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Spatial patterns of steam technology diffusion in nineteenth-century France

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Abstract

This paper introduces a unique regional panel data set reflecting steam power use in the French *départements* from 1841 to 1911 and investigates, on this basis, the time and spatial patterns of steam technology diffusion in nineteenth-century France. While in the existing literature most quantitative assessments of steam power use in French industries rely on statistical information coming from the industrial censuses conducted in 1839–1847, 1860–1865 and 1896 [see Chanut et al. (2000)], our data provide an exhaustive overview of the spread of steam power in France based on the French mining engineers's reports that followed the early introduction in France of regulations on the use of steam engines. By controlling for a number of geographical, demographical and structural factors and initial conditions, we provide statistical evidence that intensity in the use of steam engine within close proximity was a strong and robust predictor of steam engine adoption among French industries. Our results therefore confirm that economic development in the prime time of industrialization benefited from spill-overs in neighboring regions, while this is not found over longer distances.

Keywords Linked administrative data · Space time diffusion · Steam technology · Industrialization

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1 Introduction

Steam technology is one of the emblematic technological innovations of the nineteenth century. Introduced early in England, it has spread toward all sectors of industrializing economies, contributing to their mechanization. Although it has all the landmarks of a General Purpose Technology, its contribution to the growth rate of the industrial output and to the increase in labor productivity has given rise to debate (e.g., Von Tunzelmann (1978); Crafts (2004); Crafts and Mills (2004); Atack et al. (2008)). The seminal work of Von Tunzelmann[1] has initiated a literature investigating the diffusion process of steam technology in Britain (see Kanefsky (1979); Kanefsky and Robey (1980)). This early literature has emphasized the importance of factor prices (capital, coal) and has claimed that access to cheap coal played a significant role in fostering steam use in industry. Von Tunzelmann (1978) has shown that widespread use of steam power was concomitant to a significant decrease in coal prices. This view is also supported by Allen (2009), who stresses that profitability of steam technology—related to factor prices (cheap coal and relatively high wages)—was first and foremost a driver behind steam adoption. Expanding on these contributions, Nuvolari et al. (2011) have provided a reassessment of the patterns of the British diffusion process and have investigated the relative influence of various explaining factors on the diffusion of steam. They underline as well the influence of the price of an unit of steam power in the early stage of steam power diffusion in Britain. They evidence that coal prices affected the choice between Newcomen and Watt engines but they also emphasize that a convincing explanation for the diffusion of steam technology in Britain cannot be restricted to spatial variations in coal prices. They highlight the importance of the production structure (the size of different branches of industry) of the British counties in the respective use they made of steam power. The spread of steam technology in the U.S has also given rise to a number of investigations (see Temin (1966); Atack (1979); Atack et al. (2008); Hunter (1979)). Analyses of the spread of steam technology among american manufacturing firms in the USA are also mainly based on investigations related to the relative costs of steam power (*vs.* waterpower, for instance in Atack (1979)).[2]

[1] On the importance of Von Tunzelmann's work, see Bruland and Smith 2013.

[2] Another strand of research on the adoption of steam engine at the time of early industrialization analyses the influence of steam technology adoption on urbanization. Rosenberg and Trajtenberg (2004) have outlined that steam engine diffusion played a positive influence on the degree of urbanization in the U.S case. Kim (2005) study has nuanced this thesis, claiming that steam technology didn't act as a catalyst for urbanization. Gutberlet (2014) has contributed to the debate on the influence of steam technology on industrial location by providing evidence, for Germany, that more intensity in the use of steam power is associated with increased spatial concentration of industries in the period 1875–1895. Recently, Zobl (2016) has investigated a similar issue for France. The study claims that France adherence to water power—and slow diffusion of steam power—in the nineteenth century contributed to slow urbanization and constrained French economic development.

Quantitative historical analyses of steam technology diffusion have mainly concerned the British and the American cases and have focused on factor prices as a main explanation for steam adoption. In comparison, steam power diffusion in nineteenth-century France has received relatively few attention. France's industrialization has long been examined in comparison with the path of the British economy. This comparative approach led first to the idea that 'retardation' characterized the French economy in the nineteenth century. This 'retardation-stagnation' thesis, as denominated by Crouzet (2003), focuses on the idea that France was a technology laggard, experienced a low rate of economic growth, modest increase in its industrial output and that it had largely remained an agricultural economy until, at least, the mid of the nineteenth century.[3] Among the factors explaining French failure (compared to Britain), adherence to water power and, relatedly, the relative scarce use of steam technology in France are put forward.

If the historiography of the French industrialization puts emphasis on France adherence to water power, few is known, singularly, about the way steam power diffused in the nineteenth century. Technological diffusion from England to Europe had been widely discussed (Henderson 1954; Kindleberger 1995; Landes 1965; Mathias 1975; Mokyr 1990). Technology transfer from Britain to France has recently been examined by Nuvolari et al. (2023) on the basis of patent data. The impact of technological change on productivity growth in France during the first industrial revolution has also been the subject of recent research. Juhàsz et al. (2023) show that the adoption of mechanized cotton spinning in French textile industries required reorganization of production activities to bear fruit and to increase productivity. They outline that benefiting from mechanization requires complementary organizational knowledge that took time to develop.

Quantitative analysis about the use of steam engine in France remains scarce. Payen's study (1969) provides analysis of the early introduction of steam engine in the eighteen's century. Recently, a significant number of historical studies of the French industrialization process have focused on the use of steam power. The effect of mechanization—approximated by steam power use—on wages and employment are analyzed by Ridolfi et al. (2023) who rely on the statistical information contained in the French industrial surveys (1840s and 1860s). Franck and Galor (2021, 2022) analyze the impact of exogenous regional variations in the use of steam engines on long-run prosperity and on human capital accumulation. The interplay between steam adoption and human capital has also been examined by Diebolt et al. (2019, 2021); Montalbo (2020, 2021)). Lacroix (2018) relies on statistical information on the adoption of steam machines in nineteenth-century France to analyze the impact of the French industrialization process on voting behavior and opposition to autocracy. This is as well the case of Squicciarini (2020) who studies the link

[3] The performance of the French economy in the nineteenth century remains a controversial issue. From the 1960s onwards, new national income estimates (Marczewski 1961, 1963, 1965) had questioned the 'retardation-stagnation' thesis and opened the door for revisionists' approaches. They call into the question the view that the French path to industrialization was less efficient than the paths followed by other countries engaged in industrialization at that time (O'Brien and Keyder 1978).

between religiosity and economic development during the Second Industrial Revolution in France. If these approaches mobilize data on the use of steam engines in nineteenth-century France, they do not analyze the steam diffusion process in itself. Little is known about the patterns of technological catch-up in France. This gap in the French historiography is partly the consequence of the lack of available statistical information over a long period on the industrial use of steam power. Approximations of the use of steam power in France are in fact mostly sporadic, as they are derived from industrial surveys (Chanut et al. 2000). Compared to the existing literature, this paper introduces, a new panel dataset reflecting steam power use in the French *départements* from 1840 to 1911. Covering a period of more than 70 years and including high quality administrative information about the number of steam machines in use in French industries, the dataset also links information on a number of other sources, including administrative and the census. In addition, we add to the existing literature by investigating the time and spatial patterns of steam technology diffusion in nineteenth-century France. The literature on steam technology adoption in the British and American cases, has mainly focused on factor prices or more largely, on differences characterizing the economic environment (endowments in physical and human capital, wages, natural resources, size of the different industrial sectors...) to examine the diffusion process of steam technology. Less attention has been given to the space patterns of steam technology diffusion in the eighteenth and nineteenth centuries while spatial patterns are recognized to be significant factors of the diffusion of more recent technologies. There is an extensive economic literature related to modeling and estimating technology diffusion in space and regional spillovers by means of spatial econometric models (e.g., Abreu et al. 2004; Comin et al. 2012; Lin and Kwan (2016)). These studies typically employ country panel data and distance based weight matrices to estimate to what extent autogregressive components and regional diffusion determine the use of technologies. One of the ideas behind the analysis of the spatial patterns of technology diffusion is that technology adoption requires knowledge (learning about the existence of the technology, its benefits, how to use it...), which arises from interactions among economic agents. These interactions are likely to be associated with geographic proximity.

Our analysis contributes to this literature by using extensive regional panel data from the 19th century and put a number of spatial econometric panel models to the data to directly estimate the role of space time diffusion. Beside standard static panel models we consider dynamic models. We use system estimation IV techniques and GMM with a limited amount of instrumental variables in order not to incur sizable biases in our results. Our paper is to our knowledge a first analysis of technology diffusion with historic data on regional level focusing on regional spillovers. We find robust patterns for autoregressive and spatial regressive components to be important factors for the intensity of steam use. While spatial spill-overs are observed for neighboring regions, they phase out for larger perimeters. Our results therefore provide evidence for Tobler's first law of geography, which says"everything is related to everything else, but near things are more related than distant things."

The paper is organized as follows. Section 2 presents the historical background to the introduction in France of regulations concerning the use of steam in industries. The introduction of safety standards for the use of steam power in industry in the early nineteenth century was the starting point for the construction of our dataset. Section 3 describes the data, their construction, the sources and estimation sample. Section 4 presents the econometric models followed by Sect. 5 with the results. The last section summarizes.

2 Historical background

Most quantitative assessments of steam power use in France are based on statistical information coming from the industrial censuses conducted in 1839–1847 and 1860–1865 (see Chanut et al. (2000)). This is the case of the recent historical literature on the French case mentioned above which uses data from these censuses. The census of 1896 also provides statistical information about industrial activity in the French departments and displays information about steam usage. But these three censuses only provide sporadic statistical information and henceforth, partial image of steam technology diffusion in France. However, annual statistics on steam-powered equipment in use in French industries in the nineteenth century are accessible. They were drawn up by the French authorities following the introduction, in 1823, of a regulatory framework guaranteeing the safe use of steam power in France. Steam appliances caused many industrial accidents (boiler explosions) in industrialized countries and particularly, since the introduction of high-pressure boilers in factories. The French administration decided to control and to regulate their use, for safety reasons in particular. The *Compte-rendu des Ingénieurs des mines*, dating from 1834, highlights the public safety issues involved in supervising the use of steam power:"In the *département* of Seine-Inférieure, great dangers were avoided as a result of the supervision of mining engineers. A cast iron boiler, 13 feet long, was operating at a considerable tension of seven atmospheres, in a very large four-story building full of workers. It was cracked and threatened the entire workshop with the most imminent danger. The engineers immediately ordered a test using a hydraulic press, but the boiler burst long before the test pressure had been reached."(Direction Générale des Ponts et Chaussées et des Mines, 1834, p. 34, our translation).

According to Fressoz (2014), the regulations governing the use of steam machines, along with those governing lighting gas, were the driving force behind the emergence of technical safety standards, a field in which France was a pioneer. Regulations by a means of safety standards was in fact a French specificity, invented between 1822 and 1828 (see Fressoz (2014)), which was not the route taken by England at this period, despite similar safety issues. From 1823, the use of steam power in France was organized and regulated at the legislative level by several ordinances (ordinances of 2 April 1823, 29 October 1823, 7 may 1828, 25 may 1828, 23 September 1829 and 25 march 1830). While the ordinance of 2 April 1823 concerned steamboats, the ordinance of 29 October 1823 marked the beginning of regulations concerning factories. The introduction of this regulatory framework meant that French entrepreneurs had to comply with technical standards to be authorized to use steam power. Prefectorial authorizations were needed in order to introduce steam engines in factories (ordinances of 23 September 1829 and 25 march 1830). Following the ordinance of October 1823, the *Commission Centrale des Machines à* *vapeur* was created. It came under the authority of the Ministry of the Interior. The French mining ("*Ingénieurs des Mines*") and civil engineers ("*Ingénieurs des Ponts et Chaussées*") were in charge of the supervision of the use of steam. All steam engines erected in French industries were thus firstly controlled by engineers who gave their opinion for the establishment of steam-powered appliances, set the conditions under which such appliances may be authorized and, when industries were granted, checked the equipment every year to ensure the safe use of this new power source. So from 1823 onwards, it was under the supervision of mining engineers that steam technology spread in France. In the aftermath of these regulations, statistical surveys were introduced. The Act of 23 April 1833 (Art.5) introduced the obligation to publish annual reports on the activities of mining engineers. This work was directed by Frédéric Le Play. Among others information, it contains statistical tables depicting the use of steam power in the French departments. As Gille (1980) points out, these statistical sources are extremely rich. Ruhemann (2007) devoted a detailed study to them. These sources have also been digitized by the *Ecoles des Mines*.[4] The French engineers reported information about the number of steam engine erected in industries[5], the number of industries which use steam power and the total steam power (in horsepower) in use in the *département*, in the *Compte rendu des travaux des ingénieurs des mines* (Direction générale des Ponts et Chaussées et des Mines) first, and, from 1838 onwards, in the *Statistique de l'industrie minérale et des appareils à vapeur*. Our dataset compiles statistical information contained in these two historical sources. It gathers annual information on the number of steam engines used in industries, the number of industries that uses steam technology, and the steam power in use (horsepower). It is therefore a unique historic administrative data source that cannot be found in most other countries. These data provide an exhaustive appraisal of the diffusion of steam technology in France at the *département* level. This level of analysis is in line with the existing literature, which usually examines the French industrialization process using departmental data. Recent work has looked at industrialization in France using an even finer level of administrative division: the municipal level (Montalbo 2020, 2022) or even the plant level (Juhàsz et al. 2023). However, the originality of our approach lies in the use of comprehensive annual data on the use of steam power in France over a long period that allows us to investigate the the spatial patterns of steam diffusion. This is only possible at the *département* level. Figure 1 depicts the evolution of the number of steam machines in use in industries at the national level from 1841 to 1911.

[4] https://patrimoine.minesparis.psl.eu.

[5] data on the number of steam appliances are available as well on the *Compte rendu des travaux des ingénieurs des mines*.

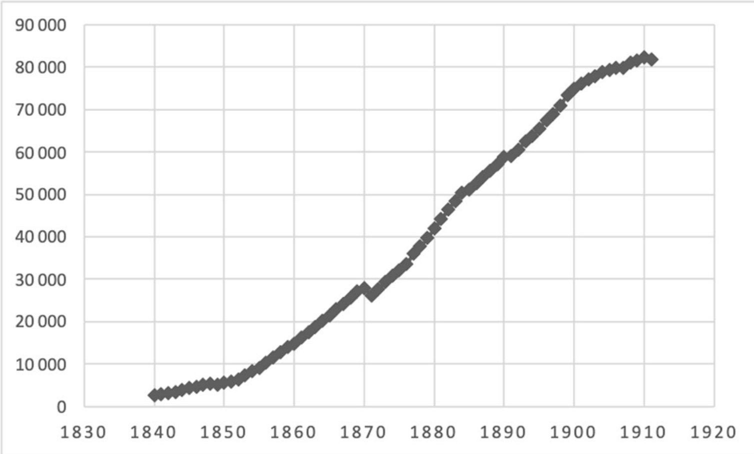

Fig. 1 Total number of steam machines in French industries 1841–1911

3 Data sources and sample description

We describe in this section the data sources and provide an explorative descriptive analysis of the development of the use of steam technology in France during the nineteenth century. This is the variable to be explained in our quantitative analysis. Then, the estimation sample is described by outlining the panel structure and defining variable groups for the econometric analysis.

3.1 The intensity of steam power use. Geographic distribution

The use of steam power in industrializing France is highly heterogeneous at regional level. In what follows we describe the geographic distribution of the intensity of steam use and its development over time. The number of steam engines per 1000 inhabitants in each department is the explained variable of our regression analysis. To construct it we use data on the size of the population that is taken from censuses conducted in France in the nineteenth century and published by the *Statistique Générale de la France*. As these censuses are available on a 5 yearly frequency, the same applies to our explanatory variable.

Figure 2 depicts strong heterogeneity among French departments regarding steam power use in early industrialization. In 1841, 14 departments stand out from other by using intensively steam power, with a North polarization. Among the 14 departments which intensively use steam engines, 6 were in fact located in the North of France. These are the Aisne *département* in which 86 steam machines were in use in industries, what corresponds to 0,159 machines per 1000 inhabitants, the Ardennes (38 machines, 0.119 per 1000 inhabitants), the Marne (54 machines, 0.151 per 1000 inhabitants), the Nord (498 machines, 0.459 per 1000 inhabitants), the Pas-de-Calais (58 machines, 0.085 per 1000 inhabitants), the Somme (55 machines, 0.098 per 1000 inhabitants). Remaining departments are the Gard (82 machines,

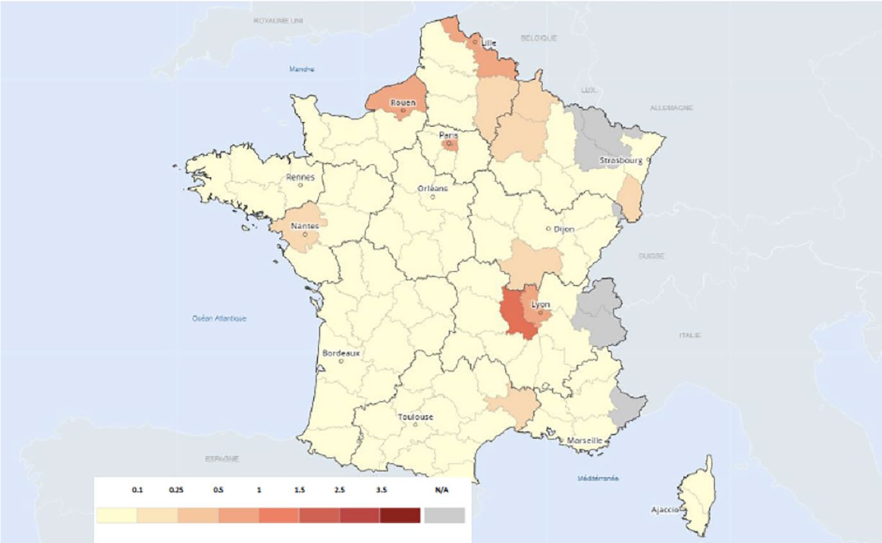

Fig. 2 Number of steam machines per 1000 inhabitants—1841

0.218 per 1000 inhabitants), the Loire (272 machines, 0.627 per 1000 inhabitants), the Loire-Inférieure (66 machines, 0.136 per 1000 inhabitants), the Haut-Rhin (94 machines, 0.202 per 1000 inhabitants), the Rhône (131 machines, 0.262 per 1000 inhabitants), the Saône-et-Loire (96 machines, 0.174 per 1000 inhabitants), the Seine (442 machines, 0.370 per 1000 inhabitants), the Seine- Inférieure (267 machines, 0.362 per 1000 inhabitants). In comparison, 12 French departments in 1841 recorded no machine at all (Hautes-Alpes, Basses-Alpes and Ariège, Corse, Côte-du-Nord, Creuse, Lot, Lot-et-Garonne, Lozère, Basses-Pyrénées, Hautes-Pyrénées, Pyrénées-Orientales).

In 1861 (Fig. 3), two departments still do not have any steam machine (Hautes-Alpes and Ariège) whereas only seven departments recorded 1 to 5 machines in total. The latter corresponds to less than 0.02 machines per 1000 inhabitants. The leading departments, in terms of their usage of steam technology, remain the Loire (1.264 machines per 1000 inhabitants), the Nord (1.684), the Seine (1.024), the Seine- Inférieure (1.095) and the Rhône (1.304) with, for each of them, more than one steam machine per 1000 inhabitants. Heterogeneity remained substantial in 1881 (Fig. 4). Steam technology adoption accelerated in the departments located in the North of France. The Aisne, the Ardennes, the Nord, the Somme recorded more than 2 steam engine per 1000 inhabitants. The Nord was yet the leading department with 3.06 machines per 1000 inhabitants. The Loire (1.97), the Seine (1.679) and the Seine- Inférieure (1.82) remained highly endowed departments with more than 1.5 machines per 1000 inhabitants. Other departments started to implement intensively steam engines (while they were weakly endowed with steam machines in 1861). This is the case of the Oise (2.828 machines per 1000 inhabitants), the Seine-et- Marne (2.90) the Seine-et-Oise (2.113) and the Saône-et-Loire (2.185), followed

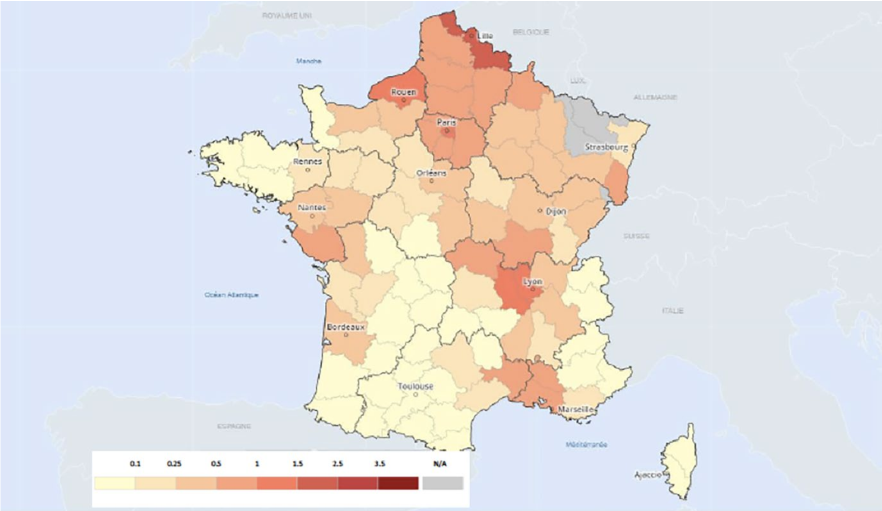

Fig. 3 Number of steam machines per 1000 inhabitants—1861

by the Gard (1.516) and the Bouches-du-Rhône (1.85), the Aube (1.825), the Allier (1.548), the Cher (1.699), the Marne (1.671) and Belfort (1.711) (Fig. 4).

At the eve of the twentieth century, steam technology was in widespread used in France. Some departments nevertheless remained under-endowed. This is the case of the Basses-Alpes, Hautes-Alpes, Alpes-Maritimes, Cantal, Corrèze, Corse, Finistère, Lozère, Manche, Hautes-Pyrénées, Pyrénées-Orientales, Savoie which

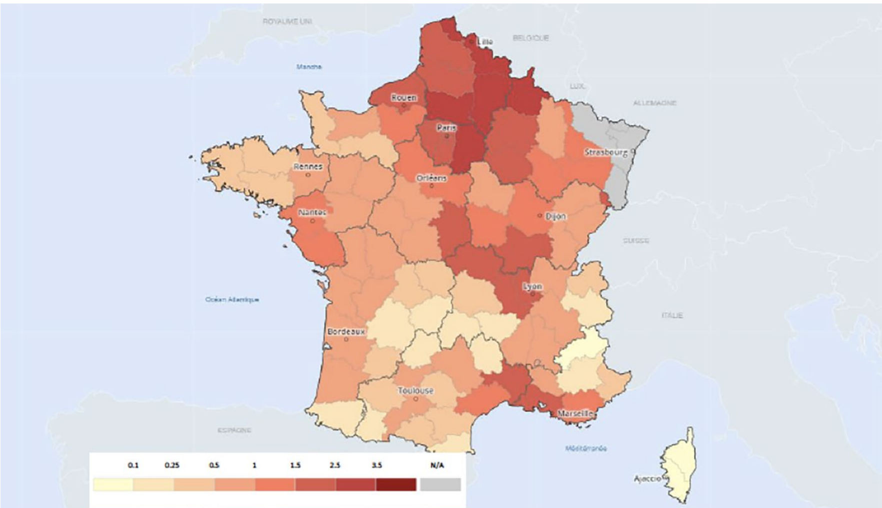

Fig. 4 Number of steam machines per 1000 inhabitants—1881

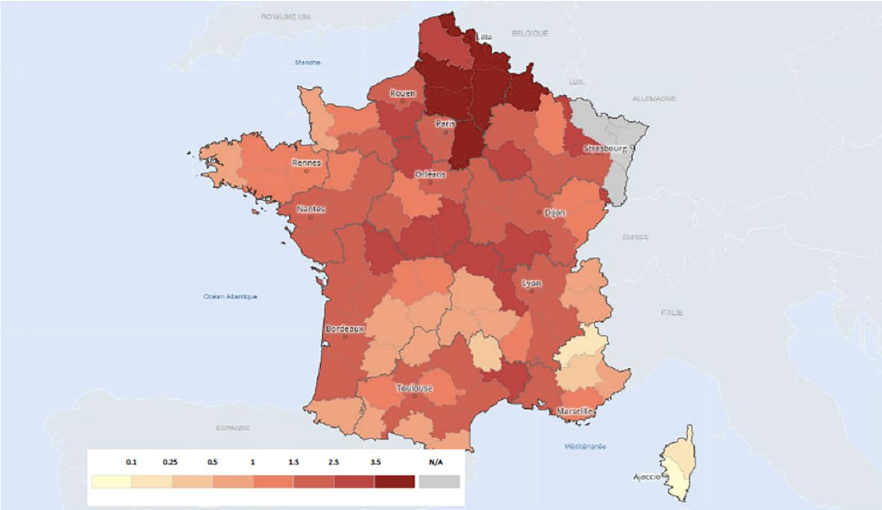

Fig. 5 Number of steam machines per 1000 inhabitants—1901

recorded less than 0.8 machines per 1000 inhabitants whereas at the same date the Oise recorded more than 5 machines per 1000 inhabitants. The Nord experienced the highest level of machines implemented with 6549 machines (3.5 per 1000 inhabitants) (Fig. 5).

3.2 Other data

We present here the other data used in the analysis.

Human capital and demographics Since the seminal contribution of Nelson and Phelps (1966), the level of human capital is recognized for playing a positive role on technological adoption by reducing the time needed for technological catch-up. To capture differences in human capital endowments between the French departments—and their potential effect on the adoption of steam technology—, we include literacy rates in the empirical analysis. These come from another historic administrative data source and correspond to the percentage of literate army conscripts (the percentage of conscripts who are able to read at least). It is therefore a measure of literacy of young men typically at the age of entering the labor force and not of the entire population. This information is available on department level for the relevant years of our analysis. The data are derived from reports ("*Statistiques de l'enseignement primaire*"published by the "*Ministère de l'instruction Publique*"). A recent trend in the literature, however, emphasizes the need to consider not only the role of literacy in the nineteenth century (basic human capital) but also the role of other forms of human capital. Recently, in the case of England, Kelly et al. (2023) have underlined the importance of useful mechanical skills and their role in the success of the British industrialisation process. They point out that it was not literacy that was of importance as regards technological change in nineteenth-century England but rather the abundance of artisan skills that facilitated the adoption of new machinery. In order to take into account this kind of human capital, we introduce in our analysis a measure of intermediate human capital endowments in nineteenth-century France. We use as a proxy for intermediate human capital—which is neither basic human capital approximated by literacy rates, nor elite human capital (see Diebolt et al. (2019, 2021))—the number of workers and apprentices (men and women) per 1000 inhabitants enrolled in evening classes. Because we have a limited number of observations for this variable and because its introduction in our model does not provide evidence of the relevance of intermediate human capital as regards steam diffusion, we present these results in the robustness checks (Sect. 5).

As religious norms and precepts are considered for playing a role on human capital accumulation (Becker and Woessmann 2009, 2010; Becker et al. 2024; Botticini and Eckstein 2005, 2007) and could affect technological absorptive capacity (by being related to receptiveness to opportunities offered by new technologies), we also include the share of Protestants and the share of Jews by department in 1861. The data are derived from the *Statistique Générale de la France*. Finally, we include in analysis the number of inhabitants per doctor in 1847 as a proxy for the presence of knowledge elites. This information and information on religious composition are only available for one time point. Finally, we control for pre-industrial demography by including in our analysis the population density in 1801 (i.e., the population density of departments prior to industrialization). Inhabitants per doctor in 1847 and population in 1801 are available from the *Statistique Générale de la France*.

Infrastructure To take into account differences in infrastructure between departments, we use the initial conditions prior to industrialization. We control for the total length of railways (in kms) per 1000 hectare land in 1834 and the total length of royal roads (in kms) per 1000 hectare land in 1824. These data are available from the *Statistique Générale de la France*.

Natural resources and geography We also use information on the availability of natural resources that are perceived as relevant for the industrialization process. As previously mentioned, the availability and price of coal is widely perceived as an important factor influencing steam power use. Von Tunzelmann (1978); Kanefsky (1979); Allen (2009)'s contributions have identified the price of coal as a decisive factor explaining the use of steam power. The importance of coal is also underlined by Nuvolari et al. (2011) in the case of the early diffusion of steam power in Britain. Since continuous indexes of coal prices are not available over the period under consideration (1841–1911), we rely on the idea that coal would be less expensive in departments potentially endowed with coal, providing hence a more favorable environment for steam technology adoption. In order to account for the availability of coal in the case of France, we include a dummy variable differentiating departments covered by carboniferous areas from department without carboniferous areas. We rely on this measure following Fernihough and O'Rourke (2014),[6] who use the

[6] We are indebted to Alan Fernihough who provided us with the data on carboniferous areas.

proximity to rock strata from the Carboniferous era as an instrumental variable to investigate the effect of coal availability on historical city population sizes. Exogenous variation in the distribution of carboniferous rock strata is also used as an instrument in de Pleijt et al. (2016). Admittedly, our time constant dummy variable reflects the availability of coal and not its actual extraction (or the use of British coal). We also include other geographical factors. We consider latitude and longitude of the administrative center of the *département* and two dummy variables to distinguish between maritime departments and departments that possess a land border with a foreign country. While our water access variable captures time constant maritime access, it does not take into account the progressive integration of regional navigable network in France. However, we are opting to model water access as time invariant process given data constraints. In order to reflect the weight of agriculture, we include information about the share of cultivable land in 1834 (from the *Statistique Générale de la France*). These variables are time constant.

3.3 Estimation sample

We have data for the $r = 1, ..., 90$ departments of France that existed during the period 1841 until 1911. The data covers $t = 1, ..., 15$ periods (5 yearly panel starting with 1841). We adopt a fixed $T = 15$ panel design by only choosing periods in the prime time of industrialization. After this period the use of steam technology gradually declined due to adoption of other technologies such as electricity and fuel powered engines. The panel is unbalanced as several of the 90 departments were newly created during this period, others were dissolved and recreated under new names and several departments were not always a part of France during the observation period. First, in 1860, following the Treaty of Turin, the Duchy of Savoie and the county of Nice were annexed to France. These territories were added to the French territory through the creation of the Haute-Savoie and Alpes-Maritimes *départements*. The second change in French borders over our period of analysis followed the franco Prussian war and the annexation of Alsace-Lorraine. After the 1870 defeat of France, the Bas-Rhin and Haut-Rhin *départements* (Belfort excepted) were ceded to the German empire. A part of the Moselle, Meurthe and Vosges *départements* were also annexed. Remaining parts of the Moselle and the Meurthe *départements*, which were not annexed, gave place to a newly created department: the Meurthe-et-Moselle *département*. However, since the reasons for redrawing of borders were not related to regional adoption of steam engines conditional on regressors, the unbalancedness of the panel doesn't induce an inconsistency of our estimation results.

The dependent variable $y_{r,t} = 1000 * se_{r,t}/pop_{r,t}$ is the number of steam engines (se) per 1000 inhabitants in region r and year t. The variable takes on values between 0 and 6.1, while it is 0 for 35 observations. Given that the variable is continuous and takes on many values, we choose a conventional linear mean regression model for our statistical analysis. In the context of our analysis the dependent variable is a measure of the intensity of steam use.

Summary statistics of the main variables and their classification into groups are given in Table 3 in the Appendix. As explanatory variables, we focus on the following sets:

- Lagged (past value) of the dependent variable, $y_{r,t-1}$. This is also called the time effect or autoregressive effect of order 1 (AR(1)).
- Variables describing the region (time constant and time varying, varying or constant in space). We denote them as V_r and $X_{r,t}$. While the set of variables in V_r is rather large and relates mainly to initial conditions and time constant geographic factors, the set of $X_{r,t}$ is rather small and only contains the literacy rate (and its first lag) and the population density. The population density is only used in the robustness analysis for the reasons outlined there.
- General national and macroeconomic trends are absorbed in our model by period dummies Q_t.
- Variables describing the space-time diffusion process base on the proximity of region r with region s (measured by the distance between the administrative centers of the French *départements*., $d_{r,s}$) combined with the intensity of steam power use in the other regions. In particular, we compute the average use of steam technology in various proximities of region r. More specifically, we compute the average number of steam machines per 1000 inhabitants in certain perimeters:

$$w_{r,t}(d_1, d_2) = \frac{1000}{\sum_{s \neq r} pop_{s,t} * \mathbb{I}(d_1 < d_{r,s} \leq d_2)} \sum_{s \neq r} se_{s,t} * \mathbb{I}(d_1 < d_{r,s} \leq d_2)$$

  with d_1, d_2 being distance thresholds and $pop_{r,t}$ is the number of inhabitants in region r in period t. In our analysis we tested various thresholds but restrict the presentation of the results for two thresholds because these limits produced the sharpest results. We focus on three $w_{r,t}(d_1, d_2)$, which are stacked into $W_{r,t}$. The first measures the intensity of steam usage in vicinity of the region (up to 150 KM). The second is the intensity of steam power usage instead in a wider surrounding (150–300 KM). The third variable (>300 KM) mainly captures national trend patterns and has only limited regional variation. For this reason, this variable is only included for illustration in the supplementary material but not in the main models.

Our modeling of the space time diffusion patterns requires some motivation as it differs from conventional spatial econometric approaches (compare Elhorst (2017); Ciccarelli and Elhorst (2018)). In the standard spatial econometrics literature an $r \times r$ weight matrix is used with known weights that typically depends on distances only. Therefore the resulting weighted sums correspond to sums of average intensities rather than the average intensity in certain perimeters. Our spatial weighting differs from the conventional models: It does not average regional intensities in a certain vicinity but constructs a regional intensity for a certain vicinity. Common weighting schemes such as binary contiguity (BC) or inverse distance (ID) weighting average regional indicators in the relevant vicinity by assigning appropriate weights. These weights only depend on geographical features such as distance or direct neighborhood. We find it more adequate to construct an overall regional indicator from the information in the vicinity. For example, if a region is in the vicinity of 3 other regions, where one is large or has a lot of inhabitants while the other two are tiny with hardly any activity, the conventional weighting assigns each of the three the same weight (provided they meet the vicinity condition or have the same distance). This will down weight quite strongly the exposure to the probably important large region. Our weighting will construct the indicator by pooling the data from the three regions and if $se_{r,t}$ and $pop_{r,t}$ are small in two of the regions, these regions will hardly contribute to the constructed $w_{r,t}$ variable. Our approach measures overall regional exposure rather than region average exposure. It is closer related to how the dependent variable is constructed. Our weighting is therefore more appropriate in the context of our application. Second, we model a piecewise constant functional form in distance. In contrast, BC weighting only uses nearest neighbors, while ID weighting specifies a global parametric functional form of known shape. Our distance function is more flexible and we provide robustness checks for the distance thresholds. Non-inclusion of $w_{r,t}$ for >300 KM in the model does the analog of ID weighting, where the weight converges to 0 as distance becomes large and it is also 0 for BC weighting. The resulting spatial variables in our model are meaningful and results can be interpreted directly. We provide robustness checks in relation to the spatial weighting, including BC weighting, in the supplementary material.

4 Econometric models

This section outlines the statistical approaches to estimating the factors of the steam power usage diffusion process. We apply various panel regression models to make use of the longitudinal and spatial data structure and to allow for plausible sources of endogeneity. These models are estimated in first differences. We apply system estimation techniques to be able to handle different sets of instrumental variables in different periods. We follow here the terminology of Wooldridge (2010), in particular Chaps. 8 and 11.6.2. These models can be adapted to capture spatial effects and diffusion and variants are considered in the spatial panel data literature (e.g., Bouayad-Agha and Védrine (2010); Lee and Yu (2009); Korniotis (2010)). For the reasons outlined in the data section, our approach of modeling spatial dependencies deviates from standard spatial weight matrices but the consequences resulting from spatial correlations are the same. Before the econometric model is presented in detail, we illustrate how spatial variation contributes to our regression analysis. Figure 6 depicts regional time series for the intensity of steam use ($y_{r,t}$) and the literacy rate ($X_{r,t}$) for 4 selected regions. It is apparent that the initial conditions and development over time are quite different across regions. This variety in patterns gives a rich additional source of variation that would not be available in a classical time series analysis with national level data. For comparison if one constructs a national time series of the regional averages of $y_{r,t}$ and $X_{r,t}$ and regresses the former on the latter, one obtains an R^2 of more than 0.90. This finding could suggest that the average literacy rate is an important variable for explaining the average intensity of steam power use. At the same time the bivariate relationship could be simply driven

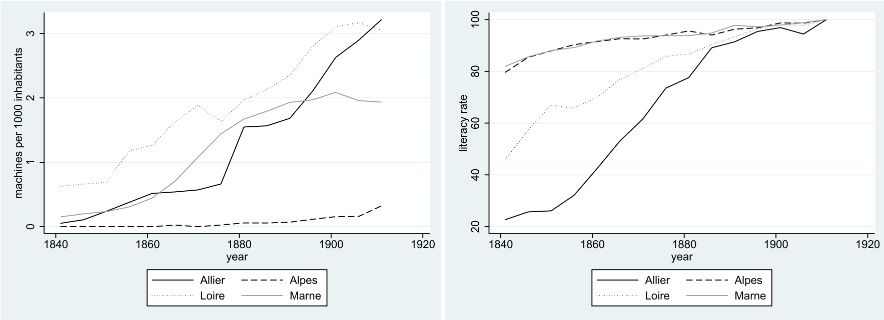

Fig. 6 Selected regional time series for the intensity of steam use and literacy rate

by identical time trends and the results of such a regression are hardly informative. In our analysis, we investigate this relationship for all 90 regions simultaneously, thus by exploiting the different regional patterns as shown in Fig. 6 and by also controlling for a number of other regional factors.

The starting point is a linear regression model that relates the intensity of steam power use ($y_{r,t}$) to various observable and unobservable variables:

$$\begin{aligned} y_{r,t} = \rho y_{r,t-1} + Q_t\theta + V_r\alpha + X_{r,t}\beta + W_{r,t-1}\gamma + e_{r,t} \\ \rho y_{r,t-1} + Q_t\theta + V_r\alpha + X_{r,t}\beta + W_{r,t-1}\gamma + a_r + u_{r,t}, \end{aligned} \tag{1}$$

for $t = 2, ..., 15$ (year 1841 is lost due to using the first lags of $W_{r,t}$ and $y_{r,t}$) and $r = 1, ..., 90$. a_r and $u_{r,t}$ are unobserved, while θ, α, β and γ are unknown and to be estimated. γ are the key parameters of interest as they describe the space-time diffusion process. Including the AR(1) component $y_{r,t-1}$ as a regressor makes the model dynamic and allows estimation of the relevance of the state dependence in the diffusion process. The model does not include $W_{r,t}$ as the erection of a steam engine requires some planning and approval. Therefore any kind of regional spill-over will occur with some delay.

By exploiting the panel structure with repeated observations of the same regions over time it is easier to tackle possible endogeneities in the key explanatory variables. This improves the prospects of obtaining consistent estimates for the diffusion process. The key is here to use a first difference version of the above model. This is

$$\Delta y_{r,t} = \rho \Delta y_{r,t-1} + \Delta Q_t\theta + \Delta X_{r,t}\beta + \Delta W_{r,t-1}\gamma + \Delta u_{r,t} \tag{2}$$

for $t = 3, ..., 15$, where Δ is the first difference operator. Compared to model (1) all time constant components disappear. Due to being eliminated, we no longer need to assume something on the relationship between $u_{r,t}$ and the time constant components. Thus, having incomplete information on the time constant features of a region does not harm estimates of model (2). The interpretation of the model parameters is the same as in Eq. (1). Equation (2) is estimated by various methods, starting with pooled OLS (POLS). In this case consistency of the estimated coefficients requires that $\Delta u_{r,t}$ has zero covariance with first differences of $y_{r,t-1}$, Q_t, $X_{r,t}$, and $W_{r,t-1}$. This is evidently a weaker requirement than what is required for model (1), but it still fails for at least some of the variables. It is well known that the AR(1) component $\Delta y_{r,t-1}$ is a function of $u_{r,t-1}$, which is also in $\Delta u_{r,t}$, implying endogeneity. For the spatial diffusion variables $\Delta W_{r,t-1}$, we may also have that they are related to the unobservable $u_{r,t}$ due to a spatially regressive structure. $\Delta X_{r,t}$ has only one component, namely the first difference of the lag of human capital. It is unclear whether this can be considered as exogenous due to simultaneity considerations between $X_{r,t}$ and $y_{r,t}$ or omitted variables that simultaneously affect the intensity of steam use and literacy. A similar dynamic spatial panel model has been considered by Korniotis (2010), who uses instrumental variables from the panel structure to address the endogeneities. We follow this route and adopt a similar strategy for estimating the model and selecting the instrumental variables. Korniotis (2010) introduces a bias correction that leads only to minor changes in a model without measurement error. Given that the spatial weighting is different in our model and that the key variables in our model ($y_{r,t}$, $W_{r,t}$) are precise, we have not adopted the bias correction of Korniotis (2010). In addition to classical just identified IV approaches, we also apply overidentified models that are estimated by system estimation techniques. System estimation methods are required if the set of instrumental variables is not the same in all time periods (compare Wooldridge (2010), Chap. 8). This is the case when one uses lags of variables as instrumental variables as not all lags may be available in the first periods. As a starting point we apply the classical (Anderson and Hsiao 1982) estimator to address the endogeneity of $\Delta y_{r,t-1}$ by using $y_{r,t-2}$ as an instrument. This instrument is valid under a sequential exogeneity assumption, which means $y_{r,t-2}$ is uncorrelated with $u_{r,t}$. This requires for example that the first difference error does not possess an autoregressive structure of an order higher than 1. The estimator is a pooled 2SLS (P2SLS) estimator that is just identified. Greater efficiency can be achieved by using more instrumental variables. This is done by using the first and second lags (whenever available) or alternatively the second and third lag of the first difference version if the multicollinearity between instruments is too large otherwise. Provided that the number of available instruments differs across periods, we apply system 2SLS estimators (S2SLS) in these cases. These system IV approaches benefit in terms of efficiency from the use of a small number of additional instruments that are not weak. Finally, we use GMM (Arellano and Bond 1991) to tackle endogeneity in the same first differences using a number of instruments and to address the autoregressive error structure more efficiently. Even though this method is asymptotically efficient, it is known to have poorer finite sample performance, whenever many weak instruments are used. This results in sizable finite sample bias. Moreover, using an excessive number of instruments can also induce asymptotic bias. For this reason we only use instruments up to lag order 2 (whenever available) to limit the weak instrument problem. These instruments are again only valid under sequential exogeneity. Any systematic differences in the results of the IV approaches will point to either endogeneities or invalidity of instruments. When working with overidentified models, it is possible to test for the validity of the excess exclusion restrictions. For this reason, we conduct the Sargan test. For model diagnosis we perform various additional tests. In particular, we apply a regression based test for AR structures in errors and spatial correlation in errors (compare Appendix A.II) as well as the Arellano and Bond (1991) test for AR error structure. In line with related models (compare Bouayad-Agha and Védrine (2010); Korniotis (2010)), we do no specify specific spatial error correlations in our model as these correlations are estimated to be small in our subsequent analysis. Since we model the spatial diffusion process in terms of observables, the spatial correlation in the unobservables becomes negligible. In contrast, as it will be shown below there is some evidence for autoregressive errors of order 1 despite the first differencing. Therefore, we report standard errors that are clustered at region level. These standard errors are also robust with respect to heteroskedasticity as another possible violation of homoskedasticity.

5 Results

The main estimation results for the first difference models are presented in Table 1. Coefficients of additional controls are reported in Table 5 in the Appendix. Before we discuss them, we briefly summarize the results that we obtained when we explore the data with a pooled OLS analysis in levels without including the AR(1) term. These models do not give consistent estimates of the model parameters but provide partial statistical relationships for the regressors, including the time constant regressors, with the dependent variable. These results for various models which differ in the regressors sets are given in Tables 4 in the Appendix and S1 in the supplement. It is apparent that there is a clear upward trend in the use of steam engines over the course of the years. Once the diffusion variables are included in the model, the calendar time pattern become less pronounced and mainly insignificant. This could suggest that the pattern of adopting steam technology is more related to a spatial process rather than calendar time itself. The coefficient on the literacy rate in contrast is small and insignificant. Most of the time constant variables are individually insignificant with the exception of the length of the rail network, the share of cultivable land and the population density prior to industrialization. While a more extensive rail network is associated with a much higher use of steam engines, there is a weak positive relationship between better cultivable land and the use of steam technology. Surprisingly, the relationship between coal extraction and intensity of steam engine use, although showing a positive sign, is not statistically significant. The association between population density and steam technology use is estimated to be negative, which can be explained by the fact that Paris had little steam engines per capita but by a huge gap the highest population density. A robust F-test for joint significance for the individually insignificant variables does not provide evidence for them being jointly significant (p-value$\approx$ 0.5). To sum up, the POLS estimates provide some first insights that the spatial diffusion process could be a key driver for the intensity of the use of steam technology, rather than calendar time, initial conditions prior to industrialization (apart from the availability of a rail network) and other time constant region specific factors.

For the reasons outlined in Sect. 4 we expect first difference versions of the model to have better properties than the model in levels. Table 1 presents estimation results for various variants of the model in Eq. (2). While Table 1 shows the results for the

Table 1 Estimation results: First difference models as in Eq. (2)

	(4) POLS	(5) P2SLS	(6) S2SLS	(7) S2SLS	(8) FD-GMM
Autoregressive process ($\Delta y_{r,t-1}$)					
Machines per 1000 inhabitants (5yr lag)		0.288	0.392 *	0.235	0.550 ***
		(0.157)	(0.170)	(0.160)	(0.088)
Time varying (ΔX_{rt})					
Literacy rate (5yr lag)	−0.001	0.000	0.001	0.002	0.005
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
Space time diffusion ($\Delta W_{r,t-1}$)					
Machines, <150 KM (5yr lag)	0.468***	0.331*	0.529 *	0.661 **	0.545 ***
	(0.114)	(0.158)	(0.255)	(0.243)	(0.149)
Machines, 150–300 KM (5yr lag)	0.213	0.157	0.053	0.004	0.122
	(0.112)	(0.092)	(0.107)	(0.115)	(0.129)
List of instruments		$y_{r,t-2}$	$y_{r,t-2}$ $\Delta W^{<150}_{r,t-2}, \Delta W^{<150}_{r,t-3}$	$y_{r,t-2}$ $\Delta W^{<150}_{r,t-2}, \Delta W^{<150}_{r,t-3}$ $X_{r,t-1}, X_{r,t-2}$	$y_{r,t-2}$ $\Delta W_{r,t-2}, \Delta W^{<150}_{r,t-3}$ $X_{r,t-1}, X_{r,t-2}$ ΔQ_{t-1}
Continued in Table 5 (supplementary material).					
Observations	1104	1101	1016	1016	1100

Cluster robust standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Underlined: Instrumented Variable

most important variables and the sets of instrumental variable used when relevant, Table 5 in the Appendix contains the results for the remaining variables. Model (4) is a static model (without $\Delta y_{r,t-1}$) and estimated by POLS using the first difference data. The results of this model are therefore comparable to the models in Table 4. It is apparent that some of the coefficients do not change statistically (such as on the literacy rate or the space time diffusion process in the perimeter 150–300 KM), while the space time diffusion in proximity of up to 150 KM reduces approximately by one half. The results suggest that there is a calendar time pattern (Table 5). Adding the autoregressive term leads to endogeneity. This is addressed in Model (5) by the classical Anderson and Hsiao (1982) estimator as outlined above. There are only minor changes in results compared to Model (4). Similarly the use of additional instrumental variables and the additional instrumenting of variables, in Models (6)–(7) does not change results statistically in the key variables but leads to a touch of higher precision. The results for the GMM model (8) appear to be even more precise with smallest standard errors. Overall, there is little statistical evidence for changes in results for key variables as coefficients are contained in the confidence intervals for other models. Putting these observations together, the intensity of the use of steam technology appears to be determined by autoregressive and space time processes in the geographic vicinity. A one unit higher intensity of steam engine use 5 years ago in the same region or on average in the neighboring regions is estimated to induce each a 0.5 higher intensity of steam power use 5 years later. The average use of steam engines in a further distant perimeter (150–300 KM) plays a weaker role. While the coefficient is often in the range 0.1−0.2 and therefore economically important, it always lacks statistical significance. This suggests that the strength of spatial time diffusion weakens considerably in distance. Surprisingly, the coefficient on the literacy rate is found to be very small and insignificant in all models. This could mean that human capital did not play a key role for the diffusion of steam power or that workers using steam engines require different skills (skills of a higher level) than literacy (see, for instance, Meisenzahl and Mokyr (2012)).

Finally, we report the results for the various error structure specification tests in Table 2. They include regression based tests, which are outlined in Appendix A.II, the Arellano and Bond test for autoregressive differenced errors and the Sargan test for the validity of overidentifying restrictions. It can be seen that there is strong evidence of autoregressive errors of order 1 and 2 in the POLS model (2) as in Table 4, pointing to a random walk. This could be due to unobserved time constant factors and motivates the use of a model in first differences. The autoregressive error structure is much weaker in the FD models, in the IV models (5)–(8), there is no or only weak evidence of AR(2) and no evidence of AR(3) errors. While the regression based tests and the Arellano-Bond test give concordant results, evidence of higher order autoregressive errors could point to the invalidity of the chosen instrumental variables. While the results for models (5) and (7) point to possible patterns, the Sargan test for the validity of the overidentfying restrictions fails to provide evidence of instrument invalidity. We have worked with different sets of IVs in these models, in particular using the 3rd lag of $y_{r,t}$ or first difference of the 2nd and 3rd lags but these specifications were either rejected by the Sargan test or suffered from too high multicollinearity between instruments. In any case, models (6) and (8) pass all tests for our chosen specification.

The table also shows that there is little evidence of spatial correlation or spatial regressive pattern in the models. There is again only little or weak evidence of spatial correlation or spatially regressive errors. While the latter is statistically rejected, there is some weak form of spatial correlation for regions in the vicinity (up to 150 KM). Given that the R^2 of the relevant regressions in Table 2 is only in the range of 2–4% and the coefficient is only 0.05, we conclude that this can only lead to minor invalidation of the inference. Adding spatial correlation error functions as additional constraints in the model is therefore not expected to result in large changes. The results for the FD models suggest that taking the first difference removes a substantial part of the auto regressive error but does not eliminate it entirely. These findings confirm our decision to report cluster robust standard errors in all tables.

6 Robustness checks

In order to explore how sensitive our results are with respect to model variations we conducted a number of robustness checks, which are reported in the supplementary material (Tables S2–S10). These include the variation of the distance threshold for the spatial diffusion process, excluding the 75'th *département* (Paris) or departments that possess a land border with a foreign country. The latter was done as the spatial diffusion process across boarders cannot be modeled due to lack of data. For the remaining departments $W_{r,t-1}$ is still computed from the full data set. We also experimented with the addition of other time varying variables X_{rt}, namely the current literacy rate and the population density. For a smaller number of years (1839, 1861, 1886, 1896) we have also access to employee numbers in four industry sectors (textile, metallurgy, steel and extraction) from which we computed the share of the population being employed in these sectors and imputed these numbers into neighboring periods of our 5 yearly panel (nearest neighbor imputation). From this, we derived information which of the sectors had largest share of employees (dominant sector) and whether the sector was present at all. Adding the additional information did not alter our main findings, although there is a loss of precision due to the smaller sample size. We also introduce a measure of intermediate human capital approximated by the number of workers and apprentices (women and men) enrolled in adult education courses (evening classes). Most coefficients are pretty robust with respect to including intermediate human capital into the model. The new variable is weakly significant in the extended model (4) but insignificant in model (2). The coefficient is small in both cases.

The results for adding time varying population density and leaving out Paris are also presented in the supplement. The main finding here is that the coefficient on the population density is found to be negative and highly significant if Paris is included. When Paris is omitted from the sample, the coefficient becomes small and insignificant, while all other coefficients do not change statistically. The reason for this is that most of our variables relate to per capita units or densities and Paris is not much different here from the other regions, except for the population density. The coefficient on the population density appears to be strongly affected by Paris which is characterized by very high population density but rather average number of steam engines per inhabitant, in particular

Table 2 Inference: Error structure specification and overidentification tests

	(2) Level—POLS	(4) FD-POLS	(5) FD-P2SLS	(6) FD-S2SLS	(7) FD-S2SLS	(8) FD-GMM
AR error (1): $H_0 : \eta = 0$ *(no AR(1))*						
$\hat{\eta}$	1.005***	0.220***	−0.09	−0.216***	−.065	−0.341***
	(0.0137)	(0.057)	(0.0615)	(0.058)	(0.059)	(0.056)
Arellano-Bond p-value		0.00	0.53	0.11	0.66	0.00
AR error (2): $H_0 : \eta = 0$ *(no AR(2))*						
$\hat{\eta}$	1.017***	0.215***	0.114**	0.068	0.12**	0.024
	(0.037)	(0.047)	(0.0445)	(0.049)	(0.046)	(0.055)
Arellano-Bond p-value		0.00	0.04	0.23	0.05	0.66
AR error (3): $H_0 : \eta = 0$ *(no AR(3))*						
Arellano-Bond p-value		0.01	0.31	0.80	0.39	0.79
Spatially correlated error: $H_0 : \eta = 0$ *(no spatial correlation)*						
Distance < 150 KM						
$\hat{\eta}$	−0.012	0.057***	0.052***	0.05***	0.05***	0.053***
	(0.034)	(0.012)	(0.01)	(0.012)	(0.012)	(0.014)
Distance 150–300 KM						
$\hat{\eta}$	−0.002	0.002	0.001	−0.001	−0.001	0.001
	(0.0146)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Spatially regressive error of order 1: $H_0 : \eta = 0$ *(no spatially regressive error)*						
Distance < 150 KM						
$\hat{\eta}$	−0.02	0.0217	.0192	−0.013	−0.019	−.019
	(0.036)	(0.023)	(0.023)	(0.000)	(0.022)	(0.022)

Table 2 (continued)

	(2) Level—POLS	(4) FD-POLS	(5) FD-P2SLS	(6) FD-S2SLS	(7) FD-S2SLS	(8) FD-GMM
Distance 150–300 KM						
$\hat{\eta}$	−0.007	−0.003	−0.005	−0.003	−0.002	−0.007
	(0.016)	(0.007)	(0.008)	(0.008)	(−0.007)	(0.009)
Overidentification test: H_0: exclusion restrictions valid						
Sargan p-value				0.11	0.51	0.82

Cluster robust standard errors in parentheses

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

during the second half of our observation period. Given that our results for the population density are not stable we decided not to include it as a time varying variable but only as time constant initial condition. The results for the alternative spatial weighting approaches are given in Table S10. While generally robust, the results for our preferred spatial weighting appear to be most stable and plausible across the various specifications. Overall, our robustness checks confirm the stability of our main result patterns.

7 Summary and conclusions

Analyses of the diffusion of steam technology at the time of the industrialization process have mainly concerned Britain and the USA and have focused primarily on factor prices (coal, capital...) as key explanations for steam adoption in industry. Our analysis adds twofold to this literature: First, it investigates the diffusion process of steam technology in France over the nineteenth century. The patterns of steam engine adoption in French industries have received less attention, mainly due to data limitations. Our contribution builds on a new and comprehensive dataset which contains information on the number of steam machines implemented in industries, per *département*. Second, by means of estimations of spatial econometric models, our analysis examines the spatial patterns of steam technology diffusion among the French departments. While the existing literature mainly puts forth the influence of factor prices heterogeneity as a main explaining factor for steam adoption, our analysis adds new pieces to the 'steam puzzle' by highlighting a spatial diffusion process. This paper shows that intensity in the use of steam engine within close proximity (lower or equal to 150 km) was a strong and robust predictor of steam engine adoption among French industries. Future research could extend our analysis to allowing the diffusion process to depend on the phase of the industrialization. It would be of interest to see whether these neighborhood effects are more relevant in early phases of the adoption process than in later.

Recent literature on the industrialization process has developed the idea that the great enrichment experienced by western European countries since the eighteenth century was not so much rooted in differences related to the economic environment (capital accumulation, human capital accumulation, institutions, coal, etc,) but the evolution of culture and ideas (Mokyr (2016); McCloskey (2006, 2010, 2016)). Though on different grounds, our approach is in line with these approaches. It supports as well the idea that better understanding of the industrialization take-off requires to go beyond an analysis of capital accumulation or of differences of factor prices only. By underlining strong and robust neighborhood effects influencing steam technology adoption, our contribution indeed suggests that information and experience sharing can have acted as key drivers for technological breakthrough in the nineteenth century. In this light open borders and any kind of facilitation of information sharing across regions and countries will contribute to the adoption of new technologies and therefore economic prosperity.

Appendix

A:I Tables

See Tables 3, 4 and 5.

Table 3 Summary statistics of the estimation sample (main variables)

	Count	Mean	SD	Min	Max
Dependent variable ($y_{r,t}$)					
Machines per 1000 inhabitants	1297	.887	.947	0	6.185
Time varying regressors ($X_{r,t}$)					
Literacy rate (5 year lag)	1294	79.202	18.889	18.4	99.9
Space time diffusion variables ($W_{r,t-1}$)					
Machines per 1000 inhabitants, <150 Km (5 year lag)	1197	.859	.749	.002	3.907
Machines per 1000 inhabitants, 150–300 Km (5 year lag)	1211	.894	.716	.007	2.88
Time constant explanatory variables and initial conditions (V_r)					
Inhab p. doctor in 1847 (in 1000s)	1249	3.895	1.521	1.157	8.151
Share protestants in 1861 (in %)	1282	1.93	4.607	.003	31.3
Share Jews in 1861 (in %)	1282	.092	.325	0	3.625
Latitude	1297	46.423	2.131	41.919	50.629
Longitude	1297	2.561	2.629	−4.098	8.739
KM of railway per 1000 hectare land	1249	.206	.392	0	3.554
KM of royal road per 1000 hectare land	1249	.636	.3	.197	2.762
Population density in 1801	1230	1327.111	2804.355	370	26,316
Share of cultivable land	1249	35.839	13.647	8.513	64.928
Sea coast	1297	.263	.44	0	1
Land border	1297	.199	.399	0	1
Coal extraction	1297	.324	.468	0	1
Distance to Paris	1297	363.881	189.506	0	917.837
Distance to Le Nord	1297	512.104	226.246	0	1061.616
Time periods (Q_t)					
1851	1297	.066	.249	0	1
1856	1297	.066	.249	0	1
1861	1297	.069	.253	0	1
1866	1297	.066	.248	0	1
1871	1297	.066	.249	0	1
1876	1297	.066	.249	0	1
1881	1297	.067	.25	0	1
1886	1297	.067	.25	0	1
1891	1297	.067	.25	0	1
1896	1297	.067	.25	0	1
1901	1297	.067	.25	0	1
1906	1297	.066	.249	0	1
1911	1297	.067	.25	0	1

Table 4 Estimation Results: POLS estimation of model (1)

	(1)	(2)	(3)
Time varying (X_{rt})			
Literacy rate (5 year lag)		−0.003	−0.0001
		(0.002)	(0.002)
Space time diffusion ($W_{r,t-1}$)			
Machines per 1000 inhabitants, <150 Km (5 year lag)		0.802***	1.026***
		(0.160)	(0.148)
Machines per 1000 inhabitants, 150–300 Km (5 year lag)		−0.034	0.145
		(0.184)	(0.183)
Time constant (V_r)			
Inhab p. doctor in 1847 (in 1000s)		0.02	
		(0.037)	
Share protestants in 1861 (in p.p.)		0.004	
		(0.014)	
Share Jews in 1861 (in p.p.)		0.107	
		(0.109)	
Latitude		−0.140	
		(0.116)	
Longitude		−0.036	
		(0.032)	
KM of railway per 1000 hectare land (in p.p.)		1.626***	
		(0.471)	
KM of royal road per 1000 hectare land (in p.p.)		−0.130	
		(0.290)	
Population density in 1801		−0.0002**	
		(0.0001)	
Share of cultivable land		0.009*	
		(0.004)	
Sea coast		0.08	
		(0.117)	
Land border		0.018	
		(0.123)	
Coal extraction		0.116	
		(0.083)	
Distance to Paris		0.0005	
		(0.001)	
Distance to Le Nord		−0.002	
		(0.002)	
Continued in Table S1 (supplementary material).			
R^2	0.499	0.776	0.704
Observations	1194	1121	1194

Cluster robust standard errors in parentheses

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 5 Estimation results: FD models, continuation from Table 1

	(4) POLS	(5) P2SLS	(6) S2SLS	(7) S2SLS	(8) FD-GMM
Calendar year					
1851	0.002	−0.004			−0.035**
	(0.009)	(0.009)			(0.013)
1856	0.071***	0.062***	0.058***	0.068***	0.01
	(0.02)	(0.019)	(0.012)	(0.016)	(0.023)
1861	0.121***	0.104**	0.082**	0.102**	−0.001
	(0.035)	(0.033)	(0.027)	(0.038)	(0.036)
1866	0.168**	0.140**	0.093*	0.131*	−0.038
	(0.051)	(0.05)	(0.045)	(0.067)	(0.054)
1871	0.188**	0.149*	0.071	0.129	−0.113
	(0.071)	(0.068)	(0.067)	(0.101)	(0.078)
1876	0.279**	0.221*	0.117	0.195	−0.111
	(0.086)	(0.087)	(0.088)	(0.130)	(0.096)
1881	0.409***	0.334***	0.197	0.289	−0.08
	(0.099)	(0.100)	(0.103)	(0.155)	(0.114)
1886	0.461***	0.362**	0.178	0.285	−0.166
	(0.126)	(0.130)	(0.138)	(0.196)	(0.136)
1891	0.491**	0.368*	0.140	0.265	−0.268
	(0.150)	(0.154)	(0.164)	(0.236)	(0.162)
1896	0.596***	0.452**	0.189	0.331	−0.270
	(0.168)	(0.173)	(0.185)	(0.266)	(0.179)
1901	0.669***	0.502**	0.196	0.352	−0.322
	(0.192)	(0.194)	(0.214)	(0.303)	(0.203)
1906	0.673**	0.479*	0.133	0.304	−0.436*
	(0.205)	(0.211)	(0.233)	(0.329)	(0.220)
1911	0.721**	0.507*	0.138	0.320	−0.462*
	(0.219)	(0.218)	(0.248)	(0.348)	(0.227)

Cluster robust standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

A.II Regression based tests for AR and spatially correlated errors

In what follows the regression based tests for autoregressive errors, spatial correlation and spatial regressive errors are outlined. For a detailed description of regression based tests for autoregressive errors see Wooldridge (2020). Let U and ΔU be the stacked vectors of all $u_{r,t}$ and $\Delta u_{r,t}$, respectively. These tests provide evidence whether var($U|y_{r,t-1}, Q_t, V_r, X_{r,t}, W_{r,t-1}$ for all r, t) and var($\Delta U|\Delta y_{r,t-1}, \Delta Q_t, \Delta X_{r,t}, \Delta W_{r,t-1}$ for all r, t) in the models of Eqs. (1) and (2), respectively, possess zero off-diagonal elements. Serial or spatial correlation can make some blocks of these matrices nonzero. To test for this we directly estimate auto regressive and spatial correlation error functions on the grounds of residuals $\hat{u}_{rt}$ and $\widehat{\Delta u}_{rt}$. As long as the model is consistently estimated, these residuals will be consistent estimates for the errors. By regressing $\hat{u}_{rt}$ on $\hat{u}_{r,t-1}$, the coefficient, say η, on the latter is then an direct estimate of the first order autoregressive relationship. A zero coefficient implies that errors are not correlated across adjacent periods. A coefficient of one implies a random walk. A Wald test is then applied to test for the true parameter to be zero. The test can be easily adapted to other orders of serial correlation say p, by regressing $\hat{u}_{rt}$ on $\hat{u}_{r,t-p}$. Similarly, the spatial correlation structure can be estimated by regressing $\hat{u}_{rt}$ on $\sum_{s\neq r} w_{rs}\hat{u}_{st}$, with d_{rs} is a weight function that typically depends on the distance between regions r and s. In our application we use binary weights that are 1 if region s is located in a certain distance range from region r and 0 otherwise as described in the data section. Again, spatial correlation is rejected if the coefficient on the regressor is not significant. In the same way, the spatial regressive error function can be estimated by regressing $\hat{u}_{rt}$ on $\sum_{s\neq r} d_{rs}\hat{u}_{s,t-1}$, which reveals if errors in t are related to errors in the previous period in other regions that are in a certain distance range from region r. The same approach can be applied by using the residuals of the model in first differences in Eq. (2), i.e., $\widehat{\Delta u}_{rt}$, instead of the model in levels.

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