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Patterns of Innovation during the Industrial Revolution: a Reappraisal using a Composite Indicator of Patent Quality

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Patterns of Innovation during the Industrial Revolution: a Reappraisal using a Composite Indicator of Patent Quality*

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Abstract

The distinction between macro- and microinventions is at the core of recent debates on the Industrial Revolution. Yet, the empirical testing of this notion has remained elusive. We address this issue by introducing a new quality indicator for all patents granted in England in the period 1700-1850. Our findings indicate that macroinventions did not exhibit any specific time-clustering, while microinventions were correlated with the economic cycle. In addition, we also find that macroinventions were characterized by a labor-saving bias and were mostly introduced by professional engineers. These results suggest that Allen's and Mokyr's views of macroinventions, rather than conflicting, should be regarded as complementary.

Keywords: Industrial Revolution; Patents; Macroinventions; Microinventions.

JEL Code: N73, O31, O33

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1 Introduction

Technical change has traditionally occupied a central place in the historiography of the Industrial Revolution. Not surprisingly, both contemporaries and historians have regarded technology as one of the key-factors shaping the dramatic economic and social transformations taking place in Britain during the XVIII and XIX centuries. This interest in technical change has resulted in a rich literature providing vivid descriptions of technical advances both in a broad, aggregate perspective (Landes 1969; Mokyr 1990; Trinder 2013) and at a level of specific technologies such as steam power (Hills, 1989), textiles (Hills, 1970) and iron production (Hyde, 1977).

In this context, the distinction between microinventions and macroinventions originally proposed by Joel Mokyr (1990) has established itself as a particularly useful interpretive tool for delineating an effective characterization of the patterns of technical change during this crucial historical period. In Mokyr's original formulation (Mokyr 1990, p.13), microinventions are "small, incremental steps that improve, adapt and streamline existing techniques", whereas macroinventions are "inventions in which a radical new idea, without a clear precedent, emerges more or less ab nihilo"[1]. The subsequent literature has expanded on this intuition by sketching several conjectures on the sources and effects of macro- and microinventions and on their interconnections (Allen 2009; Mokyr 2010; Crafts 2011).

The notions of macroinventions and microinventions are intuitively appealing and indeed resonate well with influential qualitative accounts of the contours of technical advance during the Industrial Revolution (Landes 1969; Mathias 1969). However, at closer inspection, the distinction between macro- and microinventions appears of difficult empirical implementation, especially if one is interested in reconstructions of broad patterns of technical change spanning more than a specific technology or industry.

In economic history, an established research tradition has resorted to patents to provide quantitative assessments of the rate and scope of technical change (see Sullivan 1989, 1990, and Sokoloff 1988 for some early contributions). One of the main limitations of the use of "raw" patent counts for characterizing patterns of technical of change is precisely that they do not take into account the relative importance of the underlying inventions (O'Brien et al., 1995), preventing the systematic identification

[1]Mokyr's perspective on technical change based on the interplay between macro- and microinventions has many commonalities with the application of Thomas Kuhn's notions of paradigms and revolutions to technical change proposed by Constant (1973) and Dosi (1982). In Constant and Dosi's interpretation, microinventions are, by and large, the outcome of inventive activities taking place within the boundaries of the prevailing "technological paradigm" – a cognitive framework guiding the search for innovations jointly adhered to by a relevant community of technological practitioners. In this perspective, a macroinvention in this sense of Mokyr is akin to the emergence of a new "technological paradigm" in Constant and Dosi's formulations.

of macroinventions. In the case of modern patents, economists of innovation have addressed this issue by designing a number of indicators of "patent quality" based on the use of patent characteristics such as citations, jurisdictions coverage and renewals (Jaffe and Trajtenberg 2002; Van Zeebroeck 2011; Squicciarini et al. 2013). Unfortunately, these indicators are not immediately applicable to the case of the English patent system during the Industrial Revolution. Remarkably, when writing *The Lever of Riches*, Mokyr pessimistically concluded "... patent statistics [in the Industrial Revolution period] do not permit to distinguish between radical and minor inventions" (Mokyr 1990, p. 82).

In this paper, we introduce a new composite indicator of the quality of English patents for the period 1700-1850. Our indicator of patent quality is a substantial refinement of the bibliographic indicator proposed by Nuvolari and Tartari (2011) based on Bennet Woodcroft's *Reference Index of Patents of Invention, 1617-1852.* We construct our new composite indicator by complementing Woodcroft's *Reference Index* with information collected from a wide array of sources on the history of technology and biographical dictionaries. We combine these different sources using the approach introduced by Lanjouw and Schankerman (2004) for constructing composite quality indicators for modern patents. We validate the reliability of the new index of patent quality, which we term *Bigliographic Composite Index* (BCI), by means of several robustness checks.

The Bibliographic Composite Index provides the opportunity for a large-scale empirical implementation of the notions of macro- and microinventions, at least for the subset of patented inventions. In this way, we can reappraise a number of interpretive conjectures on the sources and effects of macro- and microinventions that have featured prominently in recent debates on the Industrial Revolution (Allen 2009; Mokyr 2010; Crafts 2011; Allen 2018).

We find that the distinction between macro and microinventions is supported by the patent evidence. In particular, the time series of macroinventions exhibits statistical properties consistent with a major role of serendipity in determining their occurrence as originally suggested by Mokyr (1990). Vice versa, microinventions take place after the appearance of major breakthroughs and tend to be correlated with the economic cycle. We also document that macroinventions were possibly characterized by a labour-saving bias which could be consistent with the so-called "high wage interpretation" of the Industrial Revolution proposed by Allen (2009). However, we find that macroinventions were not the results of the activities of "outsiders", that is of inventors with occupations unrelated with the trade of the invention as Allen (2009) had suggested. Rather, in line with some recent contributions, we document that engineering specialists played a significant role in the development of macroinventions (Zeev et al. 2017; van der Beek et al. 2020; Hanlon 2020).

The rest of the paper is organized as follows. In Section 2 we review the literature on macro- and microinventions. In Section 3 we introduce the Bibliographic Composite Index of patent quality (BCI) and we perform extensive robustness checks to assess its reliability. Finally, in Section 4 we use the BCI to test a number of conjectures concerning the dynamics and impact of the two types of inventions. Section 5 presents our conclusions.

2 Macro- and Microinventions during the Industrial Revolution

The conceptualization of macro- and microinventions has informed much of the recent historiography on the origins of the Industrial Revolution. Notably, the acceleration of productivity growth taking place from the early 1820s is now generally interpreted as the delayed impact of the macroinventions of the second half of the XVIII century, which had to be refined and adapted by means of streams of microinventions before manifesting their economy-wide effects (Crafts 1995; Allen 2009; Broadberry and Gupta 2009). While this account of the connection between technical change and productivity growth is largely accepted, there is surely less consensus on the sources and effects of macro- and microinventions (Allen 2009; Meisenzahl and Mokyr 2012; Crafts 2011; Allen 2018).

Mokyr (1990) originally argued that macroinventions were the result of serendipitous discoveries and as such they were not responsive to economic forces. In subsequent contributions, Mokyr (2010, but see also Mokyr 2002, pp. 52-53) has rehearsed this theme by pointing to the connection between the relatively autonomous expansion of the stock of useful and reliable knowledge (driven, during the XVIII century, by the emergence and consolidation of the "culture of improvement" of the "Industrial Enlightenment") and technical advances (Crafts, 2011). In an analogous vein, O'Brien (1997) uses the example of Edmund Cartwright to press a similar point: the activities of the "macroinventors" of the Industrial Revolution cannot be subsumed as the outcomes of broader economic, social or cultural forces. On the contrary, the history of the Industrial Revolution must remain open to the "contingent character of technological discovery at this time" (O'Brien 1997, p. 205) and, therefore, is bound to contain an irreducible element of biography and narrative.[2] The stochastic nature of macroinventions is also a theme developed by Crafts (1977, 1995) when pointing out that much of the literature on the origins of industrialization in European comparative perspective may be vitiated by "post hoc,

[2]Relatedly, Constant (1973) argues that "technological revolutions" are instigated by "individual provocateurs" and that the answer to the question of why one inventor develops a macroinvention while another with similar training and background does not, may be lost "in the inaccessible personalities of individual men... no conception of paradigmatic change that confines itself to economic factors, however sophisticated its definitions of demand and expected costs might be, would be likely to grasp the full complexity of technological revolution. New paradigms are the progeny of beings, somewhat less, or somewhat more than 'economic man' " (Constant 1973 , p. 557, 559).

propter hoc" fallacies. Indeed, according to Crafts, "[t]echnological history suggests that seeking for socio-economic explanations of macroinventions is likely to be a fruitless pursuit" (Crafts 1995, p. 596).

Allen (2009) has challenged these interpretations suggesting an alternative economic deterministic view of technological change which comprises not only microinventions, but also macroinventions. Allen claims that the salient feature of the macroinventions of the Industrial Revolution is that they brought about major shifts in factor proportions with respect to the technology in current use. In particular, they substituted capital and energy for (high wage) labor. The development of inventions that were very distant in terms of factor proportions from the existing best-practice technology required major investments and costly experimentation. Therefore, it is highly unlikely that inventors and their financial backers would have incurred in the developing costs necessary to move from ideas to workable prototypes, without the prospect of substantial economic returns.

Furthermore, Allen (2009, p. 149) argues that macroinventions were typically the brainchild of "outsiders" which could more easily steer away from current technological practices and imagine radically alternative solutions, involving major changes in factor proportions.[3] On the other hand, microinventions were due to insiders who improved and refined the prototype macroinventions by means of localized processes of learning-by-doing and learning-by-using. In this way, Allen maintains that the patterns of innovation of the industrial revolution can be accounted for using Paul David's model of localized technical change in his influential interpretation of the "Habakkuk debate" on the labor-saving character of American inventions during the XIX century (David, 1975).

By and large, the characterizations of macro- and microinventions of Allen, Mokyr and other historians have been formulated by drawing generalizations from the history of specific inventions or inventors' biographies. This, once more, testifies that systematic quantitative evidence on macroinventions is generally not readily available in the sources. In a seminal paper on the contours of technological change in XIX century America, Khan and Sokoloff (1993) have shown the potential of biographical dictionaries as a source for the study of macroinventions. Their paper contains a detailed quantitative scrutiny of the careers and patents of 160 "great inventors" retrieved from the *Dictionary of American Biography* (see also Khan 2005, chap. 7). The underlying assumption is precisely that this sample of "great inventors" can represent a suitable vantage-point for the study of macroinventions in the sense of Mokyr.[4] Khan and Sokoloff show that the inventive activities of the "great inventors"

[3]Interestingly enough, the hypothesis that macroinventors will typically be "outsiders" is also entertained by O'Brien (1997).

[4]Allen (2009, chap 10) adopts the "great inventors" approach to study the character of macroinventions during the

were responsive to the economic cycle and they tended to cluster geographically in areas with low-cost transportation networks which were more suited for the economic exploitation of their inventions. In their interpretation, this result suggests that, at least in the American case, commercial considerations were a major driver of macroinventive active, against the original conjecture proposed by Mokyr. In a subsequent contribution, Khan (2018) applies the "great inventors" approach to the British case during the period 1750-1930 using a sample of 439 inventors. In this case the main concern of the paper is the role played by human capital in the generation of macroinventions and the conclusion is that a scientific background or a formalized education were not critical for inventive activities until at least the second half of the XIX century. Furthermore, Khan (2018) documents that the inventors responsible for macroinventions had substantial knowledge of their trade accumulated by means of apprenticeships and protracted practical experience.

This paper expands on this line of research by introducing a new quality indicator for English patents. By means of this indicator, it will be possible to provide a complete mapping of the quality distribution of English patents and to identify its upper tail containing the macroinventions.

3 The construction of the Bibliographic Composite Index of Patent Quality

3.1 Sources

Our composite index combines three quality indicators for the 13,070 English patents granted during the period 1700-1850. The first indicator captures the visibility of each patent in the contemporary engineering and legal literature, as summarized in Bennet Woodcroft's *Reference Index*.[5] This quality indicator (dubbed WRI) has been originally proposed by Nuvolari and Tartari (2011) and it counts the number of times each patent was mentioned in the set of specialized publications scrutinized by

Industrial Revolution using a sample of 79 inventors. His main conclusion is that the connection between the "Industrial Enlightenment" and macroinventions was weak and irregular. Meisenzahl and Mokyr (2012) construct a sample of 759 inventors active in Britain during the Industrial Revolution period. Since the focus of their paper is on the adaptation and refinement of technological breakthroughs, rather than on the origins of macroinventions, they decide to adopt a relatively large sample.

[5]The *Reference Index* was a component of larger set of volumes that were published following the requests of the Patent Office Commissioners after the patent reform of 1852. Before the reform of 1852, a patent application could be lodged in any of these public offices in London: Rolls Chapel, Petty Bag and Enrolment Office. The system did not have an effective search catalogue, so that the consultation of patent specifications was difficult and time-consuming. The Patent Office Commissioners addressed this issue by funding the publications of a series of indexes and abridgments for all patents granted in the period 1617-1852. Bennet Woodcroft, professor of machinery, inventor and patent agent, was entrusted with the publications of the indexes. Together with the *Reference Index*, Woodcroft and his team published an *Alphabetical Index of Patentees*, a *Chronological Index of Patents*, a *Subject Index of Patents* and a series of *Abridgments of Patent Specifications* (Nuvolari and Tartari, 2011).

Woodcroft and his team of clerks.[6]

The second patent quality indicator is based on the relative visibility of patents in modern reference books on the history of science and technology. This approach is based on the original intuition of Schmookler (1966), who compiled lists of "important inventions" on the basis of the detailed scrutiny of specialized historical and engineering sources for a selection of sectors (agriculture, railroading, petroleum refining and paper making) as a robustness check for using patents as a proxy of inventive activities. In our case we have considered ten reference volumes (the full list is reported in the Appendix). For each patent we count the number of times it is mentioned in this set of sources, obtaining in this way a quality score that we call Patent Eminence (PAT_EM). A similar aggregation procedure was adopted by Kleinknecht (1990) for constructing a quality indicator based on the integration of different lists of radical innovations in the context of the literature on "long waves". Table A2 in the Appendix reports the patents with the highest values of PAT_EM. It is important to remark that the set of sources that we use to construct this quality indicator has a high degree of internal consistency (i.e., agreement in the identification of high-quality patents), with a Kuder-Richardson 20 coefficient of 0.7792.[7]

The third quality indicator considers the relative visibility of the patentee in biographical dictionaries and similar sources. As we have already mentioned, Khan and Sokoloff (1993) were the first to use this method for identifying the inventors responsible for the most significant innovations in XIX century America. As in Khan (2018), instead of relying on a single source, we have collected data from nine biographical dictionaries and analogous sources (the details are again provided in the Appendix). This third quality indicator that we term Inventor Eminence (INV_EM) is constructed in a similar way to the previous two by counting the number of sources the mention each patentee. Table A4 in the Appendix reports the inventors with the highest scores of INV_EM. Also in this case, the set of sources used displays a high degree of internal consistency with a Kuder-Richardson 20 coefficient equal to 0.8511.[8]

Table 1 summarizes the number of patents and inventors mentioned in each of the sources used for constructing PAT_EM and INV_EM.

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[6]The WRI has been used in several recent studies (Crafts and Wolf 2014; Bottomley 2014a, 2014b; Squicciarini and Voigtländer 2015; Dowey 2017) while Hanlon (2015) has adopted a similar approach to construct a quality indicator for patents in cotton textiles in the period 1855-1876.

[7]The Kuder-Richardson 20 coefficient is an indicator of internal consistency for binary variables, analogous to Cronbach's alpha (Gwet, 2014).

[8]Table A5 in the Appendix shows that the Kuder-Richardson 20 coefficients remain substantially unchanged when excluding one source at the time, both in the case of patents and patentees. This provides further corroboration of the substantial homogeneity of the set of sources used for constructing the quality indicators.

[Table 1 about here]

3.2 Properties of the Quality Indicators

Table 2 contains two examples that illustrate some interesting properties of the three quality indicators. The first panel compares John Kay's patent for the flying shuttle (1733), which has a surprisingly low value of WRI, and Jonathan Hulls' patent for a steam-boat (1736), which, although of limited practical significance, raised a good deal of attention among contemporaries.[9] Clearly, in this case, PAT_EM and INV_EM provide a more sensible assessment of the relative historical significance of the two patents than WRI. The second panel of Table 2 compares Richard Arkwright's famous patents for the water-frame (1769) and for the carding machine (1775). The first invention was the fundamental breakthrough that revolutionized the cotton industry, while the second patent was involved in a contentious legal trial and it was ultimately repealed. The controversial legal case accounts for the higher value of WRI for this second patent, relatively to the water-frame. In this case the PAT_EM indicator seems more in tune with the established historical interpretations on the importance of the two patents. Both examples show the potential of PAT_EM and INV_EM to complement and correct some limitations of WRI, thereby increasing the signal-to-noise ratio.

[Table 2 about here]

It turns out that the three quality indicators that we have constructed are characterized by significant positive correlations, but the size of the correlations is quite low.[10] In our interpretation, this suggests that the three indicators capture different dimensions of the quality of innovations. Figure 1 displays the behavior of INV_EM and WRI* by means of a scatterplot.[11] Clearly, biographical dictionaries highlight all the patents taken by the leading historical inventors of the Industrial Revolution. In this way, INV_EM reinstates the importance of patents such as James Heargreaves' spinning jenny (patent n. 962) and Henry Cort's puddling process (patent n. 1351) that were relatively overlooked by WRI*. Another merit of INV_EM is that it can mitigate the tendency of WRI* to emphasize patents that were renowned for reasons that were not directly connected with their technological and economic significance. For example, John Liardet's patent (n. 1040) was the subject of the famous

[9] The patent of Jonathan Hulls (1699-1758), even if sketching an awkward design, attained a certain degree of popularity and may have provided some inspiration to Symington and other pioneers of steam navigation, but there is no recorded evidence of any practical trial of the steam tugboat described in the specification (Robinson, 2004).

[10] The Spearman correlation coefficients are: WRI/PAT_EM =0.0710, WRI/INV_EM =0.0645, INV_EM/PAT_EM =0.3001. All correlations are significant at the 0.1% level. See Table A6 in the Appendix for further details.

[11] The index WRI* is the index WRI adjusted for time-effects. This is the favorite quality indicator based on Woodcroft's *Reference Index* proposed by Nuvolari and Tartari (2011). For the examples of Table 2 we did not use the time adjustment because the patents involved were belonging to the same time cohort.

ruling *Liardet vs Johnson* which, traditionally, has been regarded as firmly settling the issue of the specification requirements.[12] In this case, the relatively high score of WRI* is essentially due to legal references, while the underlying invention was of rather modest technical significance (Adams and Averley, 1986). Conversely, also INV_EM is fraught by some limitations. By construction, it is not able to discriminate the historical significance of the patents granted to the same inventor. The problem is severe for the case of prolific patentees such as Joseph Bramah. One of the most important inventions of Bramah was the hydraulic press (patent n. 2045), while patent n. 2840 for improvements in "paper manufacture and printing" was a relatively minor invention. As Figure 1 shows, in this case, INV_EM neglects this distinction, while WRI* is instead able to discriminate the relative importance of the two patents of the same inventor.

[Figure 1 about here]

Similar considerations can be made for PAT_EM, whose correlation with WRI* is depicted in Figure 2. In this case, in the bottom right corner there are several patents with low values of WRI* that are characterized by high values of PAT_EM, such as John Wilkinson's boring machine (patent n. 1063) and Richard Arkwright's water-frame (patent n. 931). The compilers of the *Reference Index* had to examine a very large and heterogeneous set of sources without the benefit of hindsight, so it is not surprising that a few patents covering significant technological breakthroughs have a low number of references. It is indeed difficult to tell, in each specific case, whether the low number of references is due to a minor impact of the patent in the literature, or to some oversight of the compilers. Furthermore, the bulk of the literature scrutinized by the examiners was published in the early XIX century, which can perhaps explain why some significant XVIII century inventions were short-changed in the Reference Index. Clearly, PAT_EM has the advantage of the benefit of hindsight, since the compilers of the sources used for its construction could rely on a large historiographical literature debating the technological and economic significance of the inventions of the period in question. On the other hand, PAT_EM is not very granular and while it is well suited for pointing to the major breakthroughs, it tends to overlook the heterogeneity characterizing the bulk of the patent quality distribution. For instance, both Cornelius Whitehouse's process for manufacturing iron tubes (patent n. 5109) and Sir William Congreve's engine (patent n. 5461) have a score of PAT_EM of 0. However, the former was a commercial blockbuster that allowed the production of cheap gas pipes, while the latter was a technically flawed design that wishfully hoped to create a perpetual motion by means of

[12] (Bottomley, 2014a) actually shows that the contractual conceptualization of the patent involving the requirement of a sufficiently clear specification had several legal antecedents in the previous fifty years.

waters capillary attraction.[13] In this case, WRI* seems to provide a more sensible assessment of the relative quality of the two patents.

[Figure 2 about here]

This discussion suggests that the three indicators are plausibly capturing complementary dimensions of patent quality. WRI* seems better equipped to assess the quality of incremental innovations, for which only very fragmentary information is available today, while INV_EM and PAT_EM are more suited to gauge technological breakthroughs by virtue of the benefit of hindsight. In the Appendix we further discuss the properties of these three indicators.

3.3 The Bibliographic Composite Index (BCI)

The integration of different quality indicators into a single composite index is an intuitively appealing approach to retain the common information signaling patent quality, while mitigating the noise and idiosyncrasies of the individual sources (Van Zeebroeck, 2011). Here, we adapt the approach introduced by Lanjouw and Schankerman (2004) for composite quality indicators in modern patents to our sample of historical patents.

Figure 3(a) shows the average number of references per year and per decade in Woodcroft's *Reference Index*, whereas Figure 3(b) shows the average scores of PAT_EM and INV_EM per decade. The main point emerging from Figures 3(a) and 3(b) is that the three quality indicators may be affected by significant time-variations and, therefore, using the "raw" scores for comparing patents granted in different periods may lead to biased results. Note that a similar concern is present also in modern patent data where patent citations are typically adjusted considering time and industry effects (Hall et al., 2002).

[Figure 3 about here]

In order to take into account possible temporal and sectoral effects, we estimate the following three regressions with robust standard errors:[14]

$$\begin{aligned}
WRI_i &= e^{(\alpha+\sum_{m=1}^{M}\beta_m Dyear_m+\sum_{n=1}^{N}\delta_n Dsector_n)} \\
PAT_EM_i &= e^{(\alpha+\sum_{m=1}^{M}\beta_m Dyear_m+\sum_{n=1}^{N}\delta_n Dsector_n)} \\
INV_EM_i &= e^{(\alpha+\sum_{m=1}^{M}\beta_m Dyear_m+\sum_{n=1}^{N}\delta_n Dsector_n)}
\end{aligned}$$

[13] Congreve was a prolific inventor (18 patents) and his most famous invention is probably the "Congreve rocket". This explains why the patents of this inventor have a relatively high score of INV_EM (6). This example further shows the potentialities of using WRI*, PAT_EM and INV_EM in combination.

[14] As a robustness check, we have also carried out negative binomial regressions obtaining nearly identical results.

where $Dyear_m$ are the dummies for the decades from 1700 to 1850 ($M = 15$), $Dsector_n$ are the sectoral dummies ($N = 21$),[15] and WRI_i, PAT_EM_i, INV_EM_i are the raw scores of the three quality indicators for patent i. The intuition is that the residuals of each regression will capture the share of variance due to the intrinsic quality of the individual patent.

The final step is to extract from the residual a latent common factor using the structural equation model (SEM) represented in Figure 4 (Lanjouw and Schankerman, 2004). This is tantamount to estimating a multiple indicator model with one latent common factor:

$$y_{ki} = \alpha_k + \lambda_k q_i + \epsilon_{ki} \tag{1}$$

where y_{ki} indicates the value of the k^{th} indicator for the patent i ($k = 1, 2, 3$ and $i = 1, \ldots, 13, 070$) and q is the common factor with loadings λ_k. From the estimation of the structural equation model we can derive for each patent the value of the latent factor (q_i). As noted by Lanjouw and Schankerman (2004), the common factor captures all the unobserved characteristics of patents that influence the three original quality indicators. Accordingly, we can interpret the latent common factor q as a composite measure of patent quality that we label *Bibliographic Composite Index* (BCI). The factor loadings of the common factor are reported in Table3.

[Figure 4 about here]

[Table 3 about here]

Figure 5 displays the distribution of BCI. The index is very skewed with an extremely long tail. This result is fully in line with the distribution of patent quality found in modern patent data (Silverberg and Verspagen, 2007). Typically, the replication of this stylized fact has been regarded as preliminary validation for composite indicators of patent quality (De Rassenfosse and Jaffe, 2015). In this paper, however, we prefer to use the composite quality index only as an ordinal, rather than a cardinal indicator. Accordingly, we will consider only the ranking of patents according to the index. In this respect, it is worth noting that the rankings we have obtained are robust to alternative aggregation procedures (factor analysis, Borda ranking, non-linear SEM specifications). At the same time, by constructing the BCI using the three "raw" quality scores or using the residuals of Poisson regressions with different sets of time and industry controls, we have obtained highly overlapping sets of top quality patents, confirming the general robustness of the procedures adopted for the construction of the BCI (see Appendix).

[15] We have used the sectoral classification introduced by Nuvolari and Tartari (2011).

[Figure 5 about here]

3.4 Validation of the Index

We carry out a number of robustness checks to assess the reliability of our composite quality indicator. *Prima facie*, the list of top-quality patents (Table A12 in the Appendix) seems to provide a very plausible selection of the fundamental technological breakthroughs of the Industrial Revolution, comprising Watt's separate condenser, Hargreaves' spinning jenny, Arkwright's water-frame and Wheatstone's telegraph.

The BCI seems also effective in the assessment of the significance of some lesser known inventions. Consider the case of the power-loom studied by Allen (2018). The macroinvention developed by Cartwright was a functioning prototype, but still plagued by defects that greatly limited its application. Thanks to the improvements introduced by Thomas Johnson and later by Richard Roberts, the machine successfully led to major productivity improvements. The importance of these inventions is indeed captured by the BCI that collocates the patents in question in the 95$^{\text{th}}$ percentile of the quality distribution.

As a further validation, in Table 4, we study the behavior of BCI with respect with some alternative independent measures of patent quality. We consider: i) patents whose inventors paid additional fees in order to extend their coverage to Scotland and Ireland (Bottomley, 2014b), ii) patents that were litigated in court (Bottomley, 2014a), iii) patents whose inventors petitioned the Parliament asking for an extension. The logic for considering these characteristics is based on studies on modern patents that suggest that more valuable patents tend to have larger families (Lanjouw et al., 1998), are likely to be involved in court cases (Lanjouw and Schankerman, 2001) and are renewed for longer timespans (Lanjouw et al., 1998). Fligner-Policello tests of stochastic equality confirms that these types of patents are systematically characterized by higher scores of BCI.

Interestingly enough, for the case of steam engineering, there are sources that point out flawed designs: i) the list of patents covering perpetual motion engines scorned by Dircks (1861), ii) the list of technically unfeasible steam engines constructed by MacLeod et al. (2003). In this case, Fligner-Policello tests of stochastic equality confirm that these "flawed" patents are systematically characterized by lower scores of BCI.[16] All these results are also confirmed if we employ the Mann-Wilcoxon test.

[16] In Appendix (Table A8) we show that WRI* (possibly because reflecting some bouts of over-enthusiasm of contemporary observers) is less effective in discriminate these flawed patents than the BCI.

[Table 4 about here]

Finally, Figure 6 presents a scatterplot comparing BCI and WRI* for all patents in our sample. BCI recognizes the major historical importance of Kay's flying shuttle (patent n. 542), while Hull's invention (patent n. 556) is only in the 75$^{\text{th}}$ percentile of the quality distribution. Similarly, the BCI correctly assess the relative significance of Arkwright's patent for the water-frame (patent n. 931) and for the carding engine (patent n. 1111). Also for other cases of patents of the same inventor, the BCI seems to offer a sensible assessment. James Watt's separate condenser (patent n. 913) is rated as the most significant invention of our period, while his patent for improvements in the construction of furnaces (patent n. 1485) is considered a fairly average invention. More examples are reported in the Appendix (Table A7).

[Figure 6 about here]

In a nutshell, the use of quality indicators derived from modern sources substantially mitigates some of the idiosyncrasies of Woodcroft's *Reference Index*, plausibly leading to an improvement of the signal-to-noise ratio of the BCI with respect to the WRI*.

4 Patterns of Innovation during the Industrial Revolution

Figure 7 shows the whole range of the distribution of BCI by means of percentiles. The point in the right upper-corner is James Watt's patent for the separate condenser (n. 913) which is the maximum value of BCI in our sample. The absolute value of BCI declines rapidly as soon as one moves away from the patents with the highest value. Accordingly, following the modern literature on innovation studies, we identify as macroinventions the patents in the extreme upper tail of the patent quality distribution (Trajtenberg 1990; Ahuja and Lampert 2001; Kelly et al. 2018). In particular, Figure 7 shows a very sharp drop-off in the value of BCI between the maximum and the 99.5% percentile. This suggests that considering the top 0.5% patents would extract the salient segment of the upper tail of the quality distribution. It is worth noting that our results are robust if we adopt alternative cut-off points for the definition of macroinventions such as the top 1% or the top 100 patents.

[Figure 7 about here]

4.1 The Time Profile of Inventive Activities

Mokyr's view is that macro- and microinventions are the outcomes of two distinct generating processes (Mokyr 1990, p. 295). Macroinventions are generated by an essentially serendipitous search process. On the other hand, microinventions are the result of continuous and cumulative improvements of the technologies in use and as such should display temporal persistence. To investigate this hypothesis, we test whether the arrival process of macroinventions exhibits any degree of time-clustering. In particular, we adopt the approach introduced by Silverberg and Verspagen (2003; see also Sahal 1974) and we assume that inventions are count data generated by a point process. Accordingly, we can use Poisson and Negative Binomial regressions to estimate the yearly number of macro- and microinventions (Cameron and Trivedi, 1998). A time homogeneous Poisson process is characterized by complete randomness since each event (an invention in this case) is independent from the occurrence of other events. On the contrary, a negative binomial process is characterized by realizations that tend to cluster in specific spells of time (overdispersion). The main thrust of our exercises consists in fitting these distributions to the actual time series of macro- and microinventions, in order to see if they provide a good description of the observed patterns. We also control whether the arrival rate of the distribution follows time trends of different orders. More specifically, indicating with Y_i the yearly number of either macro- or microinventions, we estimate the following type of specifications:

$$Y_i = Poisson(\mu) \quad \text{with} \quad ln(\mu) = c + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \tag{2}$$

$$Y_i = NegativeBinomial(\mu) \quad \text{with} \quad ln(\mu) = c + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \tag{3}$$

where μ is the arrival rate parameter and t is a time trend. The Negative Binomial distribution is characterized by a mean μ and a variance $\mu(1 + \alpha\mu)$. A test of the Poisson against the negative binomial specification can be implemented by means of a Likelihood Ratio test of the null hypothesis that $\alpha = 0$. Finally, we also carry out a Box-Ljiung test of the residuals to further assess the possible existence of unexplained time clustering in the arrival rate of inventions (Silverberg and Verspagen, 2003).

[Tables 5 and 6 about here]

Our results (Tables 5 and 6) show that macroinventions display neither overdispersion nor autocorrelations in the residuals.[17] This basically suggests that the occurrence of macroinventions does not display any time clustering in the sense of time spells of low and high innovation activity. For microinventions, instead, the hypothesis of equidispersion is rejected in favor of the Negative Binomial

[17]These results are robust to alternative definitions of macroinventions (eg, top 100 or top 1% patents) and to the inclusions of sectoral dummies in the regressions. One might be afraid that the procedure through which we cleansed the raw quality indicators might lead to the absence of time-clustering. However, this is not the case since the ranking of the top quality inventions is extremely robust even when we construct the BCI without time controls or with the raw indicators (Table A9 in Appendix).

specification. Furthermore, the series of the residuals shows strong autocorrelation, suggesting that the data generating process of microinventions is probably characterized by some mechanisms that induce time persistence.[18] In this respect, we find that microinventions are positively correlated with the economic cycle. The Pearson's correlation coefficient between the yearly growth rate of microinventions and variation in the GDP series (Broadberry et al., 2015) is equal to 0.1715 and significant at 5% level, and it grows to 0.4313 if we only consider the period after 1800. Our result is consistent with earlier findings of pro-cyclicality in the fluctuations of patent count (Bottomley, 2014b), but notably this does not apply to the set of macroinventions. The different structure between the process generating macroinventions and microinventions is also impressionistically apparent from Figure 8, which compares the number of inventions of each type per year. Overall, the dynamics of macroinventions is described by a simple time-homogenous Poisson process, which is well in tune with a large role played by serendipity.

[Figure 8 about here]

Some further considerations on the time profile of macro- and microinventions emerge when we observe the cumulative distribution of inventions over time (Figure 9). The thick black line in each figure represent the cumulative distribution of macroinventions vis-á-vis microinventions for different set of patents (textiles, engines, machinery and all patents in the sample). In each panel of the figure, the curve shows the cumulative share of macroinventions that have taken place in correspondence of the cumulative share of microinventions indicated in the horizontal axis. For instance, the upper left figure shows that by 1800, over half of the macroinventions of the period 1700-1850 had already occurred, while the corresponding cumulative share for microinventions is only 16%. In other words, the diagrams represent Lorenz curves of the "time inequality" in the distribution of macro- and microinventions: a perfectly equal co-occurrence in the cumulative arrival of the two type of inventions would be depicted by a straight line with a 45 degree slope. The figure shows that most macroinventions occurred in the period 1750-1800, consistently with the traditional chronology of the Industrial Revolution (Landes 1969; Nuvolari and Tartari 2011). Figure 9 also indicates that the cumulative distribution of macroinventions precedes the cumulative distribution of microinventions. This is again

[18] In their analysis of radical innovations, Silverberg and Verspagen 2003 find time clustering in the form of overdispersion. This result is in contrast with the one reported and may be explained, besides by the very different data used, by the later time period they consider (second half of the XIX and first half of the XX century). An alternative way to study the difference between the time profile of macro- and microinventions is by means of test of stationarity of the time series. In an unreported augmented Dickey-Fuller test we find that the test strongly rejects the null hypothesis of the presence of a unit root in the macroinvention series. In other words, macroinventions seem to follow a stable mean reverting process, which can be interpreted in terms of a substantially stochastic (and therefore exogenous) occurrence of macroinventions in this historical phase as suggested by Crafts (1977, 1995).

aligned with Mokyr's original intuition that macro- and microinventions are complementary features of technological progress, with macroinventions prompting cumulative streams of microinventions, albeit with varying lags and knock-on effects (Rosenberg 1982, pp. 62-70).[19] Interestingly enough, this result is robust across sectors and technologies. If anything, this behavior is even more pronounced for textiles and engines, two of the most dynamic industries of the Industrial Revolution, possibly indicating that some prototype macroinventions in this fields required protracted streams of microinventions for their full exploitation.

[Figure 9 about here]

4.2 Characteristics of micro- and macroinventions

Allen (2009, p. 136) has argued that macroinventions drastically changed factor proportions by substituting capital and energy for labor. In his account, high wages prompted the search for labor-saving new technologies. Microinventions, on the other hand, were, by and large, the outcome of cumulative processes of learning by doing and learning by using that increased the overall efficiency of both capital and labor and, consequently, they were neutral with respect to factor utilization. To test these conjectures, we exploit the short description of inventions contained in Woodcroft's volume, *Title of Patents of Inventions Chronologically Arranged, 1617-1852* (1854). The description is essentially a verbatim excerpt of the original patent specification. For many patents granted before 1800, it is possible to surmise from these compact descriptions the "stated aim" of the invention (from the inventor's perspective).

We follow the approach of Christine Macleod (1988, pp. 158-181) in her analysis of the goals of invention in the full corpus of patent specifications during the XVIII century: from each invention we identify two main stated aims. If only one aim is clearly described, we count this once and mark the second aim as "unspecified". This ensures the comparability between our analysis of macroinventions and MacLeod's findings on the full patent corpus. Table 7 illustrates the application of this method for three macroinventions.[20]

[Table 7 about here]

Table 8 compares the stated aims of inventions in our set of macroinventions with MacLeod's anal-

[19] The point is also stressed by Constant (1973, p. 572): "... our model and its application raise questions about those analyses that attempt to use gross patent statistics or 'leading' macro-investment patterns as indicators of all forms of technological progress. Neither gross investment nor number of patents in a field is an adequate guide to emerging paradigmatic change... Both patenting and investment follow rather than lead paradigmatic change."

[20] Obviously, this method does not consider product innovations (e.g. canned food). However, more than 85% of our set of macroinventions pertains to production processes (mostly with the aim of reducing cost or improving quality).

ysis of the whole patent sample in the period 1700-1799. The table suggests that microinventions were mostly concerned with saving capital, raw materials and other inputs. Among macroinventions, the share of innovations in that category is significantly smaller, while the incidence of other motivations is very similar. At all events, the results of Table 8 must be interpreted with caution: in this historical period, not surprisingly, inventors were still reluctant to boast the possible labor-saving impact of their inventions (MacLeod 1988, p. 166). Hence, it is likely that the share of labor-saving inventions in Table 8 understates their actual proportion. Following again MacLeod (1988), we repeat the analysis using a different classification approach which seeks to discern from the patent description the actual labor-saving effect of the invention beyond the explicit wording of the specification.[21]

[Table 8 about here]

Table 9 compares the labor-saving potential (using this broader classification) of macro- and microinventions. In this case, we find a considerably larger share of labor-saving inventions for macroinventions (38%) than for microinventions (15% of all patents). The reason for this difference is that a large share of macroinventions consisted of machines: they accounted for about half of the top-quality patents, while only little more than 20% of microinventions were related to machines. In this way, Table 9 highlights that, in this historical phase, the search for labour-saving innovation largely consisted in the design and developments of machines. Overall, these findings are consistent with Allen (2009)'s view of a structural difference in the factor-saving biases between macro- and microinventions, and, in particular, with the notion that macroinventions were characterized by a stronger labor-saving bias.[22]

[Table 9 about here]

4.3 The Determinants of Macro- and Microinventions

Our data allow to study the determinants of macro- and microinventions by means of a simple multivariate regression analysis. The results are reported in Table 10 . We consider three main models: i) a logit specification with the top 1% and top 0.5% patents as dependent variables, ii) a simple OLS

[21]MacLeod regards as "genuine" labor-saving inventions "[...] those labor-saving machines and techniques which contemporaries identified as such, e.g. spinning, carding, threshing machines or power-looms". However, in the labor-saving category are not included "machines and techniques whose labor-saving potential was commonly overlooked by contemporaries, unless a particular invention would increase its labor productivity further. Thus, wind, water, horse and steam engines were excluded, as were e.g. handlooms, the majority of stocking-frame attachments, sugar mills, the printing press (but not mechanical textile printing)." (MacLeod 1988, p. 257).

[22]It should be noted that our findings do not imply that technical change in this period was generally characterized by a labor-saving bias, but simply that there was a higher incidence of machinery among macroinventions. At the same time, our study does not permit to assess whether the impetus towards mechanization was actually prompted by high wages (Allen, 2009) or by the limitations of traditional techniques and production systems with respect to a burgeoning demand (Landes 1969; Cookson 2018) possibly reinforced by attempts of "dilution" of skilled labor using women and children (Berg 1994; Humphries 2013). For a recent discussion of the geography of the Industrial Revolution from this second perspective see Kelly et al. (2020).

regression with BCI as dependent variable, iii) a quantile regression model of different percentiles of BCI. As predictors we use a number of characteristics of patentees retrieved from Woodcroft (1854).

[Table 10 about here]

Allen (2009, p. 149) has argued that macroinventions were mostly due "outsiders" who could rely on insights originating "outside their immediate industrial experience" and experiment with factor configurations distant from the current best-practice. This conjecture is not confirmed by the results of Table 10: the coefficient of the variable outsider is not statistically significant. Being resident in a metropolitan area, co-patenting with other inventors or being a foreign inventor are also characteristics that are not significant positive predictors of a macroinvention.[23] The only positive predictor of macroinventions is an engineering occupation. The role played by inventors with specialized engineering competences in the development of macroinventions resonate well with the findings of some other recent contributions (Cookson 2018; Hanlon 2020; van der Beek et al. (2020)). This result links with the high incidence of machinery among macroinventions pointed out in the previous section and is in line with the notion that "mechanical engineering" was the fundamental "technological paradigm" of the Industrial Revolution (Von Tunzelmann, 1995).

Finally, it is interesting to note that the previous experience in patenting –measured as the number of previous patents– is in general positively correlated with higher patent quality, but this result does not extend to the uppermost part of the quality distribution. Again, this finding is suggestive of the essentially serendipitous nature of macroinventions.

4.4 A Tentative Interpretation

In a perceptive study of the conceptualizations of macroinventions of Mokyr (1990) and Allen (2009), Crafts (2011) has noted that they actually focus on different phases of the innovation process. Ideally, we can posit that the development of innovations consists of a three main stages: i) ideas, ii) "research and development" investments, iii) incremental improvements. Mokyr considers macroinventions as referring mostly to the first stage. Accordingly, he is keen to highlight the role played by flashes of genius and serendipity (Yaqub, 2018). For Allen, macroinventions encompass both the first and the second stage (in particular the investments and the efforts necessary to transform the idea in a working prototype).[24] If we take this perspective, economic inducements may clearly represent a critical determinant for the occurrence of macroinventions.

[23] The insignificant coefficient of metropolitan areas is again in line with Mokyr's intuition that the occurrence of high-quality inventions is relatively insensitive from economic determinants.

[24] Allen (2009) cites approvingly Edison's quip "invention is 1% inspiration and 99% perspiration".

In our interpretation, which is similar to that of Crafts (2011), Mokyr and Allen are emphasizing complementary dimensions of macroinventions. More precisely, they are pointing to two necessary, but not sufficient, conditions for the occurrence of macroinventions. On reflection, in most cases, both favorable contingencies and investment and research efforts are simultaneously necessary for a successful macroinvention. For example, if we consider the case of James Watt's separate condenser, one can easily point to the flash of inspiration during the usual Sunday walk in May 1765 and to the more than ten years of experiments before the development of a satisfactory engine (Hills 2002, p. 53). On the other hand, it is possible to mention inventions, that notwithstanding major investments, were technological failures. Perhaps one of the most revealing examples of this period is Brunel's atmospheric railway (Buchanan, 1992).

This perspective fits well with our reconstruction of the patterns of macro- and microinventive activities. As we have seen, the occurrence of macroinventions can be accounted by means of a time homogeneous Poisson process, which is in line with the notion of a very significant role of serendipity. On the other hand, our scrutiny on the inventions' aims point to economic factors as possible determinant of the character of macroinventions. In this perspective, economic inducements demarcate the relevant portions of the space of technological opportunities where inventors will search, while serendipity and contingencies will affect the success of the search process within this domain.[25] In this respect, the results concerning the role of engineers indicate that specialized mechanical skills and competences were in many cases also necessary for the effective search of space of technological opportunities.

5 Conclusions

In this paper, we have introduced a new composite indicator of the quality of English patents during the period 1700-1850. This new *Bibliographic Composite Indicator* (BCI) synthesizes two different, but complementary assessment of the quality of patents: the technical and economic significance as perceived by the specialized contemporary literature, measured by the number of references in Woodcroft (1862), and the historical importance as assessed by the modern historiography, informed by the benefit of hindsight. We have carried out a thorough examination of the properties of the BCI and tested its reliability with several robustness checks. The results are rather encouraging and it would seem that this new indicator may represent a significant improvement over the WRI* introduced

[25]This perspective is reminiscent of Crafts (1977, p. 437) who regarded macroinventions as the outcome of "stochastic search processes in which both economic inducements and scientific supply-side considerations play a part".

by Nuvolari and Tartari (2011).[26]

We have used the BCI for providing an empirical characterization of macro- and microinventions. We have established a significant difference in the time-profile of the two type of inventions. Furthermore, we have also found evidence that the sample of macroinventions was characterized by a large share of "machines" with a likely labor-saving bias. Finally, inventors with competences in mechanical engineering seem more effective in the generation of patents of higher quality, including macroinventions.

Our findings resonate with Crafts' assessment of the Allen-Mokyr debate (Crafts, 2011). Allen and Mokyr are pointing to two distinct but complementary characteristics of inventive activities in this period. Accordingly, their analyses rather than opposing may be more fruitfully regarded as compatible. In this respect, as adumbrated by Crafts, an intriguing research agenda for the future would be the development of a new synthesis which could provide a comprehensive account of the patterns of innovation reconstructed in this paper.

The main limitation of our study is obviously that we are only considering patented innovations. Moser (2005) has shown that in this period many innovations were not patented. However, some shreds of evidence suggest that the patenting propensity of breakthrough inventions was probably higher than for ordinary ones. For example Moser estimate an aggregate patenting rate of 11.1%, while Meisenzahl and Mokyr (2012) reckon that 60% of the notable inventors of their sample took patents, with even higher shares in sectors such as textiles, iron and metallurgy. Similarly, Khan (2018) estimate a patenting rate of 80% in her sample of British "great inventors".[27] Accordingly, we do not consider far-fetched to assume that the "representativeness" of our sample of macroinventions may be somewhat more accurate than for ordinary inventions.

[26]For preliminary applications of BCI to the pottery industry and to the engineering trades, see Lane (2019) and Hanlon (2020).

[27]These patenting rates are in line with Dutton's view (1984, p. 112) who noticed: "Knowledgeable contemporaries believed that almost all the important inventions were patented". In any case, it is important to reckon that some fundamental breakthrough such as Crompton's spinning mule or Maudslay's lathe were not patent and, therefore, our empirical characterization of macroinventions should be regarded as a preliminary exercise to be complemented by further research on non-patented inventions.

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6 Figures and Tables

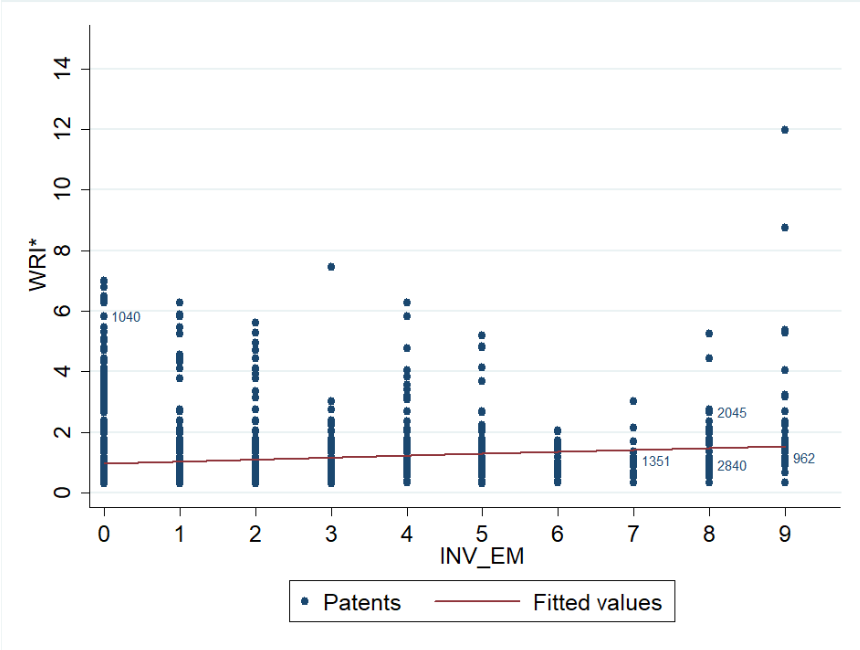


Figure 1: Scatterplot of WRI* and INV_EM

Note: WRI* is the time-adjusted index of patent quality proposed by Nuvolari and Tartari (2011) based on the number of references listed in Woodcroft (1862).

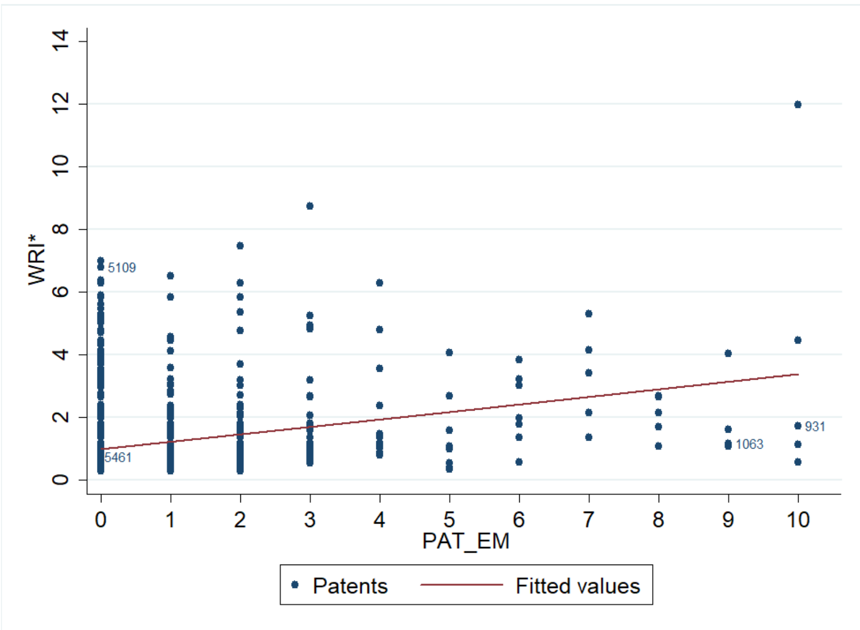
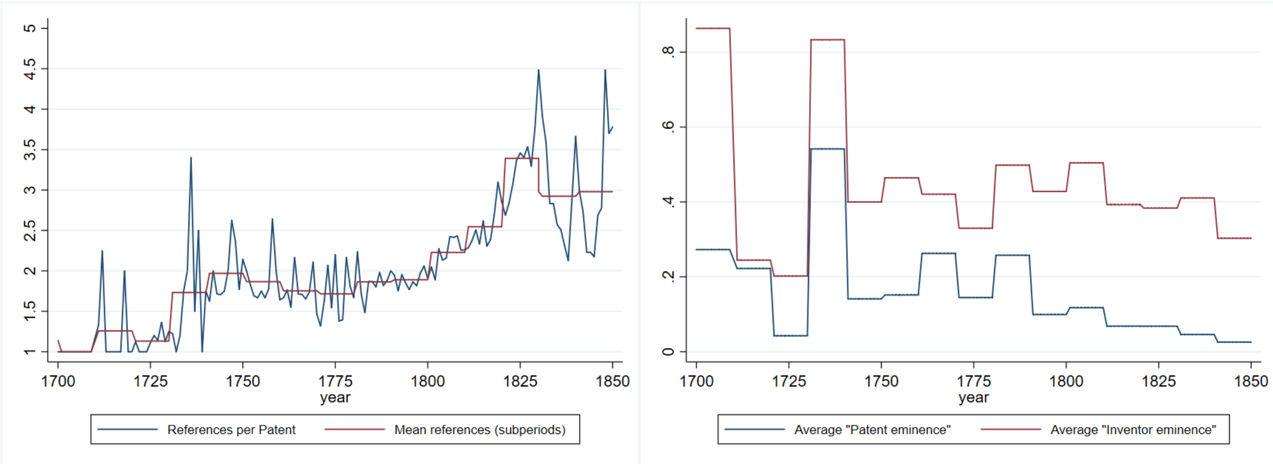


Figure 2: Scatterplot of WRI* and PAT_EM



(a) Average number of references per patents in Woodcroft (1862), yearly and by decade.

(b) Average number of references per patents by decade.

Figure 3: Average number of references per patents over time

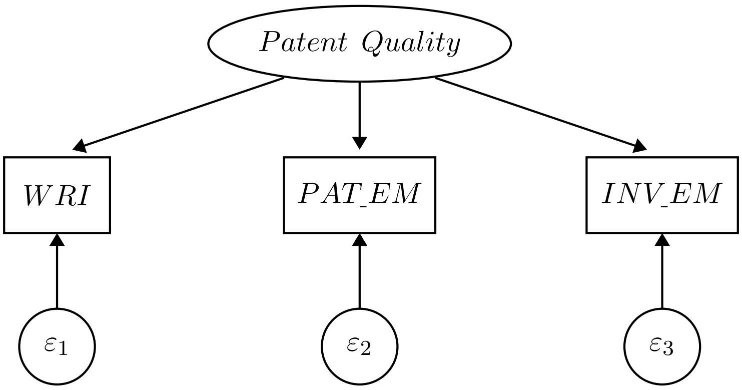


Figure 4: Structural equation model used to extract a latent common factor from the residuals of Poisson regressions that control for time and industry effects.

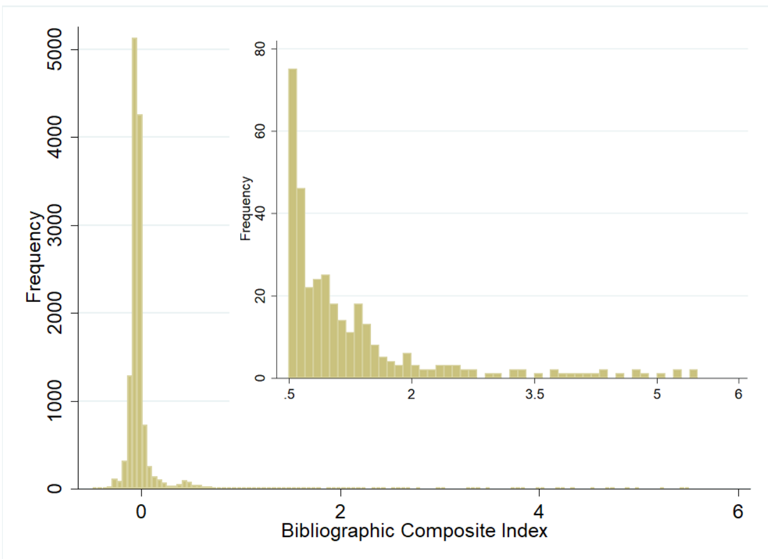


Figure 5: Empirical distribution of the Bibliographic Composite Index; the box in the top-right of the figure reports the upper-tail of the distribution (BCI > 0.5).

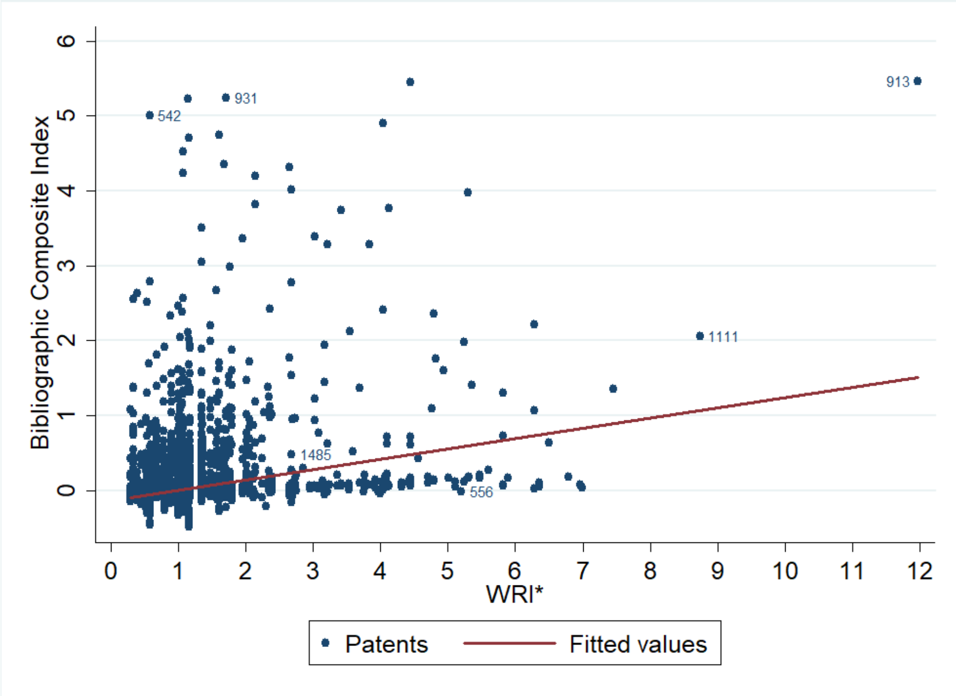


Figure 6: Scatterplot of BCI and WRI*

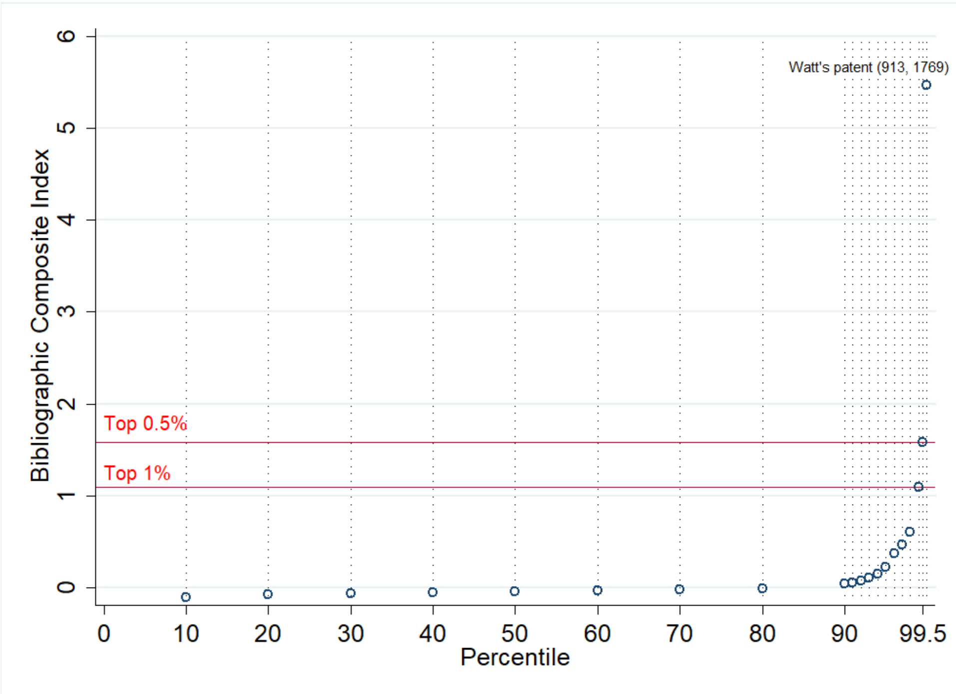


Figure 7: Percentile plot of BCI

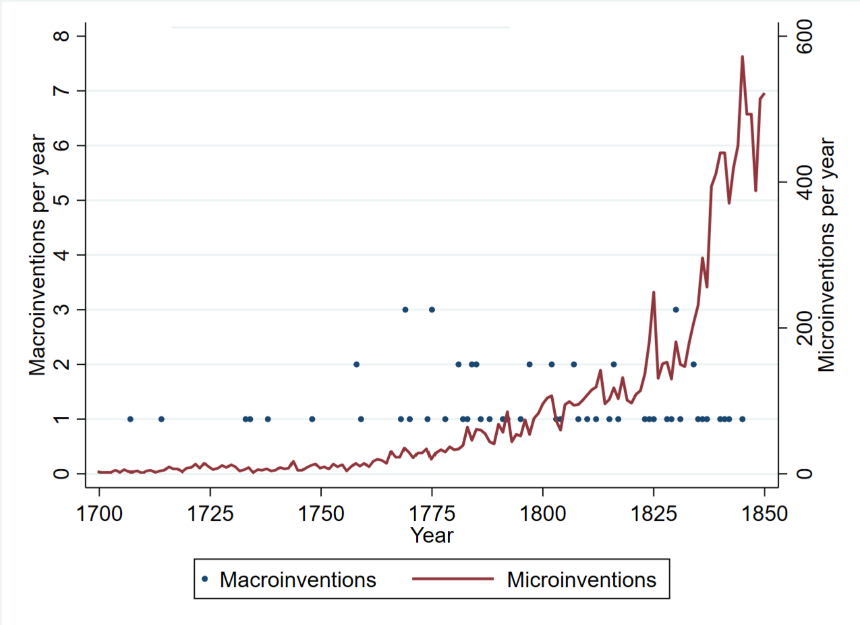
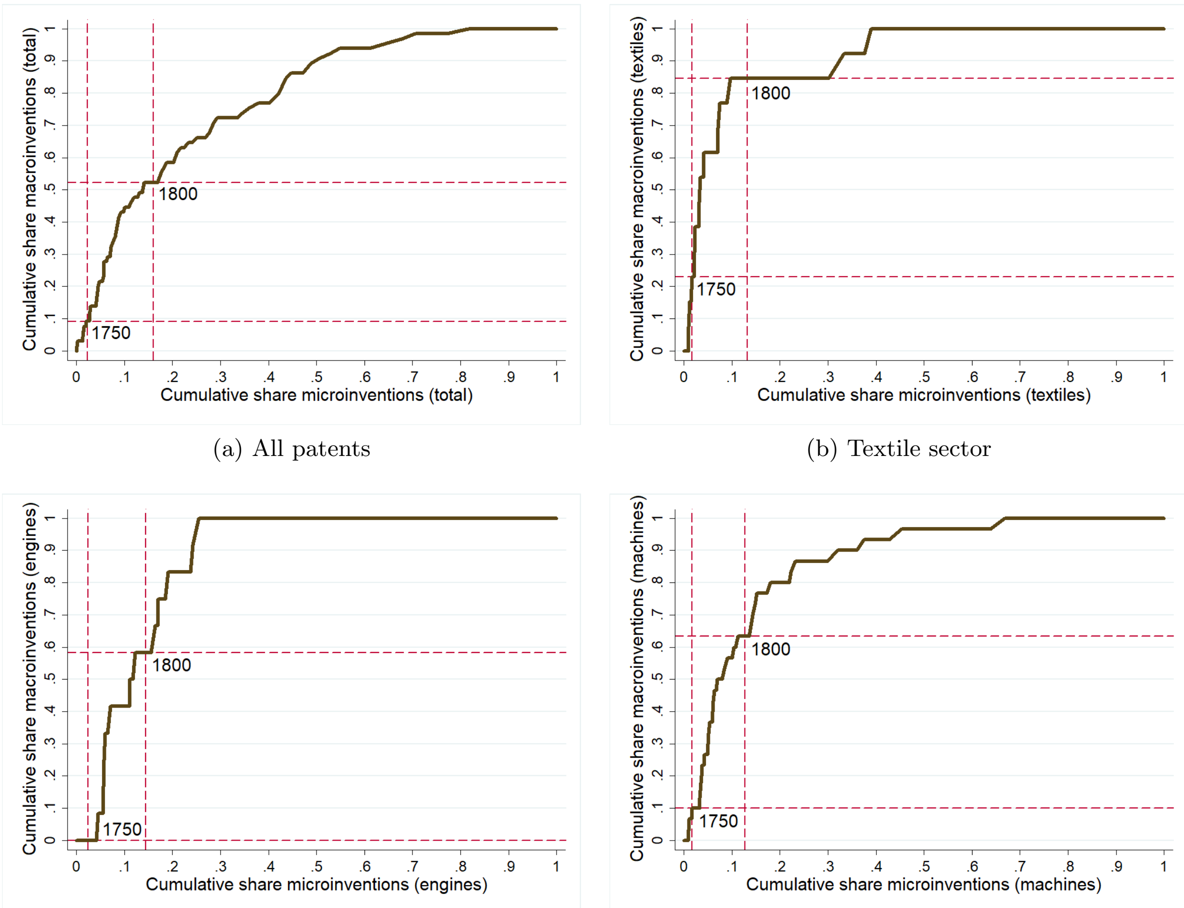


Figure 8: Number of micro- and macroinventions per year

Note: the dots plot the yearly number of macroinventions (patents in the 99.5^{th} percentile of quality) while the line shows the number of microinventions patented each year.



(a) All patents

(b) Textile sector

(c) Engine sector

(d) Machines

Figure 9: Lorenz curves of microinventions vs macroinvention shares over time.

Note: patents related to engine and textile sectors are taken from the classification of Nuvolari and Tartari (2011); machines are identified from the title of the patent in Woodcroft (1854).

Table 1: Patents and Inventors coverage of the sources used to construct Patent Eminence and Inventor Eminence

Patent Eminence			Inventor Eminence		
Source	Inventors	Patents	Source	Inventors	Patents
Baker (1976)	123	150	Oxford DNB	291	893
Carter (1978)	201	266	Allen (2009)	76	234
Desmond (1987)	128	157	Day and McNeil (1996)	240	708
Inkster (1991)	27	44	Abbott (1985)	57	246
Dudley (2012)	33	55	Murray (2003)	54	199
Challoner (2009)	41	49	De Galiana (1996)	102	333
Bridgman (2002)	33	38	Meisenzahl and Mokyr (2012)	536	1519
Bunch and Hellemans (2004)	71	93	Benson (2012)	59	206
Ochoa and Corey (1997)	23	24	Gergaud et al (2016)	179	595
Lilley (1948)	28	33			

Note: This table reports the number of patents and inventors mentioned in each source. The left side pertains sources grouped into the indicator of Patent Eminence, while on the right side there are those concerning Inventor Eminence.

Table 2: Quality indicators for selected patents

Patent N°	Year	Inventor	Invention	Woodcroft References	Patent Eminence	Inventor Eminence
542	1733	John Kay	Flying shuttle	1	10	8
556	1736	Jonathan Hulls	Steam-propelled ship	9	0	5
931	1769	Richard Arkwright	Water frame	3	10	9
1111	1775	Richard Arkwright	Carding machine	15	3	9

Table 3: Factor loadings of the Bibliographic Composite Index (BCI) resulting from the SEM estimation

	Residuals WRI	Residuals PAT_EM	Residuals INV_EM
λ	1	1.1746***	1.8698***
	-	(0.1401)	(0.2619)

Note: *** denotes significance at 0.1% level. λ_k are the factor loadings on the common factor q, representing the BCI. Standardized root mean squared residual= 0.000; Coefficient of determination= 0.698.

Table 4: Fligner-Policello tests of stochastic equality for BCI validation

	Fligner-Policello statistics
Extended to all UK	11.072***
Time Extension	15.292***
Litigated Patents	35.430***
Perpetual Motion	-5.062***
“Impossible” Engines	-2.765**

Note: **,*** denote significance at 1% and 0.1% level. The Fligner-Policello test determines whether for two random variables X and Y it is statistically significant that $Prob[X > Y] > 0.5$. In all cases, the null hypothesis of stochastic equality is rejected at a high significance level. Data for geographical coverage are taken from Bottomley (2014a) (1247 patents extended to the entire United Kingdom), while the lists of patents that were litigated (355 cases) and for which a time extension was petitioned (95) are taken from Woodcroft (1862). Data for perpetual motion machines are taken from Dircks (1861) (23 patents) and the lists of 83 engines that were not technically feasible is the same employed by MacLeod et al. (2003). A negative sign of the Fligner-Policello statistics indicates that patents in the list considered are of lower average value than the excluded remainder. All the results hold if we employ Mann-Whitney-Wilcoxon median test.

Table 5: Regression results, Poisson and negative binomial models with arrival rate for macroinventions as a function of time.

Model	Patents	c	β_1	β_2	β_3	α	LR test	logL	Wald test	Pseudo R^2	Q test
Poisson	Top 0.5%	-0.8429***						-131.402			50.936***
		(0.1319)									
Neg Bin	Top 0.5%	-0.84292***				0.3107	NOT reject	-130.869			50.936***
		(0.1321)									
Poisson	Top 0.5%	-1.809***	0.011***					-124.187	19.13***	0.055	30.1501*
		(0.2879)	(0.0026)								
Neg Bin	Top 0.5%	-1.8285***	0.0114***			0.1280	NOT reject	-124.071	13.60***	0.052	30.1211*
		(0.3307)	(0.0032)								
Poisson	Top 0.5%	-3.689***	0.064**	-0.030**a				-118.626	14.07***	0.097	23.0980
		(0.8409)	(0.0193)	(0.0104)a							
Neg Bin	Top 0.5%	-3.689***	0.064**	-0.030**a		0.0048c	NOT reject	-118.626	24.49***	0.094	23.0985
		(0.8013)	(0.0185)	(0.0101)a							
Poisson	Top 0.5%	-3.045*	0.0312	0.0144a	-0.0178c			-118.381	21.08***	0.099	25.8504
		(1.1938)	(0.0505)	(0.0628)a	(0.0024)b						
Neg Bin	Top 0.5%	-3.045**	0.0312	0.0143a	-0.0179c	0.0001a	NOT reject	-118.381	24.98***	0.095	25.8504
		(1.129)	(0.0485)	(0.0633)a	(0.0025)b						

Note: *,**,*** denote significance at 5%, 1% and 0.1% level. c, β_1, β_2 and β_3 are the coefficients on the constant and the polynomials of time (first, second and third degree, respectively). Estimated coefficients are sometimes multiplied by the following factors: a=100, b=1000, c=10000. α is the parameter for overdispersion in the negative binomial model for which a likelihood-ratio test (LR test) of $H_0 : \alpha = 0$ (i.e. no overdispersion) is carried out. The last column give the Box-Ljung Q statistics on the standardized residuals of H_0: no time autocorrelation. In this case, a significant value of the test statistics means that we reject H_0. Following Silverberg and Verspagen (2003), we set $k = 20$. The period considered is 1700-1850 (151 observations).

Table 6: Regression results, Poisson and negative binomial models with arrival rate for microinventions as a function of time.

Model	Patents	c	β_1	β_2	β_3	α	LR test	logL	Wald test	Pseudo R^2	Q test
Poisson	All	-4.4608***						-10950.859			1091.1466***
		(0.1211)									
Neg Bin	All	4.461***				1.827	reject	-803.643			1091.1466***
		(0.1103)									
Poisson	All	0.4222***	0.038***					-824.490	1993.45***	0.9247	159.5699***
		(0.0957)	(0.0009)								
Neg Bin	All	0.641***	0.036***			0.0585	reject	-572.144	463.00***	0.2881	193.2231***
		(0.0724)	(0.0006)								
Poisson	All	1.127***	0.023***	0.073***b				-789.415	3047.81***	0.9279	122.4661***
		(0.1468)	(0.0034)	(0.0018)a							
Neg Bin	All	0.851***	0.030***	0.034*b		0.0565	reject	-570.130	467.03***	0.2906	146.7201***
		(0.1249)	(0.0030)	(0.0016)a							
Poisson	All	0.310	0.059***	-0.037**a	0.016**c			-765.420	2777.19***	0.9301	92.4250***
		(0.2766)	(0.0114)	(0.0001)	(0.0054)c						
Neg Bin	All	0.795***	0.033***	-0.001a	0.0018c	0.0559	reject	-570.047	467.19***	0.2907	135.6694***
		(0.1875)	(0.0086)	(0.0115)a	(0.0045)c						

Note: *,**,*** denote significance at 5%, 1% and 0.1% level. c, β_1, β_2 and β_3 are the coefficients on the constant and the polynomials of time (first, second and third degree, respectively). Estimated coefficients are sometimes multiplied by the following factors: a=100, b=1000, c=10000. α is the parameter for overdispersion in the negative binomial model for which a likelihood-ratio test (LR test) of $H_0 : \alpha = 0$ (i.e. no overdispersion) is carried out. The last column give the Box-Ljung Q statistics on the standardized residuals of H_0: no time autocorrelation. In this case, a significant value of the test statistics means that we reject H_0. Following Silverberg and Verspagen (2003), we set $k = 20$. The period considered is 1700-1850 (151 observations).

Table 7: Examples of stated aims of invention for three macroinventions.

Patent N°	Year	Inventor	Invention	Excerpt from Woodcroft (1854)	Stated aims
962	1770	James Hargreaves	Spinning jenny	"[...] making an engine [...] to be managed by one person only, which will spin, draw, and twist 16 or more threads at a time by a motion of one hand and a draw of the other"	Save labour; save time
1420	1784	Henry Cort	Puddling process	"[...] manufacturing iron and steel into bars [...] of purer quality, in larger quantity, by a more effectual application of fire and machinery, and with greater yield"	Save capital and raw materials; improve quality
1645	1788	Andrew Meikle	Threshing machine	"[...] the corn is thereby separated from the straw in less time, and in more effectual manner than by threshing or any other manner"	Save time; improve quality

Note: descriptions are taken from Woodcroft (1854) and stated aims are classified using the methodology of MacLeod (1988).

Table 8: Patentees' stated aims of invention, 1700-1799.

Stated aim	Top 0.5%	Top 1%	Top 2%	All patents
Create employment	0	1.7	1.2	1.9
Improve working conditions	0	0	2.3	1.4
Save labour	2.9	3.4	4.7	4.2
Save time	11.8	8.5	7	5.2
Save capital and raw materials	8.8	5.1	7	30.8
Reduce consumer price	5.9	5.1	3.5	3.7
Improve quality	32.4	27.1	25.6	29.3
Import substitution	0	1.7	1.2	3.6
Government revenue	0	0	0	1
Other government benefits	5.9	3.4	2.3	2.1

Note: Columns 2, 3 and 4 report the share of patents in that percentile of quality that mention each of the listed aims of invention. Figures are expressed as a percentage of the 34, 59 and 86 patents respectively granted for macroinventions in the period 1700-1799 (see text for details). The last column is taken from MacLeod (1988), Table 9.1 p. 160, who considered 2240 patents in the period from 1660 to 1799. This means that unfortunately the data are not strictly comparable, but given the low number of patents granted before 1700 (on average, less than four per year) and that the only macroinvention that we excluding is Thomas Savery's steam engine of 1698, the comparison presented remains informative.

Table 9: Patents for inventions intended to save labour, 1700-1799.

Patent aim	Top 0.5%	Top 1%	Top 2%	All patents
Labour-saving stated	2.9	3.4	4.7	3.9
Effectively labour-saving	38.2	38.9	38.4	15.3

Note: The last column is taken from MacLeod (1988), Table 9.2 p. 170. Unfortunately, the data are not strictly comparable because MacLeod considered the entire period from 1660 to 1799 (see the note to Table 8). The methodology used to find patents covering inventions effectively labour saving is described in the text and is the same of MacLeod (1988, pp. 170 and 257).

Table 10: Determinants of micro- and macroinventions.

	Logit		OLS	Quantile Regression					
	Top 1%	Top 0.5%		Q(0.25)	Q(0.50)	Q(0.75)	Q(0.95)	Q(0.99)	Q(0.995)
Number of inventors	-0.5389*	-0.1006	0.0004	0.0011	0.0002	0.0000	0.0132	0.1405*	0.0667
	(0.28607)	(0.30428)	(0.00680)	(0.00103)	(0.00066)	(0.00163)	(0.02273)	(0.08122)	(0.22226)
Previous patents	0.9094***	0.4404	0.0445***	0.0014*	0.0058***	0.0266***	0.1695***	0.2582***	0.1437
	(0.18850)	(0.28354)	(0.00520)	(0.00075)	(0.00091)	(0.00227)	(0.02624)	(0.08002)	(0.11009)
Engineer	1.0026***	1.1294***	0.0517***	0.0036***	0.0067***	0.0268***	0.2602***	0.3359**	0.6839***
	(0.21796)	(0.30896)	(0.00779)	(0.00126)	(0.00109)	(0.00265)	(0.04491)	(0.13821)	(0.24117)
Foreign Inventor	0.0448	-0.4461	-0.0032	-0.0023*	-0.0018	-0.0019	-0.0144*	-0.1153**	-0.2746***
	(0.53756)	(1.05258)	(0.00577)	(0.00122)	0.00132	(0.00149)	(0.00747)	(0.05396)	(0.09774)
Metropolitan	0.0318	-0.0440	0.0009	-0.0002	-0.0001	0.0000	0.0124*	0.0626	0.1295
	(0.17808)	(0.25465)	(0.00477)	(0.00041)	(0.00037)	(0.00065)	(0.00732)	(0.06193)	(0.08767)
Outsider	0.2375	0.3403	0.0035	0.0000	-0.0001	0.0000	-0.0032	0.0144	0.1487
	(0.22144)	(0.30296)	(0.00762)	(0.00038)	(0.00054)	(0.00092)	(0.00973)	(0.12262)	(0.19670)
Constant	-5.7500***	-7.3290***	0.0022	-0.0637***	-0.0437***	-0.0299***	-0.0150	-0.0474	0.3115
	(0.46132)	(0.75203)	(0.11964)	(0.00194)	(0.00195)	(0.00352)	(0.02561)	(0.16049)	(0.35806)
Industry dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-340.008	-623.989							
(Pseudo) R2	0.1509	0.1446	0.0126	0.2462	0.1180	0.0438	0.1058	0.2232	0.2970
Observations	12690	11356	13070	13070	13070	13070	13070	13070	13070

Note: *,**,*** denote significance at 10%, 5% and 1% level. Dependent variable for the first two columns is a dummy equal to 1 for inventions in the top 1% and top 0.5% of the quality distribution, respectively. Dependent variable for the remainder of the table is the absolute value of BCI of each patent. The variable "outsider" has been constructed in such a way to consider only the cases in which the invention was clearly not connected with the occupation of the patentee. When this dummy variable takes a value of 0 this does not mean that the inventor in question is an insider; this is also the case for all those inventors listed as "esquire", "gentleman" or "baronet". We also excluded from the count of outsiders patent agents and inventions imported from abroad. Metropolitan is a dummy variable indicating whether any of the patentees was living in a town with more than 50,000 inhabitants at the time he was granted the patent. Logit and OLS models are estimates using robust standard errors, while standard errors for the quantile regression coefficients are obtained using 500 bootstrap replications. We included time dummies for each decade and industry dummies from Nuvolari and Tartari (2011).

A Appendix: The Bibliographic Composite Index (BCI) of patent quality

This Appendix contains a description of the sources of the BCI and some further robustness checks on the results reported in the paper.

A.1 Sources used for the construction of WRI, PAT_EM and INV_EM

The BCI is a composite index that integrates three different quality indicators: the Woodcroft Reference Index (WRI), Patent Eminence (PAT_EM) and Inventor Eminence (INV_EM).

The WRI is computed as the number of bibliographic references listed for each patent in Woodcroft (1862). Figure A1 and A2 shows the entries for two different patents (a technological breakthrough and an ordinary invention) in Woodcroft's volume.

[Figures A1 and A2 about here]

Not surprisingly Watt's separate condenser is mentioned in a significantly higher number of references than the William Watts' invention for improvements in the production of small shots (making them "solid, round and smooth").

The Patent Eminence (PAT_EM) score is computed as the number of times each patent is mentioned in specialized reference volumes on the history of invention and engineering. The sources used for the construction of this variable are:

1. Baker, R. (1976): *New and Improved... Inventors and Inventions that Have Changed the Modern World*, London: British Library.
2. Carter, E. F. (1969): *Dictionary of Inventions and Discoveries*, London: F. Muller.
3. Desmond, K. (1987): *The Harwin chronology of inventions, innovations, discoveries: From pre-history to the present day*, London: Constable.
4. Inkster, I. (1991): *Science and technology in history: an approach to industrialisation*, London: Macmillan.
5. Bridgman, R. (2014): *1000 inventions and discoveries*, New York: Dorling Kindersley Ltd.
6. Bunch, B. H. and A. Hellemans (2004): *The History of Science and Technology*, New York: Houghton Mifflin.

7. Ochoa, G. and M. Corey (1997): *The Wilson chronology of science and technology*, New York: HW Wilson.

8. Dudley, L. (2012): *Mothers of innovation: How expanding social networks gave birth to the Industrial Revolution*, Newcastle upon Tyne: Cambridge Scholars Publishing.

9. Lilley, S. (1948): *Men, machines and history: a short history of tools and machines in relation to social progress*, London: Cobbett Press.

10. Challoner, J. (2016): *1001 inventions that changed the world*, Sydney: Pier 9.

Table A1 shows the overlap in the coverage of the patent sample between the sources used for the construction of PAT_EM.

[Table A1 about here]

Table A2 shows the patents with highest score of PAT_EM.

[Table A2 about here]

The Inventor Eminence (INV_EM) score is computed as the number of times each inventor is mentioned in biographical dictionaries and other compilations of important inventors and historical figures. All the patents of the same inventor have the same score of INV_EM. The sources used for the construction of this variable are:

1. Matthew H. and B. Harrison (2004): *Oxford Dictionary of National Biography*, Oxford: Oxford University Press (www.oxforddnb.com).

2. Allen, R. (2009): *The British Industrial Revolution in Global Perspective*, Cambridge: Cambridge University Press.

3. Day, L. and I. McNeil (1996): *Biographical dictionary of the history of technology*, London: Routledge.

4. Abbott, D. (1985): *The Biographical Dictionary of Scientists, Engineers and Inventors*, London: F. Muller.

5. Murray, C. (2003): *Human accomplishment: The pursuit of excellence in the arts and sciences, 800 BC to 1950*, London: Harper Collins.

6. Benson, A. K. (2012): *Inventors and inventions. Great lives from history*, Pasadena: Salem Press.

7. De Galiana, T. and M. Rival (1996): *Dictionnaire des inventeurs et inventions*, Paris: Larousse.

8. Meisenzahl, R. R. and J. Mokyr (2012): "The rate and direction of invention in the British Industrial Revolution: Incentives and institutions," in *The rate and direction of inventive activity revisited*, ed. by J. Lerner and S. Stern, Chicago: University of Chicago Press, pp. 443-479.

9. Gergaud, O., M. Laouenan, and E. Wasmer (2016): "A Brief History of Human Time. Exploring a database of 'notable people'," *LIEPP Working Paper*, Sciences Po.

Table A3 shows the overlap in terms of inventor coverage between the sources used for the construction of INV_EM.

[Table A3 about here]

Table A4 reports the inventors with the highest scores of INV_EM.

[Table A4 about here]

Table A5 examines the consistency of the sources used for the construction of INV_EM and PAT_EM by means of Kuder-Richardson 20 coefficients. The results are robust even when excluding one source at the time.

[Table A5 about here]

Figure A3 displays the distributions of PAT_EM and INV_EM. Both distributions are very skewed, with the large bulk of patents having a score of zero and few selected patents with high scores. Table A10 reports the descriptive statistics by sectors of WRI, PAT_EM and INV_EM.

[Figure A3 about here]

[Table A10 about here]

A.2 The construction of BCI and some further robustness checks

Table A6 reports Spearman correlation coefficients among WRI, PAT_EM and INV_EM. The correlations are strongly significant, but the coefficients are rather low. The highest coefficient is between PAT_EM and INV_EM and is around 0.3. This suggests that the indicators provide relatively independent assessments of patent quality. In this context, integrating these three indicators in a composite quality index may lead to significant improvement of the signal-to-noise ratio (Lanjouw and Schankerman, 2004).

[Table A6 about here]

In particular, some important innovations of the Industrial Revolution such as John Kay's flying shuttle, John Hadley's octant, James Heargreaves' spinning jenny, Henry Cort's puddling process and

John Wilkinson's boring machine have relatively low scores of WRI*. Table A7 shows the scores of WRI* and BCI and the percentiles in which these patents are located in the distributions of the two indicators. Notably, all these inventions are in the top 0.5% patents when using the BCI.

[Table A7 about here]

Table A8 compares the performance of BCI and WRI* in assessing patents on flawed designs in steam engineering (MacLeod et al. 2003; Dircks 1861). The comparison is carried out by means of Fligner-Policello of stochastic equality. Interestingly enough, in this case patents with flawed designs have significantly lower score of BCI, while WRI* is not able to tease them apart from the rest of the patent corpus.

[Table A8 about here]

Figure A4 contains a scatterplot that compares BCI and INV_EM. In this case, it is worth noting that several patents of "great inventors" are characterized by relatively low scores of BCI. This suggests that the BCI is correctly able to discriminate between important inventions and marginal improvements even when they were made by same inventor.

[Figure A4 about here]

Figure A5 contains a scatterplot that compares BCI and PAT_EM. The two measures are very consistent. As noted in the text, the main limit of PAT_EM is that is not very granular. The BCI shows more variation and allows a more fine-grained evaluation of microinventions.

[Figure A5 about here]

Table A9 contains a number of robustness checks on the construction of BCI. In particular, we experiment with different time and industry controls in the Poisson regressions for WRI, PAT_EM and INV_EM and examine the resulting set of the top 0.5% patents in the upper tail of the quality distributions (in the paper we use BCI as an ordinal variable). In all cases there is an almost complete overlap. This finding bolsters our confidence that we are selecting the subset of macroinventions for the period of the Industrial Revolution.

[Table A9 about here]

Figure A6 shows the frequency of macroinventions in our data-base and the prediction of the Poisson model. The fit is remarkable, suggesting that the occurrence of macroinventions is consistent with a data-generating process in which serendipity play a significant part.

[Figure A6 about here]

Table A12 contains a list of the top 0.5% patents in terms of BCI. Remarkably, the table shows technological breakthroughs spanning many different sectors of economic activity.

[Table A12 about here]

16 REFERENCE INDEX OF PATENTS OF INVENTION.

Progressive Number.	REFERENCE.
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.

Figure A1: Entry in Woodcroft's *Reference Index* for James Watt's patent of the separate condenser (1769)

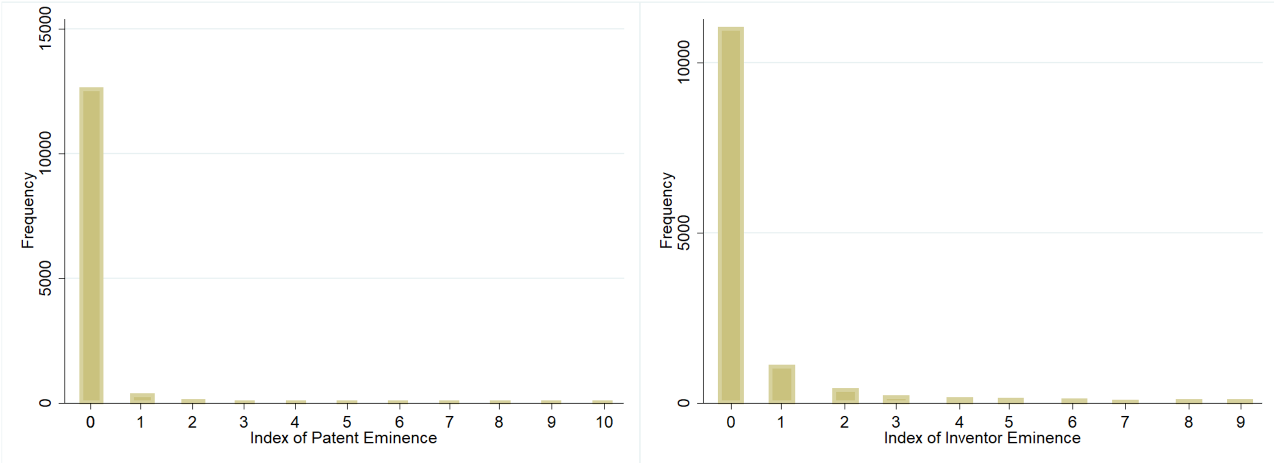
Note: the entry gives references to technical and legal literature where the patent is mentioned, while the last line of the table indicates in which office the specification was lodged (in this case Rolls Chapel). The Index also notes of the Fire Engines Patent Act (1775) that extended the patent to 1800.

REFERENCE INDEX OF PATENTS OF INVENTION. 65

Progressive Number.	REFERENCE.
2544	Mechanics' Magazine, vol. 17, page 385; also vol. 20, page 98.
	Rolls Chapel Reports, 6th Report, page 151.
	Rolls Chapel.

Figure A2: Entry in Woodcroft's *Reference Index* for William Watts' patent for making better small shots (1782)

Note: Not surprisingly, Watt's separate condenser received a much higher number of citations than the incremental improvements patented by William Watts.



(a) Patent Eminence (b) Inventor Eminence

Figure A3: Distribution of the quality indicators Patent Eminence and Inventor Eminence.

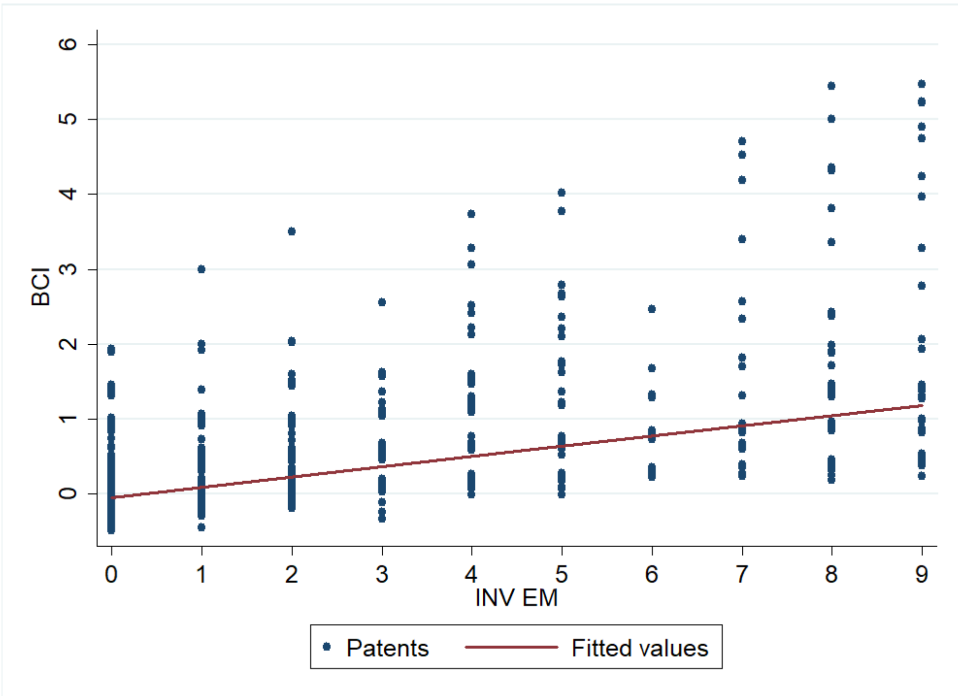


Figure A4: Scatterplot of BCI and INV_EM

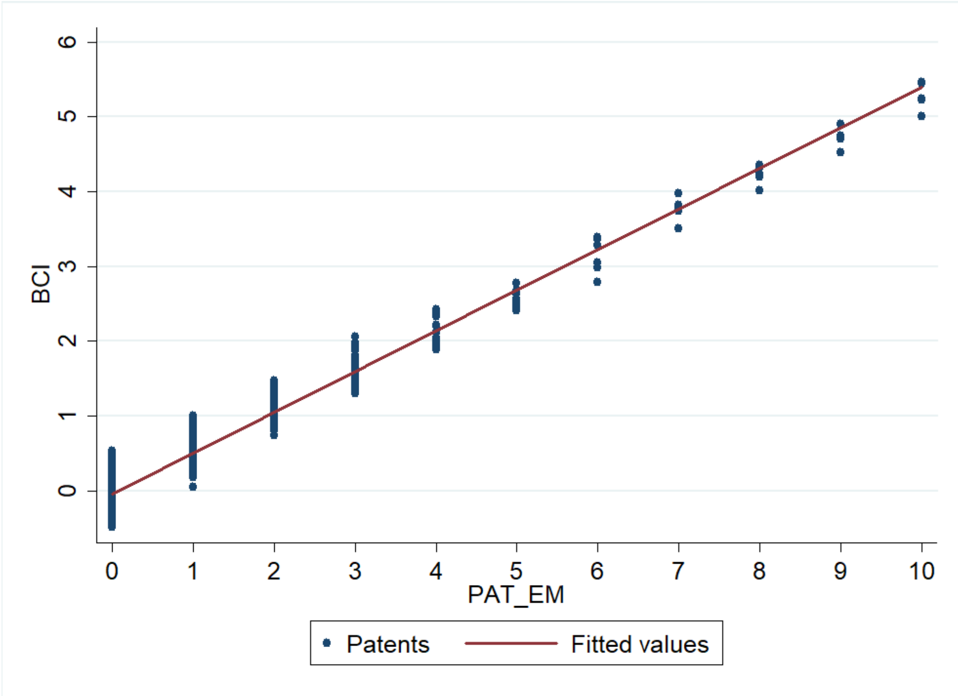


Figure A5: Scatterplot of BCI and PAT_EM

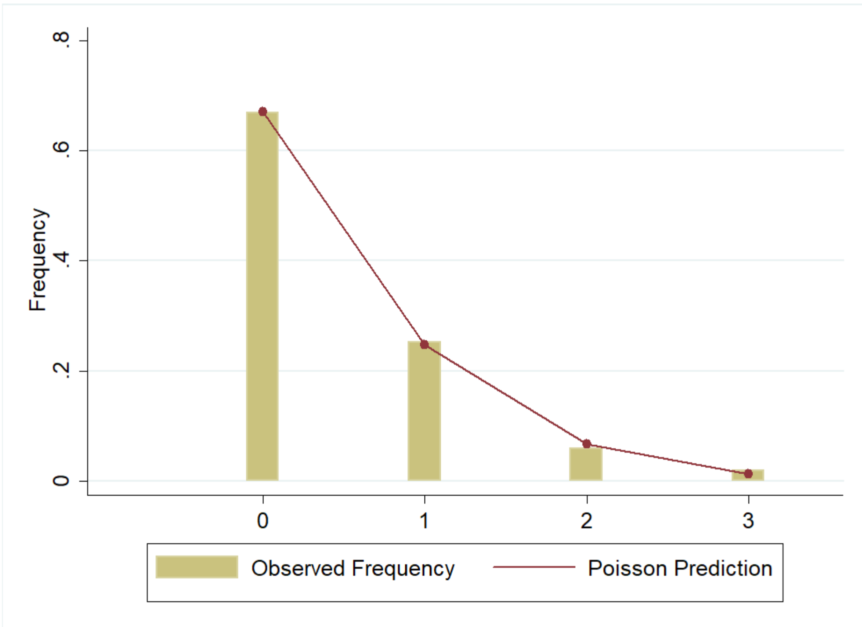


Figure A6: Frequency of years characterized by a certain number of macroinventions, actual vs predicted by the Poisson model.

Note: the unit of observation is the year and the graph shows the frequency of years with zero to three macroinventions. The Poisson model is estimated using a quadratic time trend.

Table A1: Overlap between the sources used for Patent Eminence

	Source	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Baker (1976)	150									
(2)	Carter (1978)	48	266								
(3)	Desmond (1987)	45	68	157							
(4)	Inkster (1991)	21	29	20	44						
(5)	Dudley (2012)	29	37	26	27	55					
(6)	Challoner (2009)	31	28	29	14	20	49				
(7)	Bridgman (2002)	22	26	24	16	18	18	38			
(8)	Bunch and Hellemans (2004)	39	52	31	19	27	23	23	93		
(9)	Ochoa and Corey (1997)	16	15	17	12	13	10	11	15	24	
(10)	Lilley (1948)	21	24	17	21	21	14	15	17	12	33

Note: This table shows the number of patents cited in every sources along with the number of these that are also mentioned in each of the other sources used. The diagonal cells contain the total number of patents in each of these lists, while cells outside the diagonal show the number of patents mentioned simultaneously in both sources.

Table A2: Patents with the highest scores of Patent Eminence

Patent N°	Year	Inventor	Invention	Patent Eminence
542	1733	John Kay	Flying shuttle	10
913	1769	James Watt	Separate condenser	10
931	1769	Richard Arkwright	Water frame	10
962	1770	James Hargreaves	Spinning jenny	10
7390	1837	Charles Wheatstone	Telegraph	10
1063	1774	John Wilkinson	Boring machine	9
1351	1783	Henry Cort	Rolling of metals	9
1470	1785	Edmund Cartwright	Power loom	9
2599	1802	Andrew Vivian, Richard Trevithick	High pressure steam engine	9
1298	1781	Jonathan Hornblower	Compound steam engine	8
1565	1786	Edmund Cartwright	Power loom	8
1645	1788	Andrew Meikle	Threshing machine	8
2045	1795	Joseph Bramah	Bramah's lock	8
9382	1842	James Nasmyth	Steam hammer	8

Table A3: Overlap between the sources used for Inventor Eminence

	Source	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Oxford DNB	292								
(2)	Allen (2009)	45	77							
(3)	Day and McNeil (1996)	105	50	241						
(4)	Abbott (1985)	41	29	48	58					
(5)	Murray (2003)	32	29	35	28	55				
(6)	De Galiana (1996)	60	36	66	40	35	103			
(7)	Meisenzahl and Mokyr (2012)	153	55	178	45	39	75	538		
(8)	Benson (2012)	38	28	38	26	27	37	45	60	
(9)	Gergaud et al (2016)	86	22	66	29	25	45	84	36	135

Note: This table shows the number of inventors cited in every sources along with the number of these that are also mentioned in each of the other sources used. The diagonal cells contain the total number of inventors in each of these lists, while cells outside the diagonal show the number of inventors mentioned simultaneously in both sources.

Table A4: Patents with the highest scores of Inventor Eminence

Inventor	Inventor Eminence
Andrew Vivian	9
Edmund Cartwright	9
Henry Bessemer	9
Henry Maudslay	9
James Hargreaves	9
James Nasmyth	9
James Watt	9
John Kay	9
Richard Arkwright	9
Richard Trevithick	9
Thomas Savery	9
William Murdock	9

Table A5: Robustness of Kuder-Richardson 20 coefficients after excluding a source of Patent and Inventor Eminence at the time.

Patent Eminence		Inventor Eminence	
Source Excluded	KR20	Source Excluded	KR20
Baker (1976)	0.7632	Oxford DNB	0.8351
Carter (1978)	0.7864	Allen (2009)	0.8369
Desmond (1987)	0.7640	Day and McNeil (1996)	0.8173
Inkster (1991)	0.7569	Abbott (1985)	0.8326
Dudley (2012)	0.7490	Murray (2003)	0.8363
Challoner (2009)	0.7562	De Galiana (1996)	0.8290
Bridgman (2002)	0.7567	Meisenzahl and Mokyr (2012)	0.8568
Bunch and Hellemans (2004)	0.7526	Benson (2012)	0.8388
Ochoa and Corey (1997)	0.7666	Gergaud et al (2016)	0.8385
Lilley (1948)	0.7583		

Note: This table reports the Kuder-Richardson 20 coefficients for Patent and Inventor Eminence indicators after each of the sources used is excluded from its computation, one at the time. The table shows great stability of the coefficients, which when all sources are considered together are equal to 0.7792 and 0.8511 for Patent and Inventor Eminence, respectively.

Table A6: Spearman's rank correlation coefficients of the raw quality indicators

	Woodcroft Reference Index	Patent Eminence	Inventor Eminence
Woodcroft Reference Index	1		
Patent Eminence	0.0710***	1	
Inventor Eminence	0.0645***	0.3001***	1

Note: *** denotes significance at 0.1% level.

Table A7: Scores of WRI* and BCI for some technological breakthroughs of the Industrial Revolution.

Patent N°	Inventor	Invention	N°Woodcroft Refs	WRI*	Percentile WRI*	BCI	Percentile BCI
542	John Kay	Flying shuttle	1	0.578	20	5.006	99.5
550	John Hadley	Octant	1	0.578	20	2.783	99.5
962	James Hargreaves	Spinning jenny	2	1.140	68	5.221	99.5
1063	John Wilkinson	Boring machine	2	1.165	69	4.700	99.5
1351	Henry Cort	Rolling of metals	2	1.072	67	4.525	99.5
1951	Samuel Bentham	Woodworking machinery	2	1.058	63	1.144	99

Table A8: Fligner-Policello tests of stochastic equality: comparison of WRI* and BCI for flawed steam engineering patents.

	Perpetual Motion		"Impossible" Engines	
	BCI	WRI*	BCI	WRI*
Entire sample (1700-1850)				
Fligner-Policello statistics	-5.062***	-0.887	-2.765**	1.822

Note: *,**,*** denote significance at 5%, 1% and 0.1% level. Data for perpetual motion machines are taken from Dircks (1861) (23 patents), while the lists of 83 engines that were not technically feasible is the same employed by MacLeod et al. (2003). A negative sign of the Fligner-Policello statistics indicates that patents in the list considered are of lower average value than the excluded remainder. All the results hold if we employ Mann-Whitney-Wilcoxon median test.

Table A9: Overlap between Top 0.5% patents when changing the time and industry controls used in the Poisson regression.

	(1)	(2)	(3)	(4)	(5)	(6)
(1)	65					
(2)	63	65				
(3)	62	63	65			
(4)	63	64	62	65		
(5)	62	63	62	63	65	
(6)	62	63	62	63	63	65

Note: This table shows the number of top 0.5% patents (65 patents) that overlap when the Bibliographic Composite Index is constructed using residuals of the raw proxies coming from different sets of regressions. In particular: (1) preferred specification, controls for time decade and industry (2) control for time windows of 50 years and industry (3) control for time windows of 25 years and industry (4) control for time decades only (5) control for industry only (6) no controls at all.

Table A10: Descriptive statistics of quality indicators, detailed by sector of economic activity as defined by Nuvolari and Tartari (2011)

Industry	Patents	Woodcroft Reference Index					Patent Eminence					Inventor Eminence				
		Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max
Agriculture	432	2.5717	2	1.3433	1	7	0.0856	0	0.5655	0	8	0.2152	0	0.8300	0	7
Carriages	812	2.8140	2	1.6593	1	15	0.0615	0	0.3384	0	4	0.3645	0	1.1752	0	9
Chemicals	1118	2.9758	3	1.6713	1	19	0.0286	0	0.2009	0	2	0.2504	0	0.9759	0	9
Clothing	322	2.3074	2	1.3814	1	13	0.0465	0	0.3879	0	6	0.2732	0	0.9952	0	6
Construction	640	2.8687	3	1.6238	1	16	0.025	0	0.2078	0	3	0.3078	0	1.1135	0	9
Engines	1637	2.7874	3	1.5135	1	21	0.0989	0	0.6136	0	10	0.5534	0	1.5464	0	9
Food	716	2.6955	2	1.6118	1	17	0.0488	0	0.3873	0	7	0.1955	0	0.8743	0	9
Furniture	659	2.4962	2	1.5021	1	18	0.0515	0	0.3313	0	4	0.1638	0	0.8124	0	9
Glass	123	2.8130	2	1.5436	1	9	0.0569	0	0.3213	0	3	0.5934	0	1.7547	0	9
Hardware	834	2.6163	2	1.5798	1	13	0.0611	0	0.3948	0	7	0.2170	0	0.8385	0	8
Instruments	598	2.5953	2	1.4642	1	13	0.1371	0	0.6833	0	10	0.5083	0	1.3815	0	8
Leather	218	2.6559	2	1.3799	1	9	0.0137	0	0.1511	0	2	0.1605	0	0.7840	0	6
Manufacturing	685	2.6087	2	1.6064	1	16	0.0701	0	0.3797	0	4	0.2919	0	1.0328	0	8
Medicines	288	2.1527	2	1.1404	1	10	0.0243	0	0.1754	0	2	0.1423	0	0.6443	0	7
Metallurgy	682	3.1568	3	1.9808	1	23	0.1114	0	0.6520	0	9	0.6436	0	1.6546	0	9
Military	252	2.4603	2	1.2944	1	11	0.1111	0	0.7221	0	9	0.4246	0	1.2264	0	7
Mining	81	2.9876	3	1.9202	1	14	0.0987	0	0.5149	0	4	0.4691	0	1.0849	0	5
Paper	480	2.9041	3	1.6648	1	14	0.1	0	0.4266	0	4	0.5812	0	1.3683	0	9
Pottery	277	2.8483	3	1.5738	1	12	0.0649	0	0.4030	0	4	0.2454	0	0.9465	0	9
Ships	590	2.8932	3	1.8280	1	17	0.0355	0	0.3302	0	7	0.3067	0	0.9935	0	9
Textiles	1626	2.5645	2	1.6636	1	19	0.0805	0	0.6451	0	10	0.5405	0	1.3496	0	9
Total sample	13070	2.7223	2	1.6161	1	23	0.0695	0	0.4797	0	10	0.3774	0	1.2031	0	9

Table A11: Macroinventions (top 0.5%) according to the Bibliographic Composite Index.

Rank	Patent number	Year	Patentee	Invention
1	913	1769	James Watt	Separate condenser
2	7390	1837	Charles Wheatstone	Telegraph
3	931	1769	Richard Arkwright	Water frame
4	962	1770	James Hargreaves	Spinning jenny
5	542	1733	John Kay	Flying shuttle
6	2599	1802	Andrew Vivian, Richard Trevithick	High pressure steam engine
7	1470	1785	Edmund Cartwright	Power loom
8	1063	1774	John Wilkinson	Boring machine
9	1351	1783	Henry Cort	Rolling of metals
10	9382	1842	James Nasmyth	Steam hammer
11	2045	1795	Joseph Bramah	Hydraulic press
12	1565	1786	Edmund Cartwright	Power loom
13	1645	1788	Andrew Meikle	Threshing machine
14	1298	1781	Jonathan Hornblower	Compound steam engine
15	1876	1792	Edmund Cartwright	Wool-combing machine
16	1430	1784	Joseph Bramah	Bramah's lock
17	5701	1828	James Beaumont Neilson	Hot blast furnace
18	7104	1836	Francis Pettit Smith	Screw propeller
19	3372	1810	Peter Durand	Tin cans
20	8842	1841	William Henry Fox Talbot	Calotype
21	3887	1815	George Stephenson	Locomotive
22	4804	1823	Charles MacIntosh	Macintosh waterproof cloth
23	1321	1782	James Watt	Double acting steam engine
24	2772	1804	Arthur Woolf	Improvements in steam engines
25	5990	1830	Edwin Budding	Lawnmower
26	550	1734	John Hadley	Octant
27	1306	1781	James Watt	Rotary crank
28	4136	1817	David Brewster	Kaleidoscope
29	4081	1816	Robert Stirling	Stirling air engine
30	1420	1784	Henry Cort	Iron puddling
31	6909	1835	Samuel Colt	Revolving firearm
32	722	1758	Jedediah Strutt	Stocking rib
33	380	1707	Abraham Darby	Iron casting
34	4067	1816	George Stephenson	Half-lap joint for railways
35	562	1738	Lewis Paul	Spinning machine
36	2196	1797	Joseph Bramah	Beer pump
37	6159	1831	William Bickford	Safety fuse
38	5803	1829	Charles Wheatstone	Concertina
39	2708	1803	John Gamble	Paper making machine (Foudrinier)
40	5949	1830	Richard Roberts	Self-acting mule
41	636	1748	Lewis Paul	Spinning machine
42	939	1769	Josiah Wedgwood	New method for decorating earthenware
43	1111	1775	Richard Arkwright	Carding machine
44	6733	1834	Joseph Hansom	Hansom cab
45	1105	1775	Alexander Cumming	Flush toilet
46	5022	1824	Joseph Apsdin	Portland cement
47	1177	1778	Joseph Bramah	Watercloset
48	2202	1797	Edmund Cartwright	Steam engine
49	6014	1830	Andrew Ure	Thermostat
50	395	1714	Henry Mill	Typewriter
51	3611	1812	Joseph Bramah	High-pressure hydraulic mains
52	3105	1808	William Newberry	Scroll bandsaw
53	2652	1802	Joseph Bramah	Making gun stocks
54	6675	1834	Henry Shrapnel	Fire-arms
55	5138	1825	Richard Roberts	Self-acting mule
56	721	1758	John Dollond	Lenses for telescopes
57	8447	1840	George Richards Elkington	Electroplatingprocess.
58	1478	1785	Joseph Bramah	Screw propeller
59	896	1768	Andrew Meikle	Machine for dressing grain
60	1112	1775	Jesse Ramsden	Astronomic telescope
61	734	1759	Jedediah Strutt	Derby patent rib machine
62	10990	1845	Robert William Thomson	Carriage wheel (pneumatic tyre)
63	3032	1807	Alexander John Forsyth	Fulminate-primed gun firing mechanism
64	3041	1807	William Cubitt	Self-regulating windmill sails
65	1833	1791	John Barber	Gas turbine