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

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Introduction

Technology is presented in the policy debate either as the main driver of societal change or as a major threat to employment

Assessing how innovation affects employment has long been at the centre of economic debates

In the contemporary economic scenario one can envisage at least two relatively new challenges:

- The type of jobs affected is much more diffused and difficult to identify (routine-intensive rather than manual; cf. Autor 2015; Autor et al. 2003; Frey and Osborne 2017; Furman and Seamans 2018; Goos et al. 2014; Trajtenberg 2018)
- The type of firms and sectors impacted is also much larger (general rethinking of production processes; cf. Caliendo and Rossi-Hansberg 2012)

Literature review

Evidence on direct effect of the most recent wave of automation technologies is scarce and typically aggregate (Acemoglu and Restrepo, 2017; Dauth et al., 2018; Graetz and Michaels, 2018)

At the micro level:

- Bessen et al., (2019), using a Dutch survey on automation costs, find that automation leads to a higher probability of separation, especially for higher-skilled workers
- Koch et al., (2019), using a survey of Spanish manufacturing firms with info on the use of robots, find that robot adoption leads to net job creation at a rate of 10%

This paper

Our work studies the relationship between investment in automation and within-firm job creation and destruction

We rely on exhaustive and detailed data on French manufacturing firms involved in international trade which allows us to:

- identify imports of capital goods that are related to automation
- decompose firm growth into the contributions of hiring and separation
- study patterns and dynamics for different types of workers

We not only contribute to the literature on the impact of automation or robotisation on employment, but also to that on investment spikes (Asphjell et al., 2014; Grazzi et al., 2016; Letterie et al., 2004)

Data sources

DADS *Postes*: employer-employee database (social security forms)
Data on all French firms *with employees*

DGDDI data: customs database
Data on quantity, value, product sector, and country of destination of every international transaction of goods

FICUS/FARE: balance-sheet and revenue-account data, general firm information (fiscal statements)

We match different sources by firm ID (SIREN)

We focus on the manufacturing sector (NAF rev. 2 divs. 10-33), 2002-2015

Definitions: gross worker flows

Based on job-level indicators denoting principal jobs that are present on December 31 of years t and t-1 (I_t and I_{t-1}), we construct:

- Stocks of employment in years t and t-1 (Emp_t and Emp_{t-1}) as the firm-level aggregations of I_t and I_{t-1}
- Flow of hirings (H_t): jobs for which $I_t = 1$ and $I_{t-1} = 0$
- Flow of separations (S_t): jobs for which $I_t = 0$ and $I_{t-1} = 1$
- $\Delta Emp_t = Emp_t - Emp_{t-1} = H_t - S_t$

Rates (g, h, s) obtained by dividing flows by $\frac{Emp_t + Emp_{t-1}}{2}$ (Davis-Haltiwanger)

Net growth, hiring, and separation rates

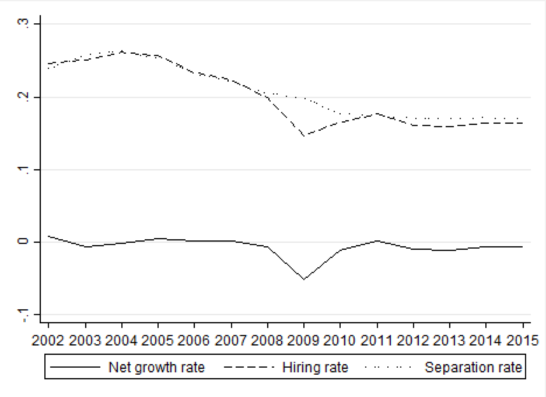


Figure 1: Average (unweighted) net growth rates, hiring rates, and separation rates, 2002-2015. Source: our elaborations on DADS and DGDDI data. Note: entering and exiting firms are excluded.

⇒ Net growth rates hide most of the turbolence

Definitions: types of work(er)s

We consider three classifications:

(1) *Catégorie Socio-professionelle*, CS, based on worker-level occupation code

Standard in empirical literature using French data (Abowd et al., 1999; Biscourp and Kramarz, 2007; Harrigan et al., 2016, 2018)

Five categories identified:

- Engineers, professionals, and managers (CS3; 16.54% of all workers)
- Supervisors and technicians (CS4; 23.17%)
- Clerical workers (CS5; 7.38%)
- Skilled blue-collar workers (CS61-CS65; 36.49%)
- Unskilled blue-collar workers (CS66-CS68; 16.41%)

It reflects 'production hierarchies' (Caliendo et al., 2015; Guillou and Treibich, 2017)

Definitions: types of work(er)s

(2) 'Techies' (CS38 and CS47): workers who facilitate the adoption and use of new technology (Harrigan et al., 2016)

(3) Routine task intensity, RTI (Autor and Dorn, 2013; Autor et al., 2003, 2013; Goos et al., 2014)

We map French occupational classifications into the International Standard Classification of Occupations (ISCO88), using a toolbox by Falcon, (2015)

We match an RTI value (from Goos et al. 2014) to 4-digit ISCO88 codes

We classify the set of occupations that are in the top RTI tercile in 2009 as routine task-intensive occupations (Autor and Dorn, 2013)

Definitions: automation spikes

We construct a measure of investment in automation from customs data: imports of intermediate goods that embed automation technologies, following a taxonomy by Acemoglu and Restrepo, (2018) at the 6-digit Harmonized System (HS) product code level

These include industrial robots, industrial dedicated machinery, numerically-controlled machines, and subsets of other categories

Imports of such goods display the spiky behaviour typical of investment: *rare across firms*: in each year, only 10% of importers buy such goods (52% do it at least once).

Automation spikes are *rare within firms*

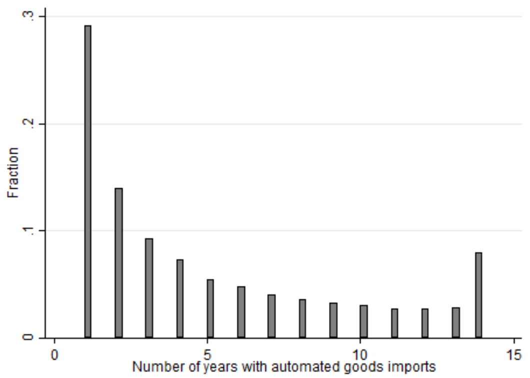
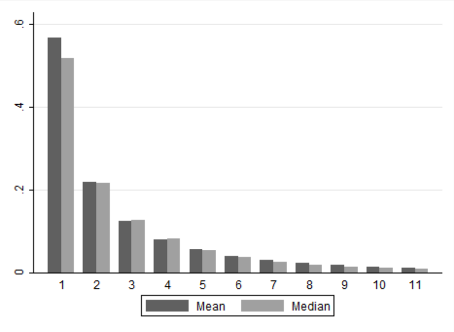


Figure 2: Number of years with imports of automated goods. Source: our elaborations on DADS and DGDDI data. Note: entering and exiting firms are excluded.

Spikes account for very high share of investm within firms

(a) Total physical investment



(b) Investment in imported automated goods

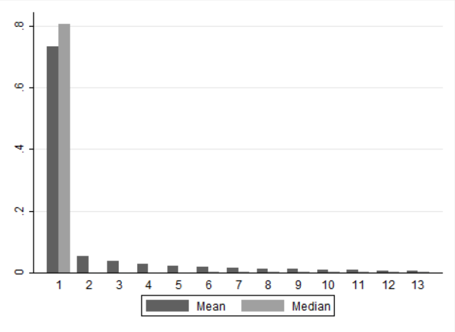


Figure 3: Investment shares by rank. Source: our elaborations on DADS, DGDDI, FICUS, and FARE data. Note: entering and exiting firms are excluded.

In line with this, we define a firm's largest event as an *automation spike*

Automation spikes and employment

From a theoretical perspective, capital can be seen as a possible substitute for labour. Yet, empirical results show that in most cases, there is *interrelation* between investment and employment spikes

Table 1: Mean worker flow rates around an automation spike.

Years since spike	Net growth rate	Hiring rate	Separation rate	Nb. obs.
-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 after an automation spike.

Regression analysis

Fixed-effects estimations of the following models:

$$Flow_{it} = \alpha + \sum_{k=-2}^{2} \beta_i Spike_{t+k} + \gamma_i + \delta_t + \epsilon_{it} \tag{1}$$

where $Flow \in \{g, h, s\}$

and

$$Share^j_{it} = \alpha + \sum_{k=-2}^{2} \beta_i Spike_{t+k} + \gamma_i + \delta_t + \epsilon_{it} \tag{2}$$

where $Share^j$ is the within-firm share of occupational category j

Since our automation measure is based on import data, our sample is all French manufacturing firms that import at least one year over 2002-2015

This represents 29.2% of all firms, and 84.0% of all employment

We focus on continuing firms, which represent 90.8% of such firms

Regression analysis: growth rates, aggregate employment

Table 2: Automation spikes and gross worker flows

Dep. var.:	Net growth rate	Hiring rate	Separation rate
Spike_{t-2}	0.022***	0.001	-0.021***
Spike_{t-1}	0.033***	0.008***	-0.025***
Spike_{t}	0.038***	0.013***	-0.025***
Spike_{t+1}	-0.005*	-0.006***	-0.001
Spike_{t+2}	-0.012***	-0.012***	-0.000
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 1. Coefficients on the year dummies and the constant 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). Entering and exiting firms are excluded.

Regression analysis: shares, by occupational category

Table 3: 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
Spike_{t-1}	-0.005***	-0.000	-0.000	0.001	0.007***	-0.001
Spike_{t}	-0.006***	-0.001	-0.001	0.005**	0.006***	0.000
Spike_{t+1}	-0.003***	-0.000	-0.002**	0.003*	0.004**	0.002*
Spike_{t+2}	-0.002**	0.001	-0.000	0.002	0.002	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 2. Coefficients on the year dummies and the constant 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). Entering and exiting firms are excluded.

Regression analysis: shares, routine intensity

Table 4: Automation spikes and routine-intensive category's share

	2002-2015	2009-2015
Spike_{t-2}	0.008***	-0.000
Spike_{t-1}	0.007***	0.000
Spike_{t}	0.006***	0.001
Spike_{t+1}	0.003	0.002
Spike_{t+2}	0.002	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 1. Coefficients on the year dummies and the constant 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). Entering and exiting firms are excluded.

Regression analysis: extensions

Robustness checks:

- Separate subperiods 2002-2008 and 2009-2015
- Sample restricted to firms with at least ten employees
- Sample restricted to firms with an automation spike

Sectoral analyses:

- By Pavitt, (1984) sector
- By OECD digital intensity taxonomy sector (Calvino et al., 2018)

The main message from our regressions does not change

Conclusions

We observe that investment in imported capital goods embedding automation technologies shares the typical 'spiky' features of investment in general

We find that net firm employment growth is above within-firm average before and during an automation spike, which is mainly due to lower-than-average separation rates; and (slightly) below average afterwards, which is due to lower-than-average hiring rates (labour-friendly technological change)

The relationship between automation spikes and worker flows does not change much across types of workers; although a slight shrinking of the highest occupational category is observed (before, during, and after a spike), compensated by an expansion of the lowest