Innovation, localized knowledge spillovers, and the British Industrial Revolution, 1700–1850

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Introduction

Spatially localized efficiency gains

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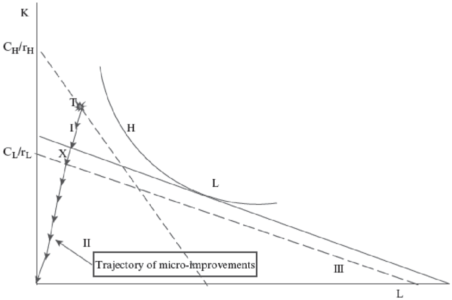
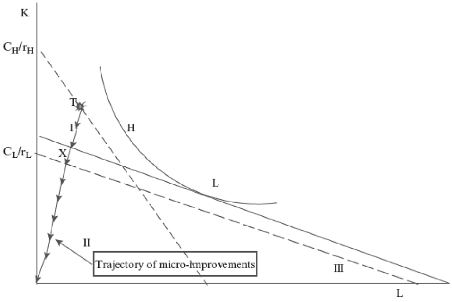
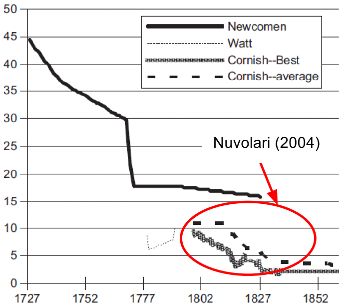


Allen (2009), Figure 6.4.

Spatially localized efficiency gains



Allen (2009), Figure 6.4.



Allen (2009), Figure 8.

Knowledge Access Institutions (KAIs)

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Table 9.6 **Publishers and members of societies**

Sector	Publishers only	*% of sector total*	Members of societies only	*% of sector total*	Publishers and members of societies	*% of sector total*	Sector total
Textiles	7.5	*4*	6.0	*3*	3.0	*2*	193.0
Ships	6.5	*24*	2.0	*7*	11.0	*41*	27.0
Road & rail & can	11.0	*12*	29.5	*33*	23.0	*26*	89.5
Other eng	25.0	*17*	31.0	*21*	55.0	*37*	148.0
Med & chem	4.0	*14*	3.5	*12*	13.5	*46*	29.5
Instruments	13.0	*14*	13.5	*15*	40.5	*45*	90.5
Iron & met	6.5	*13*	9.0	*18*	6.5	*13*	51.0
Mining	4.5	*18*	3.0	*12*	8.0	*31*	25.5
Agr & farm	6.5	*31*	1.5	*7*	3.5	*17*	21.0
Construction	8.0	*19*	2.5	*6*	18.0	*43*	42.0
Print & photo	3.0	*15*	2.5	*13*	4.0	*21*	19.5
Others	1.5	*7*	1.0	*4*	5.0	*22*	22.5
Category total	97.0	*13*	105.0	*14*	191.0	*25*	759.0

Meisenzahl & Mokyr (2010): The 759 key inventors of the Industrial Revolution are argued to be crucially connected via scientific societies and publication activities enhancing the **dissemination** of "useful knowledge".

Mokyr (2009): Codified and tacit knowledge

"Mokyr's own view of the matter seems to be that tacit knowledge was **quickly incorporated** into the canon of encoded and stored knowledge thanks to the Industrial Enlightenment and as a result the all-important data on which technological progress was predicated could easily move across boundaries and national frontiers".

– Peter Jones (2008). *Industrial Enlightenment. Science, technology, and culture in Birmingham and the West Midlands, 1760–1820*.

Our proposal

Our proposal

County-level patent data with quality indicator

(Nuvolari and Tartari, 2011)

$+$

Discrete choice model with localized externalities

(Bottazzi and Secchi 2007, Bottazzi and Gragnolati, 2015)

$=$ Insights on the nature of innovation during the IR

Data and descriptive statistics

Inventive activities and patents: A premise

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- The localization of inventive activities is identified by the address of the inventor/patentee.
- There is innovation also outside the patent system (MacLeod, 1988; Nuvolari, 2004; Moser 2005).
- Non patented inventions are more likely to be localized (Moser, 2011; Nuvolari, 2004).

Sources

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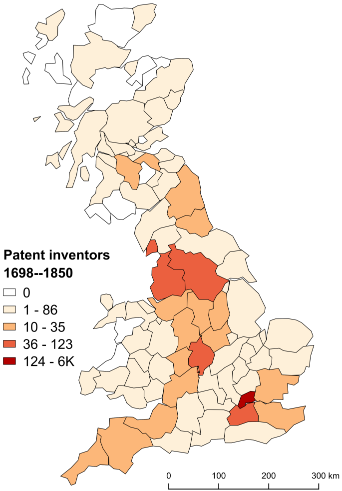
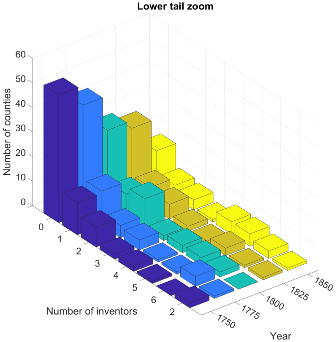
VARIABLE BY COUNTY	YEARS AVAILABLE	SOURCE
Patents and/or inventors	1698–1850	[Nuvolari and Tartari(2011)]
Population	1698–1850	[HCPP(1831), HCPP(1851), Kyd(1952), Wrigley(2007)]
Urbanization rate	1698–1850	[Bairoch et al.(1988)Bairoch, Batou, and Chevre]
Core KAIs	1698–1850	[Dowey(2017)]
High-quality inventors	1698–1850	Own elaboration
Coal output	1698–1850	[Nuvolari and Tartari(2011)]
Distance from London (km)	Fixed	Own elaboration
Employment by industry	1841; 1851	[CAMPOP(2009)]

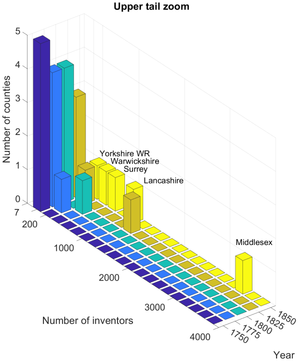
Coverage: The analysis regards 13,630 inventors, amounting to 90% of all patents filed in England and Wales over the span 1617–1850. Inventions are classified in 22 industries following Nuvolari and Tartari (2011). Spatial units consist of 85 historic counties covering the whole of Great Britain.

Inventors by county, 1698–1850

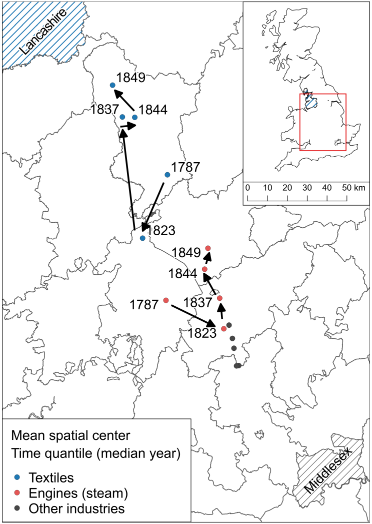


Evolution of spatial distributions – Aggregate





Evolution of spatial distributions – Industry level



Woodcroft Reference Index (WRI)

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16 REFERENCE INDEX OF PATENTS OF INVENTION.

Progressive Number.	REFERENCE.
910	Rolls Chapel Reports, 6th Report, page 136. Rolls Chapel.
911	No Specification :—Letters Patent printed.
912	Petty Bag.
913	Repertory of Arts, vol. 1, page 217. Mechanics' Magazine, vol. 1, page 4. Practical Mechanics' Journal, vol. 1, page 285. Register of Arts and Sciences, vol. 4, pages 24 and 346. Engineers' and Mechanics' Encyclopædia, vol. 2, page 725. Webster's Reports, vol. 1, page 31 (note p.), page 56 (note), and pages 230, 282, and 285. Webster's Patent Law, page 46 (also page 127 cases 30, 31, and 32); and Supplement pages 2, 18, and 20. Webster's Letters Patent, pages 6, 17, and 20. Blackstone's Reports, vol. 2, page 463. Carpmael's Reports on Patent Cases, vol. 1, pages 117, 155, and 156. Davies on Patents, pages 155, 162, and 221. Collier's Law of Patents, pages 71, 75, 83, 90, 94, 100, 128, 139, and 181. Parliamentary Report, 1829 (*Patent Law*), pages 187, 189, and 190. Vesey, junr.'s, Reports, vol. 3, page 140. Holroyd on Patents, pages 35, 48, and 55. Durnford and East's Term Reports, vol. 8, page 95. Patentees' Manual, page 8. Billing on Patents, pages 20, 22, 23, 26, 27, 28, 29, 31, 32, 48, 82, 89, 90, and 145. Rolls Chapel Reports, 6th Report, page 160. Extended by Act of Parliament for 25 years. (*See* No. 913*.) Rolls Chapel.
913*	Act of Parliament for extending No. 913 for 25 years.
914	Rolls Chapel Reports, 6th Report, page 136. Rolls Chapel.

Index entry for Watt's separate condenser.

Each patent is associated to a WRI, which we **normalize** by time-period average. More about Woodcroft and patents

Importance of patent quality and industry

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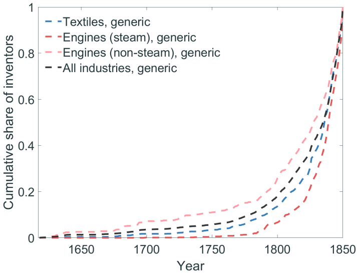
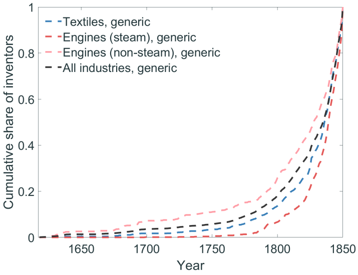


Generic patents.

Importance of patent quality and industry



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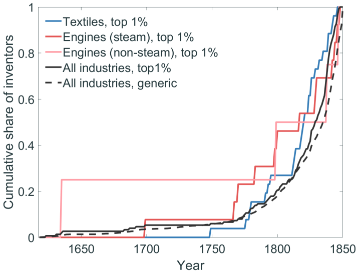

High quality patents.

Model and estimation

Disentangling localization externalities from intrinsic features

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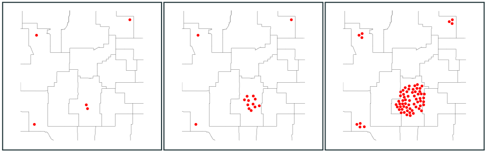

$t = 0$ $t = 10$ $t = 100$

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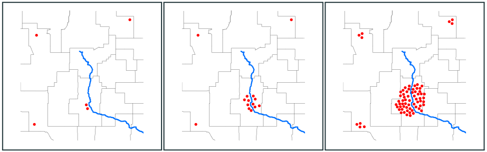

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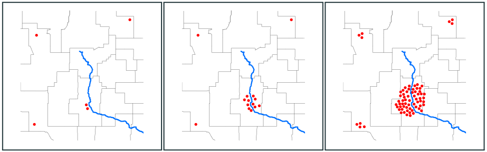

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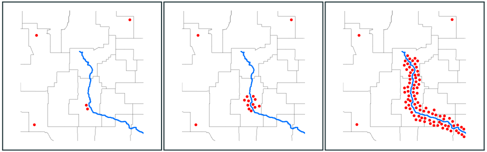

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A localization model

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An agent drawn at random retires from location m, while a new agent enters the economy. The new agent selects location l with probability

$$p_l = \frac{c_l}{\sum_{j=1}^{L} c_j} \, . \tag{1}$$

Linear externalities

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If $b > 0$, we refer to the effect of bn_l as **localized externalities**.

Polya vs. Multinomial

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$$c_l = a_l + b n_l \qquad a > 0,\ b \geq 0$$

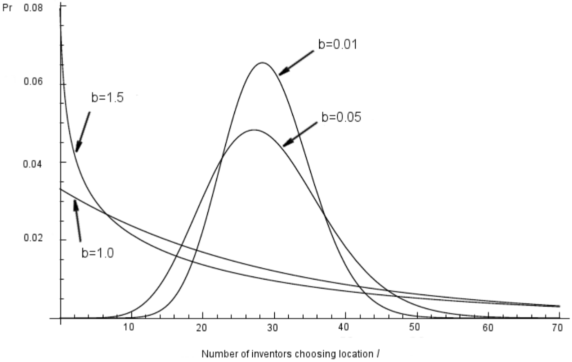
$b > 0$ → Polya distribution

$$\pi(\boldsymbol{n}; \boldsymbol{a}, b) = \frac{N!\Gamma(A/b)}{\Gamma(A/b+N)} \prod_{l=1}^{L} \frac{1}{n_l!} \frac{\Gamma(a_l/b+n_l)}{\Gamma(a_l/b)}$$

$b = 0$ → Multinomial distribution

$$\pi(\boldsymbol{n}; \boldsymbol{a}, b = 0) = N! \prod_{l=1}^{L} \frac{1}{n_l!} \left(\frac{a_l}{A}\right)^{n_l}$$

Alternative scenarios



Deriving p_l

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Define $\boldsymbol{x}_l = (x_l^1, \ldots, x_l^H)$ variables that describe the intrinsic attractiveness of locations, so that $a_l = g_l(\boldsymbol{\beta}, \boldsymbol{x}_l)$ or $\frac{a_l}{b} = g_l(\boldsymbol{\beta}, \boldsymbol{x}_l)$.

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where $G = \sum_l g_l(\boldsymbol{\beta}, \boldsymbol{x}_l)$.

Effect of x^h and n on p_l

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The marginal elasticity associated to an intrinsic advantage:

$$\frac{\partial p}{\partial \log x^h} = \sum_{l=1}^{L} \frac{\partial p_l}{\partial \log x_l^h} \ .$$

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The marginal elasticity associated to localization externalities:

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The marginal elasticity associated to localization externalities:

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Since p_l is bounded from above, we compute the effects on the transformation $q_l = -\log(1 - p_l)$.

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$$\mathrm{AICc} = 2k - 2\ln(\ell) + \frac{2k(k+1)}{L-k-1}\ ,$$

where L is the sample size, k is the number of parameters in each model, and ℓ is the maximized value of the likelihood function.

Results and discussion

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$$\begin{aligned}\log g(\beta, x_l) = &\beta_1 \log(\text{Population}) + \\ &\beta_2 \log(\text{Urbanization}) + \\ &\beta_3 \log(\text{Coal output}) + \\ &\beta_4 \log(\text{Top 1\% inventors}) + \\ &\beta_5 \log(\text{Core KAIs}) + \\ &\beta_6 \log(\text{Distance from London})\,.\end{aligned} \tag{3}$$

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\end{aligned} \tag{3}
$$

Except for high-quality inventors, all controls are **lagged** to minimize concerns on simultaneity. Also, controls are standardized, so as to guarantee full comparability.

Resulting marginal elasticities

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Given specification (3), the resulting marginal elasticity associated to the intrinsic feature x^h reads

$$\frac{\partial q}{\partial \log x^h} = \sum_{l=1}^{L} \frac{\partial q_l}{\partial \log x_l^h} = \beta^h \frac{G}{N+G} \ . \tag{4}$$

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On the other hand, the marginal elasticity associated to localization externalities reads

$$\frac{\partial q}{\partial \log n} = \sum_{l=1}^{L} \frac{\partial q_l}{\partial \log n_l} = \frac{L}{N + G} \ . \tag{5}$$

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But **how strong** are they relative to other drivers?

In the aggregate: a basic result

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Marginal elasticities as obtained from the spatial distribution of all patent inventors active between 1698–1850. Controls are in year 1697 except for Top 1% inventors, which is simultaneous to the inventors spatial distribution.

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Marginal elasticities as obtained from the spatial distribution of all patent inventors active between 1698–1850. Controls are in year 1697 except for Top 1% inventors, which is simultaneous to the inventors spatial distribution.

Driver	Marginal elasticity
Population	$1.10e{-}02^{**}$
Urbanization	$3.14e - 04$
Coal output	$5.89e{-}03^{**}$
Top 1% inventors	$2.69e{-}03^{**}$
Core KAIs	$1.03e - 03^{*}$
Distance from London	$-5.10e{-}03^{**}$
Localized externalities (n)	$9.87e{-}01^{**}$

Note: ** indicates a 99% confidence level.

At different time periods: important variations over time

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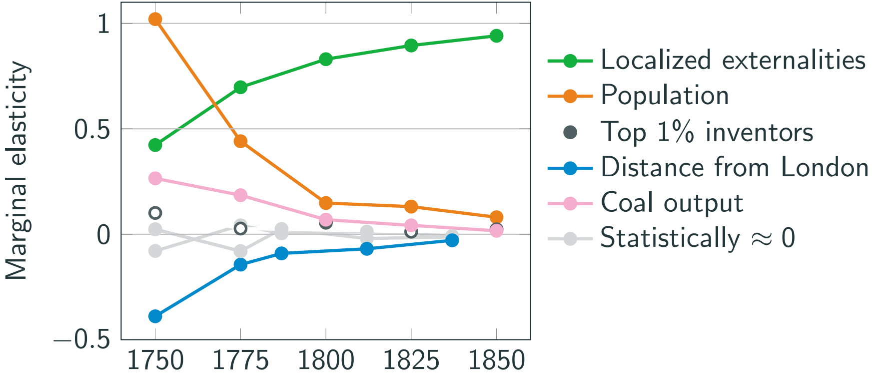

At industry level: further insights

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Marginal elasticities as obtained from the spatial distribution of all patent inventors active in the textiles and steam engines industry between 1826–1850. Controls are in year 1825 except for Top 1% inventors, which is simultaneous to the inventors spatial distribution. Also, the first available data for industry-level employment is in 1841.

At industry level: further insights

Marginal elasticities as obtained from the spatial distribution of all patent inventors active in the textiles and steam engines industry between 1826–1850. Controls are in year 1825 except for Top 1% inventors, which is simultaneous to the inventors spatial distribution. Also, the first available data for industry-level employment is in 1841.

Driver	Textiles	Engines (steam)
Population	$-8.89e-03$	$3.33e-01^{*}$
Urbanization	$6.53e-02^{**}$	$-1.16e-02$
Coal output	$2.02e-02$	$-2.57e-02$
Top 1% inventors	$2.56e-02^{*}$	$8.25e-02^{*}$
Core KAIs	$-3.58e-03$	$1.39e-02$
Distance from London	$-2.88e-02$	$-5.93e-02$
Industry-level employment	$9.57e-02^{**}$	$6.37e-01^{**}$
Localized externalities (n)	$9.13e-01^{**}$	$5.35e-01^{**}$

Note: The symbol ** indicates a 99% confidence level.

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- "[. . .] Engineering firms had to be technically competent, but it was vital to be connected into a local network of technical and commercial information".
  – Cookson (1997), on Yorkshire textile engineers.

Resonance of the results with the literature

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- "The productive system as a whole mattered in fostering technical progress. Mutual interaction of producers and users widened the pool of talent available, and deepened competitive strength. The complexity of interactions and accumulated skills restricted the degree to which such knowledge could be portable to new regions".
  – Von Tunzelmann (1994).

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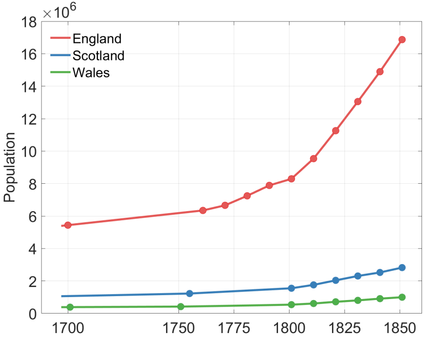
- "Elite" vs "Democratic" invention.

More on population estimates

A consistency check at the macro-regional scale



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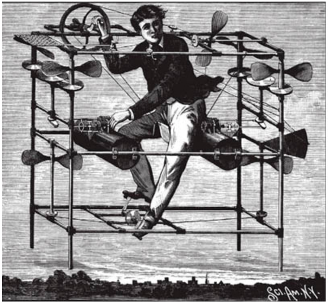
More on population estimates

More on Woodcroft and patents

Patent data: pros, cons, and value added

Cons:

- Not all inventions are patented.
- Patented inventions differ in quality.



Pros:

- Comprehensive data.
- Possibility to make quantitative analysis.

The valued added of the present patent dataset is to have a reliable indicator of **patent quality** (Woodcroft Reference Index, WRI).

More on Woodcroft and patents

Bennet Woodcroft

Bennet Woodcroft, 1803-1879

- Inventor; Professor of “Machinery”; Patent agent; Historian of technology.
- Owner of a rich personal technical library which was the initial seed for the Patent Office Library.
- Advocate of patents as “information systems”.
- Appointed in 1852 as Assistant to the Commissioners of Patents.
- He took care of the publication of the first official patent indexes Alphabetical, Chronological, Reference, Subject Indexes (1850-1860).

More on Woodcroft and patents

Publications referenced in the Woodcroft Index

- Technical books and engineering journals

  Mechanics Magazine, Heberts Encyclopedia, Artizan, Engineer and Architect Journal, etc.

- Legal commentaries on patent law and cases

  Webster, Carpmael, etc.

- Journals showcasing developments in science and technology (they published "judicious selections" of patent specifications)

  Repertory of Arts, London Journal of Arts and Sciences, Register of Arts and Sciences, Inventors Advocate and Patentees Recorder, etc.

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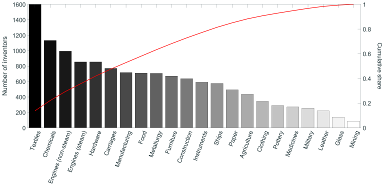
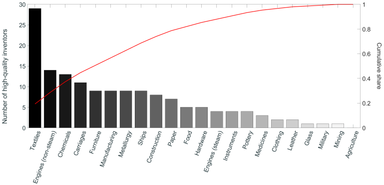
Patent count and cumulative share by industry



Generic patents.



High quality patents.

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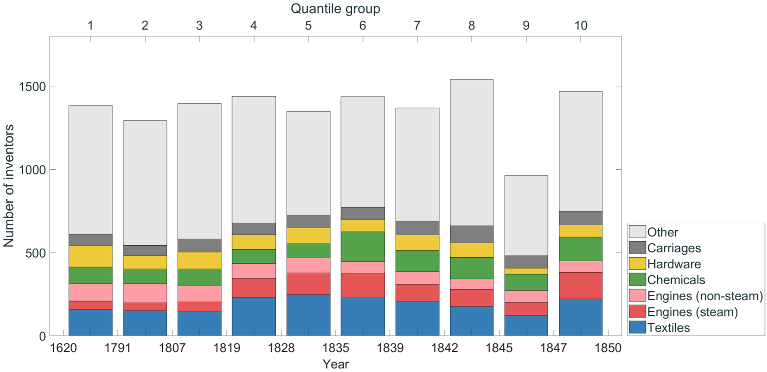
Patent count by industry over time



More on Woodcroft and patents