Back to the past: the historical roots of labour-saving automation

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Outline

1. Context and motivation
2. Data and methodology
3. Discussion

Context

- the existence of labour-saving (LS) heuristics driving the rate and direction of technological change is a documented pattern since the inception of the First Industrial Revolution

von Tunzelmann (1995)
: time-saving heuristics in the cotton-industry: a spinner was able to produce in a day as much yarn as previously required by a full year of work, without mechanisation

Freeman (2019)
: First Industrial Revolution as the combination of time-saving heuristics and demarcation between working- and life-time for wage labourers

Atack et al. (2020)
: *Hand and Machine Labor Study* (1899) commissioned by the US Department of Labor: only one-third of the increase in labour productivity in the late nineteen century was due to "inanimate power" and division of labour plays a prominent role

Empirical detection of labour-saving heuristics

- attempts to infer heuristics and knowledge bases appear in

Castaldi et al. (2009) at the artefact level, focussing on the tank technology and the evolution of its attributes over time

Martinelli (2012) patent-citation networks to infer the emergence of new paradigms at the knowledge level

Taalbi (2017) relies on specialistic trade magazines, collects information about drivers of innovative activities relevant to innovators, and investigates eventual distinct patterns across industry and over time

- currently, heuristics are usually inferred from the technical engineering literature and related case-studies
- patents and their textual content also provide a good source of information to detect codified knowledge and the ensuing search heuristics

Our starting point

Montobbio et al. (2020) identify labour-saving patents among USPTO robotic applications (2009–2018)

1. robotics patents identified by technological classification and keyword search
2. labour-saving patents identified by text query and manual validation (no false positives)

$\Rightarrow$ 1,276 *truly* labour-saving patents

3. probabilistic topic modelling to rank most important technologies therein, and their respective CPC codes

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

Examples of labour-saving patents

> *"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."* [US20170178485A1]

> *"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."* [US20100223134A1]

Objective of the paper

- automation/mechanisation are not the result of a single dominant product design (GPT), but rather of a bundle of technological artefacts
- long term patterns of [anti-]comovements, explosion, and dissipation require investigation
- overcome the periodic cycle approach (Kondratiev) and address issues of non-stationarity, short-time horizon, and data trimming (Silverberg, 2007) using wavelet analysis

In a nutshell

- provide empirical evidence on the history of LS automation back to early 19th Century
- adopt a 'technological constellation perspective' (Freeman and Louçã, 2001; Nuvolari, 2019)
- analyse the emergence and evolution of the bundle of technologies underlying current LS heuristics detected in robotic innovations (Montobbio et al., 2020)

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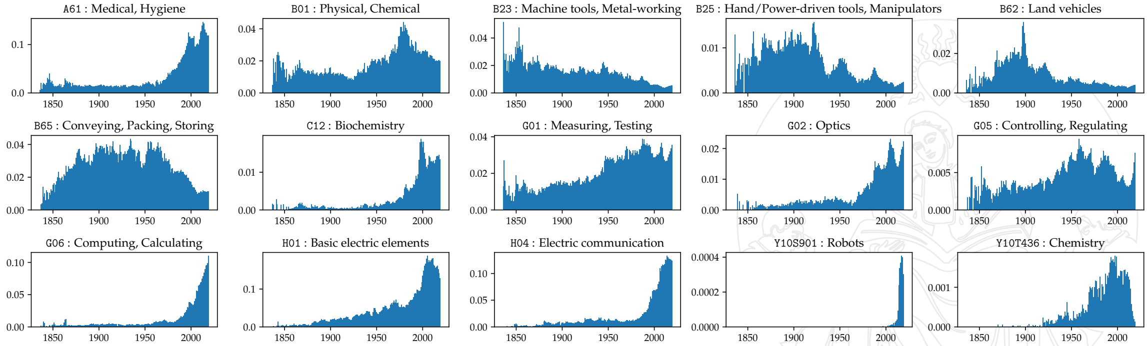
Data and patent intensity

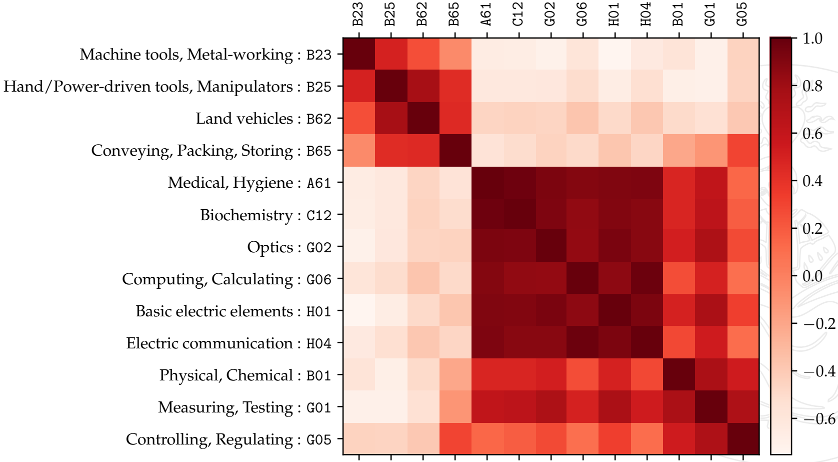
- USPTO Master Classification File (MCF)
- CPC classification of US patent grants since 1790
- usable data starts in 1836
- our analysis is restricted to the period 1836–2019
- we compute patent intensity for a set of CPC codes relevant to LS technologies

$$\text{patent intensity of code } CPC \text{ in year } t = \frac{\text{number of } CPC \text{ assignments in year } t}{\text{number of all assignments in year } t}$$

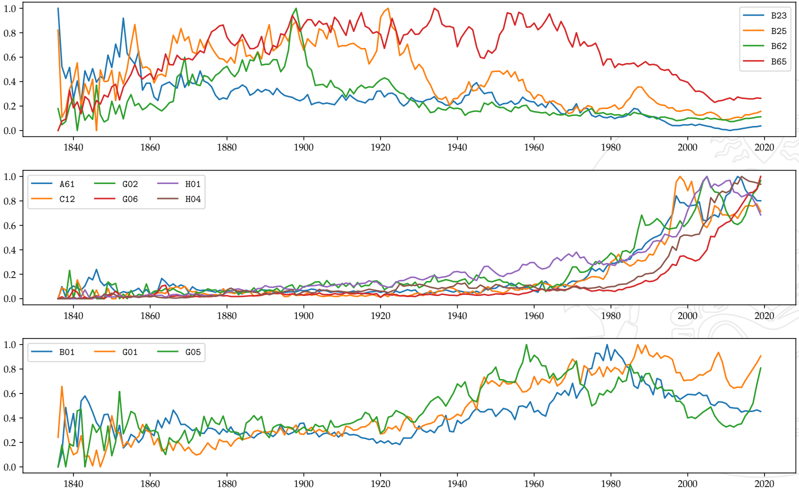
Patent intensity series



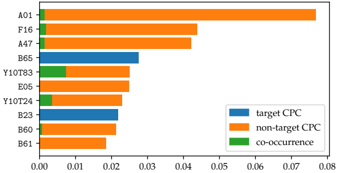
Cross-correlation



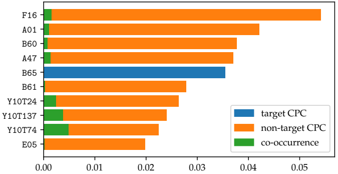
Patent intensity clusters



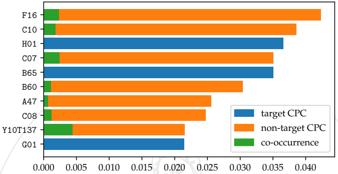
Sub-periods



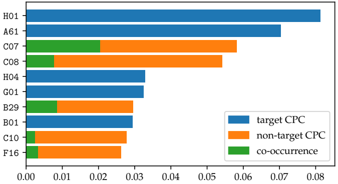
(a) 1836 to 1880



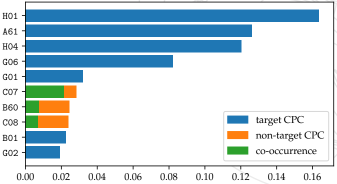
(b) 1881 to 1920



(c) 1921 to 1960



(d) 1961 to 2000



(e) 2000 to 2019

Wavelet analysis

- signal processing is an appropriate tool to detect the presence of long waves
- the Fourier transform (FT) decomposes a signal into its constituent frequencies

$$\boxed{\textit{time}} \quad \Longrightarrow \quad \boxed{\textit{frequency}}$$

- however, the FT only captures periodic behaviours detectable throughout the *whole* time frame with *constant* wavelength
- the wavelet transform (WT) decomposes a signal into a complete time–frequency representation

$$\boxed{\textit{time}} \quad \Longrightarrow \quad \boxed{\textit{time} \times \textit{frequency}}$$

- the WT retains all the relevant information carried by the signal

Wavelet analysis (cont'd)

- Morlet wavelet

$$\psi_{\omega_0}(t) = \pi^{1/4} \left(e^{i\omega_0 t} - e^{-\omega_0^2/2} \right) e^{-t^2/2}$$

- continuous wavelet transform of signal $f(t)$

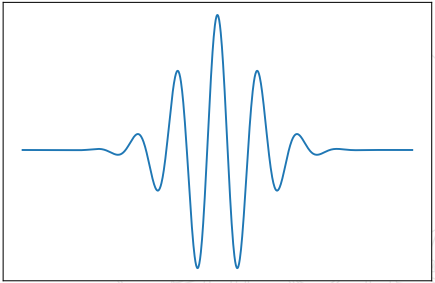
$$W_{f,\psi}(s,\tau) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} f(t)\, \psi^* \left(\frac{t-\tau}{s} \right) dt$$

- wavelet power spectrum

$$WPS_{f,\psi}(s,\tau) = \left| W_{f,\psi}(s,\tau) \right|^2$$

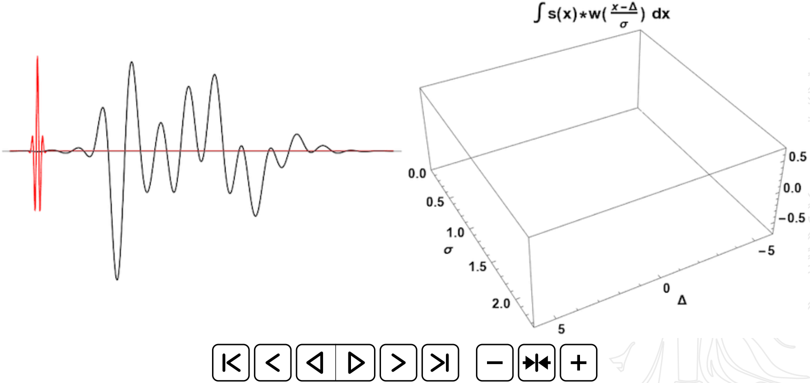
- cross wavelet power spectrum of signals $f(t), g(t)$

$$XPS_{f,g,\psi}(s,\tau) = \left| W_{f,\psi}(s,\tau) \cdot W_{g,\psi}(s,\tau)^* \right|$$



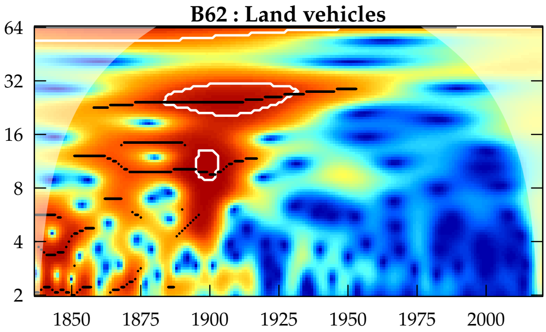
Morlet wavelet with $\omega_0 = 6$

Continuous wavelet transform



Wavelet power spectrum

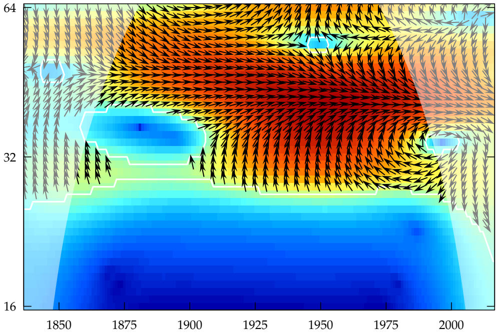
- warmer (colder) pixels represent higher (lower) underlying coefficients
- white contours mark 95% significance
- black points/lines denote local ridges of wavelet power
- shaded regions bound the *confidence cone*



Cross wavelet power spectrum

- historical GDP data from the Maddison Project Database (2018)
- we apply CF band-pass filter on all series to separate cycle and trend components
- *cross* wavelet power spectra between GDP growth and patent intensity

- $\rightarrow$ means in-phase dynamics
- $\leftarrow$ means out of phase dynamics
- $\nearrow$ or $\swarrow$ mean GDP locally leads innovation
- $\nwarrow$ or $\searrow$ mean innovation locally leads GDP



GDP growth and 3rd cluster

Outline

Heuristics in technology: Marx vs. Schumpeter

- heterogeneous dynamics among patent intensities challenge the GPT approach and supports the idea of technological constellations
- automation/mechanisation, and labour-saving heuristics therein, seem to constitute a *"natural trajectory"* in the evolution of the capitalist system, rather than a regular, recurrent periodic pattern (Nelson and Winter, 1982)
- there exist periods of coordinated innovative effort resulting in upsurges and subsequent declines, highlighting some degree of technological clustering
  - we do not confirm the presence of 50-year long Kondratiev waves
  - we are not able to identify regular periodic waves leading to new technological systems
  - dominant CPC codes characterising erratic technological constellations are in line with technological system dating proposed by Freeman and Louçã (2001)

Technology and growth: Mensch vs. Freeman

- innovation and GDP growth present delinked patterns of waves, with heterogeneous troughs and peaks
  - whenever co-movements occur, waves in GDP growth seem to precede, rather than follow, technological innovations
  - the picture gets more nuanced when looking at both time and frequency domains together
- any purported saturation of the technological frontier or of innovative ideas are not detectable from the trends in innovation directed at the automation/mechanisation of tasks
  - labour-saving efforts are present and involve a large set of technological artefacts, producers, and sectors of activity (Montobbio et al., 2020)
  - this occurs rather independently of economic cycles at the macro-level

Limitations and future developments

- level of aggregation: 3-digit CPC codes are rather heterogeneous and might also include labour-friendly innovations, even in their conception phase
- labour-saving vs. labour-friendly is a question that pertains to the use of the artefact and its implementation in the production and organisational processes occurring at the firm and sectoral level
- labour-saving innovations uniquely derived by current robotic artefacts potentially neglect other labour-saving innovations sprung by different artefacts, not specifically linked to robotic automation
- wider investigation across the whole set of patents

Thank you very much!

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this presentation is available at www.staccioli.org

Target CPCs and technological systems

Long Kondratiev waves	Dominant CPCs	Coexisting CPCs
1780–1840: Mechanisation and textile	B23	A61, C12, G02, G06
1840–1890: Steam power and railways	B01, G01, G05	B25, B62, B65
1890–1940: Electrical and engineering	H01, H04	B25, B62, B65
1940–1990: Mass production and automotive	B25, B62, B65	G06, C12
1980–*ongoing*: ICT	C12, G02, G06	G01, G05, H01, H04

Own elaboration based on Freeman and Louçã (2001)