Why Britain? The Right Place (in the Technology Space) at the Right Time.*

PRELIMINARY DRAFT

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Abstract

Why did Britain attain economic leadership during the Industrial Revolution? We argue that Britain possessed an important but underappreciated innovation advantage: British inventors worked in technologies that were more central within the innovation network. We offer a new approach for measuring the innovation network using patent data from Britain and France in the 18th and early 19th century. We show that the network influenced innovation outcomes and then demonstrate that British inventors worked in more central technologies within the innovation network than inventors from France. Then, drawing on recently-developed theoretical tools, we quantify the implications for technology growth rates in Britain compared to France. Our results indicate that the shape of the innovation network, and the location of British inventors within it, can help explain the more rapid technological growth in Britain during the Industrial Revolution.

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1 Introduction

One of the enduring questions of the Industrial Revolution is: why was Britain able to achieve more rapid economic growth than other European countries? There is now a substantial list of potential British advantages, including the country's uniquely practical Enlightenment tradition (Mokyr, 2009), its well-developed apprenticeship systems (Kelly et al., 2014), the stable institutions established in the wake of the Glorious Revolution of 1688 (North and Weingast, 1989; Acemoglu et al., 2005), higher wages (Allen, 2009), and its advantageous natural resources (Pomeranz, 2000; Fernihough and O'Rourke, 2014). Despite the substantial body of ongoing research on this topic, the debate remains largely unsettled.

In this study, we argue that there is one important British advantage that has been largely overlooked: the possibility that British inventors may have been working "at the right place" in the *technology space*. Our idea builds on emerging literature in growth economics which finds that innovation in some technologies generates more spillover benefits than innovation in others (Acemoglu et al., 2016; Cai and Li, 2019; Huang and Zenou, 2020; Liu and Ma, 2021). As a result, a country's allocation of researchers across technologies can substantially impact the overall rate of economic growth. In particular, this literature shows that technological progress will be faster in economies where more research effort is focused on technologies that generate more spillovers for other technologies; in other words, technologies that are more *central* in the technology space.

Translating these ideas into the context of the Industrial Revolution, we ask: did Britain experienced more rapid technological progress because British inventors were more focused on technologies, such as steam engines, machine tools, or metallurgy, that generated stronger spillover benefits for other technologies and were therefore more central in the technology space? In contrast, could it have been the case that Continental economies like France experienced slower technological progress because they specialized in developing technologies, such as apparel, glass, or papermaking, which were more peripheral in the technology space?[1]

Put another way, we aim to examine whether Britain's differential growth during the eighteenth and early nineteenth centuries can be explained by the distinct position of British inventors in the technology space. By starting with ideas from modern growth economics, our analysis is less subject to the type of "post hoc, proper hoc" concerns that have been raised about some other explanations (Crafts, 1977, 1995). Moreover, we offer a theoretically-grounded quantification describing exactly how much

[1]Hallmann et al. (2021) show that technological leadership in invention of Britain relative to France varied across technologies, with Britain leading, besides others, in steam engines and textile technologies, and France leading, besides others, in papermaking and shoemaking. Mokyr (1990, Chapter 5) provides a historical overview on British technological lead or lag in invention relative to Continental Europe.

of Britain's differential growth experience can be attributed to this mechanism. These two features differentiate our study from most existing work that aims to understand Britain's growth lead during the Industrial Revolution.

To structure our analysis, we begin with a growth model, from Liu and Ma (2021), that incorporates an innovation network. In this network, each node is a technology type, while each edge reflects the extent to which innovations in one technology type increase the chances of further innovation in another. This model provides a framework for thinking about how the distribution of researchers across technology sectors relates to the growth rate in the economy. It also generates specific expressions that, given the matrix of connections across sectors, allow us to quantify how different allocations of researchers across technology sectors will affect growth. The upshot is that allocations in which more researchers are working in technology sectors with greater spillovers will generate higher overall growth rates than others. Therefore, the growth maximizing allocation of researchers will feature more researchers working in more central technology sectors: specifically, those sectors with higher eigenvalue network centrality. Furthermore, the model delivers precise analytical relationships that allow us to quantify the implications of different allocations of research effort for the rate of economic growth.

To examine whether these forces operated during the Industrial Revolution, we utilize patent data for Britain, from 1700 to 1849, and for France from 1791-1844.[2] These historical patent data cover a large number of inventors and their inventions, providing a rich source of information on innovation during the Industrial Revolution.[3] We follow a long line of work, dating back at least to Sullivan (1989), using patent data to better understand innovation patterns during this period.

A key challenge in our setting is measuring spillovers across technology categories. The innovation literature typically uses patent citations, but these are not available in our historical setting. Instead, we introduce a new approach based on the idea that if there are spillovers between two technology categories, then inventors working primarily in one area will occasionally file patents in the other. In particular, we measure the extent of spillovers from technology category j to i based on the propensity of inventors who patent in j to subsequently patent in i.

Since our approach is new, we validate it using modern data. Specifically, using U.S. patents from 1970-2014, we construct innovation networks using our approach as well as the citation-based approach used in modern studies. Comparing these networks shows that the two approaches generate networks that are extremely similar. This suggests that our method does a good job of recovering the underlying innovation network. Developing and validating this new approach to measuring innovation networks is one

[2]Both of these were periods during which the patent systems were largely stable. We end just before the major British patent reform of 1852 and the French patent reform of 1844.

[3]Of course, not every useful invention was patented, as (Moser, 2012) has shown.

contribution of our study.

Using our approach, we document technology networks in Britain and France that feature a dense central core of closely related—and mainly mechanical—technologies. One important question about our estimated networks is, do they reflect fundamental features of the underlying technologies or simply reflect the local innovation environment in each country? One way to test this is to compare the networks obtained from the two countries. If they are similar, they likely reflect fundamental technological features rather than idiosyncratic conditions. Conducting a direct comparison, however, is challenging because the two countries use very different technology categorizations. Therefore, it is necessary to construct a mapping of technology categories from one country's categorizations to the other. To do so, we carefully identify a set of inventions that were patented in both countries. We can then use the categorization of these inventions in each system to construct a crosswalk between the technology categorizations used in the two countries.

Using this mapping, we construct technology spillover matrices derived from French patents but in terms of British technology categories, or derived from British patents but expressed in French technology categories. This allows us to regress the entries of the technology matrices of one country on the entries of the other country. We find they are strongly positively related, despite the noise that is inherent in any mapping between different systems of technology categorization. This indicates that our innovation matrices not just reflect the local economic environment, but that a significant part of each represents an underlying 'global' network of technology spillovers.

Next, we establish that the shape of the technology spillover network matters for innovation outcomes. As a first step, we follow existing work on modern patent data by analyzing how patenting rates vary across technology categories depending on the lagged knowledge stock in other categories, weighted by the strength of connections through the innovation matrix. Consistent with the theory, and the results in previous studies of modern data, we find a significant positive associations of patenting with the lagged network weighted knowledge stock, shrinking toward zero as lags increase. However, the lack of exogenous variation in the lagged knowledge stock means that this result could be due to common shocks that affect connected technology categories.

Thus, in the second step, we provide evidence based on a source of quasi-exogenous variation in the timing of increases in the knowledge stock at some nodes of the innovation network. Specifically, we use the unexpected arrival of "macroinventions." These are inventions which Mokyr (1990) describes as "a radical new idea, without a clear precedent, emerges more or less ab nihilo." We take three approaches to identifying macroinventions. In one, we use a a list of 65 macroinventions from Nuvolari et al. (2021). In a second, we focus on inventions that were the first listed in a particular technology subcategory. Our third measure is the intersection of the first two, which identifies patents that were both important and new.

We then examine whether the arrival of a new macroinvention in one technology category leads to a subsequent increase in patenting in downstream technology categories within the innovation network. Here, the identifying assumption is *not* that the location of macroinventions were random, but that the timing of their arrival at a given location was unpredictable within the time frame of analysis. Using pooled difference-in-difference and event study analyses for a time frame of ten years before and after the arrival of each macroinvention, we show that macroinventions are followed by significant increases of the patenting rates in technology categories sharing stronger (downstream) connections from the technology category of the macroinvention. In addition, we find no evidence of an increase in technology categories as a result of being upstream from the macroinvention technology category within the innovation network. This second result provides a useful placebo check on our analysis.

Next, we look at whether there are notable differences in the allocation of British and French inventors within the innovation network. In particular, we focus on whether British inventors were patenting in technology categories that were more central within the innovation network than French inventors. We do this by studying, within the sets of British and French patents whether foreign inventors (of British or French origin) were patenting in more central technology categories than domestic inventors.[4] We find that among French patents, patents by British-based inventors were significantly more central compared to the average patents by French domestic inventors—and all other foreign inventors—, whereas among British patents, patents by French-based inventors were less central compared to the average patent by British domestic inventors. The pattern indicates that British inventors were more likely to work in central technology categories than French inventors. As more central nodes have stronger spillover connections to other technology categories, the more central locations occupied by British inventors are consistent with a greater "bang for the buck" of British innovation on the aggregate rate of technological progress.

Finally, we quantify the growth implications of the observed innovation network and different allocations of inventors in Britain and France through the lens of the model. Existing estimates for Britain suggest that industrial production grew by between 3 and 3.5% during the first half of the nineteenth century (Broadberry et al., 2015). In France, estimates indicate growth rates of between 1.7 and 2.5% in the same period (Crouzet, 1996; Asselain, 2007). (Preliminary) Results from our quantification exercise show that differences in the allocation of inventors across technology categories led to a technology growth rate in Britain that was between 0.5 and 2.9 percent higher

[4]We also attempted to study whether British vs. French inventors were more central within the innovation network of a third country, using U.S. patent data. Unfortunately, this analysis is not possible because U.S. patents only become available starting in 1836 (earlier patent information was lost due to a fire) and there are too few British and French inventors patenting in the U.S. in the two decades after that to draw any clear conclusions on their relative centrality within the U.S. network.

than the French technology growth rate. Thus, our results indicate that Britain's more advantageous position in the innovation network can explain a substantial fraction, and possibly the entire difference, in growth rates between the British and French economies during the first half of the nineteenth century.

In sum, the evidence presented in this paper shows that Britain benefited from an advantageous distribution of inventors across technology sectors during the Industrial Revolution, and that this difference meaningfully contributed to Britain's more rapid industrialization. Our analysis takes as given the differences in the distribution of inventors across sectors. Thus, our mechanism complements explanations for the British advantage during the Industrial Revolution, in particular those that can explain why British inventors were more likely than the French to work on technologies that happened to be more central within the innovation network, in particular mechanical technologies. For example, it could be that Britain's practical Enlightenment tradition and well-developed apprenticeship system (Mokyr, 2009; Kelly et al., 2014) contributed to the British inventors' greater ability for working on mechanical technologies, or that high wages and access to cheap coal steered British inventors to focus on labor-saving mechanical devices (Allen, 2009).[5] Put differently, the contribution of our paper lies in demonstrating *that* Britain was at the right place in the technology space at the right time, rather than explain *why* it was there but France was not.

In addition to improving our understanding of one of the most important questions in economic history, our study also contributes to work by growth economists on the importance of innovation networks. Relative to studies in this area (cited above), we offer two main contributions. First, we offer new methods that can help researchers study innovation networks further back in history, when standard tools such as systematic patent citations are unavailable. This opens up the possibility of studying the influence of innovation networks in different contexts or over longer periods. Second, our analysis of macroinventions provides additional, more causal, evidence that innovation networks matter for technology development. Third, our application demonstrates empirically the value of recent theoretical advances integrating innovation networks into economic growth models.

Our work builds on a long line of literature using patent data to examine innovation during the Industrial Revolution and into the nineteenth century. Early papers in this area include Sullivan (1989) and Sullivan (1990). More recent work includes MacLeod et al. (2003), Khan and Sokoloff (2004), Moser (2005), Khan (2005), Brunt et al. (2012), Nicholas (2011), Nuvolari and Tartari (2011), Moser (2012), Bottomley

[5] A stable institutional environment and well-developed patent system may have contributed in shifting inventors from technologies that can be protected by secrecy toward technologies as mechanical devices that are easily reverse engineered and thus profit the most from patents (Moser, 2005). However, as both Britain and France had strong patent protection, it is unclear how this mechanism could explain the *differential* focus of British vs. French inventors on mechanical devices.

(2014b), Bottomley (2014a), Burton and Nicholas (2017), Khan (2018), Bottomley (2019), Nuvolari et al. (2020), Nuvolari et al. (2021), Hallmann et al. (2021), and Hanlon (2022). Relative to this extensive literature, we are the first to study the role of innovation networks in influencing inventive activity during the Industrial Revolution.

The next section of this paper presents our theoretical framework. We then introduce our data, in Section 3 and discuss our approach to measuring the innovation network, in Section 4.1. Section 4.3 describes and compares the estimated innovation networks, while Section 5 provides evidence that the structure of the network has a causal effect on innovation rates. Section 6 shows that British inventors tended to operate in more central nodes of the innovation network. Finally, Section 7 uses the structure of the model to quantify the impact of these differences on each country's growth rate.

2 Theory: Growth with Innovation Networks

This section presents a theory of growth with innovation networks based on recent work by Liu and Ma (2021). The key feature of their model is the introduction of a matrix of spillovers across technology sectors into a continuous-time closed-economy endogenous growth framework. At the outset, it is important to recognize that our aim is to study the impact of different allocations of research effort across technology categories on the growth rate of an economy. Thus, we take the allocation of researches as given.[6]

2.1 Preferences and Production

The model features a representative consumer with utility at time t that is a function of discounted log consumption c_s in period t and all future periods:

$$V_t = \int_t^\infty e^{-\rho(s-t)} \ln c_s \, ds \quad .$$

Consumption is a Cobb-Douglas aggregation of consumption of goods from K different sectors,

$$c_s = \sum_{i=1}^{K} c_{it}^{\beta_i} \quad ,$$

where the β_i parameters give the consumption shares for each sector i and $\sum_i \beta_i = 1$ (consumption is Cobb-Douglas).

Within each sector i, there is a continuum of varieties of intermediate products, denoted by ν, which can be supplied in a countably infinite set of quality levels. The highest quality level available for any variety is given by $q_{it}(\nu)$. Only the highest quality

[6] These allocations may be due to a range of factors, including individual choices, market forces, government policies, or persistent historical conditions, which we do not attempt to model.

version of each variety is used in the production process. We denote the quantity of a variety of quality q produced as $x_{it}(\nu|q)$ and total production (and consumption) of goods from sector i is:

$$\ln c_{it} = \int_0^1 \ln \left(q_{it}(\nu) x_{it}(\nu|q)\right) \, d\nu$$

Given some available quality level, production in a sector depends only on the number of workers allocated to that sector: $x_{it}(\nu|q) = l_{it}(\nu)$ where l_{it} is the quantity of labor employed in sector i.

2.2 Innovation

Following Liu and Ma (2021), we define the knowledge stock available in a sector i at time t as q_{it}, where $\ln q_{it} = \int_0^1 \ln q_{it}(\nu) \, d\nu$. These knowledge stocks are the state variables in the model. The knowledge stock in a sector improves through the efforts of researchers, r_{it}, working on developing new technologies in that sector at time t. The innovation production function is given by:

$$n_{it} = r_{it} \, \eta_i \, \chi_{it} \quad \text{where} \quad \chi_{it} = \Pi_{j=1}^{k} \, q_{jt}^{\omega_{ij}} \, . \tag{1}$$

In this expression, n_{it} is the set of new ideas in sector i generated in time t, which in our empirical application will be represented by patents, η_i is a parameter that determines the productivity of research effort in sector i, and χ_{it} reflects the impact of spillovers across the innovation network that improve the chances of generating new innovations in sector i. These spillovers depend on the stock of knowledge in every other sector and a matrix of ω_{ij} parameters that determine the extent to which existing ideas in sector j increase the changes of producing new ideas in sector i. These will be the key parameters in our study. In order to obtain balanced growth across sectors, we need to assume that $\sum_j \omega_{ij} = 1$ for all i. We denote the K $\times$ K matrix of these parameters as Ω, which we refer to as the *innovation network*.

New ideas translate into incremental quality improvements according to the following relationship:

$$\dot{q}_{it}/q_{it} = \lambda \, \ln(n_{it}/q_{it}) \tag{2}$$

where the inclusion of q_{it} in the denominator on the right-hand side of this equation reflects the idea that improving quality becomes more difficult as the quality level rises. This formulation is intuitive in that it reflects the idea is that improvements become more difficult once the "low-hanging fruit" has been harvested. It also plays an important functional role in the model, because it means that the continually increasing stock of existing knowledge, which generate a corresponding increase in useful knowledge spillovers, does not generate explosive growth.

2.3 Resource constraints

To keep the model simple, we fix the number of production workers at $\bar{l}$ and the number of researchers at $\bar{r}$. Thus, $\sum_i l_{it} = \bar{l}$ and $\sum_i r_{it} = \bar{r}$. These assumptions abstract from the potentially important possibility that changes in the productivity of research activities may cause more workers to shift into research, but they substantially simplify the model.

2.4 Key results

The model provides several results that we will use in our empirical analysis. The first of these is related to how the innovation network determines the relationship between the current stock of knowledge in one sector and the rate of innovation in other sectors. We can derive this relationship from Equations 1 and 2. We obtain:

$$\ln n_{it} = \ln \eta_i + \ln r_{it} + \lambda \sum_{j=1}^{K} \omega_{ij} \left(\int_0^{\infty} e^{-\lambda s} \ln n_{j,t-s} \, ds \right) \tag{3}$$

This is a useful expression for our purposes, because it shows how the current knowledge stock in related sectors, represented by the term on the far right, influences the current pace of technology development. Later, we will use this expression to structure our investigation of whether our estimated innovation network matters for innovation outcomes.

A second key result has to do with the relationship between the distribution of research effort across sectors and the growth rate. It is useful to start by defining $\mathbf{a}$ as the dominant left eigenvector of Ω with an eigenvalue of one. As described by Liu and Ma (2021), the vector $\mathbf{a}$ exists and is unique. Let $\mathbf{b}$ be a vector of researcher allocations across sectors, so that each element $b_i = r_i/\bar{r}$. Liu and Ma (2021) then provide the following useful result:

Proposition: For a balanced growth path with researcher allocation vector $\mathbf{b}$, the aggregate stock of knowledge and consumption in each sector grows at the rate $g(\mathbf{b}) = c + \lambda\, \mathbf{a}' \ln \mathbf{b}$ where c is a constant term that depends on the total stock of researchers, the λ and η parameters, and $\mathbf{a}$.

From this proposition we get two useful additional results:

Corollary 1: The difference in the growth rates between implied by two different distributions of researchers across sectors, $\mathbf{b}$ and $\tilde{\mathbf{b}}$ is: $g(\tilde{\mathbf{b}}) - g(\mathbf{b}) = \lambda \mathbf{a}'(\ln \tilde{\mathbf{b}} - \ln \mathbf{b})$.

This result tells us that given $\mathbf{a}$ and λ, we can easily calculate the difference in growth rates implied by different allocations of researchers across sectors. The second useful result has to do with the growth-maximizing allocation of researchers, which we label $\mathbf{b}^*$. This is,

Corollary 2: The allocation of researchers that maximizes the rate of technology growth, $\mathbf{b}^*$, solves $argmax_b \quad \mathbf{a}' \ln \mathbf{b}$ subject to $\mathbf{b} \geq 0$ and $1'\mathbf{b} = 1$. The solution to this problem is the vector $\mathbf{a}$.

This result tells us that the growth-maximizing allocation of researchers is the allocation that mirrors the vector of innovation centrality $\mathbf{a}$ obtained from the innovation network.[7] Both of these results will come in handy in our empirical analysis, which we turn to next.

3 Data

3.1 Patent data

The patent data used in our analysis were digitized from the *Titles of Patents of Invention, Chronologically Arranged* collected by the British Patent Office (BPO). These data cover England and Wales, but for ease of exposition we will refer to them as "British" patents throughout the paper. These data include the patent number and date and the inventor name and occupation for over 12,500 patents from 1700 to 1849. This was a period of stability in British patent law, which ended in 1852 when a major patent reform was adopted. The printed volumes also include information on the inventor address and the patent title. We add to these data technology classifications, produced by the BPO, which classify each patent into one or more of 147 technology categories.[8]

The most important feature of our patent data set is that patents by individual inventors have been linked using a time-consuming careful manual linking procedure. We form links using all of the available information in the patent data, and in some cases additional external biographical information, following a procedure that is described in more detail in Hanlon (2022). Starting from 13,972 patent-inventor observations, this procedure identifies 8,980 individual inventors. Most of these inventors were located in the U.K., though a small number filed patents from abroad. In addition, 1,350 patent-inventor observations were "communicated from abroad." In these cases, the location and name of the original inventor is unknown.

The French patent data used in our main analysis begin with the initiation of a modern patent system in 1791 and end in 1843, just before the major patent reform of 1844. These data, which come from the French National Patent Institute (INPI) and

[7] This is not the same as the welfare-maximizing allocation, since the welfare-maximizing social planner will be willing to sacrifice some future growth in order to increase current consumption because future consumption is discounted.

[8] See Hanlon (2022) for additional details about these data.

were previously used in Hallmann et al. (2021), include patent number, patent title, inventor name, inventor occupation, inventor address, and additional details such as the type of patent and the patent term. French patents are divided into three main types: patents of invention, the standard format for new inventions, patents of importation for inventions imported from abroad, and patent of improvement for improvements on existing designs. Our analysis focuses on the first two of these, as they are the categories that represent truly new inventions.[9] The French patent data also include a technology category classification for each patent. Unlike the British classifications, each French patent is matched to exactly one out of 85 technology categories.

As in the British data, we have manually linked patents by the same inventor in the French patent data using the full set of available information.[10] Starting with 14,277 patent-inventor observations based on just over 11,000 patents, this matching procedure identifies around 10,500 unique inventors.

3.2 Mapping between technology categories

An important challenge in our analysis is constructing a reliable mapping between the French and British technology categories. The difficulty is that the two nation's patent offices employed structurally different systems of classifying patents into technology categories.

We build our mapping by matching patents that were filed both in Britain and in France. Using the technology categorizations applied to the same patent in the two locations, we build a probabilistic mapping between French and British technology categories. The most challenging part of constructing this mapping is therefore identifying patents filed in both locations.

We can construct three sets of patents filed in both countries. For the first set, we begin with all patents filed in Britain with inventors reporting a French address and then search for matching French patents. For the second set, we begin with all patents filed in France before 1844 with an inventor reporting an address in Britain and then search for matching British patents. For both of these sets, we determine a match based on the name of the inventor, the patent title, and the temporal proximity of the patent date. This is done through a manual review in order to account for the fact that patents typically have somewhat different titles in the two countries, and one patent often appears one, and sometimes a few, years later than the other. A third set of matched patents were filed in France between 1844 and 1852. For this group, we take

[9] Patents of improvement provided a less expensive way to modify an inventor's existing design, but they did not extend the term of the original patent. Another difference between the French and British patent systems is that in France inventors could choose to apply for patents of different lengths: 5, 10, or 15 years. Longer patent terms required higher fees.

[10] These links are likely to be even more reliable than those in the British data, because French inventors were less likely to have common names and many inventors had three, four, or five names.

advantage of the fact that, as part of the 1844 French patent law reform, the length of protection for French patents of inventions were previously patented abroad depended on the filing date of the original foreign patent. As a result, the French patent office recorded the origin location and filing date of foreign patents. These data allow us to make a direct match between a number of French patents of British technologies filed after 1844. Combining these three groups, and eliminating any duplicate entries, we have 1,140 patents filed in both locations from which to construct our technology category mapping.[11]

This set of matched patents enables us to construct a probabilistic mapping from French to British technology categories. Specifically, if a fraction θ_{ij} of French patents filed in French category i corresponded to British patents classified into British category j, then we assign patents from French category i to British category j with a weight of θ_{ij} (see Appendix B for further details and discussion). This provides a procedure through which we can reassign all French patents into British technology categories (or vice versa). Overall, the mapping obtained using this method gives results that appear reasonable (see Appendix Tables 10 and 11), though it is also clear that differences in the technology classifications will also introduce noise into analysis where it is necessary to convert patents from one country into the technology classifications of the other.

3.3 Input–output connections

When analyzing the effect of the innovation network on patenting activity, it will be important to differentiate the influence of the technology space from the influence of the product space that operates through input-output channels (Bloom et al., 2013). To do so, we need to construct a control reflecting the extent to which our technology categories are linked through input-output connections. This requires (1) data on the input-output connections between industries and (2) a mapping between industries and our input-output categories. To our knowledge, no mapping of this kind exists for the historical period we study, and even in modern settings constructing such a mapping can be challenging (Griliches, 1990).[12]

As for the data, we use the input–output (IO) table for Britain in 1907 constructed by Thomas (1984), which gives us a matrix of upstream and downstream connections

[11]We get 127 matched patents in the first set, 167 in the second, and 855 from the third (where we have better information to identify unique matches). In case there are concerns about the matching procedure used for the first two sets of matched patents, we have also generated results using only the third set of matched patents to construct the mapping. This generates similar results, which shows that the patent matching procedure applied to the other two sets of patents does not have a substantial influence on our results.

[12]One aspect that makes this mapping challenging is that it is often not clear whether a technology category should be applied to industries that produce the technology or those that use it. Another challenge is that patents in some important technology categories (e.g., "Valves") may be both produced by and used by a number of different industries.

between 33 industries, to measure product space connections between technology category nodes.[13] This is the earliest point for which a detailed input-output matrix for the British economy is available.[14]

We introduce a novel approach to constructing a mapping between technology categories and industries based on occupation information in patent data. In particular, we use that a substantial fraction of the occupations reported by patenting inventors can be unambiguously associated with specific industries, for example, “cotton textile manufacturer,” “paper maker,” or “button manufacturer.” To construct our mapping, we reviewed just over 7,000 occupations found in the British patent data and manually linked them to industries in the IO matrix. We link just over 3,400 occupations to industries, providing us with 4,295 patents linked to industries. As these patents are also classified into technology categories, we can use these to construct a probabilistic mapping from technology categories to industries.[15]

Based on the available IO matrix together with our novel mapping from technology categories to industries, we construct matrices reflecting both upstream and downstream IO connections between technology categories. Further details on the construction of this control are available in Appendix C. As discussed in this appendix, the procedure delivers results that appear to be quite reasonable.

4 Measuring the innovation network

One of the contributions of this study is the introduction of a method for obtaining innovation matrices in historical settings where no systematic patent citation data are available. We start this section by describe how our measure of the network. We then provide evidence from modern data that our method can generate results that are very close to those obtained when using citation data. Last, we describe the innovation networks from Britain and France during the Industrial Revolution recovered using our method.

4.1 Method for measuring the innovation network

In modern settings, where citation data are available, existing studies measure the strength of spillovers from some technology category j to category i as $\omega_{ij}^{cite} = Cites_{ij}/\sum_l Cites_{il}$, where $Cites_{ij}$ is the number of patents in category i citing patents in

[13]The original dataset contains 41 sectors, from which we exclude the four service sectors (*Laundry*, *Public utility*, *Distributive services*, *Other services*), aggregate the four chemical industries to one because of difficulties to match unique occupations (*Chemicals*, *Soap and candle*,*Oils and paint*, *Explosives*), and exclude the *Motor and Cycle* industry because it did not yet exist during our period.

[14]Horrel et al. (1994) provide an input-output matrix for the British economy in 1841, but it is much less detailed than the matrix available from Thomas (1984).

[15]Specifically, we construct a set of weights ϕ_{in} reflecting the ratio of patents in technology category i that are linked to industry n to the total number of patents in category i that are linked to an industry.

category j (e.g. Liu and Ma, 2021). In the citation-based approach, the key assumptions are that some fraction of the useful ideas generated through research in technology j that increase research productivity in technology i are reflected in citations from i to j, and that this fraction is fairly stable across all i-j pairs.

Our approach to measuring connections between technology categories relies on a similar intuition. The basic idea in our approach is that by working on research in technology category j, an inventor may learn lessons that lead to a subsequent invention in technology category i. So, when there are more inventions in category j are followed by inventions in category i by the same inventor, that signals a higher the level of knowledge spillovers from j to i. The key assumptions in our measure are that some fraction of the useful ideas generated through research in technology j that increase research productivity in technology i lead to one or more patents in technology i by inventors who previously patented in technology j, and that these fractions are fairly stable across i-j pairs.

Let P_{kij} be the (weighted) count of pairs of patents by inventor k where the first patent is filed in technology category j and the next patent is filed in technology category i. By "weighted count" we mean that, for patents categorized into multiple technology categories, which only occurs in the British system, each category receives a fraction of a patent that depends on the number of categories across which the patent is listed.

Let P_{ki} be the total number of patents in technology category i by inventor k which pair with an earlier patent, which can be either in i or in another technology category. Our measure of the strength of connections from category j to i is given by:

$$\omega_{ij} = \frac{\sum_k P_{kij}}{\sum_k P_{ki}} \tag{4}$$

The result is a directed matrix of connections from j to i constructed using a method that is very similar to the approach used with patent citations by studies in modern data. Intuitively, our connection values ω_{ij} can be thought of as the fraction of knowledge flows into category i coming from category j, as reflected in the number of inventors who file patents in i just after a previous patent in j. Later, we will show that our method, when applied to modern data, generates an innovation network that is almost identical to the network obtained when using citation data.

Mapping network into foreign categories In some of the analysis below, it will be useful to have an innovation network based on British patents but expressed in French technology categories, or a network based on French patents but expressed in British technology categories. Constructing these networks requires us to use our mapping between the two technology categories. Let $\theta_{i\tilde{i}}$ be the weight used to map patents from, say, French technology category i to British category $\tilde{i}$. Given this, to construct an innovation matrix based on French patents but expressed in British technology categories (or vice versa) we use:

$$\tilde{\omega_{ij}} = \frac{\theta_{i\tilde{i}}\theta_{j\tilde{j}} \sum_k P_{kij}}{\theta_{i\tilde{i}} \sum_k P_{ki}}$$

Joint network Finally, in some of the analysis below we will use a joint matrix constructed using both French and British patents, where one of these sets has been mapped into the technology categories of the other country. A number of potential methods might be used to construct these joint matrices. Any method requires a judgment about the relative weight that should be granted to patents from each system in determining the joint matrix. However, because patents in the two systems are the product of different patent systems and institutional environments, there is no clear way to determine the correct weighting to be applied. Given this, we opt for a simple approach that gives each system equal weight in determining the joint matrix. Specifically, we construct joint matrices where each element is the average of the elements of the matrices constructed from the two different sets of patent data (but expressed in terms of the same technology category).

4.2 Validating our method

Whether the method described above provides a useful measure of the innovation network is ultimately an empirical question. To provide some confidence that our method works, before moving to our main analysis we look at how the innovation network generated using our method in modern data, where we also have citations, compares to a network based on citation links. To do so, we use data on U.S. patents from 1970-2014 from PatStat. As described in more detail in Appendix F, we generate a citation-based innovation matrix using a standard approach taken from previous studies. Our inventor-based innovation matrix is obtained using the approach described above. Once we have the two matrices, we can compare either the edge values or centrality of the nodes in the two matrices.

Table 1 presents results comparing the centrality of nodes within the citation-based and inventor-based networks. We can see that the estimated coefficients are close to one and the centrality values from the inventor-based network explain nearly all of the variation in the nodes of the citation based network. This indicates that our inventor-based approach provides a very close approximation to the network generated using the citation-based approach commonly used in modern studies. We get the same message if we instead compare the edges of the two matrices, as is done in Appendix F

The bottom line from this analysis is that our inventor-based method generates results that are very similar to those obtained using citation data and standard approaches in modern data. These findings suggest that our approach is also likely to

Table 1: Comparing the centrality of nodes in the citation-based and inventor-based networks

	Dep var: Citation-based network centrality		
	(1) Eigenvector	(2) InDegree	(3) OutDegree
Eigenvalue cent. (inventor-based)	0.947***		
	(0.026)		
InDegree cent. (inventor-based)		0.986***	
		(0.018)	
OutDegree cent. (inventor-based)			0.939***
			(0.024)
Constant	0.005*	0.006	0.025
	(0.003)	(1.603)	(0.018)
Observations	120	120	120
R^2	0.949	0.958	0.940

Observations = 3-digit IPC technology categories (network nodes). Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

work well in the historical setting considered in our main analysis, where citation data are unavailable.

4.3 Innovation networks during the Industrial Revolution

In this section, we describe and compare the innovation networks obtained when our method is applied to both British and French patent data. A first glimpse of the innovation network is shown in Figure 1, which provides a visualization of the innovation network based on British patents and expressed in terms of the British technology categories. In the figure, each technology category is a node, the size of node reflects the number of patents filed in that category, and the location of the node is determined by the strength of connections between that node and every other node in the network.

There are several interesting patterns to note. The technology space is characterized by a dense central core area. Near the center of the core area, we see categories such as Steam Engines, Water and Fluids (i.e., pumps, etc.), and Motive Power, as well as many smaller technology categories. These core technologies include a number that historians have highlighted as important for the Industrial Revolution (Landes, 1969; Mokyr, 1990), most notably steam engines. We can also see that there are clusters of related technologies. The most visible of these is the set of chemical technologies located in the northwest part of the central core. This includes Acids, Chemical Salts, Dyeing

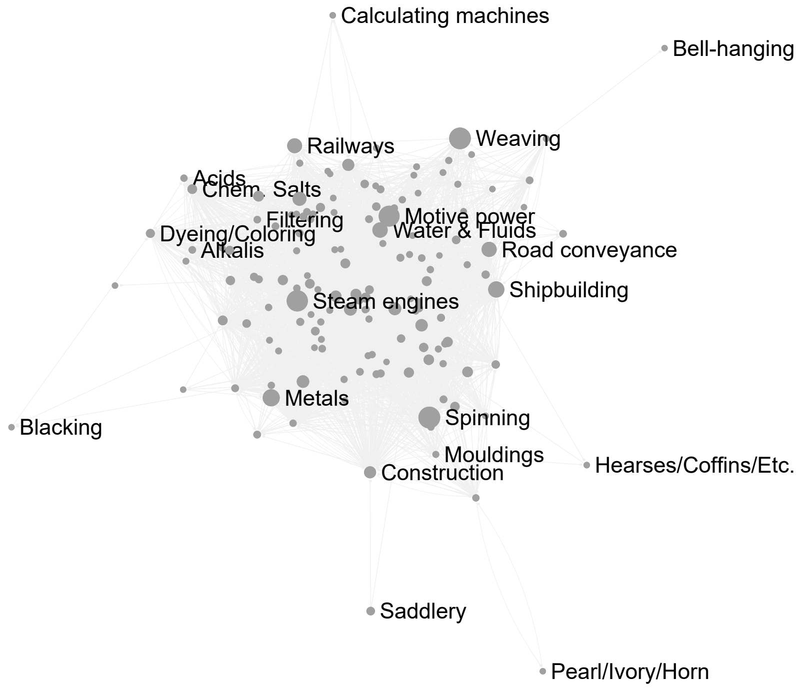


Figure 1: The technology network based on British data

Plot is generated using multidimensional scaling. Some labels are not reported to improve readability.

and Coloring, and Alkalis. Finally, there are a number of very peripheral categories, including such things as Pearl, Ivory, and Horn technologies, Blacking, Bell-hanging, Calculating Machines, and Hearses and Coffins.

Figure 2 visualizes the network obtained from the French patent data and using French technology categories. As in the British case, the French network is characterized by a dense central core surrounded by a set of more peripheral technology categories. Within the core region, we can see technologies such as Steam Engines, Spinning, Weaving, and Misc. engines. We can also see a number of more peripheral technologies, such as Umbrellas, Electricity, and Cannons.

How similar are the two networks? If they show clear similarities, these similarities could reflect fundamental features of the technologies as described by our theory, consistent with an underlying 'global' technology network rather than idiosyncratic local conditions in the British and French innovation systems. In order to make this comparison, we begin with two separate innovation networks, one constructed using only French patents and another constructed using only British patents, but both expressed in terms of the same technology categories. We then apply the following

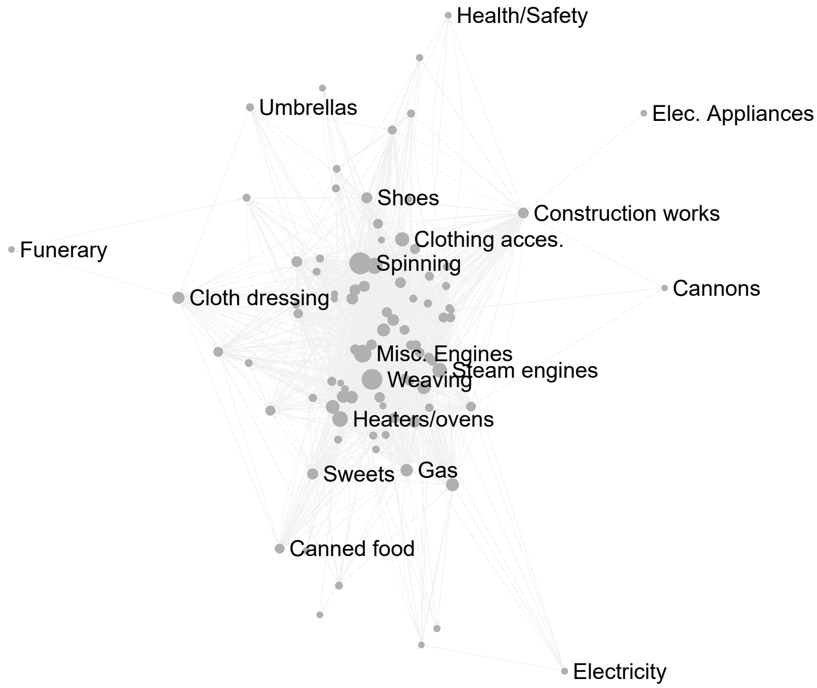


Figure 2: The technology network based on French data

Plot is generated using multidimensional scaling. Some labels are not reported to improve readability.

regression specification:

$$\omega_{ij}^{FR} = \beta_0 + \beta_1 \omega_{ij}^{UK} + \epsilon_{ij}$$

where the superscripts indicate edges from either the French or UK innovation matrices. If the networks were identical, then we would estimate $\beta_1 = 1$ with an R-squared of 1. Given that the two matrices represent two different realizations of any underlying innovation network, together with the fact that we have to map patents from one system into the technology categories of the other, which will introduce substantial noise into the comparison, it is unrealistic to hope that the two matrices will correspond so closely. However, evidence of strong similarities between the two matrices is suggestive of a common underlying network structure, as assumed by the theory.

Table 2 presents the regression results. The first two columns present results where both matrices are expressed in British technology categories. Column 1 compares all ij elements, while Column 2 looks across only those ij matrix entries with non-zero values. Both columns provide clear evidence of similarity across the two matrices. Columns 3 and 4 follow the same structure, but using matrices expressed in French technology categories. Across all four sets of results, we observe strongly significant

Table 2: Comparing the edges of French and British innovation networks

	Dep var: French network edges			
	in UK categories		in French categories	
	(1) incl zeros	(2) excl zeros	(3) incl zeros	(4) excl zeros
UK network edges	0.182***	0.311***	0.063**	0.621***
	(0.033)	(0.043)	(0.025)	(0.193)
Constant	0.029***	0.036***	0.006***	0.027***
	(0.000)	(0.001)	(0.001)	(0.004)
Observations	21462	3401	9120	1435
R^2	0.006	0.080	0.006	0.136

OLS. Observations are network edges connecting nodes (technology categories) i and j. Observations are weighted by the sum of patents in i and j (Stata analytical weights). Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

positive coefficient estimate as well as R-squared values indicating that the patterns observed in one matrix can explain a meaningful fraction of the variation observed in the other matrix.

An alternative approach to assessing matrix similarity is to focus on the centrality of the network nodes, which provides a useful way to summarize the shape of the network. This approach is motivated by our theoretical results, which highlight the importance of centrality in determining outcomes. Table 3 presents regression results comparing the centrality of nodes based French patents to the centrality of nodes based on British patents, where both are expressed in terms of British technology categories.[16] The first column contains results for eigenvector centrality. The next two columns present results for two alternative centrality measures, indegree and outdegree centrality. Across all three, we see clear evidence of commonalities in the network structure, despite the noise induced by the need to map from one system of technology categorizations to another. This provides further evidence that there is some common underlying structure in the innovation networks in Britain and France. We interpret these estimates as indicating that there is a substantial 'global' underlying innovation network.

5 Effect of the network on innovation

In this section, we examine the effect of the network on innovation. In the first step, we follow existing studies on modern innovation networks by running panel regressions using

[16]Equivalent results are obtained if we instead express the matrices in terms of the French technology categories.

Table 3: Comparing node centrality in the French and British networks

	Dep var: French network centrality (in UK categories)		
	(1) Eigenvector	(2) In Degree	(3) Out Degree
UK Eigenvector centrality	0.177***		
	(0.032)		
UK in Degree centrality		0.521***	
		(0.114)	
UK out Degree centrality			0.571***
			(0.129)
Constant	0.072***	96.051***	0.722***
	(0.003)	(4.728)	(0.034)
Observations	132	132	132
R^2	0.253	0.157	0.173

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. OLS regressions with robust standard errors. Observations are network nodes based on U.K. technology categories. A small number of technology categories are dropped (e.g., wigs) because of insufficient data to generate a mapping from French technology categories to those British technology categories.

lagged values of the network-weighted knowledge stock based on Eq. 3. Identification in this approach relies on the assumption of no common shocks to connected technology categories, which can be difficult to establish. To address this concern, we introduce in the second step a novel approach that uses the unexpected arrival of important inventions in certain technology categories to isolate variation in knowledge stocks.

5.1 Effect of knowledge stocks on patenting

Equation 3 expresses the log number of patents in a particular technology category i and year t as a function of the log knowledge stock in other categories that generate spillovers for technology i through the innovation matrix. This expression has been used by existing studies, such as Liu and Ma (2021), to provide evidence that the innovation network has an impact on innovation outcomes. Following this approach, we operationalize this relationship by regressing log patents in category i and year t, n_{it} (plus 1), on lagged patents in other technology categories j in previous years $t-s$, $n_{j,t-s}$ (also plus 1), weighted by the strength of connection in the innovation network between the categories ω_{ij}, conditional on a set of technology category fixed effects A_i and year t fixed effect B_t:

$$\ln(n_{it}+1) = A_i + B_t + \beta_s \sum_{j \neq i} \omega_{ij} \ln(n_{j,t-s}+1) + \epsilon_{it} \quad \text{where } t > s \tag{5}$$

One notable difference in Eq. 5 relative to the model is that we add one to the number of patents in each technology category and year. This is necessary because at the technology category by year level we end up with a large number of cells with zero patents.

Figure 3 presents the estimated β_s for lags from one to ten years using British patent data and the British innovation network. The network proximity weighted lagged knowledge stock is significantly and positively associated with patenting rates. The association decreases over time, consistent with the pattern we would expect given the model. As the finding is fairly similar to those obtained by studies using modern data, it appears that our novel network measures are representing the innovation network well.[17] In Appendix D, we show that similar patterns are also obtained if we include lagged patents in category i as a control. We can also estimate effects for the knowledge stock downstream of category i. Those results show that only knowledge stocks upstream from a category in the innovation affect subsequent patenting in that category, while knowledge stocks in downstream categories have no effect.

5.2 Effect of macroinventions on patenting

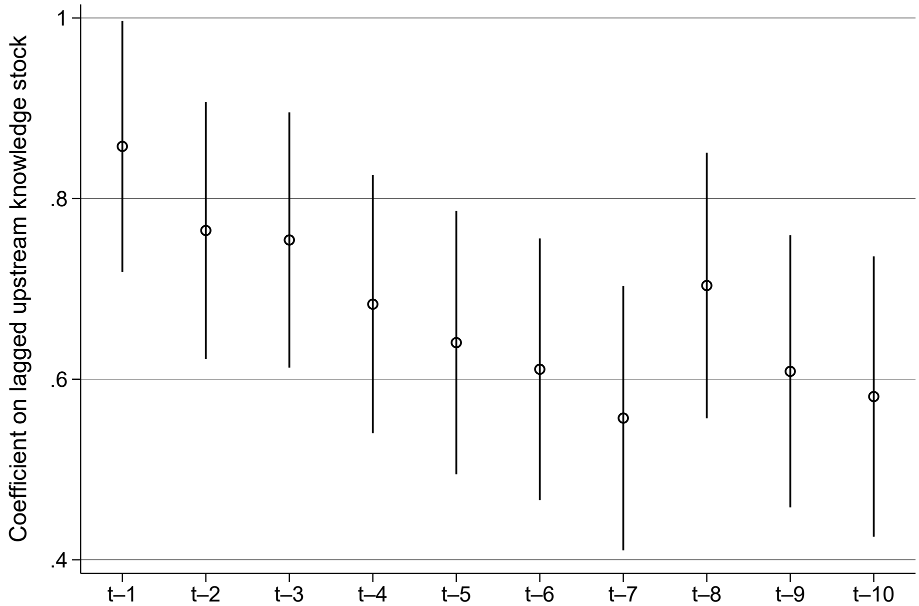
One important concern with the approach above is that there may be common shocks to connected technology categories, which would result both in greater knowledge stocks in some categories as well as higher rates of patenting in other connected technologies, but not as a result of spillovers through the innovation network.

To provide a stronger test of the role of innovation networks, in the next part of our analysis we use the arrival of unexpected macroinventions in certain technology categories as a source of quasi-exogenous variation in knowledge stocks. Macroinventions are ideal for this exercise because (1) they represent substantial increments to existing knowledge and (2) they are thought to be largely unpredictable. Mokyr (1990), for example, described macroinventions as "inventions in which a radical new idea, without a clear precedent, emerges more or less *ab nihilo*." According to Crafts (1995) (p. 596), "Technological history suggests that seeking for socio-economic explanations of macroinventions is likely to be a fruitless pursuit."

The key identifying assumption will be that the exact timing of arrival of macroinvention is unpredictable within the analysis window. The analysis does *not* assume that the technology category in which a macroinvention appeared was random. To illustrate the variation harnessed in our analysis, take the example of steam engines. After Thomas Newcomen introduced the atmospheric engine in 1712, there were consistent

[17] See, e.g., Liu and Ma (2021) Figure 4.

Figure 3: The lagged effect of the knowledge stock on patenting rates



The figure presents estimated coefficients and 95% confidence intervals for PPML regressions based on Eq. 5 applied to all British patents and using the British innovation matrix. We include only patents by domestic inventors. Patents appearing in multiple (N) technology categories count as only a fraction (1/N) of a patent in each of category. Because there are many zeros in the data, we actually use $\ln(n_{it} + 1)$ in place of the $\ln(n_{it})$ terms shown in Eq. 5. Each estimate comes from a separate regression, though joint estimation yields similar results.

efforts to improve the efficiency of the design. Thus, it was likely that a major advance would occur in the area of steam engines at some point in time. However, it took until 1769 that James Watt invented the separate condenser. From the historical accounts, there is no apparent reason why that idea may not have occurred earlier—and it may well have occurred many years later if genius had not struck Mr. Watt.

We use three different approaches to identifying macroinventions. Our first approach relies on a list of 65 British macroinventions provided by Nuvolari et al. (2021).[18] Nuvolari et al. (2021) provide evidence that this was a particularly impactful set of patents, though there may be questions about how unexpected they were. Second, we use a set of 406 patents that were the first patent in a particular technology subcategory.[19] This set of patents is more likely to be unexpected since each patent

[18]These are identified using a wide variety of sources, including contemporary citations to patents complied by Bennett Woodcroft and the British Patent Office, biographies of famous inventors such as the Oxford Dictionary of National Biography, and modern histories of technology such as Bunch & Helleman's *History of Science and Technology.* Nuvolari et al. (2021) define macroinventions as the top 0.5 percentile of patents in a composite citation score that is based on all of the sources they review.

[19]We exclude patents from this list before 1750 since they may appear to be the first patent in their subcategory only because our data began in 1700.

opened up a new technology (sub-)type, but we may have questions about how impactful each of these patents was. As a third measure, we use the intersection of the two sets, which generates a small set of six patents that are likely to be both important and novel. This may seem like a small set of experiments to work with but recall that we can examine the impact across all other technology categories for each event. We call these three alternative macroinvention lists the “Nuvolari et al. list”, the “First patent list”, and the “Intersection list”.

Data and empirical specification We structure the dataset as a stacked panel. We define ‘event’ e as a year t in which at least one macroinvention occurred in technology categories $j \in J^e$. For each event, we construct a sub-panel dataset with four five-year periods τ: Two periods before the event year ($t-10$ to $t-6$ and $t-5$ to $t-1$) and two after ($t+1$ to $t+5$ and years $t+6$ to $t+10$), excluding the year of event t itself. For the cross-sectional dimension, we calculate for each sub-panel technology categories i's upstream connection to the technology category where the macroinvention occurred, $j(e)$, as $Proximity_{ie} = \omega_{ij(e)}$. If there were multiple macroinventions in the year t, then we sum the proximity across all macroinventions. By sub-panel, we omit any technology category in which a macroinvention occurred. Thus, the level of observation will be macroinvention–event e by period τ by technology category i cells.

We begin by estimating a more parsimonious “stacked difference-in-difference” specification,

$$\ln(Patents_{ie\tau}) = \beta_{post}\, Proximity_{ie} \cdot post_{e\tau} + X_{ie\tau}\Gamma + \gamma_{ie} + \eta_{e\tau} + \epsilon_{ie\tau} \tag{6}$$

where $Patents_{ie\tau}$ is the number of patents in technology category i in time period τ of event e, β_{post} the coefficient of interest, $post_{e\tau}$ an indicator for the periods after the arrival of the macroinvention, $X_{ie\tau}$ a set of control variables (interacted with post indicator) defined later, γ_{ie} a set of technology categories by event fixed effects, $\eta_{e\tau}$ a set of periods by event fixed effects, and $\epsilon_{ie\tau}$ an error term that may be correlated across i. The coefficient β_{post} estimates whether patenting changed after the macroinvention differentially in technologies closer in technology space to the category of macroinvention relative to technologies further in technology space from the category of macroinvention.

We also estimate a more demanding “stacked event study” specification,

$$\ln(Patents_{ie\tau}) = \sum_{\tau} \beta_\tau Proximity_{ie} \cdot \mathbb{1}(\tau) + X_{ie\tau}\Gamma + \gamma_{ie} + \eta_{e\tau} + \epsilon_{ie\tau} \tag{7}$$

where, different than before, we estimate β_τ flexibly for periods $\tau \in \{1,3,4\}$—period $\tau = 2$ being the omitted reference period—, and also interact the controls $X_{ie\tau}$ with period indicators $\mathbb{1}\tau$).

Both specifications 6 and 7 effectively average coefficients from separate difference-in-difference or event study regressions, respectively, by stacking the panels to obtain common β_{post} or β_τ coefficients. Given the distribution of the dependent variable, (log) number of patents, we estimate 6 and 7 using Pseudo–Poisson Maximum Likelihood (PPML) regressions.

We focus this analysis on British patents in the period 1700–1830. We do not use data after 1830 because there was a massive increase in the number of patents during that decade, a surge that has been attributed to the influence of a series of legislative and court decisions that made patenting more attractive (see Figure 5).[20] This change appears to have been differential across technology types, so including this period can affect our results substantially.

One potential concern with these regressions is that macroinventions may affect innovation patterns in other technology categories through input-output linkages rather than spillovers across the innovation network (Bloom et al., 2013). To address this concern, we can include controls for upstream and downstream IO linkages to the macroinvention technology category. Another potential concern is that technology categories that are more proximate to the macroinvention categories may be more central within the network. As a result, they might grow more rapidly overall. To deal with this concern, we can include a control for the eigenvalue centrality of each technology category within the network. Moreover, the directed nature of the network provides a natural placebo exercise for all specifications, namely, to use i's downstream proximity to the category of macroinvention $j(e)$, $\textit{proximity downstream}_{ie} = \omega_{j(e)i}$ (the macroinvention happens downstream), instead of the upstream proximity.

Results Table 4 presents results for equation 6. Columns 1 and 2 present results using the Nuvolari et al. list, without and with our full control variables. Columns 3 and 4 present similar results using the first patent list, while columns 5 and 6 present results using the intersection of the two lists. The results show that as a result of a macroinvention upstream, patenting increases significantly in closer connected technology categories. This effect is not explained by any of our control variables—neither upstream and downstream input-output linkages to the macroinvention technology category, a measure of the eigenvalue centrality of each technology category within the network, or the placebo downstream proximity. The coefficients are smaller for the first patent list, arguably less impactful on average than the Nuvolari list. In contrast, the intersection list has substantially larger coefficients—these macroinventions are plausibly more important breakthroughs, and we find significantly larger effects for them.

Figure 4 summarizes event study results based on Eq. 7 using the Nuvolari et al.

[20] Bottomley (2014a) describes (p. 22) how, "around 1830, when there was a 'sea change' in attitudes, that judicial hostility was replaced by a growing appreciation of patenting's role in encouraging innovation...placing patent rights on a much more secure footing."

Table 4: Macroinventions baseline regression results

	Dep var: Ln (number of patents)					
	Nuvolari et al		1^{st} in subcat.		Intersection	
	(1)	(2)	(3)	(4)	(5)	(6)
Proximity upstream × post	0.061***	0.058**	0.034**	0.030*	0.199***	0.205**
	(0.021)	(0.026)	(0.016)	(0.017)	(0.077)	(0.085)
Proximity downstream × post		−0.001		0.010		0.014
		(0.026)		(0.015)		(0.047)
EV centrality × post		−0.012		0.002		0.028
		(0.015)		(0.014)		(0.022)
Upstream I–O × post		−0.008		−0.007		−0.004
		(0.007)		(0.006)		(0.007)
Downstream I–O × post		0.001		−0.006		−0.044
		(0.013)		(0.010)		(0.041)
Category × event FE	✓	✓	✓	✓	✓	✓
Period × event FE	✓	✓	✓	✓	✓	✓
Observations	11591	11519	21595	21455	1925	1911
Estim. FE coef.	3535	3508	6643	6591	572	567
Number of clusters	138	136	139	137	129	127
Pseudo R^2	0.199	0.198	0.198	0.197	0.197	0.196

Poisson pseudo maximum likelihood (PPML) regressions. Observation = category–event–period, with four periods per event, two before the event ($[t-10, t-6]$ and $[t-5, t-1]$) and two after the event ($[t+1, t+5]$ and $[t+6, t+10]$). Standard errors are clustered at the level of technology category. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

list. The results in Figure 4 indicate that, prior to the arrival of a macroinvention, there was no differential patenting trends in technology categories that were more proximate to (upstream) macroinvention technology categories. After the arrival of the macroinvention, we observe a substantial increase in the number of patents in technology categories that were more proximate to the upstream macroinvention category relative to those less proximate within the same period. These patterns are apparent using either approach to identifying macroinventions.

Results obtained using the first patent or intersection list, provided in Appendix Figure 7, are also very similar. The only notable difference between the results in these two panels is that when using the first patent list, the effects seem to die out over time, as the model would lead us to expect, while there is some evidence of an increased effect over time when using the Nuvolari list (though the standard errors rule out drawing any clear conclusions regarding this pattern). We also observe no evidence that having

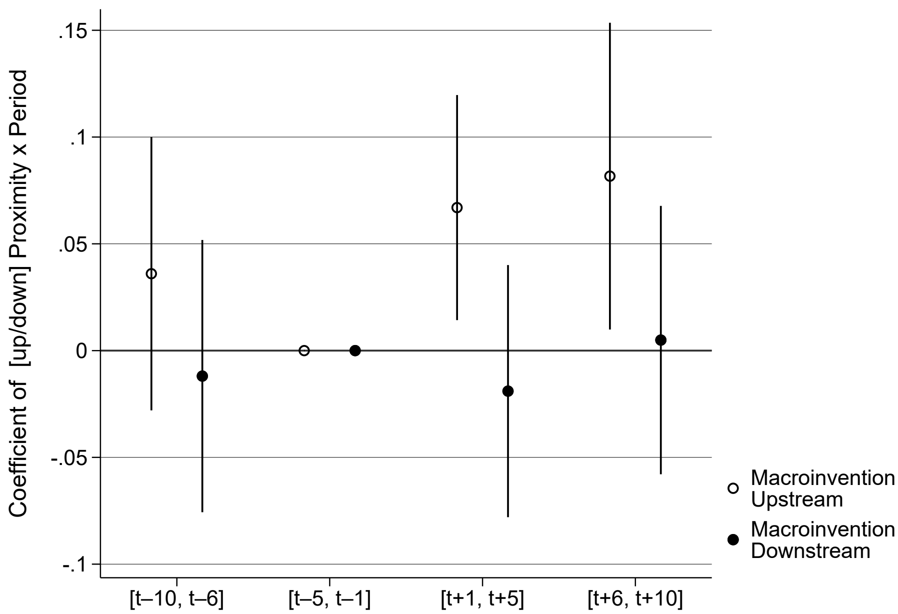


Figure 4: Macroinvention event study, Nuvolari et al definition

The figure presents estimated coefficients and 95% confidence intervals (robust standard errors) for PPML regressions of log patents on the interaction of proximity to a macroinvention ($proximity_{ie}$) either upstream or downstream of a technology category and indicators for every five years before and after the event. The five-year period just before the macroinvention is the omitted reference category. Additional results using this event study approach are available in Appendix E. The regression includes controls for upstream and downstream IO connections to the macroinvention technology category and the eigenvalue centrality of each technology category, each interacted with time-period indicators.

a macroinvention arrive downstream in the innovation network affects patenting rates. This provides additional confidence that our directed innovation network is capturing meaningful spillovers from upstream to downstream technology categories.

In Appendix E, we provide some additional robustness checks for our macroinvention analysis. Specifically, we show that similar results are obtained if we run regressions in levels rather than logs, which allows us to include those category-period bins with zero patents.

6 Centrality of inventors by country

The previous section provides evidence that the shape of the innovation network matters for technological progress. In this section, we look at whether there are systematic differences between Britain and France in terms of the distribution of researchers across technology categories, which could have implications for their rate of technology growth.

Motivated by the theoretical results, in this section we focus on comparing the relative centrality of British and French inventors. These results provide suggestive evidence relating to the growth outcomes that we can expect from the different distributions of research efforts (as reflected by patents) in these two economies. However, the analysis in this section, which has some advantages from an empirical point of view, will not map directly into the model. In the next section, we take the model more seriously and analyze the differential growth outcomes implied by the theoretical framework given the observed differences in the allocation of research effort between the British and French economies.

To generate a fair comparison between the centrality of British and French inventors within the innovation network, we compare in both countries foreign inventors to domestic inventors, using the domestic innovation network. If we find that foreign inventors were always patenting in more central categories, in Britain as in France, differences in centrality could be due to a foreign inventor selection effect. If, however, we find that only inventors from one country are more central, we can rule out such selection effect. For example, using French patents and the French network, we estimate

$$Centrality_{pkt} = \beta_{\mathrm{UK}}\mathrm{UK}_k + \beta_{foreign}\ OtherForeign_k + \phi_t + \epsilon_{pkt} \tag{8}$$

where $Centrality_{pkt}$ is the centrality of the technology category associated with patent p patented by inventor k in year t, UK_k is an indicator for whether inventor k reported a UK address when filing the patent in France, and $OtherForeign_k$ is an indicator for whether the inventor listed some other location outside of France as their address, for example in the USA, or the patent type is "of unspecified origin" (*communication* in British patents, *importation* in French patents). We also include a set of year-of-patent-filing fixed effects ϕ_t.

Table 5 shows that British inventors patenting in France patented in substantially more central technology categories than any other group of patentees in France, foreign or domestic. This holds for three different centrality measures, *eigenvalue centrality*—the main centrality measure from the theory—as well as both *indegree* and *outdegree* centrality. Whereas the first columns of each centrality measure (1, 3, 5) report that foreign inventors patenting in France were generally patenting in more central categories, the second columns (2, 4, 6) show that this is particularly due to British based inventors.

Table 5 shows that French inventors patenting in Britain did *not* patent in more central technology categories than British or other foreign patentees across all centrality measures. In fact, foreign inventors in Britain patent generally in significantly less central categories than the average British inventor (columns 1, 3, 5). Splitting up foreign inventors by origin (columns 2, 4, 6), we see that this association is driven both by French foreign inventors and other foreign inventors. The coefficient on French inventors is not significant, but it has the same magnitude (negative). Due to the irregular reporting of addresses in the British patent data, the majority of "other foreign inventors" are most likely from France. Interestingly, US-based inventors patenting in

Table 5: Centrality of British inventors within the French innovation network

	Dep var: French patent centrality (standardized)					
	Eigenvector		Out Degree		In Degree	
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign inventor	0.080***		0.076***		0.092***	
	(0.018)		(0.018)		(0.018)	
UK inventor		0.141***		0.138***		0.138***
		(0.035)		(0.036)		(0.037)
US inventor		−0.065		−0.077		0.009
		(0.138)		(0.138)		(0.138)
Other foreign inventor		0.065***		0.061***		0.081***
		(0.020)		(0.020)		(0.020)
Year FE	✓	✓	✓	✓	✓	✓
Observations	14145	14145	14145	14145	14145	14145
R^2	0.012	0.012	0.011	0.012	0.013	0.013

Observation = inventor–patent in France (French patents, French categories). The dependent variables are the centrality of the technology category associated with a patent, standardized to mean zero and standard deviation of one. Foreign inventors are identified based on the reported addresses and an indicator for unspecified foreign origin (*imported patent*). Robust standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Britain are more central than the average British inventor.

In sum, it appears that British inventors were systematically working in more central technology categories than French inventors. This fact is derived from both British and French patents and innovation networks and is thus independent from the mapping of categories across countries. Furthermore, the result cannot be explained by the fact that inventors patenting in a foreign country might generally have patented in more central categories.

The results in this section provide a first piece of evidence showing that British inventors tended to work in technology categories that were located more centrally within the innovation network. From the theoretical results, we know that the optimal allocation of researchers, from a growth perspective, involves a larger allocation of researchers working in more central technology categories. However, these results alone don't tell us that the more central allocation of British inventions that we observe will necessarily translate into a higher growth rate. In order to take that next step, we need to use the theory in order to assess the growth implications of the different allocations of research effort that we observe in the two different economies.

Table 6: Centrality of French inventors within the British innovation network

	Dep var: UK patent centrality (standardized)					
	Eigenvector		Out Degree		In Degree	
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign inventor	−0.111***		−0.069***		−0.064***	
	(0.024)		(0.024)		(0.023)	
French inventor		−0.066		−0.087		−0.110
		(0.076)		(0.076)		(0.074)
US inventor		0.185**		0.103		0.065
		(0.079)		(0.086)		(0.084)
Other foreign inventor		−0.143***		−0.083***		−0.072***
		(0.026)		(0.025)		(0.025)
Year FE	✓	✓	✓	✓	✓	✓
Observations	12384	12384	12384	12384	12384	12384
R^2	0.014	0.015	0.012	0.012	0.011	0.011

Observation = inventor–patent in Britain (UK patents, UK categories). The dependent variables are the centrality of the technology category associated with a patent, standardized to mean zero and standard deviation of one. For patents with multiple technology categories, centrality is averaged across categories. Foreign inventors are identified based on the reported addresses and an indicator for unspecified foreign origin (*communicated patent*). Robust standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7 Quantification of growth effects

In this section, we assess the quantitative importance of the different allocations of research effort observed in France and Britain. To do so, we start with one of the key results generated by the theory, which expresses the difference in growth rates between two allocations of research activity across different technology sectors ($\mathbf{b}$ vectors):

$$g(\tilde{\mathbf{b}}) - g(\mathbf{b}) = \lambda\, \mathbf{a}'(\ln \tilde{\mathbf{b}} - \ln \mathbf{b}) \tag{9}$$

This expression tells us that the difference in growth rates (in the BGP) depends on the interaction of the allocations of researchers across technology sectors (the $\mathbf{b}$ and $\tilde{\mathbf{b}}$ vectors) and the shape of the technology space, reflected in the $\mathbf{a}$ vector, as well as the λ parameter, which represents the size of each technology step in the model.

We have constructed a set of alternative innovation networks that can be used to obtain the $\mathbf{a}$ vector. We infer $\mathbf{b}^{\mathrm{FR}}$ and $\mathbf{b}^{\mathrm{UK}}$ from the number of patents filed by inventors from each country in each technology category. When calculating these, we use only the French patents filed by inventors who list a modal address in France, and

Table 7: Technologies most associated with inventors in each country

	Highest relative British allocations		Highest relative French allocations
1	Steam engines	1	Lamps
2	Shipbuilding	2	Wearing apparel
3	Metals	3	Stationary and bookbinding
4	Coaches and road conveyance	4	India-rubber and gutta-purcha
5	Railways and rolling stock	5	Sugar manufacturing
6	Fireplaces, stoves, furnaces	6	Paper and pasteboard
7	Motive power and propulsion	7	Gas manufacture and consumption
8	Brewing and distilling	8	Games, exercises and amusements
9	Cloth fulling and dressing	9	Heat, heating, evaporating
10	Harbors and lighthouses	10	Pipes, tubes and drain tiles

The table lists by country the top ten categories in which either British inventors hold the highest relative share of patents (left, highest $\mathbf{b}^{\mathrm{UK}} - \mathbf{b}^{\mathrm{FR}}$) or French inventors (right, lowest $\mathbf{b}^{\mathrm{UK}} - \mathbf{b}^{\mathrm{FR}}$). For example, steam engines accounts for 3.9% of British patents but only 2.2% of French patents, while Lamps accounts for 3.5% of French patents but only 1.9% of British patents. The results are expressed in terms of British technology categories. The pattern is very similar if one uses French technology categories.

for the British patents we drop all of those communicated from abroad or listing a foreign address.

Before moving on, it is interesting to observe how the allocations $\mathbf{b}^{\mathrm{FR}}$ and $\mathbf{b}^{\mathrm{UK}}$ differ. We do this, in Table 7, by comparing the allocation of patents for both countries but expressed in terms of the British technology categories. We can see that British inventors hold the highest relative share of patents ($\mathbf{b}^{\mathrm{UK}} - \mathbf{b}^{\mathrm{FR}}$) in several categories that feature importantly in historical accounts of the Industrial Revolution, including steam engines, metals, railroads, shipbuilding, and motive power. Relative to this set, the technology categories most associated with French inventors are typically not those we think of as crucial to the Industrial Revolution.

The final missing piece in Eq. 9 is the λ parameter. Recall from Eq. 2 that this parameter determines how much patents augment the stock of available technology. Below, we offer two approaches to dealing with this issue. First, we offer a less parametric approach that allows us to generate relative growth results without needing an estimate of λ. The downside of these results is that they are difficult to interpret. Second, we use a range of λ parameter estimates from existing studies to obtain more easily interpretable estimates of the difference in growth rates implied by the different allocations that we observe.

For the less parametric approach, we begin by noting that the model provides a method for calculating the optimal allocation (from a growth perspective) of researchers across the different technology sectors, $\mathbf{b}^*$. Using this fact, we can express the differences in growth rates implied by the allocations observed in Britain and France relative to

Table 8: The effect of the innovation network on relative growth in Britain vs France

Network based on patents from:	Expressed in categories of:	British allocation, distance from optimum	French allocation, distance from optimum	Ratio of growth differences
Both countries	Britain	0.38	0.44	1.179
Both countries	France	0.28	0.30	1.080

Table 9: Differences in growth in Britain vs. France for different λ values

Network based on patents from:	Expressed in categories of:	Low estimate ($\lambda = 0.13$)	Medium estimate ($\lambda = 0.173$)	High estimate ($\lambda = 0.22$)
Both countries	Britain	0.0088	0.012	0.035
Both countries	France	0.0029	0.004	0.024
Average		0.0058	0.0077	0.0292

The table presents the differences in the growth rates between Britain and France, obtained from Eq. 9, for various values of λ. In the first column of results, we use a low estimate from existing studies, of $\lambda = 0.13$ from Acemoglu et al. (2018). In the second column of results, we use a medium estimate from existing work, 0.173 from Liu and Ma (2021). In the third column, we use a high estimate of 0.22 based on Aghion et al. (2019).

the optimal allocation:

$$\frac{g(\mathbf{b}^{\mathrm{FR}}) - g(\mathbf{b}^{*})}{g(\mathbf{b}^{\mathrm{UK}}) - g(\mathbf{b}^{*})} = \frac{\mathbf{a}'(\ln \mathbf{b}^{\mathrm{FR}} - \ln \mathbf{b}^{*})}{\mathbf{a}'(\ln \mathbf{b}^{\mathrm{UK}} - \ln \mathbf{b}^{*})} \tag{10}$$

At the cost of expressing the difference in growth rates relative to the (unknown) maximum rate of growth, the expression allows us to avoid taking a stand on the value of λ.

Table 8 presents estimates based on Eq. 10 showing that, within an innovation matrix based on patents from both countries, France was consistently further away from the maximum attainable technology growth rate than Britain. Column (1) shows that the British inventor allocation generates growth rates that are substantially below the optimum achievable growth rate. However, the French inventor allocation (column 2) generates growth rates that are even further from the optimum—and always more remote than the British. As a result, in each scenario the British allocation generates more rapid technology growth than the French allocation (column 3). Specifically, these results indicate that the French technology growth rate was between 8 and 17 percent further from the maximum achievable growth rate than the British allocation.

For the parametric approach, we consider a range of λ values obtained from existing studies and then study the implications of our results under each. Table 9 presents the growth difference between the British and French economies that are implied by the innovation network and different inventor allocations for low, medium, and high λ values found in previous studies.

These estimates indicate that differences in the allocation of researchers across sectors generate growth differences ranging from, on the low end. 0.5%, to 2.9% on the high end. Available estimates suggest that growth of industrial production in Britain was around 3 to 3.5% during the first half of the nineteenth century (Broadberry et al., 2015) and in the growth rate in france was around 1.7 to 2.5% in the same period (Crouzet, 1996; Asselain, 2007). This suggests growth rate differences ranging from 0.5 to 1.8 percentage points. Thus, our results indicate that the impact of differences in the allocation of researchers within the technology network was large enough to explain a meaningful fraction, and possibly the entirety, of the difference in growth rates estimated for Britain and France during this period.

8 Conclusions

Did it matter that in the early decades of the Industrial Revolution many British researchers worked in technology areas, such as steam engines or textile machinery, rather than technologies such as papermaking or chemicals? We argue that the answer to this question is that, yes, it did matter. Specifically, we show that the distribution of British inventors within the technology space differed in fundamental ways from the distribution of inventors in the most natural comparison country, France, and that this distribution had a meaningful impact on the difference in technology growth rates in the two countries. To make this argument, we bring together frontier theoretical tools, rich historical patent data, and a novel approach to measuring the structure of the innovation network in a historical setting.

Our results enrich our understanding of the factors that contributed to Britain's industrial dominance during the Industrial Revolution. They also contribute to a broader literature looking at the importance of innovation networks in economic growth, by providing direct evidence on the role that the structure of the innovation network played during an important period of economic history.

In addition to helping us better understand the nature Britain's advantages during the early decades of the Industrial Revolution, our findings may also shed light on why these advantages slipped away in the late-nineteenth and early-twentieth centuries. It seems likely that the structure of the innovation network was slowly evolving over the nineteenth century, with the rising importance of chemical and electrical technologies that characterized the the Second Industrial Revolution. This change in the technology space away from the mechanical technologies may help explain why Britain found it increasingly difficult to maintain its position as industrial leader. One interesting direction for future work is assessing the extent to which slow-moving changes in the underlying innovation network may have undermined Britain's advantages and contributed to the erosion of British leadership in the late nineteenth and early twentieth century.

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A Additional details on the British patent system

Figure 5 describes the number of patents filed in England and Wales from 1700 to 1849. The large increase in the number of patents starting in 1830 has been attributed to a set of court decisions that made it more likely that patents would be upheld in court, thereby making patenting more attractive (Bottomley, 2014a).

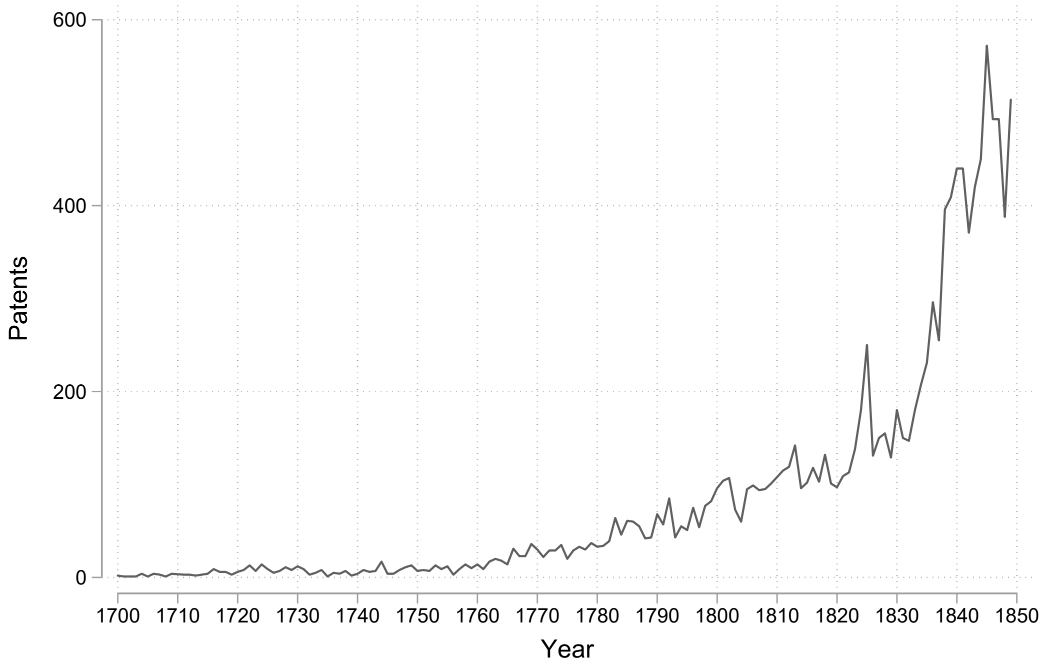


Figure 5: British patents over time

B Mapping French to British technology categories

This appendix provides some additional details regarding the construction of the mapping between the different British and French technology category classifications. As described in the main appendix, we construct three groups of patents where we can identify the same patent filed in both Britain and France:

1. Starting with French patents filed before 1844 and searching for corresponding patents in England, with matches constructed using a manual review based on inventor name, patent titles, and the patents being filed within a few years of one another. We identify 167 matched patents using this method.

2. Starting with English patents filed up to 1849 and searching for corresponding patents in France, with matches based on the same criteria as above. We identify 127 patents using this method.

3. Starting with French patents filed after 1844 and matched to English patents using the exact filing date of the English patent recorded by the French patent office. For these patents, as long as the title indicates that we have identified a correct match, we allow variation in the inventor name (common when patent agents appear as the inventor). We identify 855 matched French patents using this method, which correspond to 808 matched British patents, since some British patents correspond to more than one French patent.

Using these data, we construct a set of weights mapping French technology categories (i) to British categories (j) (and vice versa from British to French categories) where each weight is given by:

$$\theta_{ij} = Pat_{ij}/Pat_i \quad .$$

To provide a sense of what these category mappings look like, Table 10 presents, for the first twenty British technology categories, the most closely related French technology category, as well as the corresponding weight of the mapping between them. Table 11 presents similar information for the mapping for the first twenty French technology categories. While the mapping is clearly imperfect, we can see that it generally seems quite reasonable.

Focusing on Table 10, in a number of cases we observe a clear correspondence between the French and British technology categories. In some cases, such as "Aerial Conveyances" into "Aviation" or "Alkalis" into "Chemicals-General," the British category fully maps into a French category. In a number of others, such as "Boots, Shoes, Clogs, Pattens, etc." into "Shoemaking", the weight is close to one. However, there are others–"Bearings, Wheels, Axles, And Driving-Bands" for example–where the mapping between the two

Table 10: Mapping from British to French technology categories with weights

British category (first 20)	Closest French category	Mapping weight
Accidents, Prevention Of	Railroads	.26
Acids	Chemicals-General	.88
Adhesive Substances	Canned food	.5
Aerated Liquors, Mineral Waters, etc.	Drinks	.75
Aerial Conveyances	Aviation	1
Agricultural Produce	Milling	.82
Agriculture	Agricultural Machines	.61
Air and Gas Engines And Windmills	Misc Engines	.42
Alarms, Snares, And Vermin Traps	Construction fittings	1
Alkaline Lees, Wash Waters, And Bleaching	Chemicals-General	1
Alkalis	Chemicals-General	1
Assurance: Preventing Forgery And Fraud	Paper making	1
Baths And Bathing-Machines	Chemicals-Rubber etc.	1
Bearings, Wheels, Axles, And Driving-Bands	Railcars	.23
(tie)	Machine components	.23
(tie)	Misc Engines	.23
Bell-Hanging	Locks	1
Blacking		
Bleaching, Washing, And Scouring	Textile finishing	.57
Boilers And Pans	Steam engines	.74
Boots, Shoes, Clogs, Pattens, etc.	Shoemaking	.87
Boring, Drilling, Punching	Machine tools	.46

categorizations is less clear. There are a small number of categories, such as “Blacking” (i.e., shoe polish) where it is not possible to construct a mapping. Any patents in those categories, which tend to be very small, will be dropped in any analysis where we map patents from one classification system to the other. Similar patterns are visible when focusing on the mapping from French into British categories in Table 11. Overall, we can conclude that our mapping approach is largely reasonable, though it is also clear that converting from one categorization to another will also introduce a meaningful amount of noise into our analysis.

Table 11: Mapping from French to British technology categories with weights

French category (first 20)	**Closest British category**	**Mapping weight**
Agricultural Machines	Agriculture.	.8
Fertilizer	Manure; Deodorizing Fecal Matters	.43
Rural Engineering	Agriculture.	.5
Breeding etc	Weaving, And Preparing For Weaving	.5
Milling	Agricultural Produce	.56
Baking	Cooking: Making Bread And Confectionery	.67
Sweets	Sugar Manufacture	.76
Canned food	Preserving & Curing Provisions, other Substances, Liquids	.53
Drinks	Brewing, Distilling, Rectifying, And Preparatory Processes	.4
Railroads	Railways And Railway Rolling-Stock	.64
Locomotives	Railways And Railway Rolling-Stock	.49
Railcars	Railways And Railway Rolling-Stock	.7
Spinning	Spinning And Preparing For Spinning	.8
Textile finishing	Printing	.36
Weaving	Weaving, And Preparing For Weaving	.57
Knitting	Spinning And Preparing For Spinning	.4
Lace etc	Weaving, And Preparing For Weaving	.71
Other textiles	Rope Manufacture	.75
Paper making	Paper And Pasteboard	.85
Carton	Calculating-Machines: Apparatus for Teaching	.25
(tie)	Games, Exercises, And Amusements	.25
(tie)	Lighting; Lamps And Luminaries; Matches	.25
(tie)	Paper And Pasteboard	.25

C British IO matrix construction

This appendix provides some additional details and discussion of the methods used to construct input-output links between technology categories. Note that these links are primarily used in our analysis of the impact of macroinventions, which uses only British data. Thus, our focus is on construct input-output controls for that context.

The main challenge in constructing these matrices is mapping technology categories to the industries available in the IO matrix. To do so, we first try to match the occupation found in the patent data to IO industries. This is done through a manual review of the roughly 7,000 occupation titles listed in British patents from 1700-1849. A subset of these occupations unambiguously match to industries present in the IO table. Note that this does not always mean that the patented invention is associated with that industry; our assumption is that on average individuals working in a particular industry are likely to be invention technologies associated with that industry.

To provide a sense of the types of occupations corresponding to different industries, Table 12 lists by IO industry the three most common "topics" contained in occupations that help us to establish unambiguous matches. Generally, we do not match generic occupations that refer to professions or class/status (e.g. merchant, manager, worker, officer) unless they are qualified by a topic that refers unambiguously to one industry. For example, we do not match "engineers" to the industry "Engineering" because the unqualified occupation title refers to a profession rather than an industry. However, we match coal mining (colliery) engineer to the coal mining industry because in this case, the qualifying topic is unambiguous.[21]

Once we have a mapping from occupations to industries, the mapping from technology categories to industries is straightforward given that occupations are associated with patents which are classified into technology categories.[22] We can use this mapping, together with the information included in the IO matrix, to construct measures of the upstream and downstream links between different technology categories.

The resulting probabilistic mapping from technology categories to industries appear quite reasonable. To illustrate this, Table 13 lists, for each IO industry, the most important technology category (highest weight). In cases where a technology category exists that is broadly similar to the IO industry, this technology category receives the highest weight: e.g. the *Agriculture* technology category to the *Agriculture, Forestry, etc* industry; the *Ship-Building, Rigging, And Working* technology category to the *Shipbuilding* industry. Furthermore, industries that one would expect to be more

[21]Some professions are ambiguous even if qualified by a topic, for example "coal merchant" or "cloth merchant" because we do not know if this occupation worked in industry or in the excluded distribution services. One exception to the rule are composite occupations like "woollen manufacturer and merchant" because there the "manufacturer" clearly indicated involvement in production.

[22]Two minor technology categories are missing because we were unable to map their associated occupations to any IO industry. These are "Diving, engines for diving" and "Maps and Globes".

Table 12: Information used for matching input–output industries to occupations

	Most common occupation theme		
Input–output industry	ranked 1st	2nd	3rd
Agriculture, Forestry, etc	farmer	agriculturalist	planter
Coal Mining	coal	colliery	viewer
Other mining	quarry	quarryman	engineer
Coke ovens	coke	burner	breeze
Iron and Steel	iron	steel	founder
Non-ferrouse metals	brass	founder	tin
Engineering	machine	agricultural	engine
Metal Goods, NES	tool	lock	wire
Shipbuilding	ship	builder	shipwright
Railway Rolling stock	railway	builder	carriage
Cotton and silk	cotton	spinner	silk
Woolen and worsted	wool	spinner	worsted
Hosiery and lace	lace	hosier	hosiery
Other textiles	carpet	elastic	cloth
Jute, hemp, and linen	flax	spinner	rope
Textile finishing	dyer	finisher	printer
Clothing	hat	tailor	clothier
Boot and shoe	boot	shoe	gutta-percha
Leather and fur	leather	harness	currier
Food processing	miller	baker	sugar
Drink	brewer	water	distiller
Tobacco	cigar	tobacco	snuff
Chemicals	chemist	oil	chemical
Paper	paper	card	stainer
Printing and publishing	printer	stationer	publisher
Rubber	india-rubber	rubber	gutta-percha
Timber trades	sawyer	mill	saw
Furniture	cabinet	dressing	case
Other wood	block	bobbin	wood
Building materials	brick	tile	stone
Building, etc.	builder	architect	painter
Misc. Manufactures	instrument	glass	watch
Gas, electricity, water	gas	meter	apparatus

The topics are obtained from breaking splitting the occupation string in parts, e.g. “iron founder” into “iron” and “founder”. The table excludes generic themes such as manufacturing, manufacturer, maker, worker, master, manager, agent, proprietor. Note that we do not match the occupations to industries based on individual themes but based on the information contained in the full occupation string.

technologically diverse tend to place relatively low weight on the top technology category (e.g. Metal Goods, NES; Chemicals), while industries that one would expect to be more technologically specialized typically place a higher weight on the top technology category (e.g. *Boot and Shoe* to *Boots, Shoes, Clogs, Pattens, etc.*).

Table 14 lists, for the first 50 technology categories (in alphabetical order), the most important IO industry. Note that the difference in the weights between the two tables comes from a different normalization—here, weights are normalized to one by technology category. Again, this mapping conforms reasonably well to what we would expect. Highly specialized technologies are mapped with high precision into one industry (and the "correct" one), as in the cases of Bell-Hanging (to Non-ferrous metals), Blacking (to Boot and Shoe), Calculating Machines, and Combs (to Mixed Manufacture). This pattern holds consistently even when many specialized technologies should connect to the same industry (e.g. Chemicals industry, Acids, Alkaline Lees, Alkalis, and Chemical salts all receive high weights). Moreover, as one would expect, technology categories are mapped with low weights on many different industries when they are based on principles like "Prevention of Accidents," or composites like "Bearings, Wheels, Axles, And Driving-Bands," that are not particular to any one industry.

Table 13: Most important technology category by input–output industry

Input–output industry	Top technology category	Weight IO←TC
Agriculture, Forestry, etc	Agriculture.	0.495
Coal Mining	Water And Fluids	0.135
Coke ovens	Fireplaces, Stoves, Furnaces, Ovens, And Kilns.	0.5
Coke ovens	Heat, Heating, Evaporating, And Concentrating	0.5
Iron and Steel	Metals And Metallic Substances	0.31
Non-ferrouse metals	Lighting; Lamps And Luminaries; Matches	0.089
Engineering	Spinning And Preparing For Spinning	0.309
Metal Goods, NES	Locks And Other Fastenings.	0.101
Shipbuilding	Ship-Building, Rigging, And Working.	0.577
Railway Rolling stock	Railways And Railway Rolling-Stock	0.5
Cotton and silk	Spinning And Preparing For Spinning	0.494
Woolen and worsted	Spinning And Preparing For Spinning	0.487
Hosiery and lace	Weaving, And Preparing For Weaving.	0.775
Other textiles	Weaving, And Preparing For Weaving.	0.602
Jute, hemp, and linen	Spinning And Preparing For Spinning	0.429
Textile finishing	Printing.	0.244
Clothing	Wearing-Apparel	0.33
Boot and shoe	Boots, Shoes, Clogs, Pattens, &C.	0.567
Leather and fur	Tanning And Preserving: Treatment Of Skins; Curriery	0.434
Food processing	Agricultural Produce	0.161
Drink	Brewing, Distilling, Rectifying, And Preparatory Processes	0.476
Tobacco	Gas Manufacture And Consumption	0.4
Tobacco	Tobacco And Snuff	0.4
Chemicals	Chemical Salts, Compositions, Gases, And Processes	0.106
Paper	Paper And Pasteboard.	0.512
Printing and publishing	Printing.	0.453
Rubber	India-Rubber And Gutta-Percha	0.667
Timber trades	Lighting; Lamps And Luminaries; Matches	0.5
Furniture	Furniture and Cabinet-ware	0.398
Other wood	Ship-Building, Rigging, And Working.	0.379
Building materials	Building Materials.-Burning Lime	0.406
Building, etc.	Building And Relative Processes	0.149
Misc. Manufactures	Musical Instruments	0.197
Gas, electricity, water	Gas Manufacture And Consumption	0.419

The tables lists by input–output industry the most important technology, including the associated weight to map technology categories into industries.

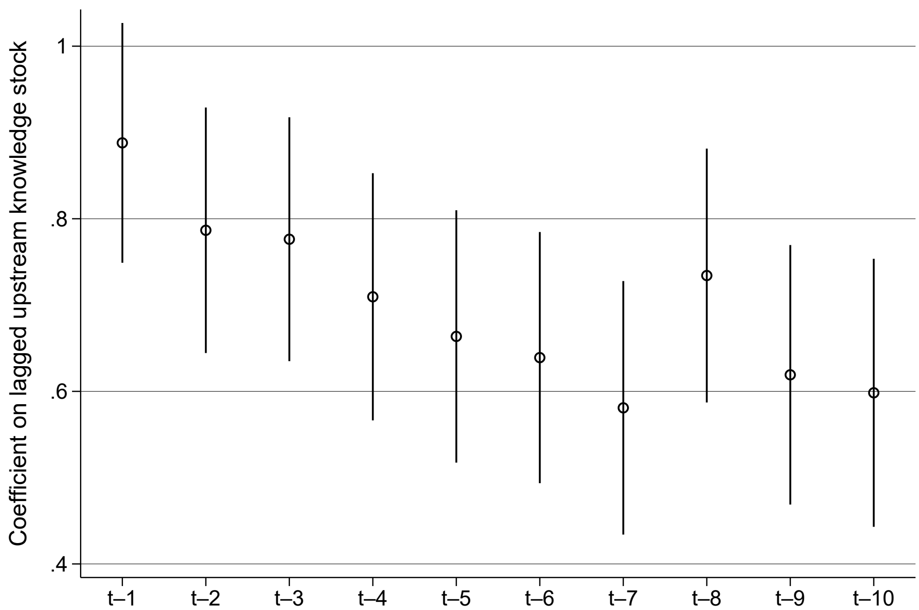
Table 14: Most important input–output industry by technology category

Technology category	Top input–output industry	Weight TC←IO
Accidents, Prevention Of	Non-ferrouse metals	0.155
Acids	Chemicals	0.753
Adhesive Substances	Chemicals	0.5
Aerated Liquors, Mineral Waters, etc	Chemicals	0.658
Aerial Conveyances	Furniture	1
Agricultural Produce	Food processing	0.299
Agriculture.	Agriculture, Forestry, etc	0.447
Air And Wind ;-Air And Gas Engines And Windmills	Misc. Manufactures	0.282
Alarms, Snares, And Vermin Traps	Misc. Manufactures	0.334
Alkaline Lees, Wash Waters, And Bleaching	Chemicals	0.676
Alkalis.	Chemicals	0.865
Assurance: Preventing Forgery And Fraud.	Printing and publishing	1
Baths And Bathing-Machines.	Misc. Manufactures	0.481
Bearings, Wheels, Axles, And Driving-Bands.	Metal Goods, NES	0.169
Bearings, Wheels, Axles, And Driving-Bands.	Cotton and silk	0.169
Bearings, Wheels, Axles, And Driving-Bands.	Boot and shoe	0.169
Bearings, Wheels, Axles, And Driving-Bands.	Rubber	0.169
Bearings, Wheels, Axles, And Driving-Bands.	Building, etc.	0.169
Bell-Hanging.	Non-ferrouse metals	1
Blacking	Boot and shoe	1
Bleaching, Washing, And Scouring	Textile finishing	0.458
Boilers And Pans	Chemicals	0.164
Boots, Shoes, Clogs, Pattens, etc	Boot and shoe	0.613
Boring, Drilling, Punching	Engineering	0.569
Bottles, Vessels, And Jars, Covers And Stoppers	Misc. Manufactures	0.43
Brewing, Distilling, Rectifying, And Preparatory Processes	Drink	0.545
Bridges, arches, viaducts, aquaducts	Building, etc.	0.522
Brushes.	Misc. Manufactures	0.808
Building And Relative Processes	Building, etc.	0.479
Building Materials.-Burning Lime	Building, etc.	0.364
Buttons, Buckles, Studs, And Other Dress-Fastenings.	Misc. Manufactures	0.469
Calculating-Machines; Apparatus for Teaching	Misc. Manufactures	1
Candle Manufacture;-Preparing Candle And Other Wicks.	Chemicals	0.91
Casks And Barrels	Drink	0.571
Casting.	Iron and Steel	0.5
Chains And Chain-Cables.	Iron and Steel	0.375
Chemical Salts, Compositions, Gases, And Processes	Chemicals	0.844
Clocks, Watches, Chronometers, And Other Timekeepers.	Misc. Manufactures	0.991
Cloth Fulling, Dressing, Cutting, And Finishing	Textile finishing	0.319
Coaches And Other Road Conveyances	Iron and Steel	0.224
Coffee, Cocoa, Chocolate, And Tea.	Food processing	0.522
Combs For The Hair.	Misc. Manufactures	1
Condensing.	Chemicals	0.636
Cooking; Culinary Apparatus.	Non-ferrouse metals	0.484
Cooking; Making Decoctions And Infusions.	Non-ferrouse metals	0.667

D Additional results for the impact of knowledge stocks on innovation

Here we present some additional results related to those shown in Figure 3 in the main text. In Figure 6 we present results using the same approach as in Figure 3 except that we also include a lag of the dependent variable in the regression. Our motivation for examining this alternative specification is that the inclusion of a lagged dependent variable may help pick up the effect of the number of researchers working in a technology area on patenting in that area (the $\ln r_{it}$ term in Eq. 3). In modern studies, this is dealt with through the inclusion of controls for R&D expenditures in particular technology areas. It is impossible to obtain such measures for the historical setting that we consider, but these values should be closely related to lagged patents. The results in Figure 6 show that the inclusion of the lagged dependent variable does not substantially affect our results.

Figure 6: The lagged effect of the knowledge stock on patenting rates



The figure presents estimated coefficients and 95% confidence intervals for PPML regressions based on Eq. 5 applied to all British patents and using the British innovation matrix. We include only patents by domestic inventors. Patents appearing in multiple (N) technology categories count as only a fraction (1/N) of a patent in each of category. Because there are many zeros in the data, we actually use $\ln(n_{it} + 1)$ in place of the $\ln(n_{it})$ terms shown in Eq. 5.

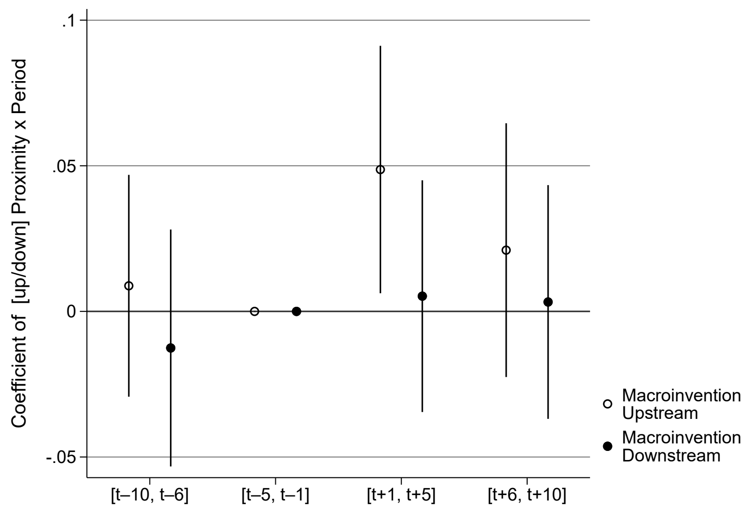
E Additional Macroinvention analysis results

This appendix provides some additional results related to our macroinvention analysis. Figure 7 presents event study results using the intersection list of macroinventions. These results are very similar to those reported for the other two macroinventino lists in the main text.

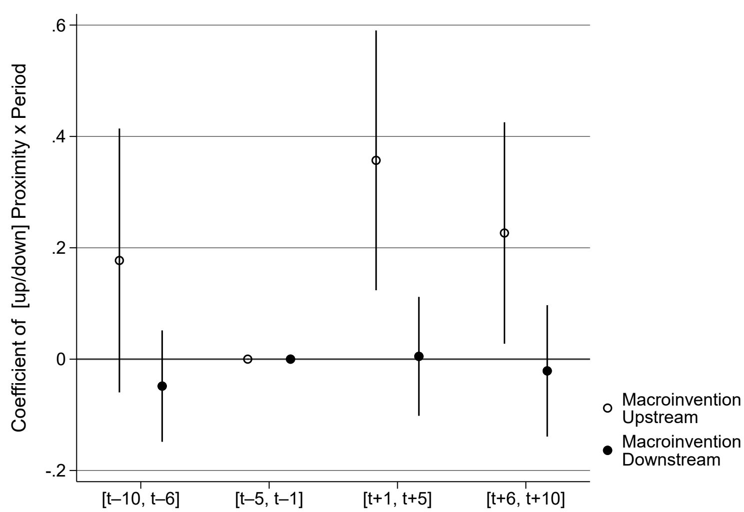
One potential concern in our main analysis is that, by using the log number of patents as the dependent variable, we are dropping some observations. In many cases this is sensible. For example, this causes us to omit observations for the Railroad technology category for many years because, prior to the invention of railroads, there were zero patents in this category. We also end up dropping observations for very small technology categories, such as Wigs, which often have zero patents even when aggregating up to five year periods.

To ensure that omitting these categories by taking logs is not critical to our results, in Table 15 we present results from regressions where the outcome variable is the number of patents, rather than log patents. Other than that change, the format of the table follows that used in Table 4 in the main text. These results are similar to those presented in the main text, though less statistically significant in some specification. However, the overall similarity in the patterns shows that the omitted categories are unlikely to be key to our results. One notable difference here is that the eigenvalue centrality control is now more important.

Figure 7: Macroinvention event study—different definitions



(a) Macroinvention: First patent in subcategory



(b) Macroinvention: Intersection

The figure presents estimated coefficients and 95% confidence intervals (robust standard errors) for PPML regressions of log patents on the interaction of proximity to a macroinvention ($Proximity_{ie}$) either upstream or downstream of a technology category and indicators for each five-year period before and after the event. The five-year period just before the macroinvention is the omitted reference category. The regression includes controls for upstream and downstream IO connections to the macroinvention technology category, as well as the eigenvalue centrality of each technology category, each interacted with time-period indicators.

Table 15: Macroinventions regression results in levels

	Dep var: Number of patents					
	Nuvolari et al		1st in subcat.		Intersection	
	(1)	(2)	(3)	(4)	(5)	(6)
Proximity upstream × post	0.052**	0.037*	0.028*	0.021	0.172**	0.141*
	(0.022)	(0.022)	(0.015)	(0.016)	(0.083)	(0.076)
Proximity downstream × post		0.005		0.014		0.036
		(0.022)		(0.014)		(0.041)
EV centrality × post		0.072***		0.077***		0.080***
		(0.022)		(0.018)		(0.025)
Upstream I–O × post		−0.003		−0.001		0.017
		(0.009)		(0.014)		(0.018)
Downstream I–O × post		0.008		−0.001		−0.084
		(0.016)		(0.013)		(0.052)
Category × event FE	✓	✓	✓	✓	✓	✓
Period × event FE	✓	✓	✓	✓	✓	✓
Observations	19342	19086	36860	36368	3052	3016
Estim. FE coef.	5008	4944	9523	9400	787	778
Number of clusters	145	143	145	143	145	143
Pseudo R^2	0.656	0.656	0.638	0.638	0.642	0.643

Poisson pseudo maximum likelihood (PPML) regressions. Observation = category–event–period, with four periods per event, two before the event ($[t-10,\, t-6]$ and $[t-5,\, t-1]$) and two after the event ($[t+1,\, t+5]$ and $[t+6,\, t+10]$). Standard errors are clustered at the level of technology category. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F Validating our approach using modern data

Because our approach to measuring the innovation matrix is novel, it is useful to provide some additional evidence showing that our approach provides an accurate measure of the underlying innovation network. To validate our approach, we turn to modern patent data, where we can observe both citations and individual identifiers for inventors that allow us to link their patents.

Our comparison focuses on the U.S. patent data provided in the 2015 version of PatStat. The PatStat database provides individual identifiers, International Patent Classification (IPC) technology categories for each granted patent, and bilateral patent citations. Using these inputs, we can construct and compare innovation matrices based on either citations or on the inventor-based approach that used in our main analysis. To keep the size of the networks manageable, we focus on the "three digit" IPC level (e.g., A41: Wearing Apparel) and classify each patent based on the first (primary) IPC code provided by the U.S. Patent and Trademark Office (PTO). The result is a 123 x 123 matrix, a similar level of detail to the technology classifications used in our main analysis.

Our inventor-based innovation network is constructed using the approach shown in Eq. 4. Our citation-based network is generated using the approach used in Liu and Ma (2021) as well as other modern studies:

$$\omega_{ij} = Cites_{ij} / \sum_{l} Cites_{il}$$

where $Cites_{ij}$ is the number of patents in category i citing patents in category j.

We focus on citations between U.S. patents for this measure. Also, because we are interested in knowledge flows that contribute to the development of new technologies, we limit our analysis to only those citations provided by the patent applicant in the original submission. This excludes other citations, such as those added by the patent examiner in the search phase or those added during opposition, which identify related technologies but may have been unknown to the inventor at the time of invention. After these cuts, we are left with a total of just over 30 million bilateral citations between U.S. patents.

After generating these two network measures, we compare the similarity of the resulting measures using the same methods that we apply to comparing the French and British innovation networks in Section 4.3. In Table 1 in the main text, we compare the centrality of nodes of the two networks, which we find to be very similar. Alternatively, in Table 16 below, we compare the edges of the two networks. This is a more demanding specification, but despite that we continue to find strong evidence that our method generates an innovation network that is very similar to the one obtained using citations. In particular, the estimated coefficients are close to one and the inventor-based network

Table 16: Comparing the edges of French and British innovation networks

	Dep var: Citation-based edges	
	(1)	(2)
	incl zeros	excl zeros
Inventor-based edges	1.078***	1.162***
	(0.084)	(0.061)
Constant	−0.000	−0.001**
	(0.000)	(0.000)
Observations	14884	7961
R^2	0.788	0.843

OLS. Observations are network edges connecting nodes (technology categories) i and j. Observations are weighted by the sum of patents in i and j (Stata analytical weights). Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

can explain a substantial fraction of the total variation in the citation-based network.