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

Giacomo Domini $^{1,3}$ Marco Grazzi $^2$ Daniele Moschella $^3$ Tania Treibich $^4$

$^1$Erasmus University College, Erasmus University Rotterdam (The Netherlands)
$^2$Department of Economics, Università Cattolica del Sacro Cuore, Milano (Italy)
$^3$Institute of Economics, Scuola Superiore Sant’Anna, Pisa (Italy)
$^4$School of Business and Economics, University of Maastricht (The Netherlands)

CONCORDi 2019: Industrial innovation for transformation
Seville, 25-27 September 2019
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).
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 and variables

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 turbulence
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)
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.

<table>
<thead>
<tr>
<th>Years since spike</th>
<th>Net growth rate</th>
<th>Hiring rate</th>
<th>Separation rate</th>
<th>Nb. obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2</td>
<td>0.019</td>
<td>0.196</td>
<td>0.176</td>
<td>5,977</td>
</tr>
<tr>
<td>-1</td>
<td>0.014</td>
<td>0.188</td>
<td>0.173</td>
<td>5,977</td>
</tr>
<tr>
<td>0</td>
<td>0.014</td>
<td>0.175</td>
<td>0.161</td>
<td>5,977</td>
</tr>
<tr>
<td>1</td>
<td>-0.011</td>
<td>0.150</td>
<td>0.162</td>
<td>5,977</td>
</tr>
<tr>
<td>2</td>
<td>-0.021</td>
<td>0.134</td>
<td>0.155</td>
<td>5,977</td>
</tr>
<tr>
<td>3</td>
<td>-0.039</td>
<td>0.124</td>
<td>0.162</td>
<td>5,977</td>
</tr>
</tbody>
</table>

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:

\[ Flow_{it} = \alpha + \sum_{k=-2}^{2} \beta_{i}Spike_{t+k} + \gamma_{i} + \delta_{t} + \epsilon_{it} \] (1)

where \( Flow \in \{g, h, s\} \)

and

\[ Share_{ijt} = \alpha + \sum_{k=-2}^{2} \beta_{i}Spike_{t+k} + \gamma_{i} + \delta_{t} + \epsilon_{it} \] (2)

where \( Share_{ij} \) 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

<table>
<thead>
<tr>
<th>Dep. var.:</th>
<th>Net growth rate</th>
<th>Hiring rate</th>
<th>Separation rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spike_{t-2}</td>
<td>0.022***</td>
<td>0.001</td>
<td>-0.021***</td>
</tr>
<tr>
<td>Spike_{t-1}</td>
<td>0.033***</td>
<td>0.008***</td>
<td>-0.025***</td>
</tr>
<tr>
<td>Spike_{t}</td>
<td>0.038***</td>
<td>0.013***</td>
<td>-0.025***</td>
</tr>
<tr>
<td>Spike_{t+1}</td>
<td>-0.005*</td>
<td>-0.006***</td>
<td>-0.001</td>
</tr>
<tr>
<td>Spike_{t+2}</td>
<td>-0.012***</td>
<td>-0.012***</td>
<td>-0.000</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th></th>
<th>Engineers, professionals, and managers</th>
<th>Supervisors and technicians</th>
<th>Clerical workers</th>
<th>Skilled blue-collar workers</th>
<th>Unskilled blue-collar workers</th>
<th>Techies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spike_{t-2}</td>
<td>-0.005***</td>
<td>-0.001</td>
<td>-0.000</td>
<td>0.001</td>
<td>0.007***</td>
<td>-0.000</td>
</tr>
<tr>
<td>Spike_{t-1}</td>
<td>-0.005***</td>
<td>-0.000</td>
<td>-0.000</td>
<td>0.001</td>
<td>0.007***</td>
<td>-0.001</td>
</tr>
<tr>
<td>Spike_{t}</td>
<td>-0.006***</td>
<td>-0.001</td>
<td>-0.001</td>
<td>0.005**</td>
<td>0.006***</td>
<td>0.000</td>
</tr>
<tr>
<td>Spike_{t+1}</td>
<td>-0.003***</td>
<td>-0.000</td>
<td>-0.002**</td>
<td>0.003*</td>
<td>0.004**</td>
<td>0.002*</td>
</tr>
<tr>
<td>Spike_{t+2}</td>
<td>-0.002**</td>
<td>0.001</td>
<td>-0.000</td>
<td>0.002</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Nb. firms</td>
<td>55,043</td>
<td>55,043</td>
<td>55,043</td>
<td>55,043</td>
<td>55,043</td>
<td>55,043</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.610</td>
<td>0.559</td>
<td>0.568</td>
<td>0.591</td>
<td>0.550</td>
<td>0.667</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Spike_{t-2}</td>
<td>0.008***</td>
<td>-0.000</td>
</tr>
<tr>
<td>Spike_{t-1}</td>
<td>0.007***</td>
<td>0.000</td>
</tr>
<tr>
<td>Spike_{t}</td>
<td>0.006***</td>
<td>0.001</td>
</tr>
<tr>
<td>Spike_{t+1}</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Spike_{t+2}</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Nb. Obs.</td>
<td>518,108</td>
<td>252,542</td>
</tr>
<tr>
<td>Nb. firms</td>
<td>55,043</td>
<td>44,590</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.542</td>
<td>0.772</td>
</tr>
</tbody>
</table>

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 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.