between t-1 and t".[10] Consistently with this definition, we identify a job as a *hiring* if it exists at time t but not at t-1; and as a *separation* if the contrary is true, i.e. if it exists at t-1 but not at t.[11]

Two qualifications should be added in this regard. The first is that we define worker flows as *one-year transitions* from December 31, of year t-1 to December 31, of year t. In other words, we do not count all events that occur during a year, but only compare the same point in time in two different years. This allows ignoring short-lived jobs and temporary fluctuations, due e.g. to seasonal dynamics.[12] The second qualification is that we only consider jobs labeled as 'principal' (*non-annexes*) by the INSEE, which exceed some duration, working-time, and/or salary thresholds.[13] These can be seen as the 'true' jobs that contribute to the production process (see e.g. INSEE 2010, p. 17), and account for the large majority (three-fourths) of total jobs.

Based on these definitions, we construct job-level indicators denoting principal jobs that are present on December 31 of years t and t-1 ($I_{j,t}$and $I_{j,t-1}$,respectively, where *j* indexes jobs, defined again as worker-establishment pairs).[14] We then aggregate this information at the firm level (a firm being identified with subscript *i*) and obtain employment stock and flow variables based on these job-level indicators. $Emp_{i,t}$ and $Emp_{i,t-1}$refer to total employment stocks in firm *i* in years t and t-1, respectively. A firm's hirings in year t ($H_{i,t}$) are obtained as the aggregation of jobs for which the job-level presence indicators are $I_{j,t} = 1$and $I_{j,t-1} = 0$; separations in year t ($S_{i,t}$) are all jobs for which $I_{j,t} = 0$and $I_{j,t-1} = 1$. Continuing employees are such that $I_{jt} = 1$and $I_{jt-1} = 1$and so they will be part of firm total employment at both t and t-1. Net employment change in year t is defined as the difference between the stock of employment at t and at t-1, and is also equal to the difference between hirings and separations:

[6] Establishments can be easily aggregated at the firm-level using their SIRET identification number, whose first nine digits correspond to the SIREN code.

[7] In the data, the APE code is expressed in terms of the NAF rev. 1 classification from 2002 to 2007, and in terms of the NAF rev. 2 classification since 2008. To ensure consistency over the observed time span, we establish a one-to-one mapping between the 4-digit classes of the NAF rev. 1 classification and those of the NAF rev. 2. To do this, we use the following criterion: if the majority of firms active in sector A (NAF rev. 1) in 2007 is active in sector B (NAF rev. 2) in 2008, then we map sector A into sector B. The few remaining ambiguous cases have been solved manually.

[8] In case more than one mode is present, we assign the code referring to the latest year.

[9] FARE is the successor of FICUS since 2008 and collects data from a larger set of tax regimes than FICUS. For details about the matching of FICUS and FARE with DADS, see Domini and Moschella (2018).

[10] Also see Davis and Haltiwanger (1992, p. 833).

[11] Notice that the reason for a separation (e.g. retirement, death, ...) is not stated in DADS *Postes*.

[12] This approach is followed, among others, by Abowd et al. (1999); Bassanini and Garnero (2013); Davis et al. (2006); Golan et al. (2007).

[13] To be classified as *non-annexe*, a job should last more than 30 days and involve more than 120 worked hours, with more than 1.5 hours worked per day; or the net salary should be more than three times the monthly minimum salary; else, it is classified as *annexe*.

[14] Although an indicator of presence on December 31, is available in DADS, starting from 2005, we build our own indicator and employ it in identifying worker flows. We do this for two reasons: the first is that the indicator from DADS is not available in the first years of our observation period; the second is to ensure a time-consistent treatment of the 'pay shift' phenomenon (*décalage de paie*). This refers to jobs for which working in year t runs from December 1, of year t-1 to November 30, of year t, rather than from January 1, to December 31, of year t. As pointed out by the INSEE (2010, p. 123, our translation), "the treatment of these pay shifts in DADS has changed over time. In order to have a period-consistent correction, you may correct just for the jobs with a negative starting date."

Table 1
Occupational categories and their share (%) in employment, 2002-2015.

		Average within-firm share	Aggregate share
1-digit categories			
CS3	Engineers, professionals, and managers	11.03	16.51
CS4	Supervisors and technicians	19.40	22.85
CS5	Clerical workers	12.70	7.44
CS6	Production workers	54.19	52.45
Total		97.33	99.25
2-digit categories			
CS37	Top managers and professionals	4.68	5.38
CS38	Technical managers and engineers (techies)	6.05	10.95
CS46	Mid-level managers & professionals	7.53	6.53
CS47	Technicians (techies)	7.75	11.76
CS48	Supervisors and foremen	3.41	4.24
CS54	Office workers	10.23	6.29
CS62	Skilled industrial workers	26.60	30.35
CS63	Skilled manual laborers	4.74	1.66
CS67	Unskilled industrial workers	17.04	15.28
Total		88.03	92.45

Notes: (i) values are calculated on our sample (see below) over the entire 2002–2015 period; (ii) shares do not add to 100 due to the existence of residual categories, not displayed, whose CS codes start by 2, such as artisans and shopkeepers. Source: our elaborations on DADS and DGDDI data.

$$\Delta Emp_{i,t} = Emp_{i,t} - Emp_{i,t-1} = H_{i,t} - S_{i,t} \quad (1)$$

Following Davis and Haltiwanger (1990, 1992), we express worker flows from t-1 to t as rates, normalizing the worker flows by firm size. To do so, we divide them by the average of employment in those two years, $Z_{i,t} = \frac{Emp_{i,t}+Emp_{i,t-1}}{2}$. The hiring, separation, and (net) employment growth rates to be used in our empirical analysis are then obtained as:

$$h_{i,t} = \frac{H_{i,t}}{Z_{i,t}}$$

$$s_{i,t} = \frac{S_{i,t}}{Z_{i,t}}$$

$$g_{i,t} = \frac{\Delta Emp_{i,t}}{Z_{i,t}} = h_{i,t} - s_{i,t}$$

2.2.2. *Types of workers*

We use different classifications of workers to identify the heterogeneous impact of automation technology on worker flows, namely 1-digit and 2-digit occupational categories, and routine-intensive versus non-routine intensive tasks (following the classification by Goos et al., 2014).

The first classification follows the structure of the French occupational codes, namely the *Catégorie Socio-professionelle* (CS). While this is strictly speaking an occupational taxonomy, which reflects the hierarchical structure within firms and the levels of management or 'production hierarchies' (see also Caliendo et al., 2015; Guillou and Treibich, 2019), it has also been employed as a measure of jobs' skill level in the empirical literature using French data, notably by Abowd et al. (1999), Biscourp and Kramarz (2007), and Harrigan et al. (2018, 2020). As illustrated in Table 1, we consider the largest 1-digit and 2-digit CS codes, which account for almost the entirety of workers in the firms of our sample (97-99% in the case of the 1-digit codes, 88–92% in the case of 2-digit ones). Notice that 2-digit categories 38 (Technical managers and engineers) and 47 (Technicians) are identified by Harrigan et al., 2020) as 'techies', i.e. workers who facilitate the adoption and use of new technology, and should therefore receive a particular attention in our analysis.

Furthermore, to better compare our results to the literature on job polarization, we match the French occupational classification to the international one in order to identify routine-intensive occupations. In order to do so, we use the toolbox developed in Falcon (2015) which allows to map the French occupational classification (*Professions et Catégories Socio-professionnelles*, PCS2003) into the International Standard Classification of Occupations (ISCO88). Then we use the Routine Task Intensity (RTI) measure, originally developed by Autor and Dorn (2013) and matched to the European ISCO classification by Goos et al. (2014), to obtain a RTI measure for each 4-digit occupation. We classify the set of occupations that are in the top RTI tercile in 2009 as routine task-intensive occupations, following Autor and Dorn (2013). Since the source includes 4-digit PCS2003 codes starting from 2009, this analysis only applies to the subperiod 2009–2015.

For the period 2002–2008, the occupational information is less precise: we have the CS classification, which corresponds to the first 2 digits of the PCS2003. In order to extend the analysis to the whole period, we classify a 2-digit occupation as a routine task-intensive occupation if the majority of its 4-digits subcategories are routine task-intensive according to the above criterion. Based on this procedure, two major 2-digits occupations are considered routine intensive: occupational categories 54 (office workers, the largest subcategory of clerical workers) and 67 (unskilled industrial workers, the largest subcategory of production workers). In this part of the analysis we leave category 48 (supervisors) out, as they are difficult to assign to a definite routine class.[15]

2.2.3. *Automation*

Data on the adoption of digital and automation technologies at the firm level is only recently starting to be collected by national statistical offices, and is not yet included in main innovation surveys such as the Community Innovation Survey. Notably, the Dutch statistical office (CBS) includes a question on automation costs in their national survey (see Bessen et al., 2019). Instead, trade flows reported by firms to customs offices are decomposed at a very fine product level (for reasons related to heterogeneous tariffs). We construct our measure of investment in automation from such product-level customs data.

We identify imports of capital goods that embed automation technologies based on their 6-digit Harmonized System (HS) product code, following a taxonomy presented by Acemoglu and Restrepo (2018). They partition all HS codes referring to capital goods (divisions 82, 84, 85, 87, and 90) into several categories of automated and non-automated goods. Imports of capital goods embedding automation technologies include, among the others, industrial robots, dedicated machinery, numerically-controlled machines, and a number of other automated capital goods.[16] To the categories from the paper by Acemoglu and Restrepo (2018), we add 3-D printers, the HS code of which is identified by Abeliansky et al. (2020). In Section 3 we provide evidence that imports of such capital goods behave in a way consistent with an investment variable, and in particular they occur in *spikes*.

Our choice of focusing on imports of automation-intensive goods, driven by data availability,[17] has some limitations, which, however, we expect not to greatly affect our findings, nor to do so in the more harming direction. *First*, our analysis does not capture what happens among firms not involved in international trade: these firms may well buy automation technologies from domestic suppliers, and the impact of investment in automation on their employment dynamics may be different, also because domestic firms tend to be different from firms

[15] The 4-digits subcategories of supervisors are almost evenly splitted among the second and the third tercile of the employment-weighted distribution of routine task-intensity in 2009. Notice that the supervisor category represents just a tiny fraction of total employment (around 3.5%).

[16] For a full list, including the specific 6-digit HS codes falling under each of the above-mentioned categories, see Table A1 in Appendix A.

[17] Detailed information on the purchase of goods are indeed available only through customs data of firms' imports.

Table 2
Sample composition per year, 2002–2015.

Year	Nb. firms	Share in total manuf. firms (%)	Share in total manuf. employment (%)
2002	37,703	31.12	84.40
2003	37,790	31.69	84.87
2004	37,659	32.27	85.17
2005	38,065	33.13	85.21
2006	39,058	33.72	85.35
2007	38,469	33.64	85.25
2008	37,912	33.75	85.32
2009	38,085	33.66	85.05
2010	37,179	34.00	85.33
2011	36,592	34.19	85.34
2012	36,122	34.19	85.42
2013	35,461	34.06	85.30
2014	34,847	33.86	85.07
2015	34,122	33.50	84.73

Source: our elaborations on DADS and DGDDI data.

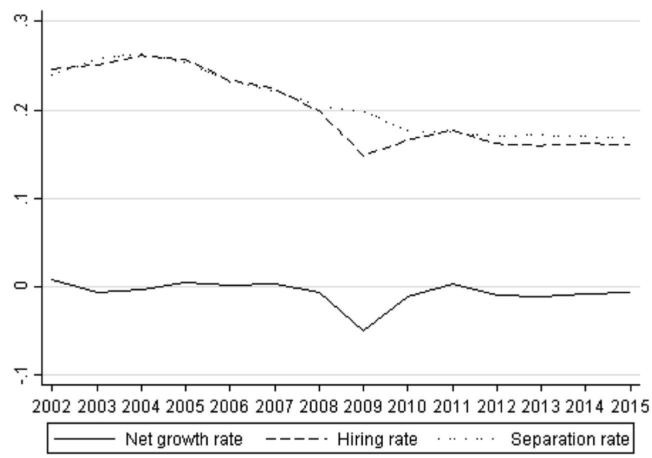

Fig. 1. Mean net growth rate, hiring rate, and separation rate, 2002–2015. Source: our elaborations on DADS and DGDDI data.

involved in international trade, e.g. they tend to be smaller and less productive on average. Notice, however, that in the case of France, investment in domestically-produced automation technologies presents a limited impact because, given the production structure of the French economy, imports are likely to be the most important source of automation goods. Indeed, France only has a revealed comparative advantage (cf. Balassa 1965) in the production of robots (see Table A2), which represent less than 3% of the total imports of the automation-intensive goods considered here. *Second*, firms might in general resort to an intermediary to purchase goods abroad (there exists a growing literature on the role of intermediaries in international trade; see Ahn et al., 2011; Bernard et al., 2010; Blum et al., 2010); however they are much less likely to do so for more complex goods (Bernard et al., 2015), involving higher relation specificity such as the ones we are focusing on here. *Finally*, also some importing firms in our sample might purchase automation-intensive capital goods only domestically, and thus they may be wrongly labelled as non-adopters of automation technologies. With respect to this, again notice that the structure of the French economy makes this possibility quite unlikely (see Table A2). Moreover, our within-firm identification mostly relies on what happens within firms that do import automation-intensive capital goods. Firms that purchase automation goods only domestically are in our control group in the propensity score approach; as such, their misclassification as non-automating firms is likely to make our estimates at most imprecise on the conservative side. Overall, we think we are able to keep under control any bias associated to not considering investments in domestically-produced automated-intensive goods.

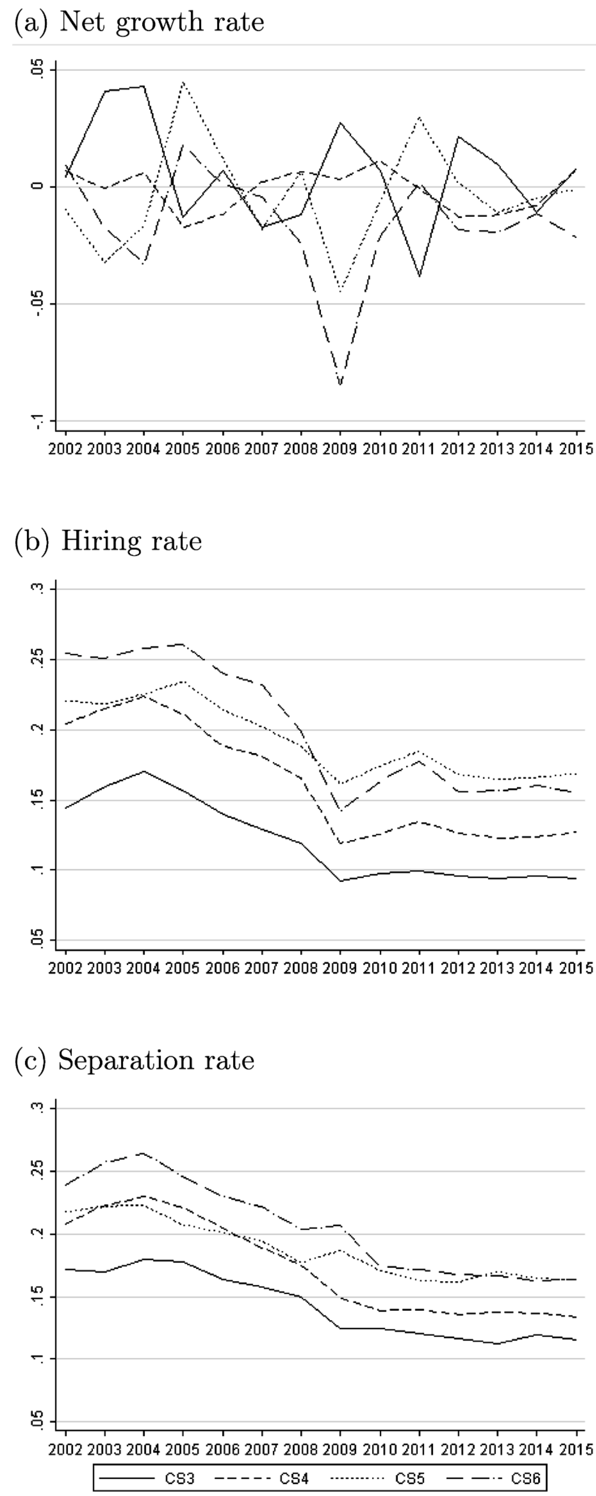

Fig. 2. Mean net employment growth rate, hiring rate, and separation rate, by 1-digit occupational category, 2002–2015. Source: our elaborations on DADS and DGDDI data. Note: CS3 denotes engineers, professionals, and managers; CS4 denotes supervisors and technicians; CS5 denotes clerical workers; CS6 denotes production workers.

2.3. Sample definition and descriptive statistics

As we identify automation investment through imports embedding

Table 3
Distribution of imports embedding automation technologies and employment by OECD digital intensive sector taxonomy, 2007.

Digital intensity quartile	Share in imports embedding automation technologies (%)	Share in total employment (%)	Ratio
	(1)	(2)	(1)/(2)
Low	1.07	11.81	0.09
Medium-low	27.49	41.36	0.66
Medium-high	17.78	20.26	0.88
High	53.65	26.57	2.02

Note: the classification for 2001–2003 is used (see Calvino et al. 2018, Table 3); see Table A3 in the Appendix for a description of codes. Source: our elaborations on DADS and DGDDI data.

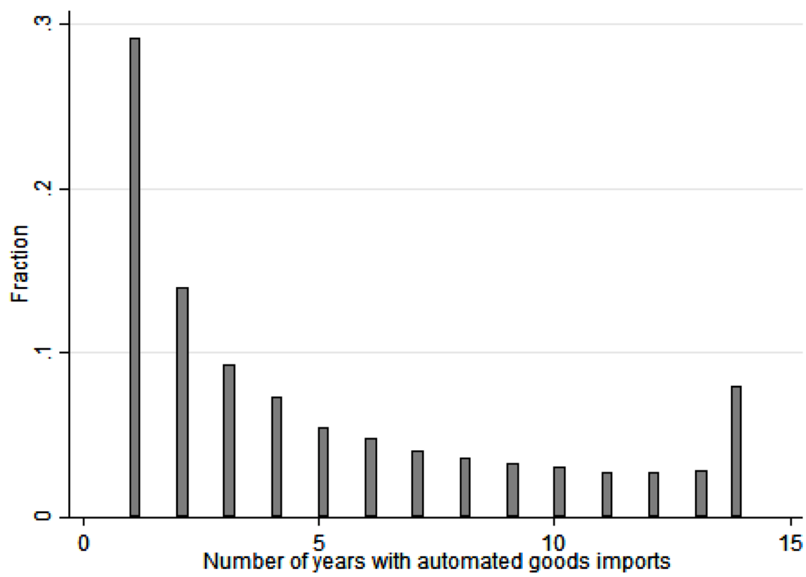

Fig. 3. Number of years with imports of automated goods. Source: our elaborations on DADS and DGDDI data.

automation technologies, we restrict our analysis to the sample of firms importing at least once in the period of analysis. Since one of the main focuses of the work is the analysis of the impact of automation on job flows (both gross and net), we require observations on firms that are continuing over at least two consecutive years. Continuing firms account for 91% of firms that import at least once between 2002 and 2015.

The yearly composition of the sample thus defined is summarized in Table 2. Notice that the number of firms decreases over time, which is in line with the manufacturing sector's secular decline (see also Domini and Moschella, 2018). Also notice that, in line with empirical international trade literature (see among others, the review in Bernard et al., 2012), importing firms in our sample represent a minority (about one third) of manufacturing firms, but a large majority (around 85%) of their aggregate employment.

Fig. 1 provides some first evidence about the different dynamics of worker flows at the firm level. The net employment growth rate fluctuates around zero, with a negative peak in 2009, due to the Great Recession. Indeed, hiring and separation rates follow a very similar pattern, starting at a level around 0.25 in the beginning of the period and gradually decreasing to 0.17 at the end of the period. The negative growth rate around 2009 is explained by a drop in the hiring rate.

Fig. 2 compares the mean net and gross rates of the four 1-digit occupational categories. It clearly emerges that hiring and separation rates decrease, as we climb the occupational ladder up: indeed, they are lowest for managers and engineers and highest for clerks and production workers. Common to all categories is the general decreasing trend in gross rates, which is consistent with what we observed in the previous figure. In terms of net employment growth, we do not observe clear patterns, except for the fact that blue collar workers were most hit during the global crisis of 2009. What can we conclude from these statistics? Fig. 2 shows a lower turnover rate (lower hiring and lower separation) among higher management levels. This can be explained by a higher degree of knowledge tacitness and idiosyncratic skills of such workers. On the one hand, managers acquire, through experience, specific knowledge about the firm's needs. On the other hand, higher skills which match the firm's operations are more difficult to find on the labour market. Such matching costs are then reflected in lower turnover rates among skilled employees. In Section 4.3 we will take into account the possible heterogeneous dynamics across occupational categories by also estimating the impact of automation on the share of those different categories.

3. Automation spikes: Identification and characteristics

This section describes and characterises investment in automation technologies in the firm-level data. As detailed above, we proxy automation technology adoption as imports of automation technologies, using the categorisation by Acemoglu and Restrepo (2018). These goods include industrial robots, numerically controlled machines, automatic machine tools, and other automatic machines (as defined in Section 2) hence their acquisition can be characterised as *investment* in tangible assets.

First we consider the sectoral distribution of imports of automation technologies in order to evaluate the relevance of our variable with respect to the digital economy. To do so, we use the new digital intensity sector taxonomy, developed by the OECD (Calvino et al., 2018). The authors use a set of indicators[18] to assess heterogeneity across sectors according to three dimensions: technology (use of digital technology), human capital (needed to embed them in production) and markets (use of online sales). As shown in Table 3 for a representative year (2007),

[18] Indicators are: share of ICT-related tangible and intangible investments; share of purchases of intermediate ICT goods and services; stock of robots per hundreds of employees; share of ICT specialists in total employment; and the share of turnover from online sales.

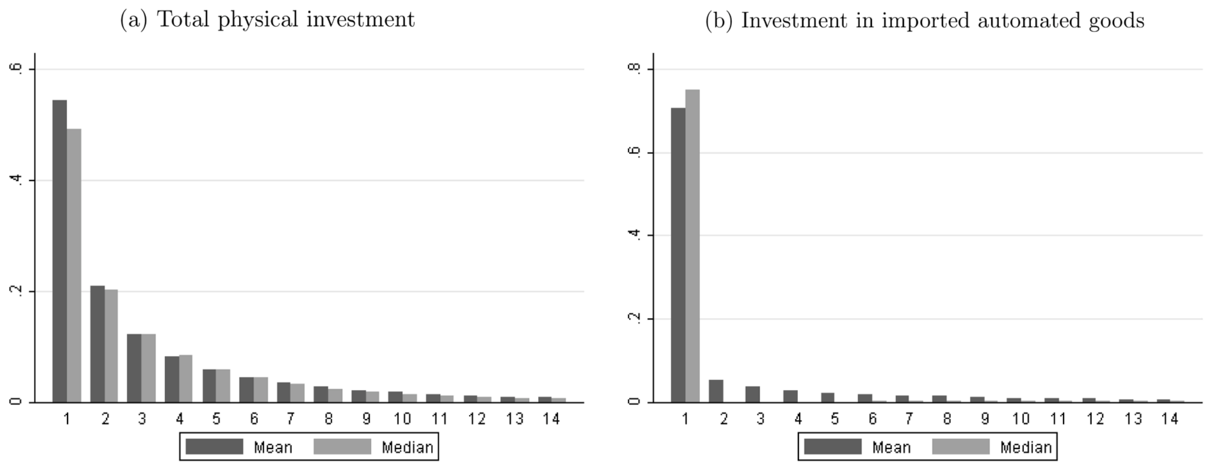

Fig. 4. Investment shares by rank. Rank 1 is the highest yearly investment share in the firm's timeline. Source: our elaborations on DADS, DGDDI, FICUS, and FARE data.

our variable measuring imports of automation technologies is aligned with the sectoral classification: we find that the share of imports in automation technologies relative to the sector's share in total employment is lowest in the first digital intensity quartile and highest in the fourth one. In particular, the share of imports of automation technologies by the high digital intensity group is twice the sector's share in employment.

3.1. Investment in automation as spikes

In what follows we show that, similarly to physical investment in general (Asphjell et al., 2014; Grazzi et al., 2016; Letterie et al., 2004), imports of capital goods embedding automation technologies happens in *spikes*: such an event is both rare across firms and within firms (cf. Fig. 3). Finally, each event represents a significantly high share of total investment within firms (cf. Fig. 4).

First, it is *rare across firms*: in each year, around 15% of importers buy automation-related goods, and 2.5–5% of these events represent spikes.[19] As a comparison, around 5–7% of firms in our sample have a general physical investment spike in a given year.[20] Overall, 38% of firms import automation goods at least once. Although few firms invest in automation technologies, it may be that we observe 'repeated' or 'continuous' investment over time in that subgroup. Therefore the second step is to check whether it is *rare within firms*, i.e. whether investment in automated goods doesn't happen regularly or is smoothed across periods. Fig. 3 shows that the latter is not usually the case. Among firms who import automated goods at least once, close to 30% does it only once, and the frequency decreases smoothly with higher values, except for a small group of firms who import automated goods in all years. A potential concern with the latter group of firms, which represent approximately 4.3% of the sample, is that they are somewhat different from other firms. When excluding them from our regression analysis, we find that in fact they are not driving our main conclusions (results are available from the authors upon request). We also test whether our results are robust to excluding firms involved in carry-along trade: notice indeed that 90% of firms that import automation goods in all years are firms that both import and export automation goods. Results, shown in the robustness tests section, are again unchanged (see Table B5).

The final check is that the event that we want to characterize as a spike represents *a very high share of total investment within firms*. Therefore we study whether, among firms showing repeated investment in automated goods, the different events are all similar in nature or, on the contrary, they are much concentrated. To answer this question, we compute, for each firm, the share of automated imports in year t over the cumulative sum of automated imports of that firm over the whole period of analysis. As a comparison, we do the same for investment in physical capital. For each firm we then rank these yearly shares from largest to lowest. Fig. 4 (left) shows that in the case of physical investment, the average across firms of the largest episode represents close to 60% of total investment (the median is a bit lower); for automated goods, the concentration of investment in a single year is even more pronounced and close to 70%.[21] The shares of lower ranks then rapidly decrease in value, and even more so in the case of automated goods.[22] Because of the very skewed nature of the variable within firms, we define as an *automation spike* only the largest event for each firm.

What makes automation adoption lumpy? We put forward two explanations. *First*, our automation variable *is* a tangible investment variable: the products we have selected are a subset of capital goods that are automated in nature. As investments, they should share similar features as the larger category of physical investment goods, previously identified in the literature (Nilsen and Schiantarelli, 2003). *Second*, even when considering other dimensions of the adoption of automation technologies which are not strictly related to investments (e.g. automation costs), Bessen et al. (2019) also point out that those share the same characteristics that make investment lumpy:[23] they are irreversible, as they

[19] The employment represented by firms with an automation spike accounts for approximately double their share in the number of firms in each year (between 5 and 11% in employment share, to compare with 2.5-5% of firms.)

[20] The value of physical assets is retrieved from the FICUS and FARE dataset (variable *IMMOCOR* in the former, *immo_corp* in the latter). Physical investment is computed as increases in physical capital (deflated employing the 2-digit sector deflators); the investment rate is the ratio with the lagged value of physical capital. Although several investment spike measures have been put forward in the literature (Cooper et al., 1999; Grazzi et al., 2016; Letterie et al., 2004; Power, 1998), we use the simplest one, defining as a spike the largest investment event within a firm time series, and with an investment ratio above 0.2, in the spirit of Cooper et al. (1999).

[21] Such evidence on the concentration of investment in few events over the observation period is in line with previous literature (see among the others Doms and Dunne, 1998; Grazzi et al., 2016; Nilsen and Schiantarelli, 2003). In order to maximize the number of observations, the plot in Fig. 4 is performed on the main unbalanced sample as per Table 2. Note, however, that restricting to the balanced sample provides very similar results.

[22] In the case of physical investment, smaller shares, corresponding to higher ranks, are typically associated to maintenance investment, therefore to be separate from the acquisition of additional or new machines.

[23] See Bessen et al. (2019, p. 10).

Table 4
Mean worker flow rates around an automation spike.

Years since spike	Net growth rate	Hiring rate	Separation rate	Nb. firms
–2	0.021	0.196	0.175	9247
–1	0.016	0.186	0.170	9247
0	0.016	0.178	0.162	9247
1	–0.011	0.151	0.162	9247
2	–0.036	0.135	0.171	9247

Source: our elaborations on DADS and DGDDI data. Note: The sample includes firms observed for at least two years before and after an automation spike.

imply idiosyncratic changes in the production process and complementarities with workers' tasks, and indivisible, since they cannot be carried out in small chunks over time (as would be instead for example worker training, involving few employees at a time).

3.2. Automation vs. physical investment spikes

The previous exercises confirm that our variable of interest identifies important single events at the firm-level. From this we may expect that the impact of imports of automation technologies on employment may share similar traits with that of general capital investment. In particular, are automation and investment spikes happening jointly? If they were, this could pose problems of identification of the relation between automation spikes and employment flows. We find that they are not: in our sample, only 8.3% of automation spikes are also investment spikes, while 4.6% of investment spikes are also automation spikes. Further, the correspondence between an automation spike and leads or lags of an investment spike is even lower than that (below 3%). One reason why we don't find a joint occurrence of the two types of spike is their different relation to the business cycle. Investment spikes have been found to be more clustered in periods of booms, as firms delay their investment projects in more uncertain times with low demand (Gourio and Kashyap, 2007). Instead, our automation spikes are quite evenly distributed over time, with the exception of a drop in 2009 due to the general decrease in imports; therefore we could characterise them as rather acyclical.

3.3. Automation spikes and employment: Preliminary evidence

In what follows we are interested in the relation between employment dynamics and automation investment spikes. The investment literature has also investigated the impact of spikes on employment. From a theoretical perspective, and similar to the ongoing debate on the impact of automation technologies on employment, capital can be seen as a possible substitute for labour. Yet, empirical results show that in most cases we observe *interrelation* between (physical) investment and employment spikes: firms increase their employment level simultaneously with an increase in capital (Asphjell et al., 2014; Letterie et al., 2004). In particular, using similar data on French manufacturing firms, Grazzi et al. (2016) show that investment spikes are positively associated with employment growth. Note however that this literature only considers net employment growth, not gross worker flows.

Table 4 gives a first insight into the unconditional relation between automation spikes and gross worker flows. It considers a subsample of firms with an automation spike, and for which we observe employment growth two years before and two years after the event. We observe positive net employment growth before and during the spike, and negative after. This sign reversal after the spike appears to be due to a drop in the hiring rate, while the separation rate is rather stable.

Notice that the descriptive evidence in Table 4 is already quite revealing of the insights offered by the analysis of gross flows: a relatively modest change in net employment around a spike is actually hiding richer dynamics of hiring and separation rates.

Table 5
Automation spikes and worker flows: fixed-effects estimation.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.022***	0.000	–0.022***
	0.002	0.002	0.002
$Spike_{t-1}$	0.032***	0.007***	–0.025***
	0.002	0.002	0.002
$Spike_{t}$	0.033***	0.011***	–0.023***
	0.002	0.002	0.002
$Spike_{t+1}$	–0.005*	–0.006***	–0.001
	0.003	0.002	0.002
$Spike_{t+2}$	–0.014***	–0.012***	0.002
	0.003	0.002	0.002
Nb. obs.	519,064	519,064	519,064
Nb. firms	54,311	54,311	54,311
Adj. R^2	0.072	0.223	0.177

Notes: FE estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

4. Automation and worker flows

After Table 4 provided some first evidence of an association between automation spikes and employment dynamics, in this section we assess this relationship more in detail. We will first use a simple fixed-effects regression framework to assess the changes in gross and net employment flows around an automation spike, relative to the firm's average. Yet, as discussed in the Introduction, there can be important differences in the performance and characteristics between firms engaging in automation and firms that never do. In order to control for such selection effects in a more consistent way, we add in a second step a propensity score reweighting estimator.

4.1. Fixed-effects regression

In our first exercise, we run a Fixed-Effects (FE) estimation of the following equation on our sample of firms that import at least once:

$$Flow_{it} = \alpha + \sum_{k=-2}^{2} \beta_k Spike_{t+k} + \gamma_i + \delta_{jt} + \epsilon_{it} \tag{2}$$

where $Flow \in \{g, h, s\}$ (i.e. it can be the net growth, hiring, or separation rate), dummies $Spike_{t+k}$identify whether firm i has experienced an automation spike in a five-year window, centered around year t, γ_i is a firm fixed-effect, and δ_{jt} is a sector-year fixed-effect (where j is the NAF division firm i belongs to; see Section 2 for details on this attribution).

In Table 5 we report results from the estimation of Eq. 2.[24] A clear temporal pattern emerges: the association between investment in automation and net firm growth is positive and significant before and during a spike (i.e. from t-2 to t); negative, but small and hardly significant, in the year after the spike (t+1); and negative and significant two years after the event (t+2). The net growth rate peaks in the spike year, when a firm experiences, on average, a growth rate 3.3 percentage points higher than its within-firm average. In other words, the net growth rate is above its within-firm average before and during an automation spike, and below it afterwards. This is in line with what we know from the literature on investment spikes, pointing out a co-occurrence of the latter with employment spikes.

Deeper insights on how this pattern emerges are provided by the

[24] Note that these results do not change when we restrict the sample to firms having a propensity score (443,577 observations, see Section 4.2).

other two columns of the table. The above-average net growth rate before and during the spike are mainly accounted for by the separation rates being significantly below its within-firm average; but above-average hiring rates are also observed, especially in the spike year. Instead, after the spike, the decrease in the net growth rate is solely driven by a decrease in the hiring rate.

4.2. Propensity score weighting

Results from Table 5 show that automation spikes are correlated, within firms, with employment dynamics at different time lags. However our simple fixed-effects identification does not allow us to interpret the coefficient in a causal way. In particular, the positive correlation between automation spikes and employment growth can be due to some form of endogeneity of the automation decision with respect to the employment performance. Indeed, within our sample of importing firms, importers of automation goods display larger values than non-importers of automation in terms of: employment, productivity, capital intensity, export intensity, age and share of high-skill workers (see Table A4). Previous positive performance can in turn provide firms with the resources and the incentive to automate.

In order to mitigate the issue of non-random selection of firms into automation, we follow Guadalupe et al. (2012) and Koch et al. (2019) and combine a fixed-effect approach with a propensity score reweighting estimator. This reweighting accounts for differences in firms' probability to automate, based on lagged performance indicators. To calculate the propensity scores, we first separate the firms in our sample into seven manufacturing industry groups.[25] The binary outcome we are interested in is the occurrence of an automation spike by firm i in year t ($Spike_{it} = 1$, automation spike) or not ($Spike_{it} = 0$, no automation spike). Following Guadalupe et al. (2012), the decision to automate can be viewed as the reflection of a latent (unobserved) variable S^*_{it} so that $Spike_{it} = 1$ if $S^*_{it} \geq 0$ and $S_{it} = 0$ if $S^*_{it} < 0$.

For each industry s, we estimate the probability ($\widehat{p}$) of observing an automation spike in firm i at time t, in the following pooled probit regression:

$$Spike_{it} = \alpha + \beta_1 X_{it-1} + \beta_2 X_{it-2} + \gamma_t + \epsilon_{it} \tag{3}$$

where X is a vector of variables including employment level, net employment growth, hourly labour productivity level, hourly labour productivity growth, capital intensity, share of the CS3 1-digit occupational category (Engineers, professionals, and managers), import and export status, and age.[26] γ_t are year dummy variables and ϵ_{it} is the error term. Those variables closely match the ones used by Guadalupe et al. (2012) and Koch et al. (2019) and should control for the relevant observable differences in performance among firms. We find that all these variables have a positive impact on the probability to automate.

We then use the propensity scores obtained from the probit regressions to construct firm-specific weights: each automating (treated) firm will get a weight equal to $1/\widehat{p}$, and each non-automating (control) firm will get a weight equal to $1/(1 - \widehat{p})$, where $\widehat{p}$ is the estimated propensity score. Note that not all treated firms can be matched with the propensity score kernel matching, as we exclude firms that are not in the common support of the propensity score distribution. As a consequence, the different steps of the propensity score approach reduce the sample from 519,064 (see Table 5) to 443,577 observations. Finally, we re-estimate equation (2) using these weights. It is important to note that the propensity score reweighting estimator allows us to control not only for time-invariant characteristics, through the firm fixed-effects, but also for time-varying characteristics through the propensity score (see Guadalupe et al., 2012).

Table 6
Automation spikes and worker flows: propensity score reweighting estimator.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.010*	0.002	–0.008
	0.005	0.005	0.005
$Spike_{t-1}$	–0.005	–0.005	–0.000
	0.006	0.005	0.005
$Spike_{t}$	0.028***	0.012**	–0.017***
	0.005	0.005	0.005
$Spike_{t+1}$	–0.012**	–0.007	0.004
	0.005	0.005	0.005
$Spike_{t+2}$	–0.014**	–0.005	0.008
	0.006	0.005	0.006
Nb. obs.	443,073	443,073	443,073
Nb. firms	40,198	40,198	40,198
Adj. R^2	0.005	0.191	0.126

Notes: Propensity score reweighting estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote $p<0.10$, $p<0.05$ and $p<0.01$, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Results from the propensity score reweighting estimation are presented in Table 6.[27] Automation spikes are not correlated anymore with previous net employment growth rates[28]: this means that our matching strategy is able to control for observable and unobservable differences among firms that affect pre-spike growth rates. Conditional on this, we still find a strong contemporaneous relationship between automation spikes and net employment growth rates: in the year of their automation spike, firms do enjoy a net growth rate 2.8 percentage points higher than their average, which is jointly due to a higher hiring rate (1.2) and lower separation rate (1.7). After the spike, the coefficient on the net growth rate tends to decrease and is negative one year after the spike, and negative but barely significant two years after. This is jointly due to lower hiring rates and higher separation rates.[29] The decision to automate therefore has a positive impact on firms' own employment in the year of the spike.[30]

4.3. Analysis by type of worker

As discussed in the introduction, one crucial dimension to consider when analyzing the joint impact of trade and technology on employment dynamics is the skill composition of the firm workforce. From economic theory, differences across types of workers may emerge if investment in automation is associated to skill-biased technical change, i.e. skill-complementarity between the machines and the workers needed to

[25] The groups combine the following 2-digit NAF sectors: [10–12], [13–15], [16–18], [19–23], [24–25], [26–30], [31–33]. The aggregation of sectors ia aimed at having a sufficient number of spikes per group, while preserving some homogeneity of activity within each group.

[26] Hourly labour productivity is calculated as the ratio between value added (deflated using 2-digit deflators) and the total number of worked hours; capital intensity is the ratio between the value of physical assets (deflated using 2-digit deflators) and the total number of worked hours. Notice that age (defined as years since foundation) is not lagged, due to its incremental nature.

[27] As mentioned above, the number of observations is lower than in Table 5. We checked that differences in results are not driven by the different sample (results are available upon request). We also checked that observed characteristics of automating and non-automating firms are balanced in all industries.

[28] There is only a small and barely significant correlation two years before the spike, which is due to lower separation rates. This residual effect however disappears in most robustness checks we perform.

[29] Although the coefficients on hiring rate and separation rate are not significant, this does not invalidate the basic decomposition as per Eq. 1.

[30] Notice that two years after the spike, automating firms are still larger then before the event. This is revealed also by additional regressions on employment levels, which are available upon request.

Table 7
Automation spikes and 1-digit occupational categories' shares (%).

Dep. var.: Share of	CS3 Engineers, professionals, and managers	CS4 Supervisors and technicians	CS5 Clerical workers	CS6 Production workers
$Spike_{t-2}$	−0.193	0.066	−0.197	0.219
	0.262	0.364	0.292	0.374
$Spike_{t-1}$	−0.223	0.430	−0.131	−0.034
	0.249	0.358	0.292	0.382
$Spike_{t}$	−0.011	−0.027	−0.166	0.344
	0.265	0.356	0.282	0.399
$Spike_{t+1}$	0.096	0.484	−0.258	−0.247
	0.278	0.372	0.304	0.405
$Spike_{t+2}$	−0.088	0.087	−0.062	0.030
	0.261	0.376	0.328	0.408
Nb. obs.	443,073	443,073	443,073	443,073
Nb. firms	40,198	40,198	40,198	40,198
Adj. R^2	0.546	0.531	0.553	0.684

Notes: Propensity score reweighting estimation of Eq. 4. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table 8
Automation spikes and 2-digit occupational categories' shares (%).

Dep. var.: Share of	CS37	CS38	CS46	CS47	CS48	CS54	CS62	CS63	CS67
$Spike_{t-2}$	0.008	−0.221	−0.022	0.132	0.002	−0.252	−0.133	-0.142	0.203
	0.165	0.210	0.245	0.241	0.145	0.267	0.413	0.218	0.374
$Spike_{t-1}$	−0.082	−0.118	−0.020	0.458*	0.019	−0.098	−0.643	-0.059	0.573
	0.176	0.187	0.251	0.255	0.141	0.255	0.409	0.223	0.403
$Spike_{t}$	−0.159	0.201	−0.057	0.104	0.008	−0.114	0.393	-0.254	0.171
	0.203	0.213	0.243	0.243	0.139	0.261	0.446	0.223	0.396
$Spike_{t+1}$	−0.126	0.277	0.246	0.168	0.105	−0.082	−0.136	-0.157	0.244
	0.190	0.224	0.255	0.259	0.153	0.283	0.458	0.244	0.401
$Spike_{t+2}$	−0.186	0.107	0.070	−0.194	0.152	0.172	−0.465	0.021	0.635
	0.161	0.216	0.248	0.252	0.169	0.301	0.441	0.217	0.415
Nb. obs.	443,073	443,073	443,073	443,073	443,073	443,073	443,073	443,073	443,073
Nb. firms	40,198	40,198	40,198	40,198	40,198	40,198	40,198	40,198	40,198
Adj. R^2	0.397	0.493	0.488	0.559	0.343	0.529	0.564	0.520	0.525

Notes: Propensity score reweighting estimation of Eq. 4. CS37: Top managers and professionals; CS38: Technical managers and engineers; CS46: Mid-level managers & professionals; CS47: Technicians; CS48: Supervisors and foremen; CS54: Office workers; CS62: Skilled industrial workers; CS63: Skilled manual laborers; CS67: Unskilled industrial workers. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

operate them (Autor et al., 2003). The alternative hypothesis is that the new wave of innovations may affect either all workers, or may have heterogeneous effects but not along the 'traditional' skill categorisations. In particular, the routine-task content of a job may be seen as the relevant variable, determining the impact of automation on employment. We take this dimension into account, first, by running regressions having on the left-hand side the occupational categories presented in Section 2; then, by doing the same for the routine-intensity classification.

An important aspect of these theories is that the adoption of new technology should affect the *relative* demand for skills within firms, in the form of the share of each worker category within the firm. To better assess the relation between automation and the *composition* of the labour force, we estimate the following equation, using the propensity score reweighting approach described in Section 4.2:

$$Share^{c}_{it} = \alpha + \sum_{k=-2}^{2} \beta_k Spike_{t+k} + \gamma_i + \delta_{jt} + \epsilon_{it} \quad (4)$$

where $Share^c$ is the share of occupational category c with respect to the total employment of firm i (in %), and the right-hand side variables are as per Eq. 2. As discussed in Section 2, our data does not reflect skill categories per se. We consider four 1-digit categories (Engineers, professionals and managers; Supervisors and technicians; Clerical workers; Production workers) and nine 2-digit categories, among which a particular attention should be devoted to categories 38 and 47, identified as 'techies' by Harrigan et al. (2020).[31]

Results considering 1-digit and 2-digit occupational categories are provided in Tables 7 and 8, respectively. None of the coefficients in both tables is statistically significant (with only one exception). Besides the lack of statistical significance, notice that the size of the estimated coefficients is indeed small, compared to the average shares of the various categories, displayed in Table 1: for example, the decrease by 0.2 percentage points at t in the highest 1-digit category (CS3) as per Table 7 looks negligible if applied to an average share of 11% for that category. This is also true at the more disaggregated 2-digit level, as shown in Table 8. Interestingly, the only statistically significant (at the 10% level) coefficient is a positive one associated with the category of technicians (CS47) at $t-1$in Table 8: this category, according to Harrigan et al. (2020), is part of the 'techies' workers who facilitate the adoption and use of new technology. Overall, the picture that emerges from the two tables is that an automation spike does not seem to be associated to a significant change in the skill composition of firms – neither at a more nor at a less disaggregated level. These results therefore do not confirm that automation spikes operate following the expectations from the skill-biased technical change theory, at least according to the classification of workers we have tested here.

[31] We remind the reader here that the groups with lowest skills, as also reflected in a wage distribution close to the minimum wage threshold, includes low-skilled white-collar workers (Clerical workers) and the unskilled production workers. The distinction between skilled and unskilled blue-collar workers is described in Biscourp and Kramarz (2007), who also point out that the distinction between the two categories is especially relevant if the aim is to assess their relative vulnerability to being substituted due to technological change: <<The French classification of occupations identifies unskilled blue-collar workers as 'those whose job requires little specific training.' They embody little specific human capital and should be more easily substitutable by foreign 'low-wage' blue-collar workers than their skilled counterparts. According to the skill biased technical change view, however, they should also be the most vulnerable to substitution by technology-intensive equipment and associated organizational change.>> (Biscourp and Kramarz, 2007, p. 38).

Table 9
Automation spikes and routine-intensive category's share (%).

Dep. var.: Share of Routine-intensive workers		
Period:	2002–2015	2009–2015
Spike_{t-2}	–0.065	–0.308
	(0.430)	(0.618)
Spike_{t-1}	0.447	–0.365
	(0.449)	(0.569)
Spike_{t}	–0.031	–0.430
	(0.433)	(0.514)
Spike_{t+1}	0.062	0.181
	(0.462)	(0.538)
Spike_{t+2}	0.737	0.480
	(0.473)	(0.471)
Nb. Obs.	440,646	218,262
Nb. firms	40,169	36,175
Adjusted R^2	0.516	0.765

Notes: Propensity score reweighting estimation of Eq. 4. Coefficients on the sector-year dummies. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients). Observations in Column 1 are slightly less than in other tables as we leave out firms with only supervisors' category (see Section 2.2.2). Column 2 reports results for the subperiod 2009–2015 in which the routine task-intensity is measured at the 4-digits level.

A large literature has emphasized that technological change may be biased toward replacing labour in routine tasks, the so-called routine-biased technological change (RBTC) hypothesis (see, among the many others, Autor and Dorn, 2013; Autor et al., 2003; Goos et al., 2014). The previous analysis by occupational category already bears some implications in terms of routine-task intensity (RTI) of occupations. Consider, for example, the result on unskilled industrial workers in Table 8: there is probably little doubt that most of these workers do routine manual work, which are supposedly most threatened by automation technologies (see, for example, Harrigan et al. 2018).

In what follows we go more in detail in this direction by investigating the relationship between employment growth and automation spikes taking into account the routine task-intensity of occupations. Using the definition of routine task-intensive occupations introduced in Section 2, we construct a new dependent variable, namely the share of routine-intensive employees, and then we estimate Eq. 4 using the propensity score reweighting approach. We use two specifications, in order to exploit the available information fully. We first run the analysis on the whole period (2002–2015), using the more aggregated occupational classification. We then repeat the analysis on the subperiod 2009–2015, for which we can use more precise and disaggregated information. In the first case, we are effectively assigning 'clerical workers' (54) and 'unskilled industrial workers' (67), which in the previous analysis were into two different occupational categories, to the same 'Routine-intensive' category, while all the others are classified as 'Non routine-intensive'. In the 2009–2015 subperiod regressions, we exploit the 4-digits PCS2003 classification to take into account the heterogeneity in routine task-intensity that exists within the same broad occupational category. So, for example, some unskilled industrial workers will be assigned to the 'Non routine-intensive' category.

Regression results are reported in Table 9. Results obtained both for the whole period (column 1) and for the subperiod 2009–2015 (column 2) do not show any significant change in the share of routine-intensive occupations.

We summarize the main results of the whole section. Automation spikes share the known features of investment spikes in general (Asphjell et al., 2014): they are associated with a contemporaneous expansion of employment. More precisely, the positive coefficient in the net employment growth regression is explained both by a reduction in the separation rate and by an increase in the hiring rate. This expansion is found to be generalised across occupational and routine-intensive categories.

4.4. Robustness checks

We ran a number of checks to verify the robustness of the results presented above. In the interest of space, we comment here the results and refer to Appendix B for the related tables. All the robustness checks were performed, unless stated differently, using the propensity-score reweighting estimator for Eq. 2.

Discontinuity in data collection

First of all, a potential drawback in the use of occupational categories arises from a discontinuity in the source regarding the coding of the underlying variable (CS) in year 2009, as a consequence of which there is an increase in clerks and a decrease in supervisors and technicians (INSEE, 2010, pp. 58-59), as well as a shift from skilled to unskilled production workers. To verify that the findings as per SubSection 4.3 are not affected by this discontinuity, in Appendix B we present the results of regressions by occupational category, separately run for the two subperiods 2002–2008 and 2009–2015, i.e. before and after the discontinuity year.[32]

Results from Table B1 replicate the non-significance picture from the whole-period regressions (Table 7) in both subperiods. Likewise, Table B2 is also largely consistent with Table 8, though showing limited significant dynamics, involving specific 2-digit categories, that are different across subperiods. Notably, in the earlier subperiod (2002–2008), the two 'techies' categories, 38 (Technical managers and engineers) and 47 (Technicians), respectively display a significant positive coefficient one year after the spike, and a negative one two years after the spike. This may reflect a switch toward higher-level technical

[32] This is also useful, as these two subperiods differ in terms of the general macroeconomic context: indeed, starting in the last quarter of 2008, the Great Recession, with the related trade collapse and credit crunch, severely hit the French economy, as well as the European and world economies. As a result, while the 2002–2008 subperiod was overall a period of growth, 2009–2015 was instead largely a time of economic stagnation and uncertainty, with particularly negative consequences for firms involved in international trade and innovative activities (see also the analysis in Domini and Moschella, 2018). Finally, the two subperiods may differ due to developments in automation technologies, modifying the benefits and costs from automation, and therefore the incentives for investment and the latter's consequences on employment.

figures, when conducting investment in automation.[33] This feature, however, disappears in the regression on the later subperiod (2009–2015).

Firm size

A second issue is related to firm size: as shown in Table A4 in Appendix A, large firms have a higher probability to automate. This may be due to lower financial constraints, which are known to matter for investment in general (Audretsch and Elston, 2002; Kadapakkam et al., 1998), but also because of heterogeneous gains from automation.

In Table B3 we address this issue, running Eq. 2 on a restricted sample that excludes firms with less than 50 employees, thus reducing the number of observations from 443,073 (40,198 firms) to 81,177 (6,846 firms). This threshold is chosen because it is one of the criteria used for defining medium and large firms by Eurostat, and because it is an important threshold in the French labour market, at which many labour-related regulations start to be binding (which has consequences on employment and productivity, as documented by Garicano et al. 2016).

The results show important differences with respect to the overall sample: in Table B3, the contemporaneous relation between employment growth and automation spikes shows a higher positive coefficient (0.046 compared to 0.028 in the overall sample). This is mainly due to a higher hiring rate (0.034 instead of 0.012), while the coefficient on the separation rate is slightly lower (-0.013 to be compared with -0.017). This is consistent with large firms having stricter firing rules so that, compared to their average, gains from automation mostly come from the hiring side.

Size also matters when considering the organization of work across or within plants of the same firm. The labor-saving effect of automation should indeed be observed more accurately within a single plant; while changes in labour demand across plants of the same firm might be instead due to the (indirect) firm-level productivity and competitiveness effect of automation. We could not conduct our analysis at the plant level since some data sources (customs data, balance sheet data) only provide firm-level information. However, we can isolate single-plant firms, in which within-plant and within-firm effects overlap. In our sample, single-plant firms represent around 80% in terms of the number of firms and, given their smaller size, account for around 40% of employment. Results in Table B4 are overall in tune with the main analysis reported in the paper: in the year of the automation spike we observe a positive effect on net employment growth, while the following two years we detect a negative effect.

Notice that in the regressions on the sample of single-plant firms, some minor differences emerge also for the estimation of Eq. 4: some coefficients gain significance at the 10% level, and – for 2-digit categories only – even at the 5% level: notably the ones associated with the categories of 'techies' (CS38 and CS47). Instead, for the sample of large firms, the positive coefficients associated to unskilled industrial workers (CS67) turn out to be significant around a spike.[34]

Taken together, these additional exercises call for a deeper investigation of the two mechanisms at play within plants and firms (the labour-saving vs. the productivity effects of automation). Data on automation investments at the plant-level would allow to disentangle these two channels, which is left for future work based on alternative sources.

[33] There is also a significant positive coefficient on the skill manual workers category (CS63), two years after the spike.

[34] Results for the other robustness checks on Eq. 4 as per the rest of this subsection, instead, present minor or no qualitative differences with respect to the main estimates, and will therefore not be commented. These additional results are available upon request.

Table 10
Distribution of the ratio between the value of automated investments in the year of the spike and the average value in all the other years in the year of the spike.

Percentile	Value
5	2.14
10	2.47
25	3.52
50	6.19
75	15.15
90	52.23
95	131.79

Source: our elaborations based on DGDDI data.

Controlling for Carry-Along Trade

Our analysis builds on the premises that the automation-investment products imported by firms are also used and adopted in the production process of those firms. However, it is also possible that some of the importing firms in our sample are engaged in re-exporting activities of such automation intensive goods, thus generating a phenomenon similar to Carry Along Trade (CAT), i.e. trade generated by manufacturing firms exporting products not produced by themselves (Bernard et al., 2019). This would bias (downward) our analysis of the relation between automation adoption and employment growth. In principle, information on both production and exports at the product level are needed to correctly identify carry-along firms, in order to separate pure re-exporters (non-users) from users that also re-export. Short of that, we make a conservative approximation by excluding firms that are involved both in the import and in the export of automation goods (even in different years). Results shown in Table B5 are in line with the main propensity score-weighted regressions as per Table 6, the only difference being the loss of significance of the coefficient on the spike's $t+2$lead in the growth-rate regression, and of the spike in the hiring-rate variable.

Controlling for investment spikes in other tangible assets

Section 3.2 discusses the limited overlap between investment and automation spikes (i.e. below 10%). Positive employment effects of physical investment spikes have been shown by several studies, for example Letterie et al. (2004) and Asphjell et al. (2014). In the (limited) cases whereby automation and physical investment spikes do overlap, the employment effects of the latter could be attributed to the former. We present below a robustness check in which we control for 'physical investment spikes'. Results in Table B6 confirm that those spikes do have employment effects, but also that automation spikes have an independent employment effect, meaning that adding such a control does not alter our results.

Alternative definition of automation spike

The employment effects of automation spikes have been documented by Bessen et al. (2019), based on Dutch worker-level data. In what follows, we perform an exercise in order to enhance comparability of our results with theirs, namely we adopt their definition of an automation spike using a relative size threshold instead of the highest rank.

Bessen et al. (2019) identify automation spikes in a year *t* if automation costs are at least thrice the average firm-level cost share. We adjust the definition to our setup.[35]Table 10 below shows the distribution of the ratio between the value of automated investments in the year

[35] In terms of other physical investment, automation spikes represent in the median 26% of physical investment in the same year, again with the largest spikes (top quartile) representing more than 95% of the yearly physical investment.

of the spike and the average value in all the other years. It shows that less than 25% of our spikes would be discarded if the threshold *à la* Bessen et al. (2019) were to be applied. Table B7 then reports the results of our baseline regression when restricting the automation spikes to those with a value of the ratio above 3; again our results are confirmed.

5. Conclusions

Although there is a certain agreement in acknowledging the impact of technological change, and in particular of the emerging digital technological paradigms, on employment, empirical evidence at the micro level is almost missing. Relying on exhaustive and detailed employer-employee and customs data on French manufacturing firms over the period 2002–2015, we investigate the relationship between automation via imports of capital goods embedding automation technologies and worker flows. We delve deep into this relationship, analysing it for various types of workers, and separating the contributions to it of within-firm hiring and separation rates.

First we characterise the decision to automate as one that happens in *spikes*. In line with Bessen et al. (2019), this supports the idea that automation represents a significant disruption in the way firms produce. We then find evidence that automation spikes are positively correlated with preceding and contemporaneous growth in employment. Accounting for endogenous selection of firms into automation, we show that, in fact, automation spikes generate a positive contemporaneous effect on net employment growth. This positive effect can be attributed to both a higher hiring rate and a lower separation rate. Moreover, automation spikes do not significantly alter the within-firm shares of different types of workers (1-digit and 2-digit occupational categories, and routine-intensive vs. non routine-intensive).

Overall, the impact of automation on firm employment within firms is generally positive: such result is, on the one hand, in tune with the evidence on investment in capital goods, irrespective of their technological content (Grazzi et al., 2016), and, on the other hand, it is consistent with labor-friendly technological change improving the relative competitiveness of firms and thus favouring their expansion (Barbieri et al., 2019).

These findings are also in line with what has been found for more specialized forms of automation, like the effects of ICT adoption in Harrigan et al. (2018) and robot adoption in Koch et al. (2019) and Acemoglu et al. (2020). Notice that labor-friendly results at the firm-level do not imply *per se* that automation is not displacing labor at a more aggregate level (on this, see Acemoglu et al., 2020, who find that negative externalities at the market level can overcome positive effects of robotisation at the firm level).

Zooming in on the within-firm occupational changes, our results do not seem to support, in general, the routine-biased technical change hypothesis and the implied polarized effects of automation technologies on employment. Our results suggest, on the one hand, that job polarization may be a less pervasive phenomenon than usually thought (Hunt and Nunn, 2019); and on the other hand that the positive effects of automation and, more in general, of technological change, may also spill over unskilled workers (Aghion et al., 2018; 2019).

The results from our study, as well as from the related literature on micro-effects of automation, challenge the widespread fear that automation represents a fatal threat to employment. We report instead the existence also of opportunities associated with new technologies that appear to boost employment evenly across different types of workers. A cautionary remark is however due. Note indeed that our work, as well as most other firm-level studies, provides direct evidence on the observed outcomes taking place within adopting firms. An effective support in view of evidence-based policies needs to be complemented by studies that also address, on the one side, the impact of new technologies across adopting and non adopting firms within the same industry (a first attempt in this direction is that in Acemoglu et al., 2020) and, more demanding, on the other side, the long term process of evolution in the shares of employment across sectors.

Our analysis is one of the first attempts to explore the determinants of firm-level gross worker flows, and to look at the impact of automation at the firm level. There are, of course, some limitations to our work: our employer-employee dataset does not allow us to follow the career paths of workers, which can be a relevant margin of adjustment following technological change (where do displaced workers get hired after an automation spike?). Our methodology also limits the analysis to firms engaged in international trade, leaving aside smaller firms that are solely active in the domestic market. On the positive side, we think there are important future lines of research stemming from our work. One possibility, using additional data on the boundaries of the firms and FDI, would be to focus on the reorganisation of production of multinational firms, as a consequence of automation spikes. Second, with plant-level data or case studies, one could follow better the changes in the production process associated with automation, and disentangle the labor-saving from the productivity channels.

Credit Author Statement

All authors contributed equally to the various stages of the work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This paper has benefited from comments of participants at several conferences: the 11th European Meeting of Applied Evolutionary Economics (EMAEE, Brighton, June 2019), the Innovation, firm dynamics, employment and growth workshop (Greenwhich University, June 2019), the internal seminar of the Dept. of Economic Policy, Università Cattolica, Milano (June 2019), the 2nd Conference on the Geography of Innovation and Complexity, Utrecht (September 2019), the UNIDO and UNU-MERIT conference on The future of industrial work, Vienna (September 2019), the CONCORDi conference on Industrial innovation for transformation, Seville (September 2019), a presentation at the Rotterdam School of Management (November 2019), the Bank of Italy conference on Recent trends in firm organization and firm dynamics, Rome (December 2019), the 5th Online workshop on Industrial Dynamics and Innovation (December 2019), the ASSA 2020 Annual Meeting, San Diego (January 2020), the Paper Development Workshop, Manchester (January 2020), the LISER-IAB conference on The digital transformation and the future of work, Luxembourg (February 2020), the 35th European Economic Association (EEA) Congress (August 2020), and the ESCoE Conference on Economic Measurement (September 2020). We are also indebted to Ariell Reshef, Mariagrazia Squicciarini and Marco Vivarelli for insightful comments. This work has been partly supported by the European Commission under the H2020, GROWINPRO, Grant Agreement 822781 and by the Italian Ministero dell'Istruzione, dell'Università e della Ricerca (PRIN-2017, project 201799ZJSN: "Technological change, industry evolution and employment dynamics"). This work is also supported by a public grant overseen by the French National Research Agency (ANR) as part of the 'Investissements d'avenir' (reference: ANR-10-EQPX-17, Centre d'accès sécurisé aux données, CASD). The usual disclaimer applies.

Appendix A. Additional information

Table A1
HS 2012 codes referring to capital goods related to the automation of blue-collar industrial jobs, based on the taxonomy by Acemoglu and Restrepo (2018), and average share in total automation investment imports in our sample.

Label	HS codes	Share (%)
1. Industrial robots	847950	2.71
2. Dedicated machinery	847989	13.62
3. Numerically controlled machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221, 846231, 846241, 84629120, 84629920	6.93
4. Automatic machine tools	845600–846699, 846820–846899, 851511–851519 (excluding the codes listed in *Numerically controlled machines*)	32.02
5. Automatic welding machines	851521, 851531, 851580, 851590	4.48
6. Weaving and knitting machines	844600–844699 and 844700–844799	0.98
7. Other textile dedicated machinery	844400-844590	0.59
8. Automatic conveyors	842831-842839	3.60
9. Automatic regulating instruments	903200–903299	32.66
10. 3-D printers	847780	2.42

Notes: (i) for further details, see Acemoglu and Restrepo (2018, A-12-A14); (ii) the mentioned source does not list the codes referring to *Numerically controlled machines*, which have been retrieved by the authors of this paper; (iii) we have added 3-D printers to the original classification by Acemoglu and Restrepo (2018), based on the code identified by Abeliansky et al. (2020).

Table A2
Revealed Comparative Advantages for the automation measure and its components (referring to the categories described in Table A1), 2003–2015.

Year	Aggr.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2003	**0.61**	1.34	0.30	0.50	0.54	0.59	0.20	0.75	0.79	1.20	0.85
2004	**0.57**	1.27	0.29	0.42	0.48	0.61	0.24	0.83	0.95	1.21	0.56
2005	**0.63**	1.82	0.38	0.43	0.51	0.64	0.28	0.82	0.82	1.28	0.54
2006	**0.63**	1.49	0.43	0.45	0.52	0.65	0.26	0.70	0.73	1.27	0.62
2007	**0.63**	1.64	0.31	0.59	0.58	0.74	0.27	0.63	0.88	1.38	0.83
2008	**0.68**	1.86	0.35	0.57	0.63	0.85	0.18	0.79	0.82	1.43	0.78
2009	**0.67**	1.45	0.37	0.49	0.66	0.98	0.20	0.75	0.71	1.26	0.69
2010	**0.58**	1.40	0.23	0.51	0.57	0.89	0.15	0.57	0.80	1.44	0.46
2011	**0.63**	1.67	0.28	0.45	0.57	1.10	0.11	0.56	0.73	1.60	0.70
2012	**0.71**	1.91	0.61	0.47	0.44	1.07	0.13	0.76	0.80	1.55	0.69
2013	**0.71**	1.64	0.62	0.51	0.44	1.01	0.09	0.72	0.83	1.51	0.71
2014	**0.65**	1.43	0.57	0.56	0.37	0.96	0.11	0.70	0.64	1.49	0.61
2015	**0.60**	1.42	0.48	0.46	0.35	0.82	0.10	0.71	0.56	1.44	0.55

Source: our elaborations based on COMTRADE data (HS 2002). Notes: (i) $RCA > 1$ denotes that a sector represents a larger share in a country's exports than in total world exports, hence the country is *specialised* in that sector (see the seminal reference by Balassa 1965); (ii) since COMTRADE data are 6-digit, the 8-digit codes listed in *Numerically controlled machines* in Table A1 are included in *Automatic Machine tools*; (iii) column *Aggr.* refers to the sum of components (1) to (10), which is our automation measure.

Table A3
OECD taxonomy of digital intensive sectors.

Sector denomination	ISIC rev.4	Quartile of digital intensity
Food products, beverages and tobacco	10–12	Low
Textiles, wearing apparel, leather	13–15	Medium-low
Coke and refined petroleum products	19	Medium-low
Chemicals and chemical products	20	Medium-low
Pharmaceutical products	21	Medium-low
Rubber and plastics products	22–23	Medium-low
Basic metals and fabricated metal products	24–25	Medium-low
Electrical equipment	27	Medium-high
Wood and paper products, and printing	16–18	Medium-high
Furniture and other manufacturing, repairs of computers	31–33	Medium-high
Computer, electronic and optical products	26	High
Machinery and equipment n.e.c.	28	High
Transport equipment	29–30	High

Source: Calvino et al. (2018), Table 3, column 2001-03.

Table A4
Descriptive statistics on firms with/without imports of capital goods embedding automation technologies.

	Non-importers of automation			Importers of automation			T-test
	mean	sd	median	mean	sd	median	
Employment (headcount)	**23.07**	60.09	10.00	**140.15**	849.04	38.00	***
Growth rate (%)	**-0.59**	29.88	0.00	**-0.78**	26.66	0.00	**
Hourly labour productivity (€ /hour)	**35.20**	276.41	26.50	**40.03**	577.70	30.04	***
Hourly labour productivity growth (%)	**0.81**	43.04	1.39	**1.22**	37.93	1.77	***
Capital intensity (€ /hour)	**43.72**	1093.99	17.08	**87.52**	6225.09	29.72	***
CS3 share (%)	**10.10**	16.63	4.00	**12.56**	14.28	8.74	***
Exporter (%)	**47.24**	49.92	0.00	**76.75**	42.24	100.00	***
Importer (%)	**51.13**	49.99	100.00	**84.49**	36.20	100.00	***
Age	**20.53**	16.47	17.00	**25.74**	19.23	21.00	***

Notes: Two-sample *t*-test of difference in means; *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively.

Appendix B. Robustness checks

Table B1
Automation spikes and 1-digit occupational categories' shares (%), by subperiod.

Dep. var.: Share of	CS3 Engineers, professionals, and managers	CS4 Supervisors and technicians	CS5 Clerical workers	CS6 Production workers
(a) Subperiod: 2002–2008				
Spike_{t-2}	0.016	0.332	–0.269	0.013
	0.333	0.482	0.388	0.487
Spike_{t-1}	0.203	0.794	–0.419	–0.253
	0.398	0.559	0.465	0.584
Spike_{t}	0.555	–0.212	–0.241	0.330
	0.431	0.523	0.487	0.656
Spike_{t+1}	0.683	0.227	–0.354	–0.212
	0.452	0.628	0.549	0.756
Spike_{t+2}	0.399	–0.617	0.265	0.406
	0.521	0.686	0.635	0.763
Nb. obs.	223,628	223,628	223,628	223,628
Nb. firms	37,135	37,135	37,135	37,135
Adj. R^2	0.623	0.618	0.634	0.739
(b) Subperiod: 2009–2015				
Spike_{t-2}	–0.108	0.259	–0.226	0.174
	0.397	0.489	0.426	0.572
Spike_{t-1}	–0.156	0.144	–0.026	0.012
	0.300	0.462	0.415	0.570
Spike_{t}	0.065	0.083	–0.291	0.204
	0.325	0.440	0.355	0.538
Spike_{t+1}	0.035	0.493	–0.468	–0.191
	0.321	0.436	0.390	0.517
Spike_{t+2}	–0.010	0.356	–0.222	–0.430
	0.285	0.406	0.342	0.461
Nb. obs.	219,445	219,445	219,445	219,445
Nb. firms	36,197	36,197	36,197	36,197
Adj. R^2	0.723	0.702	0.704	0.790

Notes: Propensity score reweighting estimation of Eq. 4. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table B2
Automation spikes and 2-digit occupational categories' shares (%), by subperiod.

Dep. var.: Share of	CS37	CS38	CS46	CS47	CS48	CS54	CS62	CS63	CS67
(a) Subperiod: 2002–2008									
$Spike_{t-2}$	0.008	0.028	0.321	0.041	0.064	–0.265	–0.137	0.219	-0.313
	0.232	0.239	0.330	0.285	0.210	0.355	0.524	0.324	0.388
$Spike_{t-1}$	–0.150	0.312	0.554	0.403	0.022	–0.132	–0.367	0.172	0.015
	0.292	0.288	0.369	0.390	0.253	0.403	0.600	0.352	0.509
$Spike_{t}$	0.016	0.557	0.140	–0.180	0.124	–0.035	0.815	0.143	-0.612
	0.334	0.358	0.366	0.350	0.254	0.427	0.651	0.362	0.585
$Spike_{t+1}$	-0.020	0.729*	0.626	–0.572	0.362	–0.303	0.299	0.498	-0.453
	0.302	0.417	0.434	0.405	0.341	0.490	0.843	0.559	0.582
$Spike_{t+2}$	0.242	0.073	0.151	–1.044**	0.298	0.402	–0.456	1.210**	0.184
	0.406	0.433	0.534	0.478	0.369	0.622	0.912	0.509	0.785
Nb. obs.	223,628	223,628	223,628	223,628	223,628	223,628	223,628	223,628	223,628
Nb. firms	37,135	37,135	37,135	37,135	37,135	37,135	37,135	37,135	37,135
Adj. R^2	0.482	0.543	0.624	0.578	0.441	0.584	0.663	0.581	0.653
(b) Subperiod: 2009–2015									
$Spike_{t-2}$	0.069	–0.298	–0.231	0.314	0.168	–0.363	–0.193	-0.197	0.267
	0.260	0.312	0.267	0.360	0.197	0.378	0.516	0.277	0.477
$Spike_{t-1}$	0.139	–0.272	–0.365	0.296	0.132	–0.216	–0.662	0.155	0.237
	0.221	0.224	0.283	0.309	0.168	0.354	0.487	0.265	0.465
$Spike_{t}$	–0.005	0.101	–0.057	0.170	–0.050	–0.313	0.267	-0.164	-0.001
	0.273	0.239	0.308	0.311	0.160	0.336	0.515	0.252	0.415
$Spike_{t+1}$	–0.023	0.107	0.163	0.227	0.074	–0.219	–0.196	-0.112	0.112
	0.255	0.240	0.270	0.309	0.167	0.375	0.510	0.275	0.402
$Spike_{t+2}$	–0.216	0.239	0.098	0.019	0.096	–0.046	–0.501	-0.107	0.203
	0.159	0.251	0.225	0.293	0.158	0.315	0.470	0.242	0.367
Nb. obs.	219,445	219,445	219,445	219,445	219,445	219,445	219,445	219,445	219,445
Nb. firms	36,197	36,197	36,197	36,197	36,197	36,197	36,197	36,197	36,197
Adj. R^2	0.591	0.684	0.635	0.723	0.561	0.698	0.769	0.719	0.766

Notes: Propensity score reweighting estimation of Eq. 4. CS37: Top managers and professionals; CS38: Technical managers and engineers; CS46: Mid-level managers & professionals; CS47: Technicians; CS48: Supervisors and foremen; CS54: Office workers; CS62: Skilled industrial workers; CS63: Skilled manual laborers; CS67: Unskilled industrial workers. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote $p<0.10$, $p<0.05$ and $p<0.01$, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table B3
Automation spikes and gross worker flows, sample restricted to firms with at least 50 employees.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.002	–0.006	–0.008
	0.010	0.005	0.009
$Spike_{t-1}$	0.017	0.008	–0.010
	0.014	0.010	0.008
$Spike_{t}$	0.046***	0.034***	–0.013**
	0.013	0.012	0.006
$Spike_{t+1}$	0.007	0.005	–0.002
	0.008	0.006	0.006
$Spike_{t+2}$	–0.011	–0.001	0.010
	0.014	0.007	0.012
Nb. obs.	81,177	81,177	81,177
Nb. firms	6846	6846	6846
Adj. R^2	0.031	0.183	0.131

Notes: Propensity score reweighting estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote $p<0.10$, $p<0.05$ and $p<0.01$, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table B4
Automation spikes and worker flows: propensity score reweighting estimator, single-plant firms only.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.010	0.005	–0.005
	0.007	0.006	0.006
$Spike_{t-1}$	–0.003	–0.009	–0.006
	0.007	0.006	0.005
$Spike_{t}$	0.024***	0.009	–0.015***
	0.006	0.006	0.005
$Spike_{t+1}$	–0.012**	–0.009*	0.003
	0.007	0.005	0.006
$Spike_{t+2}$	–0.020***	–0.013***	0.008
	0.008	0.005	0.006
Nb. obs.	237,842	237,842	237,842
Nb. firms	22,230	22,230	22,230
Adj. R^2	–0.001	0.228	0.158

Notes: Propensity score reweighting estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table B5
Automation spikes and worker flows: propensity score reweighting estimator, removing firms that both import and export automated goods.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.007	0.003	–0.004
	0.007	0.007	0.007
$Spike_{t-1}$	–0.011	–0.003	0.007
	0.007	0.007	0.007
$Spike_{t}$	0.026***	0.010	–0.016***
	0.006	0.007	0.006
$Spike_{t+1}$	–0.019***	–0.009	0.010
	0.007	0.007	0.006
$Spike_{t+2}$	–0.010	–0.004	0.006
	0.008	0.007	0.008
Nb. obs.	369,929	369,929	369,929
Nb. firms	34,335	34,335	34,335
Adj. R^2	0.002	0.192	0.127

Notes: Propensity score reweighting estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table B6
Automation spikes and worker flows: propensity score reweighting estimator, with physical investment spike (Inv. Spike) as a control.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.009	0.001	–0.008
	0.005	0.005	0.005
$Spike_{t-1}$	–0.007	–0.007	0.000
	0.005	0.005	0.005
$Spike_{t}$	0.024***	0.007	–0.018***
	0.005	0.005	0.005
$Spike_{t+1}$	–0.012**	–0.009*	0.003
	0.005	0.005	0.005
$Spike_{t+2}$	–0.012**	-0.005	0.007
	0.006	0.005	0.006
Inv. $Spike_{t-2}$	0.018***	0.011***	–0.007**
	0.004	0.003	0.004
Inv. $Spike_{t-1}$	0.034***	0.026***	–0.008**
	0.004	0.004	0.003
Inv. $Spike_{t}$	0.066***	0.083***	0.017***
	0.004	0.004	0.003
Inv. $Spike_{t+1}$	0.010***	0.033***	0.023***
	0.003	0.004	0.004
Inv. $Spike_{t+2}$	–0.014***	–0.004	0.010***
	0.003	0.003	0.003
Nb. obs.	443,073	443,073	443,073
Nb. firms	40,198	40,198	40,198
Adj. R^2	0.010	0.197	0.127

Notes: Propensity score reweighting estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

Table B7

Automation spikes and worker flows: propensity score reweighting estimator, only spikes with ratio between the value of automated investments in the year of the spike and the average value in all the other years above 3 (threshold *à la* Bessen et al., 2019).

Dep. var.:	Net growth rate	Hiring rate	Separation rate
$Spike_{t-2}$	0.007	0.002	–0.005
	0.006	0.006	0.005
$Spike_{t-1}$	–0.006	–0.005	0.001
	0.006	0.006	0.005
$Spike_{t}$	0.028***	0.012**	–0.016***
	0.006	0.006	0.005
$Spike_{t+1}$	–0.010*	–0.007	0.003
	0.006	0.005	0.005
$Spike_{t+2}$	–0.015**	–0.005	0.010
	0.007	0.006	0.006
Nb. obs.	443,073	443,073	443,073
Nb. firms	40,198	40,198	40,198
Adj. R^2	0.005	0.191	0.126

Notes: Propensity score reweighting estimation of Eq. 2. Coefficients on the sector-year dummies and the constant term are omitted. *, **, and *** denote p<0.10, p<0.05 and p<0.01, respectively (based on robust standard errors, clustered at the firm level and displayed below coefficients).

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