INSTITUTE
OF ECONOMICS

Scuola Superiore
Sant'Anna

LEM | Laboratory of Economics and Management

Institute of Economics
Scuola Superiore Sant'Anna

Piazza Martiri della Libertà, 33 - 56127 Pisa, Italy
ph. +39 050 88.33.43
institute.economics@sssup.it

LEM
Working Paper Series

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

Giacomo Domini [a]
Marco Grazzi [b]
Daniele Moschella [c]
Tania Treibich [d]

[a] Erasmus University College, Erasmus University Rotterdam, The Netherlands.
[b] Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy.
[c] Institute of Economics & Department EMbeDS, Scuola Superiore Sant'Anna, Pisa, Italy.
[d] School of Business and Economics, University of Maastricht, The Netherlands.

2019/22 July 2019
ISSN(ONLINE) 2284-0400

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

Giacomo Domini[1], Marco Grazzi[2], Daniele Moschella*[3], and Tania Treibich[4]

[1]Erasmus University College, Erasmus University Rotterdam (The Netherlands)
[2]Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano (Italy)
[3]Institute of Economics & Department EMbeDS, Scuola Superiore Sant'Anna, Pisa, (Italy)
[4]School of Business and Economics, University of Maastricht (The Netherlands)

Abstract

This paper investigates how investment in automation-intensive goods impacts on worker flows at the firm level 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 2002-2015, we identify 'automation spikes' using imports of intermediates embedding automation technologies and then test their impact on employment dynamics. We find that automation spikes are positively correlated with preceding and contemporaneous growth in employment, mainly due to lower separation rates of investing firms. These differential patterns of net and gross worker flows do not appear to change significantly across different types of workers (occupational categories, 'techies', routine-intensive vs. non routine-intensive jobs).

Keywords: Automation, Skills, Technological Change, Gross Worker Flows
JEL classification: D25, J23, L25, O33

Acknowledgments. This paper has benefited from comments of conference participants at the 11th European Meeting of Applied Evolutionary Economics (EMAEE, Brighton, June 2019); at Innovation, firm dynamics, employment and growth workshop (Greenwhich University, June 2019) and at the internal seminar of the Dept. of Economic Policy, Università Cattolica, Milano (June 2019). We are also indebted to Mariagrazia Squicciarini and Marco Vivarelli for insightful comments. All remaining errors are our own. This work has been partly supported by the European Commission under the H2020, GROWINPRO, Grant Agreement 822781. This work is also supported by a public grant overseen by the French National Research Agency (ANR) as part of the 'Investissements d'avenir' program (reference: ANR-10-EQPX-17, Centre d'accès sécurisé aux données, CASD). The usual disclaimer applies.

*Corresponding author: Daniele Moschella, Scuola Superiore San'Anna, Pisa, Italy. Postal address: Institute of Economics, Scuola Superiore Sant'Anna, Piazza Martiri della Libertà 33, 56127, Pisa, Italy, E-mail: daniele.moschella@santannapisa.it

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), 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 a recent review, see Piva and Vivarelli, 2017). 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 by a machine (see, for instance, Autor et al., 2003; Goos et al., 2014; Autor, 2015b). 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; Trajtenberg, 2018; Furman and Seamans, 2018).[1]

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 des données 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. In particular, we identify imports of capital goods that are expected to be related to automation, based on the taxonomy employed by Acemoglu and Restrepo (2018). Notice that, given the currently available datasets, this is one of the few ways available to assess the impact of automation and digital technologies at the firm level. The richness of the data at 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.

[1] 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 et al., 2003; Autor, 2015a).

We show how firms' employment growth path, also decomposed into hiring and separation rates, is affected by the adoption of digital technology through imports of automated machines.

Our work contributes to two, neighboring fields of literature. *First*, in more general terms, we provide a rather detailed empirical perspective of the magnitude and characteristics of the advent of the latest wave of innovations (see among the others, Roco and Bainbridge, 2003; Dosi and Galambos, 2012). Our investigation on the statistical properties of imports of goods embedding automation technologies reveal 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 Doms and Dunne, 1998). Indeed, similar to investment spikes, imports of intermediates 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; Letterie et al., 2004; Grazzi et al., 2016). 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 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., 2016). The latter approach is to consider jobs related to STEM fields (Science, Technology, Engineering and Math), or, as identified by Harrigan et al. (2016, 2018), 'techies'. The authors show, using data on France, that the advent of techies led to within-firm occupational polarization, 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 more scant. To begin with, the impact of robotisation at the more aggregate level is investigated in Dauth et al. (2018), Acemoglu and Restrepo (2018) and Graetz and Michaels (2018). 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 (2017) 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.

Other works have instead focused on the impact of automation at the worker level. Using a Dutch survey on automation costs, Bessen et al. (2019) study a sample of Dutch firms over the period 2000-2016 to 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.

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 firm level and on the job creation and destruction effects of automation. Indeed, while there exists an abundant literature that has shown the relevance of focusing on gross job flows as the outcome of job creation and job destruction measures *à la* Davis and Haltiwanger (1990, 1992) to study employment dynamics,[2], much less is known about the impact of technologies on job flows at the firm level.[3]

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. In this respect, notice that our choice of focusig on imports of automation intensive goods, while driven by data availabiliy[4], is not expected to greatly affect our findings, nor to do so in the more harming direction. Notice indeed that, *first*, while 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 Bernard et al., 2010; Blum et al., 2010) they are much less likely to do so for more complex goods (Bernard et al., 2015) involving higher relation specificity such as those ones we are focusing here. In addition, while it is also true that some of the firms in our sample might purchase automation intensive capital goods only domestically - and thus would not be captured by our measure - our within-firm identification mostly relies on what happens within firms that do import automation intensive capital goods. This should greatly reduce any bias related to not considering other types of firms or automation spikes.

With this in mind, our findings show that firms investing in goods which are intensive in automation technologies do not display a negative effect on employment. If anything, automation spikes are positively correlated with preceding and contemporaneous growth in employment, which is mainly due to lower separation rates of investing firms. 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, the relationship between automation spikes and worker flows doesn't seem to change across different types of workers (occupational categories, 'techies', routine-intensive vs. non routine-intensive).

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 intermediates 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] For applications to trade, see Gourinchas (1998, 1999); Klein et al. (2003)

[3] In general, also the evidence on job flows at the firm level is much scanter, see among the others, Abowd et al. 1999; Bellon 2016, on France; and Moser et al. 2010, on trade.

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

2 Data and descriptive statistics

2.1 Sources

We employ data concerning all 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).[5] 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).[6] As a firm's APE may vary across years, we assign each firm a permanent 2-digit sector based on the most frequent occurrence.[7]

DADS is then matched to 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.[8]

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.

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*

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

[6] 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.

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

[8] We also retrieve information on physical investment, to be compared to our automation investment measure in the next section, 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. 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).

and *separations*. This is made 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».[9] 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.

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.[10] 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.[11] 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_{jt} and I_{jt-1}, respectively, where j indexes jobs).[12] We then aggregate this information at the firm level and obtain employment stock and flow variables based on these job-level indicators. Emp_{it} and Emp_{it-1} refer to total employment stocks in firm i in years t and t-1, respectively. A firm's hirings in year t (H_{it}) are obtained as the aggregation of jobs for which $I_{jt} = 1$ and $I_{jt-1} = 0$; separations in year t (S_{it}) are all jobs for which $I_{jt} = 0$ and $I_{jt-1} = 1$. 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:

$$\Delta Emp_{it} = Emp_{it} - Emp_{it-1} = H_{it} - S_{it} \tag{1}$$

Following Davis and Haltiwanger (1990, 1992), we express worker flows from t-1 to t as rates. To do so, we divide them by the average of employment in those two years,

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

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

[11] 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*).

[12] 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.»

$Z_{it} = \frac{Emp_{it}+Emp_{it-1}}{2}$. The hiring, separation, and (net) employment growth rates are then obtained as:

$$h_{it} = \frac{H_{it}}{Z_{it}}$$

$$s_{it} = \frac{S_{it}}{Z_{it}}$$

$$g_{it} = \frac{\Delta Emp_{it}}{Z_{it}} = h_{it} - s_{it}$$

Types of workers

The above-mentioned variables are constructed both for total firm employment and separately for different categories of workers within firms. We use three classifications of workers to identify the heterogeneous impact of technology on worker flows: i) occupational categories, typically employed in the empirical literature using French data (Abowd et al., 1999; Biscourp and Kramarz, 2007; Harrigan et al., 2016, 2018); ii) 'techies' (as identified by Harrigan et al., 2016); and iii) 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) as described in Table 1 below. 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, 2017), 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. (2016, 2018).

Table 1: Occupational categories and their share (%) in employment, 2002-1015.

	Engineers, professionals, and managers	Supervisors and technicians	Clerical workers	Skilled blue-collar workers	Unskilled blue-collar workers
CS code	CS3	CS4	CS5	CS61	CS66
Average within-firm share	11.02	19.38	12.70	35.19	19.04
Aggregate share	16.54	22.85	7.43	36.26	16.18

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.

Second, following Harrigan et al. (2016), we identify 'techies' as workers pertaining to occupational categories CS38 and CS47. Techies are workers who facilitate the adoption and use of new technology.

Finally, in order to 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 have a RTI measure for each 4-digits 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 only includes 4-digits PCS2003 codes since 2009, this analysis only applies to the subperiod 2009-2015.

For the period 2002-2008, 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. According to 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 unskilled blue-collar workers). In this analysis we leave category 48 (supervisors) out, as they are difficult to assign to a definite routine class.[13]

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 intermediate 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 *intermediate goods* (divisions 82, 84, 85, 87, and 90) into several categories of automated and 'other' (i.e. non-automated) goods. Imports of intermediates embedding automation technologies include, among the others, industrial robots, dedicated machinery, numerically-controlled machines, and a number of other automated intermediate goods.[14] In Section 3 we provide evidence that imports of such intermediates behave in a way consistent with an investment variable, and in particular they occur in *spikes*.

[13] 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%).

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

2.3 Sample definition and descriptive statistics

As we identify automation investment through imports embedding automation technologies, we restrict our analysis to the sample of firms importing at least once in the period of analysis. Since episodes of entry and exit may introduce a bias in our estimates of the relationship between automation spikes and worker flows, we decide to focus on continuing firms over two consecutive years. Continuing firms account for 91.05% of firms that import at least once between 2002 and 2015, while (discarded) entering and exiting firms account for 4.04% and 4.91%, respectively.

Table 2: Sample composition per year, 2002-2015

Year	Nb. firms	Share in manuf. firms	Share in manuf. employment
2002	37,548	31.10	84.41
2003	37,636	31.67	84.89
2004	37,490	32.26	85.18
2005	37,932	33.09	85.21
2006	38,899	33.66	85.36
2007	38,309	33.58	85.25
2008	37,752	33.69	85.32
2009	37,912	33.60	85.04
2010	36,966	33.94	85.32
2011	36,348	34.12	85.31
2012	35,846	34.11	85.39
2013	35,163	33.99	85.27
2014	35,525	33.84	84.75
2015	34,782	33.50	84.37

Source: our elaborations on DADS and DGDDI data.

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.

Figure 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.

Figure 2 compares the mean net and gross rates of the five 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 unskilled production workers. Common to all categories is the general decreasing trend in gross rates, which is consistent with what we observed in the previous

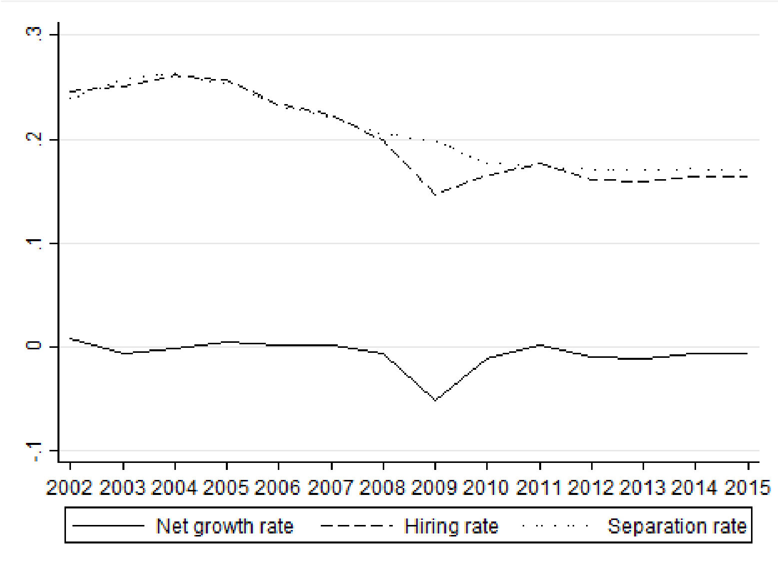
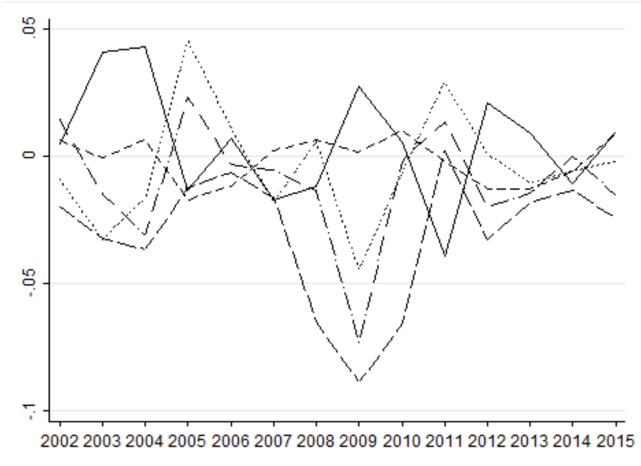


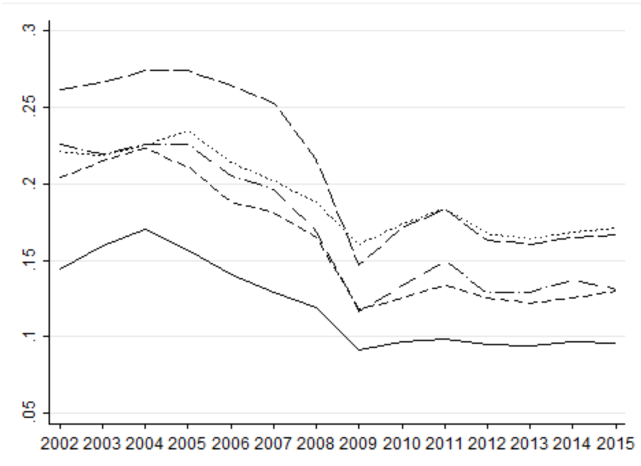
Figure 1: Mean net growth rate, hiring rate, and separation rate, 2002-2015. Source: our elaborations on DADS and DGDDI data.

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. What can we conclude from these statistics? Figure 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 we will take this into account by also estimating the impact of automation on employment dynamics for the different occupational categories separately.

(a) Net growth rate



(b) Hiring rate



(c) Separation rate

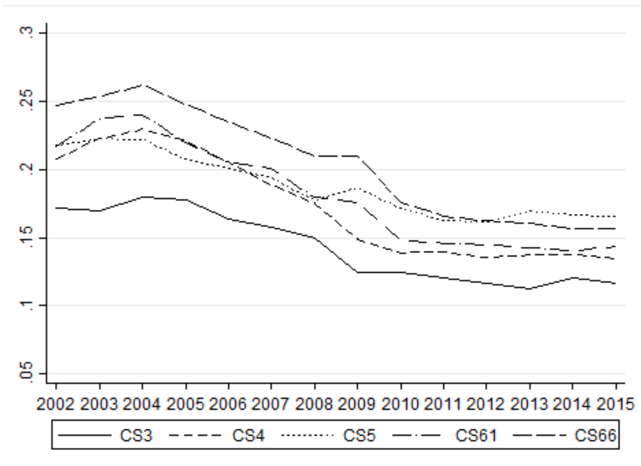


Figure 2: Mean net employment growth rate, hiring rate, and separation rate, by occupational category, 2002-2015. Source: our elaborations on DADS and DGDDI data. Note: CS3 denotes engineers, professionals, and managers; CS4 denotes supervisors and technicians; CS5 denotes clerical workers; CS61 denotes skilled blue-collar workers; CS66 denotes unskilled blue-collar workers.

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 digital 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). Not surprisingly, 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 the high digital intensity group is 1.65 times as large as the sector's share in employment.

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

Digital intensity quartile	Share in imports embedding automation technologies (%) (1)	Share in total employment (%) (2)	Ratio (1)/(2)
Low	1.7	11.7	0.15
Medium-low	38.4	41.3	0.93
Medium-high	15.8	20.3	0.78
High	44.0	26.6	1.65

Note: the classification for 2001-2003 is used; see Calvino et al. (2018, Table 3). Source: our elaborations on DADS and DGDDI data.

3.1 Investment in automation as spikes

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

First, it is *rare across firms*: in each year, only 10% of importers buy goods from such categories. Overall, 52% of firms import such goods at least once. As a comparison, around 18% of firms in our sample have positive physical investment in a given year.[15]

[15] The value of physical assets is retrieved from the FICUS and FARE dataset (variable *IMMOCOR*

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. investing in automated goods doesn't happen regularly or is smoothed across periods. Figure 3 shows that the latter is not usually the case. Among firms who import automated goods at least once (roughly half the sample), one fourth 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.

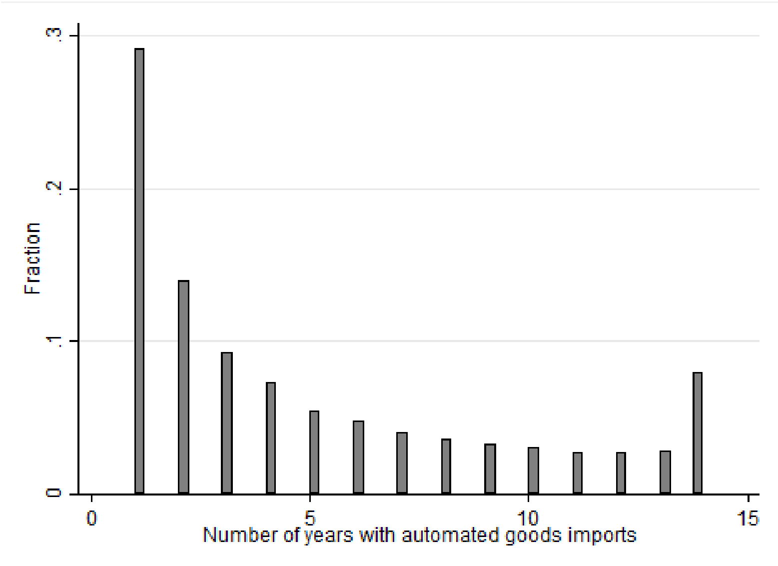


Figure 3: Number of years with imports of automated goods. Source: our elaborations on DADS and DGDDI data.

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 not. To answer this question, we compare the value of such investment across years, within firms. We compute, for each firm, the share of automated imports in year t in total automated imports of that firm in the period of analysis. We do the same for investment in physical capital. We then rank these yearly shares from largest to lowest. Figure 4 (left) shows that in the case of physical investment, the highest rank represents close to 60% of total investment on average (the median is a bit lower); for automated goods, the highest share is even higher, and close to 70%. The shares of lower ranks then rapidly decrease in value, and even more so in the case of automated goods.[16] Because of the very skewed nature of the variable within firms, we define as *automation spike* only the largest event for each firm.

in the former, *immo_corp* in the latter). Physical investment is computed as increases in physical capital; the investment rate is the ratio with the lagged value of physical capital. All variables are deflated at the 2-digit level.

[16] In the case of physical investment, the higher ranks correspond to maintenance investment, therefore to be separate from the acquisition of additional or new machines.

(a) Total physical investment (b) Investment in imported automated goods

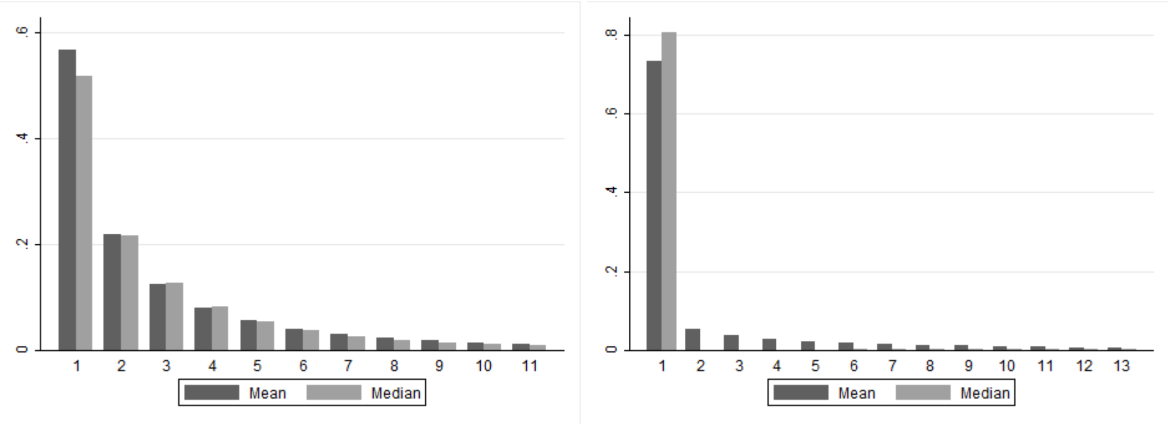


Figure 4: Investment shares by rank. Source: our elaborations on DADS, DGDDI, FICUS, and FARE data.

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 digital 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 effect of automation spikes on employment flows. We find that they are not: in our sample, only 8.27% of automation spikes are also investment spikes[17]; while 4.60% 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 employment effects of 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 digital 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

[17] Although several investment spike measures have been put forward in the literature (Power, 1998; Cooper et al., 1999; Letterie et al., 2004; Grazzi et al., 2016), we use the most simple 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).

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 have a positive effect on employment growth. Note however that this literature only considers net employment growth, not 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 two years before and three 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 (in fact, it decreases before the spike, like the hiring rate).

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 much richer dynamics of hiring and separation rates.

Table 4: Mean worker flow rates around an automation spike.

Years since spike	Net growth rate	Hiring rate	Separation rate	Nb. firms
-2	0.019	0.196	0.176	5,977
-1	0.014	0.188	0.173	5,977
0	0.014	0.175	0.161	5,977
1	-0.011	0.150	0.162	5,977
2	-0.021	0.134	0.155	5,977
3	-0.039	0.124	0.162	5,977

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

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 the detail. As a 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).

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 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, in 4.1, by running the regressions as per the equation above for the occupational categories presented in Section 2; then, in 4.2, by doing the same for a routine-intensity classification.

Furthermore, an important aspect of the skill-biased technical change theory is that the adoption of new technology should affect the *relative* demand for skills within firms. To better assess the relation between automation and the *composition* of the labour force, we also estimate the following Equation:

$$Share^c_{it} = \alpha + \sum_{k=-2}^{2} \beta_k Spike_{t+k} + \gamma_i + \delta_{jt} + \epsilon_{it} \tag{3}$$

where $Share^c$ is the share of occupational category c with respect to the total employment of firm i, and the right-hand side variable are as per Equation 2.

In Table 5 we report results from the estimation of Equation 2. 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 3.8 percent 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.

Table 5: Automation spikes and worker flows.

Dep. var.:	Net growth rate	Hiring rate	Separation rate
Spike_{t-2}	0.022***	0.001	-0.021***
	0.003	0.003	0.002
Spike_{t-1}	0.033***	0.008***	-0.025***
	0.003	0.003	0.002
Spike_{t}	0.038***	0.013***	-0.025***
	0.003	0.002	0.002
Spike_{t+1}	-0.005*	-0.006***	-0.001
	0.003	0.002	0.003
Spike_{t+2}	-0.012***	-0.012***	-0.000
	0.003	0.002	0.003
Constant	0.051***	0.273***	0.222***
	0.002	0.001	0.001
Nb. obs.	518,108	518,108	518,108
Nb. firms	55,043	55,043	55,043
Adj. R^2	0.073	0.224	0.177

Notes: FE estimation of Equation 2. Coefficients on the sector-year dummies 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).

Deeper insights on how this pattern emerges are provided by the 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.

4.1 Analysis by occupational category

Table 6 displays the results of regressions of Equation 2, run separately by occupational category, thus providing insights on how the relationship between automation and employment changes across different types of workers. Results are organised into three panels, one per each dependent variable (i.e. worker flow). Each panel displays the results of six regressions: the first five refer to the broad occupational categories, roughly corresponding to the first-digit level of the CS classification; the last refers to 'techies', i.e. types of workers that facilitate the adoption of new technologies (see Section 2 for more information).

At first sight, little differences appear, and the same statements made when commenting Table 5 above, about dynamic aspects of the automation-employment relationship, apply to all categories. Indeed, the sign is the same and, with few exceptions, even the magnitude of coefficients is close to that as per the regressions on the whole of employment. Still, a deeper inspection reveals some differences, in particular regarding gross worker flows, i.e. hiring and separation rates. While, across all categories, an increase in the hiring rate in the year of the spike and a decrease two years after it can be observed, employment dynamics are more spread out for the lowest occupational

Table 6: Automation spikes and worker flows, by occupational category.

	Engineers, professionals, and managers	Supervisors and technicians	Clerical workers	Skilled blue-collar workers	Unskilled blue-collar workers	Techies
(a) Dep. var.: Net growth rate						
Spike_{t-2}	0.014*	0.022***	0.024***	0.022***	0.020**	0.029***
	0.008	0.007	0.008	0.006	0.009	0.008
Spike_{t-1}	0.031***	0.040***	0.030***	0.034***	0.037***	0.036***
	0.007	0.007	0.007	0.006	0.009	0.007
Spike_{t}	0.037***	0.028***	0.039***	0.053***	0.027***	0.040***
	0.007	0.006	0.007	0.006	0.008	0.007
Spike_{t+1}	-0.002	0.001	-0.013*	-0.000	-0.001	0.002
	0.007	0.006	0.007	0.006	0.008	0.007
Spike_{t+2}	-0.011	-0.009	-0.001	-0.010	-0.018**	-0.011
	0.007	0.007	0.007	0.006	0.009	0.007
Constant	0.032***	0.043***	0.028***	0.053***	0.018***	0.026***
	0.004	0.004	0.004	0.004	0.005	0.005
(b) Dep. var.: Hiring rate						
Spike_{t-2}	0.006	0.002	0.002	0.001	0.008*	0.006
	0.004	0.004	0.005	0.004	0.005	0.004
Spike_{t-1}	0.006	0.010***	0.001	0.010***	0.015***	0.012***
	0.004	0.004	0.004	0.003	0.005	0.004
Spike_{t}	0.007**	0.009***	0.010**	0.020***	0.018***	0.012***
	0.003	0.003	0.004	0.003	0.004	0.003
Spike_{t+1}	-0.002	-0.004	-0.005	-0.003	0.010**	-0.004
	0.003	0.003	0.004	0.003	0.004	0.003
Spike_{t+2}	-0.009**	-0.009***	-0.015***	-0.011***	-0.007*	-0.013***
	0.003	0.003	0.004	0.003	0.004	0.003
Constant	0.152***	0.219***	0.241***	0.247***	0.283***	0.165***
	0.002	0.002	0.002	0.002	0.003	0.002
(c) Dep. var.: Separation rate						
Spike_{t-2}	-0.010**	-0.020***	-0.016***	-0.021***	-0.016***	-0.016***
	0.004	0.004	0.004	0.003	0.004	0.004
Spike_{t-1}	-0.022***	-0.026***	-0.027***	-0.029***	-0.019***	-0.024***
	0.004	0.003	0.004	0.003	0.004	0.004
Spike_{t}	-0.021***	-0.022***	-0.025***	-0.028***	-0.018***	-0.017***
	0.004	0.003	0.004	0.003	0.004	0.004
Spike_{t+1}	-0.000	-0.003	0.004	-0.003	0.009**	-0.002
	0.004	0.003	0.004	0.003	0.004	0.004
Spike_{t+2}	-0.004	-0.000	-0.004	0.004	0.004	-0.002
	0.004	0.004	0.004	0.004	0.004	0.004
Constant	0.151***	0.188***	0.200***	0.198***	0.229***	0.147***
	0.002	0.002	0.002	0.002	0.002	0.002
Nb. obs.	518,108	518,108	518,108	518,108	518,108	518,108
Nb. firms	55,043	55,043	55,043	55,043	55,043	55,043
Adj. R^2 (a)	-0.052	-0.050	-0.050	-0.039	-0.055	-0.057
Adj. R^2 (b)	0.086	0.099	0.077	0.113	0.088	0.086
Adj. R^2 (c)	0.077	0.085	0.070	0.096	0.072	0.075

Notes: FE estimation of Equation 3. Coefficients on the sector-year dummies 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).

category, i.e. unskilled blue-collar workers: growth rates are significantly above the within-firm average from t-2 to t+1, before turning to negative in t+2. Likewise, for the separation rate, significant below-average values are observed from t-2 to t for all categories, and non-significant ones afterwards. The only exception to this is, again the unskilled blue-collar category, featuring a significantly above-average separation rate at t+1. Interestingly, techies do not appear to feature any particular dynamics, despite their definition as workers that facilitate the adoption of new technologies.[18]

Table 7: Automation spikes and occupational categories' shares.

	Engineers, professionals, and managers	Supervisors and technicians	Clerical workers	Skilled blue-collar workers	Unskilled blue-collar workers	Techies
Spike_{t-2}	-0.005***	-0.001	-0.000	0.001	0.007***	-0.000
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t-1}	-0.005***	-0.000	-0.000	0.001	0.007***	-0.001
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t}	-0.006***	-0.001	-0.001	0.005**	0.006***	0.000
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t+1}	-0.003***	-0.000	-0.002**	0.003*	0.004**	0.002*
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t+2}	-0.002**	0.001	-0.000	0.002	0.002	0.001
	0.001	0.001	0.001	0.002	0.002	0.001
Constant	0.098***	0.204***	0.114***	0.363***	0.197***	0.111***
	0.001	0.001	0.001	0.001	0.001	0.001
Nb. obs.	518,108	518,108	518,108	518,108	518,108	518,108
Nb. firms	55,043	55,043	55,043	55,043	55,043	55,043
Adj. R^2	0.610	0.559	0.568	0.591	0.550	0.667

Notes: FE estimation of Equation 3. Coefficients on the sector-year dummies 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).

Further evidence on whether automation has different impact across different types of workers is provided by Table 7, which shows the results of the regressions having occupational categories' shares as dependent variable, as per Equation 3 . The picture is quite clear-cut: an automation spike is associated to a decrease in the share of the highest occupational category - peaking in the spike year, when the share decreases by 0.6 percent points (recall from Table 1 that its mean value is 11%), but also spreading before and after it. This mainly goes to the advantage of the the lowest category, i.e. unskilled blue-collar workers, and to a lower extent of skilled blue-collar workers. Other categories, including techies, feature (almost) no significant variation.

[18] Notice that the above-observed property by which a variable's coefficient in the regression having the net growth rate as a dependent variable equals the difference between those in the regressions having the hiring and separation rates, stemming from Equation 1, does not hold in this table. The reason for this is that net employment change in a certain occupational category can be due not only to employees in that category being hired and fired, but also to continuing employees (i.e., employees that are present in both t-1 and t) moving to another category. In formula:

$$\Delta Emp^c_{it} = Emp^c_{it} - Emp^c_{it-1} = H^c_{it} - S^c_{it} + N^c_{it}$$

where N^c denotes net inter-category movements in and out of occupational category c.

4.2 Automation and routine-intensive occupations

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 many others, Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014). The previous analysis by occupational category already bears some implications in terms of routine tasks occupational change. Consider, for example, the result on unskilled blue-collar workers in Table 7: 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 this section 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 (RTI). Using the definition of routine task-intensive occupations introduced in Section 2, we estimate Equation 2 first on the whole period (2002-2015) and then on the subperiod 2009-2015. In the first case, we are effectively assigning "office workers" (54) and "unskilled industrial workers" (67), which in the previous analysis were into two different groups, to the same "Routine" category, while all the others are classified as "Non-routine". 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" category.

Table 8: Automation spikes and worker flows, by routine-intensive occupations, 2002-2015

	Non-routine			Routine		
	g	h	s	g	h	s
Spike$_{t-2}$	0.023***	0.000	-0.022***	0.020***	0.005	-0.017***
	0.004	0.003	0.003	0.007	0.004	0.004
Spike$_{t-1}$	0.032***	0.008***	-0.026***	0.040***	0.010***	-0.026***
	0.004	0.003	0.003	0.007	0.004	0.003
Spike$_t$	0.041***	0.014***	-0.027***	0.033***	0.016***	-0.023***
	0.004	0.003	0.003	0.006	0.004	0.003
Spike$_{t+1}$	-0.004	-0.008***	-0.004	-0.006	-0.000	0.003
	0.004	0.002	0.003	0.006	0.003	0.004
Spike$_{t+2}$	-0.013***	-0.012***	0.000	-0.007	-0.011***	-0.000
	0.004	0.002	0.003	0.007	0.003	0.004
Constant	0.052***	0.262***	0.218***	0.032***	0.284***	0.228***
	0.002	0.002	0.002	0.004	0.002	0.002
Nb. Obs.	518,108	518,108	518,108	518,108	518,108	518,108
Nb. firms	55,043	55,043	55,043	55,043	55,043	55,043
Adjusted R^2	0.000	0.181	0.145	-0.039	0.101	0.083

Notes: FE estimation of Equation 2. Coefficients on the sector-year dummies 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).Classification based on 2-digits CS. Office workers and unskilled industrial workers are the 2-digits (P)CS categories assigned to "Routine".

Regressions results are reported in Tables 8 and 9. Before and during an automation spike, there is a net growth premium both for routine and non-routine occupa-

Table 9: Automation spikes and worker flows, by routine-intensive occupations, 2009-2015

	Non-routine			Routine		
	g	h	s	g	h	s
Spike_{t-2}	0.018*	0.004	-0.010**	0.009	-0.005	-0.014***
	0.010	0.006	0.005	0.010	0.006	0.005
Spike_{t-1}	0.032***	0.008	-0.019***	0.027***	0.003	-0.024***
	0.008	0.005	0.005	0.009	0.005	0.004
Spike_{t}	0.023***	0.013***	-0.016***	0.025***	0.006	-0.018***
	0.007	0.005	0.004	0.008	0.005	0.004
Spike_{t+1}	-0.004	-0.003	-0.001	0.002	-0.003	-0.002
	0.007	0.004	0.004	0.007	0.004	0.004
Spike_{t+2}	-0.010	-0.007*	-0.003	-0.002	-0.011***	-0.007
	0.007	0.004	0.004	0.007	0.004	0.004
Constant	0.008***	0.160***	0.176***	-0.048***	0.161***	0.185***
	0.003	0.002	0.002	0.003	0.002	0.002
Nb. Obs.	252,542	252,542	252,542	252,542	252,542	252,542
Nb. firms	44,590	44,590	44,590	44,590	44,590	44,590
Adjusted R^2	-0.053	0.156	0.132	-0.050	0.156	0.139

Notes: FE estimation of Equation 2. Coefficients on the sector-year dummies 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). Classification based on 4-digits PCS2003.

tions. Also in this case, the positive coefficient on net employment growth is mostly due to lower separation rates that a firm enjoys before and during a spike. The main difference between the two tables is due to the coefficient on the second lag, which in the subperiod regression is barely significant for non-routine occupations and not significant for routine occupations (Table 9).

We also estimate Equation 3 with respect to the share of routine-intensive occupations on the two samples; results are reported in Table 10. Results for the subperiod 2009-2015 are mostly inconclusive (column 2), whereas the coefficients obtained for the whole period show a slight increase in the share of routine-intensive occupations before and during a spike, a result which is in line with the increase in the share of unskilled blue-collar workers around a spike observed in Table 7.

Coupled with the aggregate evidence shown at the beginning of this section, the results from the analysis by occupational category and by routine-intensive occupations suggests that automation spikes share the known features of investment spikes in general: they are associated with an expansion of employment, before and during the spike year. This expansion is generalised across occupational and routine-intensive categories, though slightly more intense for (unskilled as well as skilled) production workers (and according to the second classification, for routine-workers). As a result, the highest category in terms of both skills and non-routine intensity shrinks, in relative terms.

4.3 Robustness checks

We ran a number of checks to verify the robustness of the results presented above. The results are shown in Appendices B and C.

Table 10: Automation spikes and routine-intensive category's share

	2002-2015	2009-2015
Spike_{t-2}	0.008***	-0.000
	0.002	0.003
Spike_{t-1}	0.007***	0.000
	0.002	0.003
Spike_{t}	0.006***	0.001
	0.002	0.002
Spike_{t+1}	0.003	0.002
	0.002	0.002
Spike_{t+2}	0.002	0.001
	0.002	0.002
Constant	0.333***	0.493***
	0.001	0.001
Nb. Obs.	518,108	252,542
Nb. firms	55,043	44,590
Adjusted R^2	0.542	0.772

Notes: FE estimation of Equation 3. 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).

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 4.1 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.[19]

A second issue is that small firms might lack certain occupational categories: this might introduce some noise in our analysis by occupational category. In Appendix C we address this issue, presenting the results of robustness regressions, run on a restricted sample that excludes firms with less than 50 employees. This threshold is chosen because it is one of the criteria used for defining 'small' firms by Eurostat, and because it is an important threshold in the French labour market, at which many labour-related regulations start binding (which has consequences on employment and productivity, as documented by Garicano et al. 2016). This exercise also allows isolating larger firms, which are more likely to perform investment in automation, as they have larger resources and may reap larger gains from it. A final check regards running the analysis

[19] This is also useful, as these two subperiods are different as for 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 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.

on a restricted sample, only including firms that have a spike. In fact, our baseline sample is defined as all firms that import (any good) in at least one year, of which some may never import automated goods. Although the difference between the two groups is captured by the fixed effect, it may be that firms without spikes are generally different from those with a spike, and follow different growth trajectories. The results of regressions run on the restricted sample only including firms with a spike, i.e. firms that import automated intermediate goods at least once, present negligible differences from the main regressions displayed in this section, in terms of number of observations and estimates; therefore we do not dedicate an appendix to this check, but leave results available upon request from the authors. Notice that this check also makes our analysis consistent with that by Bessen et al. (2019), who also operate such a restriction.

Neither of the checks alters the main qualitative conclusions from the analysis presented above. The regressions by subperiod (Appendix B), aiming at verifying the robustness of our results to a discontinuity in the CS classification, confirm the significant shrinking of the highest occupational category in both subperiods, though it appears stronger in the earlier than in the later one. A notable difference, with respect to Table 7, is that the shrinking of the above-mentioned category goes to the advantage of skilled, rather than unskilled, blue-collar workers, though this is only significant in the earlier subperiod. In fact, when moving from 2002-2008 to 2009-2015, coefficients generally decrease, in absolute value, and lose significance. Similarly, in the restricted sample regressions (Appendix C), the coefficients on the spike lags in the column referring to skilled blue-collar workers gain significance, with respect to Table 7, and are of similar size to that of those in the column referring to unskilled blue-collars. These additional findings confirm that the expansion of employment, associated with investment in automation, results in a relative expansion of production workers in general, i.e. both skilled and unskilled.

5 Conclusions

Although there is a certain agreement in acknowledging the impact on employment of technological change, and in particular of the emerging digital technological paradigms, 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 intermediates 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.

We find evidence that automation spikes are positively correlated with preceding and contemporaneous growth in employment, an effect which is mainly due to lower separation rates of investing firms. Moreover, the relationship between automation spikes and worker flows doesn't seem to change across different types of workers (occupational categories, 'techies', routine-intensive vs. non routine-intensive).

Our evidence is in line with that from Bessen et al. (2019), on automation happening in spikes: this supports the idea that automation represents a significant disruption in the way firms produce. Overall, the impact of automation on firm employment within firms is generally positive: such result is, on one hand, in tune with the evidence on investment in capital goods, irrespective of their technological content (Grazzi et al., 2016), on the other hand it is consistent with labor-friendly technological change (Barbieri et al., 2019) improving the relative competitiveness of firms and thus favouring their expansion (as shown, for example, in Harrigan et al., 2018).

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?). On the positive side, we think there are important future lines of research stemming from our work. One possibility, for example, would be to look at firms' involvement in international trade and its differential impact on gross worker flows as another possible threat (or opportunity) to employment growth.

References

Abowd, J. M., P. Corbel, and F. Kramarz (1999): "The Entry And Exit Of Workers And The Growth Of Employment: An Analysis Of French Establishments," *The Review of Economics and Statistics*, 81, 170–187.

Acemoglu, D. and P. Restrepo (2017): "Robots and Jobs: Evidence from US Labor Markets," Working Paper 23285, National Bureau of Economic Research.

——— (2018): "Demographics and Automation," Working Paper 24421, National Bureau of Economic Research.

Asphjell, M., W. Letterie, P. G.A., and O. Nilsen (2014): "Sequentiality versus simultaneity: Interrelated factor demand," *The Review of Economics and Statistics*, 95, 986–998.

Autor, D. H. (2015a): "Polanyi's Paradox and the Shape of Employment Growth," *Federal Reserve Bank of St. Louis: Economic Policy Proceedings, Reevaluating Labor Market Dynamics*, 2015, 129–177.

——— (2015b): "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, 29, 3–30.

Autor, D. H. and D. Dorn (2013): "The growth of low-skill service jobs and the polarization of the US labor market," *American Economic Review*, 103, 1553–97.

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–68.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration*," *The Quarterly Journal of Economics*, 118, 1279–1333.

Barbieri, L., M. Piva, and M. Vivarelli (2019): "R&D, embodied technological change, and employment: Evidence from Italian microdata," *Industrial and Corporate Change*, 28, 203–218.

Bassanini, A. and A. Garnero (2013): "Dismissal protection and worker flows in OECD countries: Evidence from cross-country/cross-industry data," *Labour Economics*, 21, 25–41.

Bellon, M. (2016): "The characteristics of worker flows by firm growth: empirical evidence from a matched firm-worker dataset from France," Tech. rep., Columbia University.

Bernard, A. B., M. Grazzi, and C. Tomasi (2015): "Intermediaries in International Trade: Products and Destinations," *The Review of Economics and Statistics*, 97, 916–920.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2010): "Wholesalers and Retailers in US Trade," *American Economic Review*, 100, 408–13.

——— (2012): "The Empirics of Firm Heterogeneity and International Trade," *Annual Review of Economics*, 4, 283–313.

Bessen, J. E., M. Goos, A. Salomons, and W. Van den Berge (2019): "Automatic Reaction-What Happens to Workers at Firms that Automate?" Law and Economics Research Paper 19-2, Boston University.

Biscourp, P. and F. Kramarz (2007): "Employment, skill structure and international trade: Firm-level evidence for France," *Journal of International Economics*, 72, 22–51.

Blum, B. S., S. Claro, and I. Horstmann (2010): "Facts and Figures on Intermediated Trade," *American Economic Review*, 100, 419–23.

Caliendo, L., F. Monte, and E. Rossi-Hansberg (2015): "The anatomy of French production hierarchies," *Journal of Political Economy*, 123, 809–852.

Caliendo, L. and E. Rossi-Hansberg (2012): "The impact of trade on organization and productivity," *The Quarterly Journal of Economics*, 127, 1393–1467.

Calvino, F., C. Criscuolo, L. Marcolin, and M. Squicciarini (2018): "A taxonomy of digital intensive sectors," OECD Science, Technology and Industry Working Papers 2018/14, OECD.

Cooper, R., J. Haltiwanger, and L. Power (1999): "Machine Replacement and the Business Cycle: Lumps and Bumps," *American Economic Review*, 89, 921–46.

Dauth, W., S. Findeisen, J. Suedekum, N. Woessner, et al. (2018): "Adjusting to robots: worker-level evidence," Institute working paper 13, Federal Reserve Bank of Minneapolis.

Davis, S. and J. Haltiwanger (1999): "Gross job flows," in *Handbook of Labor Economics*, ed. by O. Ashenfelter and D. Card, Elsevier, vol. 3, Part B, chap. 41, 2711–2805, 1 ed.

Davis, S. J., R. J. Faberman, and J. Haltiwanger (2006): "The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links," *Journal of Economic Perspectives*, 20, 3–26.

Davis, S. J. and J. Haltiwanger (1990): "Gross Job Creation and Destruction: Microeconomic Evidence and Macroeconomic Implications," *NBER Macroeconomics Annual*, 5, 123–168.

——— (1992): "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *Quarterly Journal of Economics*, 107, 819–863.

Domini, G. and D. Moschella (2018): "Reallocation and productivity during the Great Recession: evidence from French manufacturing firms," Tech. rep., Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies.

Doms, M. and T. Dunne (1998): "Capital Adjustment Patterns in Manufacturing Plants," *Review of Economic Dynamics*, 1, 409–29.

Dosi, G. and L. Galambos, eds. (2012): *The third industrial revolution in global business*, Cambridge: Cambridge University Press.

Falcon, J. (2015): "SocialPosition: Social Position Indicators Construction Toolbox," R package version 1.0.1. 2015 https://cran.r-project.org/package=socialposition.

Frey, C. B. and M. A. Osborne (2017): "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change*, 114, 254 – 280.

Furman, J. and R. Seamans (2018): "AI and the Economy," NBER Working Papers 24689, National Bureau of Economic Research, Inc.

Garicano, L., C. Lelarge, and J. Van Reenen (2016): "Firm Size Distortions and the Productivity Distribution: Evidence from France," *American Economic Review*, 106, 3439–79.

Golan, A., J. Lane, and E. McEntarfer (2007): "The Dynamics of Worker Reallocation within and across Industries," *Economica*, 74, 1–20.

Goos, M., A. Manning, and A. Salomons (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104, 2509–26.

Gourinchas, P.-O. (1998): "Exchange Rates and Jobs: What Do We Learn from Job Flows?" in *NBER Macroeconomics Annual 1998, volume 13*, National Bureau of Economic Research, Inc, NBER Chapters, 153–222.

——— (1999): "Exchange rates do matter: French job reallocation and exchange rate turbulence, 1984-1992," *European Economic Review*, 43, 1279–1316.

Gourio, F. and A. K. Kashyap (2007): "Investment spikes: New facts and a general equilibrium exploration," *Journal of Monetary Economics*, 54, 1–22.

Graetz, G. and G. Michaels (2018): "Robots at work," *Review of Economics and Statistics*, 100, 753–768.

Grazzi, M., N. Jacoby, and T. Treibich (2016): "Dynamics of Investment and Firm Performance: Comparative evidence from manufacturing industries," *Empirical Economics*, 51, 125–179.

Guillou, S. and T. Treibich (2017): "Firm export diversification and change in Workforce Composition," Working Paper 22, 2017/10/09, Sciences Po OFCE.

Harrigan, J., A. Reshef, and F. Toubal (2016): "The March of the Techies: Technology, Trade, and Job Polarization in France, 1994-2007," NBER Working Papers 22110, National Bureau of Economic Research, Inc.

——— (2018): "Techies, Trade, and Skill-Biased Productivity," Tech. Rep. 25295, National Bureau of Economic Research.

INSEE (2010): *DADS Grand Format. Guide méthodologique. Validité 2010*, Dijon: INSEE, Direction Régionale de Bourgogne.

Klein, M., S. Schuh, and R. Triest (2003): "Job creation, job destruction, and the real exchange rate," *Journal of International Economics*, 59, 239–265.

Letterie, W. A., G. A. Pfann, and J. Polder (2004): "Factor adjustment spikes and interrelation: an empirical investigation," *Economics Letters*, 85, 145 – 150.

Moser, C., D. Urban, and B. Weder (2010): "International competitiveness, job creation and job destruction–An establishment-level study of German job flows," *Journal of International Economics*, 80, 302–317.

Piva, M. and M. Vivarelli (2017): "Technological Change and Employment: Were Ricardo and Marx Right?" IZA Discussion Papers 10471, Institute for the Study of Labor (IZA).

Polanyi, M. (1967): *The Tacit Dimension*, Carden City, NY: Doubleday Anchor.

Power, L. (1998): "The Missing Link: Technology, Investment, And Productivity," *The Review of Economics and Statistics*, 80, 300–313.

Rindfleisch, A., M. OâĂŹHern, and V. Sachdev (2017): "The digital revolution, 3D printing, and innovation as data," *Journal of Product Innovation Management*, 34, 681–690.

Roco, M. C. and W. S. Bainbridge, eds. (2003): *Converging Technologies for Improving Human Performance: NANOTECHNOLOGY, BIOTECHNOLOGY, INFORMATION TECHNOLOGY AND COGNITIVE SCIENCE*, Kluwer.

Schumpeter, J. A. (1942): *Capitalism, Socialism and Democracy*, New York: Harper & Brothers.

Trajtenberg, M. (2018): "AI as the next GPT: a Political-Economy Perspective," CEPR Discussion Papers 12721, C.E.P.R. Discussion Papers.

A Definition of imports embedding automation technologies

Table A1: Product classes referring to intermediates related to the automation of blue-collar industrial jobs, based on the taxonomy by Acemoglu and Restrepo (2018)

Label	HS codes
Industrial robots	847950
Dedicated machinery (including robots)	847989
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
Machine tools	845600-846699, 846820-846899, 851511-851519
Tools for industrial work	820200-821299
Welding machines	851521, 851531, 851580, 851590
Weaving and knitting machines	844600-844699 and 844700-844799
Other textile dedicated machinery	844400-845399
Conveyors	842831-842839
Regulating instruments	903200-903299

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.

B Regressions by subperiod

Table B1: Automation spikes and occupational categories' shares, by subperiod.

	Engineers, professionals, and managers	Supervisors and technicians	Clerical workers	Skilled blue-collar workers	Unskilled blue-collar workers	Techies
(a) Subperiod: 2002-2008						
Spike_{t-2}	-0.004***	-0.002	-0.001	0.006***	0.003	-0.001
	0.001	0.002	0.001	0.002	0.002	0.001
Spike_{t-1}	-0.005***	-0.001	-0.001	0.006***	0.003	-0.002
	0.001	0.002	0.001	0.002	0.002	0.001
Spike_{t}	-0.005***	-0.003*	-0.002	0.009***	0.003	-0.001
	0.001	0.002	0.001	0.002	0.002	0.001
Spike_{t+1}	-0.001	-0.002	-0.002	0.006**	0.001	0.001
	0.001	0.002	0.001	0.002	0.002	0.001
Spike_{t+2}	-0.002	-0.002	0.000	0.006***	-0.001	0.000
	0.002	0.002	0.001	0.002	0.002	0.002
Constant	0.099***	0.203***	0.113***	0.364***	0.197***	0.109***
	0.001	0.001	0.001	0.001	0.001	0.001
Nb. obs.	265566	265566	265566	265566	265566	265566
Nb. firms	48048	48048	48048	48048	48048	48048
Adj. R^2	0.647	0.626	0.642	0.673	0.659	0.689
(b) Subperiod: 2009-2015						
Spike_{t-2}	-0.003*	-0.001	0.003	-0.000	0.001	-0.002
	0.001	0.002	0.002	0.003	0.002	0.002
Spike_{t-1}	-0.003*	-0.000	0.002	0.000	0.001	-0.002
	0.001	0.002	0.001	0.002	0.002	0.002
Spike_{t}	-0.003**	-0.001	0.000	0.003	0.001	-0.001
	0.001	0.002	0.001	0.002	0.002	0.002
Spike_{t+1}	-0.002*	-0.001	-0.002	0.004*	0.000	0.000
	0.001	0.002	0.001	0.002	0.002	0.001
Spike_{t+2}	-0.001	0.001	-0.001	-0.000	0.001	-0.000
	0.001	0.001	0.001	0.002	0.002	0.001
Constant	0.111***	0.180***	0.133***	0.337***	0.205***	0.151***
	0.001	0.001	0.001	0.001	0.001	0.001
Nb. obs.	252542	252542	252542	252542	252542	252542
Nb. firms	44590	44590	44590	44590	44590	44590
Adj. R^2	0.763	0.723	0.701	0.772	0.753	0.785

Notes: FE estimation of Equation 3. Coefficients on the sector-year dummies 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).

C Regressions on sample restricted to firms with at least 50 employees

Table C1: 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}	0.030***	0.008*	-0.022***
	0.005	0.004	0.004
Spike_{t-1}	0.040***	0.011***	-0.029***
	0.005	0.004	0.004
Spike_{t}	0.043***	0.014***	-0.030***
	0.005	0.004	0.004
Spike_{t+1}	0.003	-0.006*	-0.009**
	0.005	0.003	0.004
Spike_{t+2}	-0.004	-0.013***	-0.008*
	0.005	0.003	0.004
Constant	0.046***	0.202***	0.156***
	0.004	0.003	0.003
Nb. obs.	104,903	104,903	104,903
Nb. firms	9,937	9,937	9,937
Adj. R^2	0.078	0.184	0.157

Notes: FE estimation of Equation 2. Coefficients on the sector-year dummies 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 C2: Automation spikes and worker flows, by occupational category, sample restricted to firms with at least 50 employees.

	Engineers, professionals, and managers	Supervisors and technicians	Clerical workers	Skilled blue-collar workers	Unskilled blue-collar workers	Techies
(a) Dep. var.: Net growth rate						
Spike$_{t-2}$	0.027***	0.026***	0.032***	0.038***	0.032**	0.031***
	0.008	0.007	0.010	0.008	0.013	0.008
Spike$_{t-1}$	0.030***	0.040***	0.029***	0.043***	0.046***	0.047***
	0.007	0.006	0.009	0.007	0.011	0.007
Spike$_t$	0.043***	0.044***	0.044***	0.049***	0.033***	0.044***
	0.007	0.006	0.008	0.007	0.010	0.007
Spike$_{t+1}$	0.008	-0.000	0.006	0.009	-0.003	0.012*
	0.007	0.006	0.008	0.007	0.011	0.007
Spike$_{t+2}$	-0.002	-0.003	-0.002	0.000	-0.019*	-0.005
	0.007	0.007	0.009	0.007	0.012	0.007
(b) Dep. var.: Hiring rate						
Spike$_{t-2}$	0.009*	0.009*	0.006	0.007	0.013**	0.008*
	0.005	0.005	0.006	0.005	0.006	0.005
Spike$_{t-1}$	0.008*	0.009*	0.003	0.009**	0.021***	0.013***
	0.005	0.004	0.005	0.004	0.006	0.005
Spike$_t$	0.010**	0.014***	0.016***	0.019***	0.016***	0.014***
	0.004	0.004	0.005	0.004	0.005	0.004
Spike$_{t+1}$	-0.002	-0.008**	-0.008*	-0.005	0.001	-0.005
	0.004	0.004	0.005	0.004	0.005	0.004
Spike$_{t+2}$	-0.012***	-0.010***	-0.010**	-0.014***	-0.010*	-0.012***
	0.004	0.004	0.005	0.004	0.005	0.004
Constant	0.202***	0.190***	0.216***	0.181***	0.250***	0.197***
	0.004	0.003	0.004	0.003	0.004	0.004
(c) Dep. var.: Separation rate						
Spike$_{t-2}$	-0.020***	-0.020***	-0.016***	-0.025***	-0.018***	-0.020***
	0.005	0.004	0.005	0.004	0.006	0.004
Spike$_{t-1}$	-0.027***	-0.029***	-0.027***	-0.030***	-0.030***	-0.030***
	0.005	0.004	0.005	0.004	0.005	0.004
Spike$_t$	-0.028***	-0.031***	-0.033***	-0.030***	-0.022***	-0.028***
	0.004	0.004	0.005	0.004	0.005	0.004
Spike$_{t+1}$	-0.009*	-0.010**	-0.011**	-0.008	0.003	-0.012**
	0.005	0.005	0.005	0.005	0.006	0.005
Spike$_{t+2}$	-0.007	-0.008*	-0.007	-0.008	-0.004	-0.009*
	0.005	0.005	0.006	0.005	0.006	0.005
Constant	0.173***	0.151***	0.172***	0.142***	0.213***	0.151***
	0.003	0.003	0.004	0.003	0.004	0.003
Nb. obs.	104,903	104,903	104,903	104,903	104,903	104,903
Nb. firms	9,937	9,937	9,937	9,937	9,937	9,937
Adj. R^2 (a)	0.002	0.010	-0.013	0.005	-0.030	0.004
Adj. R^2 (b)	0.106	0.139	0.109	0.138	0.121	0.114
Adj. R^2 (c)	0.110	0.125	0.101	0.125	0.092	0.108

Notes: FE estimation of Equation 2. Coefficients on the sector-year dummies 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 C3: Automation spikes and occupational categories' shares, sample of firms with at least 50 employees.

	Engineers, professionals, and managers	Supervisors and technicians	Clerical workers	Skilled blue-collar workers	Unskilled blue-collar workers	Techies
Spike_{t-2}	-0.006***	-0.001	-0.001	0.004*	0.005**	-0.001
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t-1}	-0.006***	-0.002*	-0.001	0.005**	0.005***	-0.001
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t}	-0.006***	-0.001	-0.001	0.005**	0.006***	-0.000
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t+1}	-0.003***	-0.001	-0.001	0.003	0.003*	0.001
	0.001	0.001	0.001	0.002	0.002	0.001
Spike_{t+2}	-0.003**	0.000	-0.002***	0.005**	0.001	0.001
	0.001	0.001	0.001	0.002	0.002	0.001
Constant	0.112***	0.206***	0.074***	0.390***	0.208***	0.147***
	0.001	0.001	0.001	0.002	0.002	0.001
Nb. obs.	104,903	104,903	104,903	104,903	104,903	104,903
Nb. firms	9,937	9,937	9,937	9,937	9,937	9,937
Adj. R^2	0.746	0.739	0.707	0.745	0.745	0.848

Notes: FE estimation of Equation 3. Coefficients on the sector-year dummies 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).