Robotic patents and the origin of labour-saving technology

Fabio Montobbio[a b] **Jacopo Staccioli**[a c] M. Enrica Virgillito[a c] Marco Vivarelli[a c]

[a] *Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano*

[b] *BRICK, Collegio Carlo Alberto, Torino*

[c] *Institute of Economics, Scuola Superiore Sant'Anna, Pisa*

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Outline

Motivation

> *"Automated systems, such as robotic systems, are used in a variety of industries to* ***reduce labo[u]r costs and/or increase productivity****. Additionally, the use of human operators can involve increased cost relative to automated systems."* [US20170178485(A1)]

> *"The use of [robotic] technology results in improved management of information, services, and data, increased efficiency, significant reduction of time,* ***decreased manpower requirements****, and substantial cost savings."* [US20100223134(A1)]

Motivation (cont'd)

- the impact of robotic automation upon employment has become a major topic of discussion both in the policy and academic debate

Brynjolfsson and McAfee (2011, 2014) the root of current unemployment is not the Great Recession, but rather a 'Great Restructuring' characterised by an exponential growth in computers' processing power having an ever-bigger impact on jobs, skills, and the whole economy (*"This time is different"*)

Frey and Osborne (2017) 47% of the occupational categories are at high risk of being automated, including services and highly cognitive jobs

Our contribution

- we aim at contributing by extending the analysis beyond the IFR dataset
- by using textual patent data on robotic artefacts, we are able to identify the knowledge generation patterns behind this technology
- we intend to analyse not only those patents entailing robotic artefacts as *products* but also as *processes*
- we aim at understanding the extent to which the heuristics behind the generation of robotic patents are *truly* labour-saving

Research question

1. to what extent robotic patents make explicit reference to labour-saving technology?
2. what are the underlying patenting firms?
3. how are they distributed by country and by industry?
4. which technological realms does labour-saving innovation build upon?

Beyond traditional patent classification

- we adopt a broad definition of robotic patents that goes beyond the traditional classification by patent examiners
- we perform an in depth semantic analysis in order to distinguish those patents that *explicitly* claim to have a direct labour-saving impact
- in so doing, we restrict the analysis to a lexical domain uncommon for inventors
- in particular, we look at a dictionary of words typical of the 'economic slang'

Outline

Original data

- universe of USPTO patent applications from 1st January 2009 to 31st December 2018
- 3,557,435 full-text applications (hereafter, patents)

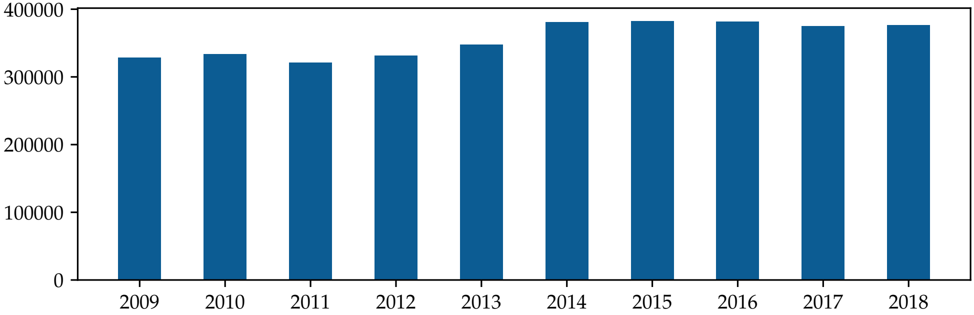


Figure: # of patents by year

Data processing

- identification of robotics[-related] patents

  1. via CPC codes
     - USPTO concordance table with USPC class 901
     - purely robotic technology
     - 10,929 `‘CPC’` patents
  2. via keyword search
     - multiple occurrence ($\times 10$) of morphological root *‘robot’*
     - process implementation and complementary technology
     - 18,860 `‘K10’` patents (once those already in 1 have been discarded)

- 29,789 total robotic patents

Data processing (cont'd)

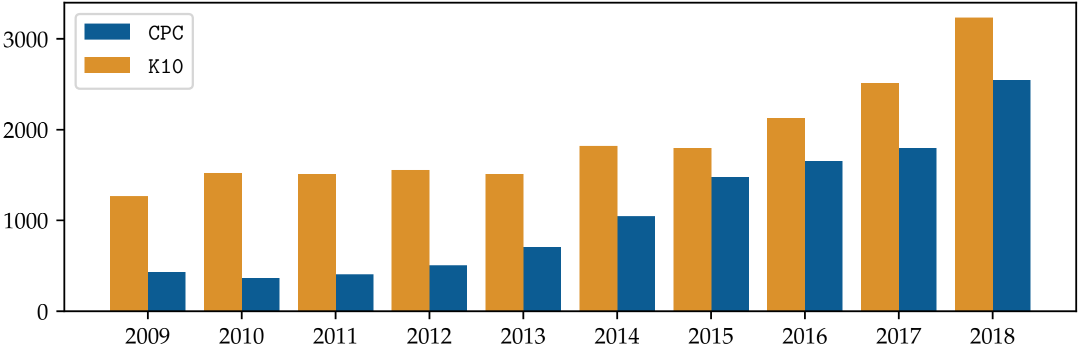


Figure: # of **robotic** patents by year

Data processing (cont'd)

tokenisation

- each patent textual body is divided into *sentences* by means of a punctuation regexp
- patent text $\Longrightarrow$ list of sentences
- sentence $\Longrightarrow$ list of words

stemming

- each word in each sentence is reduced to its morphological root with the Porter2 stemming algorithm (an improved version of the original Porter (1980) algorithm)
- patent text $\Longrightarrow$ list of lists of stemmed words

- identification of labour-saving (LS) patents by means of a word-level text query per sentence

Text query

$$\underbrace{\begin{bmatrix} \textit{`reduc'} \\ \textit{`replac'} \\ \textit{`elimin'} \\ \textit{`save'} \\ \textit{`lower'} \\ \textit{`substitut'} \\ \textit{`autom'} \end{bmatrix}}_{\text{verbal predicate}} \times \underbrace{\begin{bmatrix} \textit{`labor'} \\ \textit{`worker'} \\ \textit{`human'} \\ \textit{`employe'} \\ \textit{`manpow'} \\ \textit{`job'} \end{bmatrix}}_{\text{direct object}} \times \underbrace{\begin{bmatrix} \textit{`cost'} \\ \textit{`expenditure'} \\ \textit{`expens'} \\ \textit{`hour'} \\ \textit{`intens'} \\ \textit{`task'} \\ \textit{`time'} \\ \textit{`skill'} \end{bmatrix}}_{\text{object attribute}}$$

- 336 combinations of triplets (**not** *trigrams*, as we do not require adjacency)
- a patent is flagged as *potentially* LS if contains at least one triplet <u>within</u> a sentence
- 1,666 potentially LS patents

Validation

- all matched sentences are manually examined and flagged as *explicitly* LS if appropriate
- 1,276 explicitly LS patents ($\approx$ 77% of potentially LS; $\approx$ 4.3% of robotic patents)
- of which 461 ($\approx$ 36.1%) are CPC and 815 ($\approx$ 63.9%) are K10

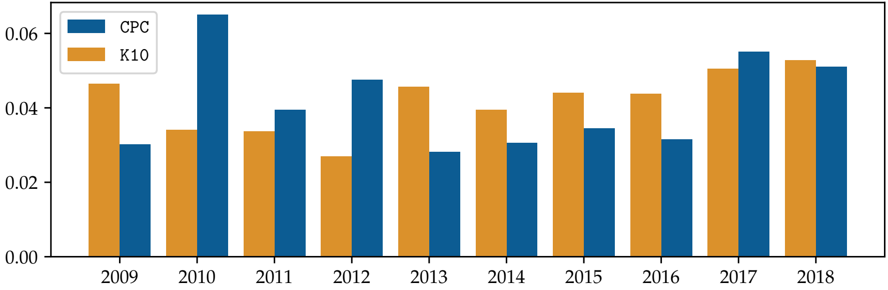


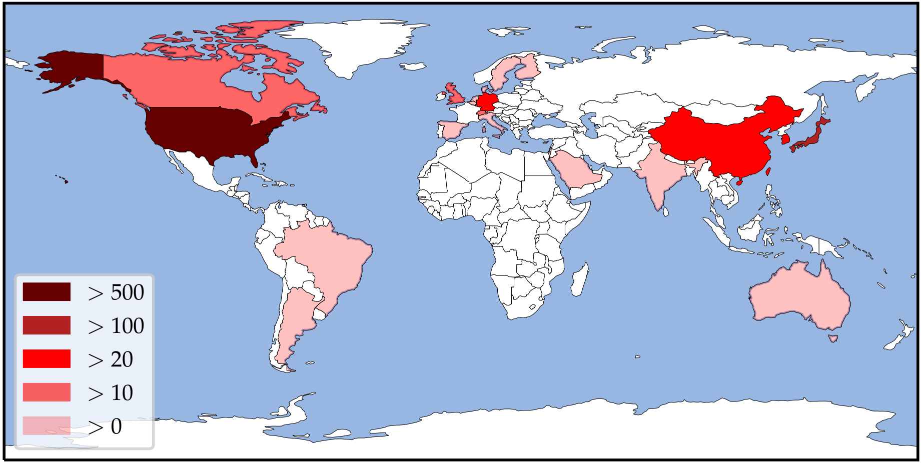
Figure: Fraction of **explicitly** LS patents over **robotic** patents by year

Firm level match

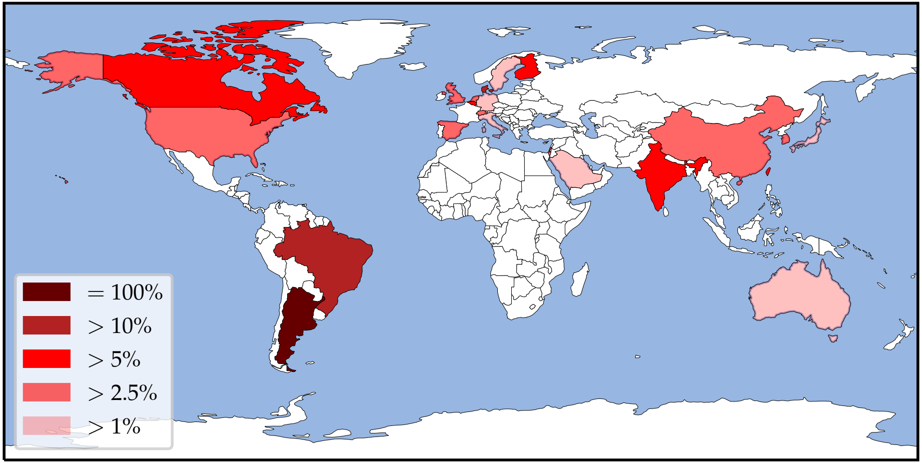
- LS patents are matched to their assignee via ORBIS (BvD)
- number reduces to 1,136 ($\approx$ 89%) due to truncation on 31st July 2018 (140 discarded)
- of these, 903 ($\approx$ 79%) are matched to at least one firm (233 find no match)
- there are 408 LS firms in total

Outline

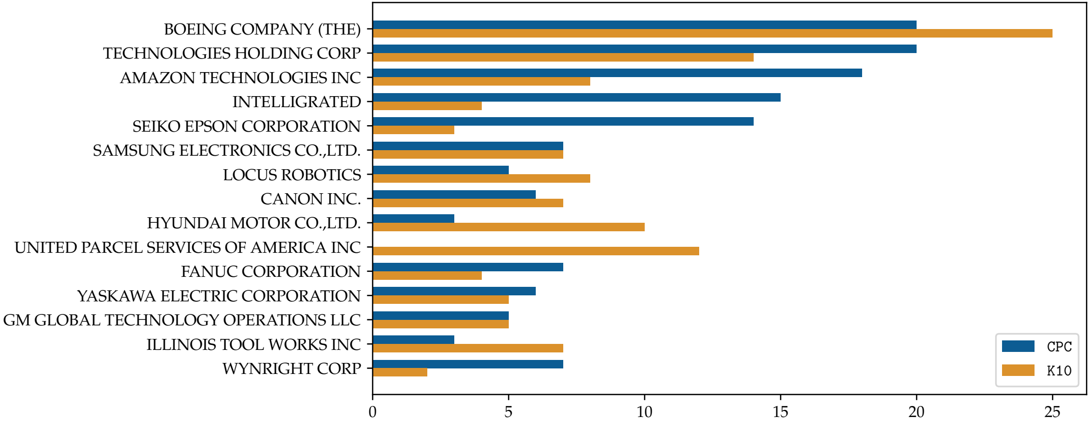
LS patents by country – absolute value



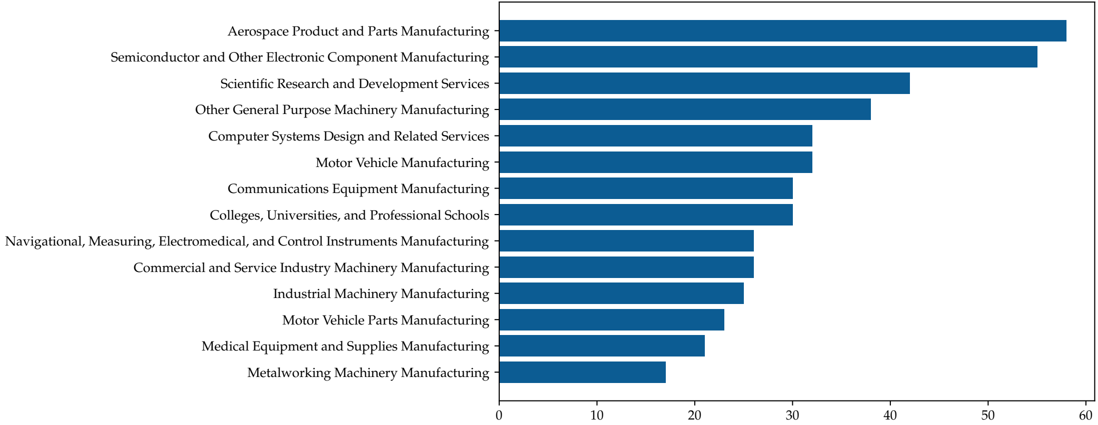
LS patents by country – as % of robotic patents



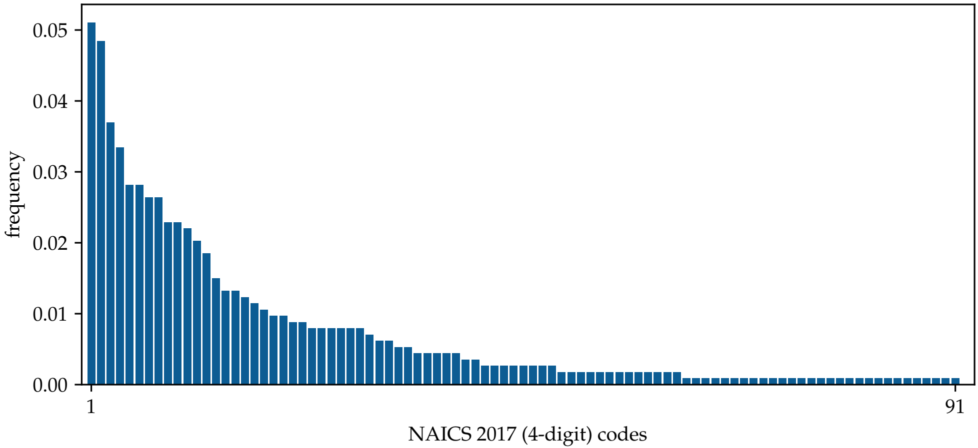
LS patents by assignee



LS patents by industry (cont'd)



LS patents by industry



Outline

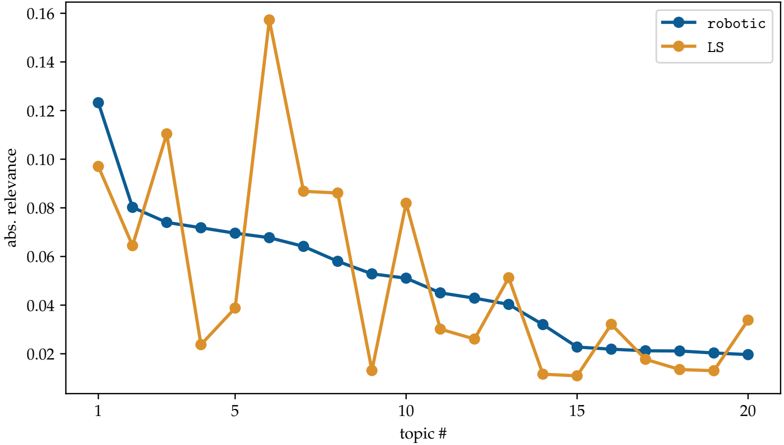
Topic model

1. we estimate a topic model with $K = 20$ topics on the whole collection of robotic patents D
   - each topic $k \in K$ is identified as a list of keywords ranked by frequency
   - each patent $d \in D$ is assigned a distribution $r(k)^d$ over the K topics
2. we assign a significance measure $M(c)^k$ of CPC codes ($c \in C$) originally attributed to patents to each topic k by leveraging on the *latent semantic structure* of the whole collection of patents, through relevance distributions $r(k)^d$ obtained in 1

$$m(c)^k = \sum_{d \in D} \mathbf{1}_{\{c \in d\}} \cdot r(k)^d \qquad \forall\ k = 1, \ldots, K; \quad \forall\ c \in C$$

   - this brings useful information for labelling the topics
3. we compare the relevance of the K topics for robotic patents and the subset of LS patents

Topic relevance for robotic and LS patents



Technological taxonomy

Topic #	LS relev.	Words	CPC	Weight	Description
6	+132.2%	carrier	B65	24.4%	Conveying; packing; storing; handling thin or filamentary material
		conveyor			
		item	H01	6.8%	Basic electric elements
		gripper	G11	6.0%	Information storage
		tape	Y02	4.6%	Technologies or applications for mitigation or adaptation against climate change
			B23	4.3%	Machine tools; metal-working not otherwise provided for
...	...	...	...	...	...
14	−63.7%	effector	A61	55.6%	Medical or veterinary science; hygiene
		surgic	Y10T29	4.9%	Metal working
		stapl	H01	4.8%	Basic electric elements
		articul	Y10T74	4.2%	Machine element or mechanism
		fire	B23	3.5%	Machine tools; metal-working not otherwise provided for

Outline

Main findings

- patenting firms are not only robots producers, but mainly users (archetypical cases are Boeing, Amazon, and UPS)
- the overall number of robotic patents is rapidly expanding (3-fold increase in a decade)
- conversely, LS patents do not exhibit a clear trend, supporting the idea that labour-saving is a rather mature heuristic
- LS robotic patents emerge along the entire supply chain, signalling pervasiveness
- LS patents are especially concentrated in labour intensive industries
- geographically, US and Japan still appear to largely dominate (possible bias from using USPTO patents), although China seems to be catching up
- but in relative terms this picture is reversed

Conceivable extensions

- analysis of economic performance of LS firms vis-à-vis the rest of patenting robotic firms
  - productivity dynamics
  - employment dynamics
- grasp the underlying *skills* and *tasks* LS patents are likely to automate
  - policy implications in terms of retraining displaced workers
- refine and fully automate the information extraction query
  - extend the analysis to the *whole* patent universe (possibly including other patent offices)
  - look for different search heuristics (e.g. mitigation of climate change)

Thank you very much!

jacopo.staccioli@unicatt.it

https://staccioli.org/