Unravelling the Trail of a GPT: The Case of Electrical & Electronic Technologies from 1860 to 1930

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Abstract

It has been argued that episodes of acceleration in economic growth can be driven by particular technologies. These revolutionary technologies, often referred to as General Purpose Technologies (GPTs), have the power to change the pace and direction of economic progress. While historical accounts and theoretical models have advanced greatly in providing both, a precise and coherent characterization of GPTs and the economic consequences of its diffusion, empirical evidence is still scattered. This paper contributes to the literature in two ways, first it provides a way of characterizing GPTs using patent data and shows that the most iconic example, electricity, fulfils these criteria. Secondly, it documents the positive impact of the diffusion of electricity-related inventions on income per capita and wages at county level in the United States from 1860 to 1930. Results are in line with previous historical accounts on the subject, and are consistent with theoretical predictions.

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1 Introduction

Technological change has marked the pace of socio-economic progress in recent western history, growing at unprecedented and continuously increasing rates. It has been argued that episodes of acceleration in technological progress were driven by particular technologies. These technologies, given their revolutionary nature, have had the power to change the pace and direction of economic progress, as well as to transform the social and political structures surrounding them. Widely known examples are the steam engine and the electricity. Information and communication technologies (ICTs) are often mentioned as a contemporaneous example.

In economics, these revolutionary technologies are referred to as 'General Purpose Technologies' (GPTs). GPTs are characterized by possessing a wide scope for continuous improvement and elaboration, on the one hand, and high complementarity on the other. The latter meaning that a GPT should be able to diffuse on a wide range of sectors, not only because it is used an input in many different products and processes but also because it is a technological complement of existing and new technologies. These characteristics are what make GPTs "engines of growth".

While theoretical models have advanced greatly, providing a precise and coherent characterization of the economic implications of the difussion of a GPT (Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1998b) ,Helpman and Trajtenberg (1998a), and Aghion and Howitt (2000)), a lack of convincing and comprehensive empirical evidence has brought to question the relevance and usefulness of the notion of GPTs (Field, 2008).

The main empirical challeges are, on the one hand, to provide a measurable way of characterizing GPTs. As Lipsey, Carlaw, and Bekar (2005) puts it: "if the concept of a GPT is to be useful, then GPTs must be identifiable". Even thought work has been done in this subject, no clear consensus has been reached. Hall, Trajtenberg, et al. (2006) propose a series of indicators based on a group of selected patents granted at the United States Patent and Trademark Office (USPTO), however, these indicators are not able to fully portray ICTs in a way that is consistent with theory. Additionally, Moser and Nicholas (2004) use a similar set of measures to evaluate whether electricity matches the GPT criteria based on a sample of historical patents assigned to publicly traded companies in the 1920's. They reject the hypothesis that electricity was a GPT. Also using patent data, Feldman and Yoon (2012) show that the Cohen–Boyer method for recombining genetic material[1] exhibits characteristics of a GPT. Therefore, empirical evidence remains inconclusive, either there isn't any particular technology capable of fulfilling the criteria set by theory, or current measures are not an appropriate way of identifying GPTs.

A second empirical challenge consist on finding evidence of a GPT having a real impact in the economy, given that theory provides clear predictions on how the diffusion of a GPT should affect growth and wages. So far, most of the evidence has been collected at an aggregated level (national); putting an immediate limitation on the possibility to directly relate economic changes to the diffusion of a GPT. See for instance David (1990), Greenwood (1997), David and Wright (1999), Crafts and Mills (2004), Crafts (2004), and Jovanovic and Rousseau (2005). A valuable contribution towards providing evidence at a finer level of disaggregation was made by Rosenberg and Trajtenberg (2004). They used county-level information on the adoption of the Corliss steam engine during the late nineteenth century and showed it had a positive effect on population growth. Additional evidence was provided in the form of detailed historical accounts on the economic and societal changes generated by several GPTs candidates throughout history (Lipsey, Carlaw, and Bekar, 2005).

Therefore, there is a lack of consensus on how to identify GPTs on the one hand, and a need for comprehensive empirical evidence about its effect over the economy on the other. This paper addresses these two issues by combining economic and demographic data provided by the U.S Census Bureau and IPUMS (the Integrated Public Use Microdata Series) with a novel database containing detailed information on the geographical location, as well as the type of technology, of patents granted at the USPTO dating back to 1836. First, I provide a way of characterizing GPTs using patent data, to later test whether the most iconic example, electricity, fulfils these criteria. After showing it does, I study the positive impact that the

[1]https://www.google.com/patents/US4237224

diffusion of electricity-related inventions had on income per capita and growth. Results are in line with previous national-level evidence and historical accounts on the subject, showing patterns that are also consistent with the predictions of theoretical models.

The paper is organized as follows: The next section describes the different sources of data used in this study, while Section 3 proposes a way to identify the main characteristics of a GPT using patent data. Section 4 evaluates whether the diffusion of E&E technologies between 1860 and 1930 affected output and wages as suggested by historical evidence and theoretical models. Section 5 concludes.

2 Data Sources

This section describes the different sources of data used in this study, which combined allow for a comprehensive overview of the emergence, evolution, development, and diffusion of E&E technologies in their historical context. Empirical studies dealing with the evolution of tecnologies are always limited in quantity and scope by the availability of data and the nature of the object of study. After all, diffusion of technologies takes decades, and the most interesting cases happened long before data started to be collected systematically. For instance, the Corliss steam engine discussed in Rosenberg and Trajtenberg (2004) was patented in 1849[2], while Edison's carbon filament incandescent lamp mentioned in David (1990) dates back to 1880[3]. This is also true for the invention of integrated circuits, allegedly to be the engine of the ICT revolution, which can be traced back in the U.S. to 1959[4]. In this study I am going to focus on the period going from 1860 to 1930, which is considered to cover the emergence, development, and diffusion of Electrical and Electronic technologies (David, 1990; Lipsey, Carlaw, and Bekar, 2005; Greenwood, 1997; Goldfarb, 2005). I overcome data limitations by merging several independently-developed datasets, containing information about the technological and geographical attributes of patented inventions in the U.S., as well as county-level economic and demographic data.

First, I use information about the technological class along with the full description of patents documents made available by the USPTO[5]. In 2006, the USPTO entered into a series of agreements with Reed Tech and Google to digitalize all available patent documents, making historical patent data available in bulk form. This bulk data contains ZIP or TAR files with TIFF or PDF images, concatenated XML or structured ASCII files with all available information in patent documents dating back to 1836. This means that for every patent

[2]See https://www.google.com/patents/US6162

[3]See https://www.google.com/patents/US223898

[4]See https://www.google.com/patents/US3138743. The first integrated circuit is attributed to Werner Jacobi (Siemens AG) in 1949 (https://www.google.com/patents/DE833366).

[5]http://www.uspto.gov/learning-and-resources/electronic-bulk-data-products.

document ever granted since 1836 it is possible to identify its technological class as well as to access the full description of the invention.

Patents are classified into technological classes according to the type of invention they claim rights to. There are currently more than 400 different technological classes in use, and whenever a new class is created, or an existing re-defined, all available patents are re-classified in order to mantain temporal consitency. Furthermore, patents can be grouped into broad economically-relevant categories (Chemical, Computer and Comunications (C&C), Drugs and Medical (D&M), Electrical and Electronics (E&E), Mechanical, and Others)[6]. Table 1 below shows the distribution of patenting activity across these broad categories over time.[7].

Table 1: Distribution of Patenting Activity Over Time

	Chemical	C&C	D&M	E&E	Mechanical	Others
1850	0.102	0.007	0.016	0.011	0.396	0.469
1860	0.096	0.001	0.008	0.019	0.355	0.522
1870	0.095	0.002	0.013	0.016	0.336	0.537
1880	0.082	0.009	0.009	0.033	0.345	0.522
1890	0.063	0.010	0.012	0.065	0.385	0.466
1900	0.089	0.013	0.012	0.053	0.379	0.453
1920	0.080	0.018	0.011	0.078	0.403	0.410
1930	0.121	0.020	0.010	0.096	0.361	0.391

Note: Shares are calculated as the number of patents within each broad category over the total

There are considerable differences among categories. Mechanical and Chemical technologies are amongst the most abundant types, which is probably a reflection of them being at a more advanced stage of maturity than C&C, D&M, and E&E. Note that while these big categories had an irregular and rather decreasing behaviour over time, the rest showed a marked and steady increase in their participation. In fact, E&E technologies have seen

[6]See Hall, Jaffe, and Trajtenberg (2001) for details. The concordance is available at http://www.nber.org/patents/.

[7]Patents can be assigned to more than one technological class or broad category depending on the scope of the claims made. In this table only the main technological classification is considered.

almost a 10-fold increase in activity during this period, going from representing a 1% of all inventive activity to almost 10%. Note that even though C&C and D&M technologies grew significantly during this period they represent, on average, around only 1% of the technological production. For this reason, and for the sake of exposition, in what follows the analysis will be carried out in terms of the most relevant technologies of this era (Mechanical, Chemical, E&E, and Others); which jointly represent approximately 98% of all technological production[8].

These broad categories differ also in terms of the number of technological classes they are composed of. There are more than 80 different technological classes within Chemical, around 120 within Mechanical, and 54 in E&E technologies. Others account for approximately 180 classes. Information about technological classes has been widely used in empirical studies, usually to create measures of technological diversity of places (**?**) as well as of the generality of particular inventions (Hall, Jaffe, and Trajtenberg, 2001; Moser and Nicholas, 2004; Hall, Trajtenberg, et al., 2006; Feldman and Yoon, 2012).

The second source of data comes from the novel data initiative in Petralia, Balland, and Rigby (2016), which provides county-level information on the location of the inventor(s) and/or assignee(s) for most patents granted since 1836[9]. This permits to track down the diffusion inventions in space. This database, HistPat, was built using optically recognized and publicly-available patent documents at USPTO, combining text-mining algorithms with a statistical model to indentify locations[10].

Figure 1 below describes the diffusion of patenting activity over space and time. It shows how it first spread from the north-eastern states, where most of the inventive activity was concentrated before the 1860's, towards the south-east to later reach the west coast by the

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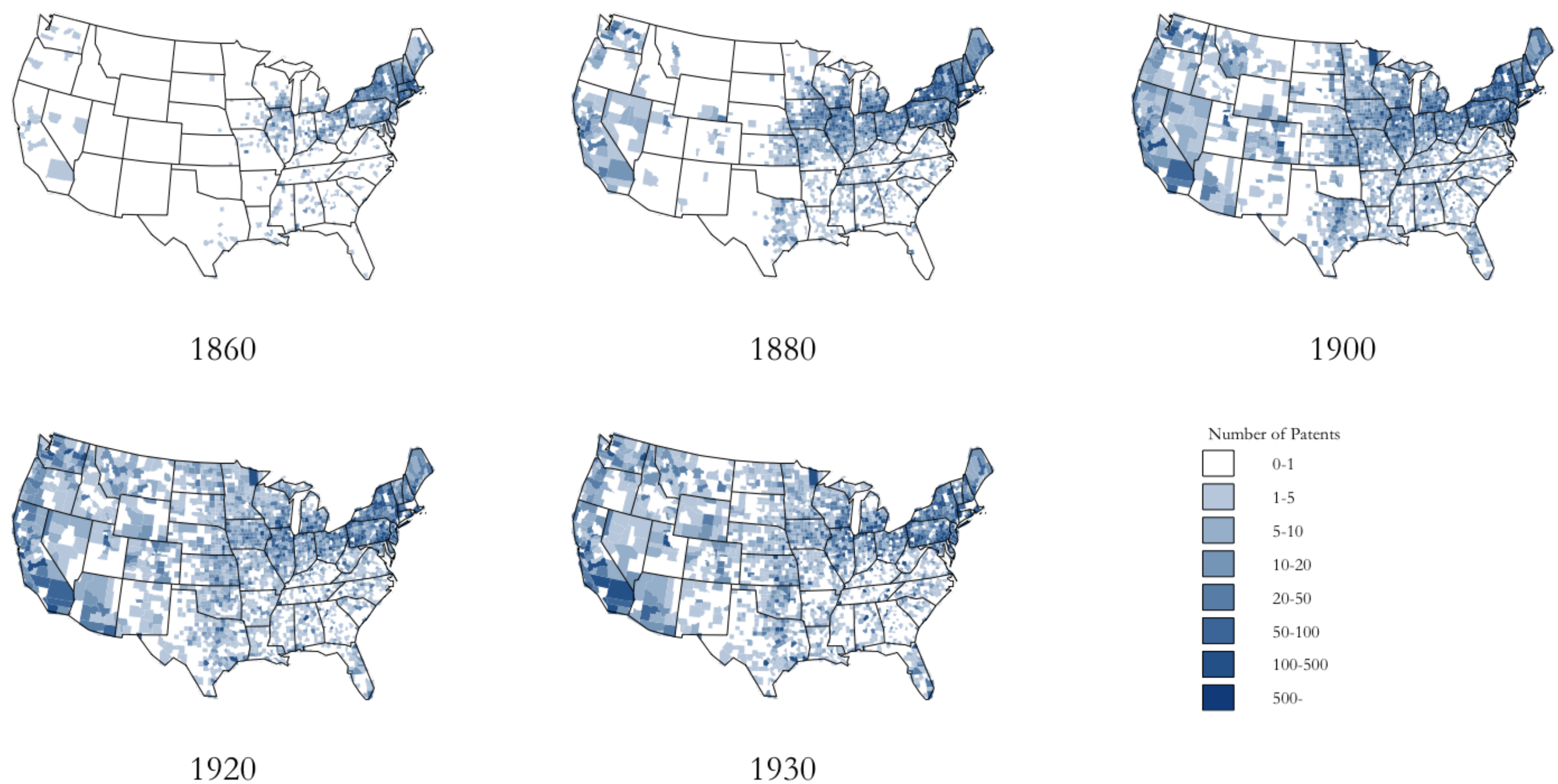
[8]C&C and D&M technologies are collapsed into the category Others. Results do not differ if they are considered as separate categories.

[9]The data can be downloaded at https://dataverse.harvard.edu/dataverse/HistPat

[10]The entire procedure is documented in Petralia, Balland, and Rigby (2016), for a summary description along with a discussion of the database see the appendix.

1880's. Patent activity closely followed the development of urban centres and migration (Ager and Brückner, 2013; Burchardi, Chaney, and Hassan, 2016). Central states joined the technological race by the turn of the century.

Figure 1: The Geography of Patenting Activity Through the Years



Source: Own elaboration based on HistPat

The geographical diffusion of inventive activities was quite heterogeneous across technologies, as shown in Table 2. This table displays the correlation of patenting activity across different categories throughout the entire period, where each vector takes value one whenever patenting activity in a county was found and zero otherwise[11]. Note that this heterogeneity in the geographical pattern of diffusion provides a great opportunity to exploit time-place differences in the adoption of technologies. This can be used evaluate the relationship between the evolution of economic outcomes and the diffusion of different technologies.

Table 2: Geographical Correlation in Patenting Activity

	E&E	Mechanic	Chemical	Others
E and E	1	0.359	0.436	0.335
Mechanic	0.359	1	0.454	0.596
Chemical	0.436	0.454	1	0.432
Others	0.335	0.596	0.432	1

This brings us to the next data source used in this paper. The county-level technological development of counties described above can be combined with economic and demographic data provided by the U.S. Census Bureau and IPUMS. In particular, I use the database provided by the Inter-University Consortium for Political and Social Research (ICPSR), which contains detailed decennial county and state level data on demographic, economic, and social variables that were collected by the U.S. Census Bureau[12]. In Addition, I use data on occupations provided at the IPUMS[13].

Table 3 below shows the evolution of the main economic and demographic variables in the sample. Note that this period evidenced a fast and continuous growth in terms of population, which cuadruplicated since 1860. Immigration certainly was one of the main explanatory

[11] All counties are included in the sample. If only counties with positive patenting activity are considered correlations are considerably lower.

[12] Downloadable at https://www.icpsr.umich.edu/icpsrweb/

[13] See https://usa.ipums.org/usa/intro.shtml

factors, by 1880 more than 10% of the population was foreign, with this number jumping to 20% if second generation immigrants are included (Burchardi, Chaney, and Hassan, 2016). Migration was mostly unregulated until World War I, after which a series of restrictions were incorporated, ultimately deriving in the establishment of a quota system in 1921[14].

Table 3: Evolution of Main Census Variables

	1860	1870	1880	1890	1900	1920	1930
Population (in millions)	31.409	38.542	50.150	62.610	75.726	105.967	123.143
Foreign Population (in millions)	4.130	5.562	6.677	9.246	10.428	13.713	13.366
Labor Force (in millions)	1.276	2.054	2.733	4.710	5.316	9.056	8.751
Output (in billions)	1.753	2.534	4.104	8.080	12.126	24.261	32.764
Output per Capita	55.827	65.740	81.825	129.049	160.130	228.950	266.061
Wages (share)	0.206	0.306	0.231	0.282	0.192	0.432	0.352

Notes: Output corresponds to ouput in manufactures at 1850's constant prices. Wages are expressed as a share of the total output, while Labor Force counts hands employed in manufacture.

The remarkable increase in terms of manufacture production of this era was determinant for the positioning of the U.S. as a world leader, which happend after the 1900's when U.S. surpassed Great Britain in terms of world share and per capita levels of total manufacturing output (David, 1990). Additionally, Field (2006) estimates that in the 1920's, manufacturing alone explained more than 80% of Total Factor Productivity (TFP) growth.

There were many factors contributing to this remarkable success. For instace, Wright (1990) argues it had to do with a greater exploitation of U.S. geological potential after examining the factor content of trade in manufactured goods, while Ager and Brückner (2013) relates higher growth with immigation and the cultural diversity of places. Additionally, (Acemoglu, Moscona, and Robinson, 2016) suggests that part of the exceptional technological dynamism in this period can be explained by an immensely capable and effective state. The existence of these explanatory factors lead to the inclusion of two more variables that were

[14]Daniels (1990) provides a detailed description of the nature and composition of immigration flows during this period.

collected independently of previous sources. One of them being the number of post offices per county, to proxy for state's presence as in Acemoglu, Moscona, and Robinson (2016)[15]. The second counts the number of working mineral deposits within counties using geo-located information provided by the United States Geological Survey (USGS)[16].

Because these variables only play a marginal role in the econometric specification (acting as controls), and their construction didn't involve any methodological challenge, I do not provide further description of them. More details can be found in the appendix.

If, as Field (2003) points out, this was one the most innovative periods in U.S. history, is it possible that E&E technologies were the engine of it? The next Section starts by discussing a way to identify the main characteristics of a GPT in data, to later conclude that E&E technologies evidenced an unusual dynamism; which was consistent with the expected behaviour of a GPT. This builds the ground for Section 4, which tests the impact of E&E adoption on economic outcomes.

[15] Original records can be found here: https://catalog.hathitrust.org/Record/002137107

[16] Available here: https://mrdata.usgs.gov/mrds/about.php

3 Towards a characterization of GPTs

This section aims at providing a mean to identify the main characteristics of a GPT in data. Given the amount of information and the level of detail contained in patent documents, it is natural to start looking for ways of characterizing GPTs using patent data. Every patent provides information on the technological nature of the invention, the geographical location of the inventor, and the prior art, among other things. This implies that one could identify whether a patent has claimed, for instance, rights on the invention of a new electrical device, or a new function for a chemical compound, or both. Meaning that a patent can claim rights on different types of components or technologies that have been created and combined to produce a product.

Even though there is no agreement on how to measure GPTs, there is a clear undestanding on what defines them. According to Helpman and Trajtenberg (1998b), Helpman and Trajtenberg (1998a), Moser and Nicholas (2004), Lipsey, Carlaw, and Bekar (2005), and Jovanovic and Rousseau (2005), GPTs must have:

1. **Wide scope for improvement and elaboration.** They should be able to go through a continuous process of technological improvement.

2. **Potential for use in a wide variety of products and processes.** They should spread and be used in most sectors.

3. **Strong complementaries with existing or potential new technologies.** They should have an impact on existing and new technologies, not only by creating the need to alter and combine many of the existing technologies, but also by increasing the opportunities to develop new technologies in combination with it.

Previous studies haven't been able to fully portray the alleged GPT-characteristics for electricity and ICTs in patent data (Moser and Nicholas (2004) and Hall, Trajtenberg, et al. (2006), respectively). If even with the wealth of information contained in patent documents it is not possible to portray a theory-consistent picture for two of the most commonly mentioned GPT examples, then we may as well start questioning whether the criteria used to identify GPTs could ever be fulfilled, or to what extent patent data is an useful instrument.

One of the main limitations imposed by patent data is the availability to go back in time long enough to cover periods that include the emergence, development, and diffusion of technologies. This is due to the fact that patent documents started to be digitalized in 1975. However, the use of citations has been a common approach to overcome this limitation, as they go back in time linking present and previous inventions (sometimes for more than a hundred years). Both, Moser and Nicholas (2004) and Hall, Trajtenberg, et al. (2006) used citation-based measures to address the question of weather electricity and ICTs, respectively, behaved as GPTs.

The possibility of tracing back in time the knowledge embodied in patents through citations relies on two assumptions, first that direct citations provide a comprehensive picture of the type of knowledge contained in a patent, and secondly, that the dynamic of patent citations is invariant enough such that the knowledge composition of patents survives over time.

In this paper I use contemporaneous patent-related measures to identify the alleged characteristics of GPTs. The scope of the data allows to have comprehensive view of the emergence, evolution, development, and diffusion of technologies in their historical context. It focuses on the most iconic example of a GPT, electricity. In what follows I propose three patent-related indicators that can be used to identify these characteristics[17].

[17]Lipsey, Carlaw, and Bekar (2005) argues that there is a fourth condition any GPT must have, i.e. a variety of uses. This refers to the number of distinct uses that are made of a single technology. He emphasises that having a variety of uses is not the same thing as being widely used (Section 3.2 here). In the particular case of the electricity, he makes a convincing argument to support that it fulfils this requirement. Note that electricity can be used as a power source, for illumination, as a mean of communication, etc.. For this reason it is not explored further.

3.1 Wide Scope for Improvement and Elaboration

As literature suggests, GPTs should be able to go through a continuous process of technological improvement. This notion is based on the fact that most technologies are originally introduced as unrefined versions of their best self. What distinguishes a GPT is the distance to this most efficient, mature version of itself; which entails developing and perfecting it for its many uses, as well as adaptation to a wide arrange of complementary and yet maybe unrelated technologies.

This is probably the least challenging characteristic to relate to data. Previous empirical approaches have often used patenting growth to measure the extent and pace at which technologies have been advancing. For instance, Jovanovic and Rousseau (2005) looked at the growth rate of total patenting activity in the U.S and related changes in its pace to the electric and ICT era. Moser and Nicholas (2004) showed that patent activity in the category of Electrical and Electronic (E&E) technologies grew the fastest in the 1920's. Similarly, Hall, Trajtenberg, et al. (2006) found classes related to Computer and Communication (C&C) technologies to grow faster than others after the 1980's.

Here I also consider growth in patenting activity, in particular, I use the Cumulative Average Growth Rate (CAGR) of patent production per technological category:

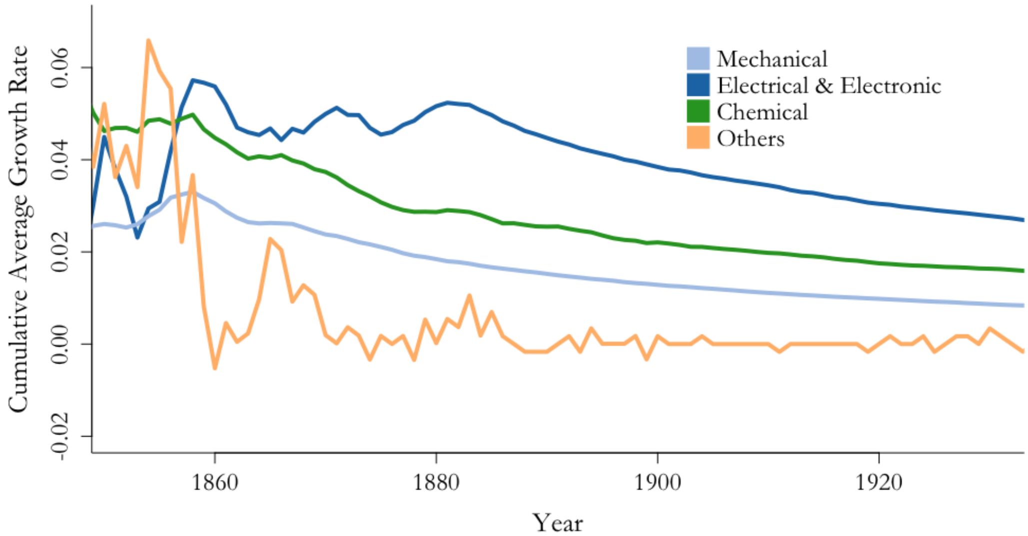
$$CAGR_{(t,j)} = \left(\frac{P_{(t,j)}}{P_{(t_0,j)}}\right)^{\frac{1}{t-t_0}} - 1$$

Where $P_{(t_0,j)}$ and $P_{(t,j)}$ stand for amount of patents produced in the initial year and at time t respectively, for category $j \in \{E\&E, Mechanical, Chemical, Others\}$. This indicator measures the geometric progression ratio of patenting activity, providing a constant rate of return over the time period.

Figure 2 below displays the CAGR of patenting for every broad category after 1850.[18] It shows that the number of E&E patents granted at the USPTO grew the fastest during the

[18]The initial year is 1840 because it is when every broad category started to show positive patenting activity.

Figure 2: CAGR of Patent Production per Category



Source: Own elaboration based on USPTO Patent Data

second half of the nineteenth century and up to the end of our period (1930). Results are in line with previous findings, regarding the prominent role of E&E technologies after the 1850's.

The above-average growth in patenting activity for E&E technologies is also evident when looking at Table 1 in Section 2. It shows they increased their participation by an order of magnitude since 1850, going from representing a 1% of all patenting activity to almost 10% in 1930.

3.2 Potential for Use in a Wide Variety of Products and Processes

It is argued that as GPTs evolve and develop they should spread throughout the economy, given their potential to be used as an input in many different applications. For example, electricity as a power source diffused through a wide range of sectors. It is used for household appliances, in transportation technologies, as well as to power a varied number of industries. Additionally, the ability of electricity to drive chemical reactions, as well as to make digital information processing possible, drastically expanded its range of uses.

Several approaches have been used to evaluate the pace and span of the electrical diffusion throughout the economy. One of them was to consider the overall, nation-wide, electrification of factories and households. David (1990) documents that the electric power used in mechanical drive capacity in the U.S. reached more than 50% by 1920, while Goldfarb (2005) and Duboff (1979) find that by 1929 the ratio of electric motor power to total motor power reached 82% on average. Jovanovic and Rousseau (2005) show that by 1929 nearly 70% of households had electrical connections.

When it comes to patent data, Moser and Nicholas (2004) and Hall, Trajtenberg, et al. (2006) relied on patent citations to measure how wide the range of applicability of E&E and C&C technologies were, respectively. They use the technological diversity of citing patents to evaluate the generality of any cited patent. Therefore, the generality of a patent depended on how technologically heterogeneous its citing patents are.

I consider a different approach, which takes advantage of the wealth of information contained in patent documents and provides a characterization of E&E technologies in their historical context. Note that all patents provide a detailed description of the invention, which can be scanned to identify key-words related the use of electronic and electrical components, notions, or principles (see the appendix to find the list of words). Therefore, patents that match this criteria but do not belong to the category of E&E can be considered as 'users of electricity'. This set of patents will typically include inventions that use electricity-related terms because they rely on electricity-related components, notions, or principles, but don't produce any particular technological improvement in that area.

Figure 3 can be used as an example. It shows the first page of the patent number 2.956.114 assigned to Ampex Corporation in 1960 for a broad band magnetic tape system (tape recorder). This particular patent falls under the category of C&C technologies, and cites patents only in C&C and Mechanical. This implies that using a citation based method, or the standard technological classification, we are not able to identify that the invention uses electrical components.

Going through the patent description provides, however, enough clues for the algorithm to detect the electrical nature of it. Figure 3 highlights electricity-related words that are used to identify that this invention uses E&E technologies as inputs.

After identifying which inventions are "users" of E&E technologies, it is therefore possible to evaluate how wide the variety of technological products and processes using E&E technologies is. The most straightforward way to do this consist on counting the number of different technological categories that are users of E&E technologies at any point in time, which provides a contemporaneous measure of the pervasiveness of E&E technologies as inventive inputs.

Figure 4 below shows the share of technological classes where E&E-related vocabulary has been found. This share is calculated with respect to the total number of different technological classes available at any point in time, which are not E&E. For instance, Figure 4 shows that by 1850 less than 5% of all non-E&E technological classes were using E&E-related vocabulary to describe inventions. By the end of the 1930's this share jumped to more than 80%.

Figure 4 shows the impressive dissemination of E&E-related vocabulary thorough the whole spectrum of available technologies. It climbed from representing a negligible share in 1850, to be present in about 90% of all non-E&E technological classes. This result points towards the wide variety of technologies using E&E technological components, principles, and notions as inputs in the innovation process. This suggests that electricity pervaded the whole inventive structure, affecting the entire nature of the technological production since its introduction.

If previous evidence showed that the use of electricity as a power source pervaded households (Jovanovic and Rousseau, 2005) and the productive structure of the U.S. economy (David, 1990; Goldfarb, 2005), Figure 4 adds a new dimension. It shows that electricity also had a simultaneous, and equally pervasive effect in the whole U.S. inventive structure. It changed the nature of the technological advance, diffusing throughout the entire space of technologies.

Figure 3: Ampex Broad Band Magnetic Tape System (1960)

United States Patent Office

2,956,114
Patented Oct. 11, 1960

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2,956,114

BROAD BAND MAGNETIC TAPE SYSTEM AND METHOD

Charles P. Ginsburg, Los Altos, Shelby F. Henderson, Jr., Woodside, Ray M. Dolby, Cupertino, and Charles E. Anderson, Belmont, Calif., assignors to Ampex Corporation, Redwood City, Calif., a corporation of California

Filed July 25, 1955, Ser. No. 524,004

8 Claims. (Cl. 178—6.6)

This invention relates generally to electromagnetic tape systems, methods and apparatus, particularly to systems and methods of this character capable of recording and reproducing signal intelligence over a wide frequency spectrum, including for example, video frequencies.

Various problems are involved when it is attempted to record and reproduce frequencies over a wide spectrum, as for example frequencies ranging higher than one megacycle, on magnetic tape. Assuming the use of reasonable tape speeds, conventional equipment is limited with respect to its usable frequency range. The recordable range can be increased by increasing the speed of the tape, but the speeds required for the recording of such high frequencies are such that the system becomes impractical because of the large amount of tape employed for a given recording period. It is possible to reduce the linear tape speed by recording successive tracks extending laterally across the tape. Equipment with this purpose involves the use of magnetic record units which are mounted to sweep successively across the coated surface of the tape while the tape is being advanced in the direction of its length. While this arrangement makes it theoretically possible to provide relative speeds such that frequencies up to four megacycles or higher can be recorded, its application necessarily involves a number of problems. For example the outputs of the several heads are subject to amplitude variations, due to various causes such as lack of exact registration on the recorded track, amplitude variations in the record because of slight variations in pressure between the several heads, and slight variations in the electrical characteristics of the heads. The conventional magnetic tape recording system, using currents varying in amplitude for application to the recording head, is particularly susceptible to undesired amplitude variations. The undesired signal variations cause distortion of the reproduced signal, and make it difficult if not impossible to reproduce the original frequency spectrum with reasonable fidelity, and particularly with sufficient fidelity to permit the recording and reproduction of television or like visual images.

The present invention is predicated upon certain discoveries which we have made, and which we utilize to advantage in the present invention. Particularly we have found that a wide frequency spectrum can be successfully recorded and reproduced by the use of a frequency modulation system in which the deviation of the carrier is small relative to the highest frequency components to be transmitted. In other words we have found that it is practical to use what can be referred to as narrow band F.-M. Narrow band F.-M. means that the ratio of $\Delta f/f_m$ is relatively small, and in actual practice can be of the order of 0.2, where Δf represents deviation corresponding to maximum signal amplitude and f_m represents the highest modulating frequency. Likewise we have found that the limit of f_m can be made reasonably close to the carrier frequency. We have also discovered that the center or carrier frequency can be so selected that it is near the upper recordable frequency limit of the apparatus, which

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as previously explained is generally determined by the relative speed between the heads and the tape and the characteristics of the head. When the carrier frequency is so selected the recording system depends upon single sideband or vestigial sideband transmission. In other words the upper band of frequencies containing the frequency modulation components is not recorded or reproduced to any substantial extent. We have found that such a magnetic record can be reproduced to provide, after demodulation, the original modulating frequencies with a good degree of fidelity.

In addition to the foregoing, a practical system for the recording and reproduction of frequencies over a wide spectrum requires highly accurate speed control means for both recording and reproduction.

It is an object of the present invention to provide a system and method for the recording and reproduction of a wide frequency band, which will be relatively immune to spurious variations in signal strength.

Another object of the invention is to provide a system and method of the above character which, when used for the recording and reproduction of video frequencies, makes possible the reproduction of visual images with good fidelity.

Another object of the invention is to provide a system and method of making use of narrow band frequency modulation for recording over a wide frequency band.

Another object of the invention is to provide improved means for controlling the speed of operation of various parts during recording and reproduction.

Another object of the invention is to provide a system and apparatus for the recording of frequency components over a wide spectrum, such as video frequencies, which utilizes a plurality of record heads sweeping laterally across a magnetic tape, but without causing troublesome distortion or disturbances of the reproduced signal due to amplitude variations.

Additional objects and features of the invention will appear from the following description in detail in conjunction with the accompanying drawings.

Referring to the drawings:

Figure 1 is a circuit diagram illustrating a complete recording and reproducing system incorporating the present invention.

Figure 2 is a circuit diagram illustrating a modification of Figure 1.

Figure 3 is a plan view schematically illustrating mechanism for mounting the magnetic heads and for transporting the tape.

Figure 4 is a cross sectional view taken along the line 4—4 of Figure 3.

Figure 5 is a cross sectional detail taken along the line 5—5 of Figure 3.

Figure 6 is an enlarged cross sectional detail illustrating the guide means for the tape and the manner in which the tape is contacted by the magnetic heads.

Figure 7 is an enlarged detail illustrating means for engaging the lower edge of the tape, while it is passing through the guide means.

Figure 8 is a cross sectional detail taken along the line 8—8 of Figure 3, and showing suitable pulse generating means.

Figure 9 is a schematic view illustrating the pulse generating means and the cathode follower which may connect to the same.

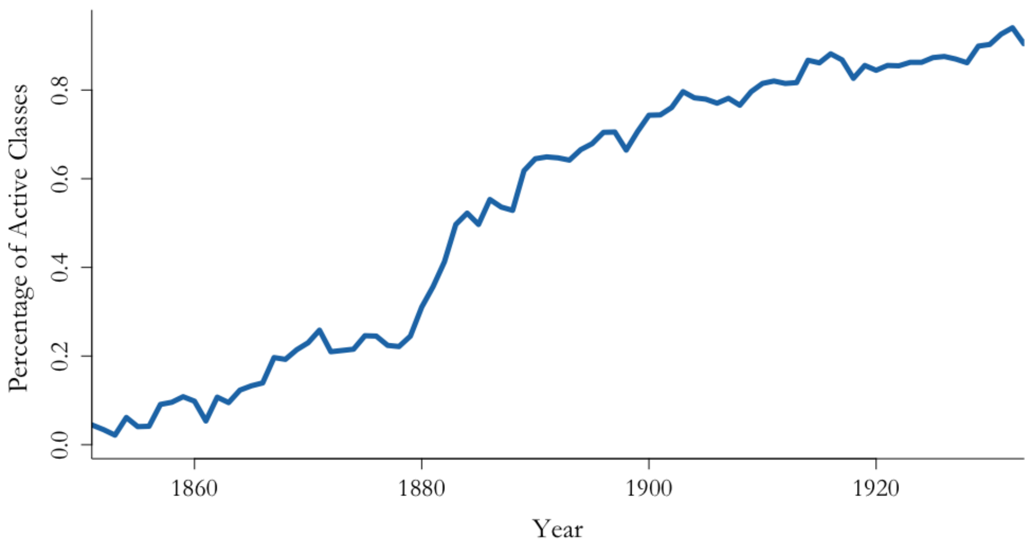
Figure 10 is a circuit diagram schematically illustrating the commutating means for making connections with the various magnetic heads.

Figure 11 is a diagram like Figure 10, but showing simplified connections.

Figure 12 is a plan view schematically illustrating a

Source: USPTO (Patent Number 2.956.114)

Figure 4: Diffusion of E&E-Related Vocabulary



Source: Own elaboration based on USPTO Patent Data

3.3 Strong Complementaries with Existing and New Technologies

It is argued that GPT's can be considered as "enabling technologies", this is because they provide a vast amount of opportunities to adapt and modify existing products, processes, and organizational technologies. They expand the space of possible inventions and innovations, creating opportunities to develop new products, processes and technologies in combination with it. For instance, Bresnahan and Trajtenberg (1995) note that: *"...the productivity gains associated with the introduction of electric motors in manufacturing were not limited to a reduction in energy costs. The new energy source fostered the more efficient design of factories, taking advantage of the new found flexibility of electric power."*

The far-reaching extent of its "innovation complementaries" (IC) is one of the most salient aspects of a GPT, as it is considered to be responsible for the creation and reinforcement of rapid technical advance and economic growth. Even though there is a vast literature collecting case-specific historical evidence (DuBoff, 1979; David, 1990; Helpman and Trajtenberg, 1998a; Rosenberg, 1998; Lipsey, Carlaw, and Bekar, 2005; Goldfarb, 2005; Bresnahan, 2010), there hasn't been any systematic and comprehensive empirical study on this subject.

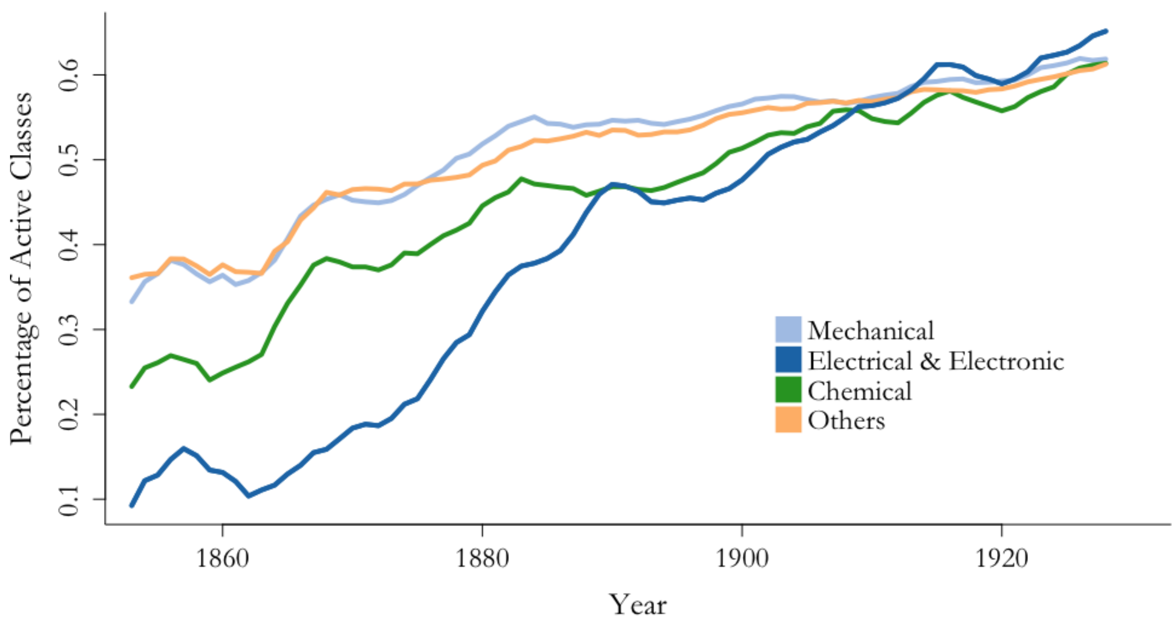
This subsection proposes a way of measuring the extent of any technology IC by looking at the co-occurrence of different classes within patent documents. Whenever a patent is issued, several claims are made regarding the inventiveness and scope of the patent. This claims specify all the inventions contained in a particular patent for a product or process, and are classified according to their technological characteristics into technological classes. Therefore a patent can be classified into different technological categories, meaning that in order for this final product or process to work, inventions in different fields had to be carried out. The extent and diversity of a technology's IC can be measured by looking at the diversity of its co-occurrence profile.

For instance, consider the Ampex broad band magnetic tape system (1960) described in Section 3.2. It has claims in two different technological classes, class 360 (Dynamic Magnetic Information Storage or Retrieval) in C&C and class 386 (Motion Video Signal Processing for Recording or Reproducing) in E&E. This is because the patent introduces two main improvements, the first has to do with a more efficient way of comprising and recording frequencies (class 360). In order for this improvement to be properly used, higher precision in the speed of the recording system needed to be achieved. This is when improvements in E&E technologies related to components regulating motion for recording systems had to be developed (class 386).

Therefore the co-occurrence of technological classes within a patent can be used to measure IC among different technologies. A GPT should co-occur with a wide variety of different technologies (classes), this is because its generality allows it to be re-combined with existing technologies to improve already existing products (such as tape systems), as well as to develop new-to-the world and yet complementary technologies.

Figure 5 below measures the IC of all the main technological categories by looking at the number of classes these technologies co-occur with, outside their own category. To avoid taking into account irrelevant, proximate combinations, co-occurrence of different classes within the same category are not counted. So for instance, if a class within chemicals co-occur with another class in the same category, then it is not consider as an IC. This figure provides a clear and straightforward message, E&E technologies have increased the variety and scope of their IC in a remarkable way since their introduction. They started as a very narrow technology to later become the most complementary of them by the beginning of the 1920's.

Figure 5: Measuring Technologies' IC



Source: Own elaboration based on USPTO Patent Data

To summarize, this section has addressed the issue of measuring empirically the main characteristics of GPTs. Using patent data, it first showed that E&E technologies where the fastest growing. Secondly, using the information contained in patent descriptions, it documents the pervasiveness in the use of E&E technologies as inputs in the innovation process. Last but not least, E&E technologies grew as no other category in terms of IC. Meaning that by the beginning of the 1920's, E&E technologies fulfilled the three main characteristics of a GPT. The timing and dynamics of this results are in line with previous evidence, which argue that the transforming power of electricity did not acquire momentum until after 1910's (David, 1990; Greenwood, 1997; Lipsey, Carlaw, and Bekar, 2005; Field, 2008).

The next section moves into evaluating whether E&E technologies, as it is argued, had a real transforming effect in the economy. In order to do so I use county-level data on the geographical location of inventors and patentees for the period of emergence and gauge of E&E technologies (1850-1940) along with county data from the U.S Census Bureau on different economic indicators.

4 Electricity: A GPT at Work

The previous section explored a way to empirically measure the key characteristics of a GPT, providing a way to identify and distinguish them that proved to work for the case of E&E technologies. It remains to be answered, however, whether such a technology can have the alleged transforming effect on the economy. This section moves in that direction and evaluates whether the diffusion of E&E technologies between 1860 and 1930 affected output and wages as predicted by theory.

Theoretical models yield a clear set of stylized facts regarding the impact of a GPT. The diffusion of a GPT throughout the economy should eventually rise real output and and real wages as it becomes widely used. At early stages of the diffusion process however, while sectors adapt and build up complementarities, there may be periods of intermittent or even negative growth. (Helpman and Trajtenberg, 1998b,a; Aghion and Howitt, 2000)

There are two widely documented characteristics of technological diffusion that should be taken into account. First, technological change can take several decades to spread (Griliches, 1957), even for the case of revolutionary technologies (David, 1990). Secondly, processes of technological diffusion tend to be highly dependent on geography, as physical proximity and collocation are crucial in the dynamics of innovative processes (Audretsch and Feldman, 1996; Feldman and Kogler, 2010; Feldman and Yoon, 2012). This effect is expected to be stronger for relatively new and unfamiliar technologies, such as electricity during the second half of the nineteenth century.

Even though theoretical models characterize the diffusion of a GPT in a geographically-deprived setup, we can profit from the uneven geographical spread of different technologies when it comes to the empirical assessment of their worth. Their unique place and time profile of diffusion provides an exceptional opportunity to exploit time-place variation in the adoption of technologies, which is key in determining the realization of their benefits.

I trace the diffusion of different technologies over space and time using the patenting activity of counties, assuming that the patenting activity of a place can be used as a suitable empirical counterpart of its capabilities to produce or use any given type of technology. This is equivalent to say, in terms of theoretical models, that finding patenting activity represents having reached the component finding stage of the Helpman and Trajtenberg (1998a) model, or the discovery phase in Aghion and Howitt (2000).

It is to be expected that engaging or adopting the new GPT should have an overall positive effect on real wages and output, meaning that irrespective of the intrinsic characteristics of a place, the long-term effect of the adoption of E&E technologies should be positive. Additionally, this effect should be increasing over time (though probably negligible at the beginning), as the economy-wide (but also place-specific) amount of complementarities increases.

The main concern when evaluating the impact of technological adoption on economic outputs lies with the possibility that, in fact, economic outputs may have also a reinforcing effect on the adoption of technologies. If such feedbacks exist Ordinary Least Squares (OLS) or Fixed Effects (FE) estimation methods would render biased estimates, as the error term will be correlated with the regressor(s). This is likely to happen in the case of E&E technologies, as they required considerable initial investments and complementary infrastructure to work. For instance, an inventor of E&E technologies in the 1900's may have faced incentives to locate near a power station after developing an electrical device, as the destination market for his/her invention was there. If the choice of the location of power stations was related to the size and prosperity of the market they will serve, then the direction of the effect reverses.

The empirical strategy adopted here relies on using measures of adoption of E&E technologies prior the 1870's as an instrument to predict the adoption of E&E technologies between 1900 and 1930, to later evaluate its impact on output per capita growth and wages. It assumes that early adoption of E&E technologies (prior the 1870s) were determinant to the inventive structure of places 50 years later, and yet couldn't be correlated with the events that will determine growth and wages between 1900 to 1930.

Using early adoption of E&E technologies as an instrument relies on three assumptions. First, that prior the 1870's it was nearly impossible to predict which future markets will be the most appropriate for E&E technologies, given that they were in a very exploratory face, such that their possible range of applicability and their scope for complementarities were barely understood. The history of the Thomson-Houston Electric Company, founded in 1883 in Lynn Massachusetts, constitutes an enlightening example. This company was a leader in the manufacture of products related to Elihu Thomson's inventions. This inventions ranged from arc-lighting systems[19], dynamos[20] , and systems for electric distribution[21], among other things. More than three decades after Elihu Thomson left his position (1880) as assistant professor of chemistry at Central High School in Philadelphia to pursue research on future applications of electricity (where he was a colleague of Edwin J. Houston), his company will be essential in the construction of the Panama canal, finished in 1914. General Electric (GE), created in 1892 by merging Edison General Electric Company and Thomson-Houston Electric Company, supplied around 1500 electric motors and electromechanical control boards which operated not only the gates and valves of the canal, but also regulated the operations of the the hydroelectric dam at Gatun Lake, which provided electricity for the canal(Nebeker, 2009). The GE manufacturing plant at Lynn played an important role in the construction of the Panama canal, which couldn't have be envisioned at its foundation[22]. If these future developments could have been predicted back in the 1880s, the Thomson-Houston Electric Company should have been located near GE headquarters in Schenectady (New York), to profit from agglomeration economies.

The second assumption requires that the location of complementary infrastructure (present or future) was not a relevant factor influencing the location decision of pioneer electrical entrepreneurs. Otherwise infrastructure-led growth may be the one responsible for the well-being of places, rather than early adoption of any particular technology. Note, however, that existence of electricity-related infrastructure was almost non-existent prior the 1870's. In

[19]See https://www.google.com/patents/US261790

[20]https://www.google.com/patents/US302963

[21]https://www.google.com/patents/US335159

[22]In fact, the importance of this initial venture remains until today, as the factory is still an essential part of GE, producing helicopter and jet engines, among other things, and employing around 45.000 people

fact, Pearl Street Station (in Manhattan, New York) was the first central power plant in the US, which opened in 1882 and served only 82 costumers (Orrok, 1930). Even the possibility of electrical illumination was uncertain by the end of the 1870's, as early experiments by Thomas Edison in 1879 produced light bulbs that lasted only 13.5 hours (Israel and Edison, 1998).

A clear example of this can be found by looking at the development of the sector of electrical appliances in the US, which was one of the fastest growing industries after the 1920's. For instance, the production of refrigerators jumped from 5.000 units in 1920 to 1.000.000 units in 1930, reaching 6.000.000 units by 1936 (Nebeker, 2009). The highest share by Kelvinator Company of Detroit, Michigan. This company, founded by engineer Nathaniel B. Wales in 1914, introduced the first refrigerator with automatic control[23]. The story of this company exemplifies to what extent its success did not relate to the existence of complementary infrastructure. Still at that time electrification of houses was primarily done for illuminating purposes, such that at the beginning of the 20th century most houses in Detroit (an for that matter in the entire US) didn't have any wall sockets to connect appliances to. Meaning that appliances had to be wired to chandeliers to connect them to the electrical current[24]. This points to the lack of appropriate infrastructure that was present at the time, which was essential for the diffusion of electrical appliances such as refrigerators.

The third assumption requires that early developments of a technology can be used to predict future adoption. Therefore, persistence over time and space of technological capabilities are essential. In this regard, there is a well established literature showing that processes of technological diffusion tend to be highly dependent on geography, as physical proximity and collocation are crucial in the dynamics of innovative processes (Audretsch and Feldman, 1996; Feldman and Kogler, 2010; Feldman and Yoon, 2012). This effect is expected to be stronger for relatively new and unfamiliar technologies. At early stages, technological diffusion is characterized by the importance of tacit knowledge; only when

[23]See for instance https://www.google.com/patents/US1438178

[24]See for instance https://www.google.com/patents/US646179 for an example of a chandelier adapter.

knowledge becomes standardized geographical dispersion tends to happen (Feldman and Kogler, 2010).

I consider two key variables to measure the economic impact of the diffusion of E&E technologies in a county, the *Average Wage* ($W_{c,t}$) paid to manufacture workers, and the *per capita Growth* ($\Delta y_{c,t}$) in those places[25]. For each county, $\Delta y_{c,t}$ measures the log difference in per capita output in manufactures, while $W_{c,t}$ is calculated as the total expenditures in manufacture wages divided by the total number of hands employed in manufactures.

To track adoption of technologies I create a set of dummies taking value 1 whenever a county had positive patenting activity in a particular technology in the five years prior the census year [26]. For instance,

$$Chemical_{c,t} = 1 \qquad if \qquad \sum_{t-5}^{t} Patents_{Chem} > 0, \; and\ zero\ otherwise$$

This implies that the entire technological profile of counties is characterized by a set of four dummy variables, *Electrical* & *Electronics*$_{c,t}$, $Mechanical_{c,t}$, $Chemical_{c,t}$, and $Others_{c,t}$. Then the estimating equation can be summarized as follows:

$$DV_{c,t} = \beta_0 + \beta_1 T_{c,t} + \beta_2 X_{c,t} + \epsilon_{c,t} \tag{1}$$

Where DV (the Dependent Variable) will be either the *Average Wage* ($W_{c,t}$) or the *per capita Growth* ($\Delta y_{c,t}$) and $T_{c,t}$ represents the vector of technological variables, which includes the full set of dummy variables described above (*Electrical* & *Electronics*$_{c,t}$, $Mechanical_{c,t}$, $Chemical_{c,t}$, and $Others_{c,t}$.).

$X_{c,t}$ comprises a set of control variables that could be determinant for $W_{c,t}$ and $\Delta y_{c,t}$. This includes the share of immigrant population (*Foreign Share*), as there exist evidence on the importance of cultural diversity and immigration on growth (Ager and Brückner, 2013;

[25] lowercase letters denote values in logs

[26] I use a window of five years because patenting activity fluctuates greatly from year to year, this is a common practice when working with patent data, see for instance REFERENCES

Burchardi, Chaney, and Hassan, 2016). Also, two variables related to the availability and explotaition of natural resources, the share of primary inputs in manufacture production (*Primary Inputs*) and the number of mineral deposits in activity (*Working Deposits*)[27]. The implications and effects of Natural Resource (NR) exploitation during this period have been discussed in detail by Wright (1990) . Additionally, I include a set of variables related to state's presence at county-level, given the critical role that has been attributed to institutional factors in the early development process of the US (Khan, 2005; Sokoloff, 1988). I use the share over population of Federal, State, and Local public employees (*Federal Employment*, *State Employment*, *Local Employment*, respectively). Additionally, and following Acemoglu, Moscona, and Robinson (2016), I include the number of post offices per county *(PO)* as a proxy of state's capacity on places. Depending on the specification, $X_{c,t}$ will include county, state, and year dummy variables.

Regression table number 4 below reports two regressions evaluating the effect of technological adoption on $W_{c,t}$ and $\Delta y_{c,t}$, they include county and year fixed effects and standard errors are clustered by county and year according to Cameron, Gelbach, and Miller (2012). It evaluates, as a starting point, to what extent differences in terms of technological adoption can be related to economic outcomes, above and beyond what can be explained by specific characteristics of places. They include the years between 1860 and 1930, covering the entire cycle of emergence, development, and diffusion of E&E technologies. Note that counties that adopted E&E technologies over-performed others in terms of both, average wages and per capita growth. Providing evidence that the adoption of E&E technologies can be related with a positive and significant differential in terms of wages and output per capita during this period.

Additionally, the degree of foreign immigration in a county was positively related to the growth of those places but negatively correlated to wages. This is consistent to what has been found earlier, see for instance Ager and Brückner (2013) and Hatton and Williamson

[27]This Variable was created geolocating all mineral deposits within counties' boundaries. Data on geolocated mineral deposits, including their operational status, can be found here: WWW.USGS

(2008) . The intensity of use of primary inputs is positively related to growth, which is in line with previous findings on the role of the exploitation of geological potential and non-reproducible natural resources in U.S. manufacturing (Wright, 1990). When it comes to the role of the state's presence, it only seems to be associated with a positive shift on wages in places with higher number of post offices. This is not surprising since they represented a high share of the employment of places, putting pressure on local labour markets. For instance, by 1831 already, postal employees accounted for 76% of the civilian federal workforce and postmasters outnumbered soldiers, being the most widespread representatives of the federal government (Service, 2007; Acemoglu, Moscona, and Robinson, 2016).

Table 4: Effect of the Adoption of E&E Technologies

	Growth ($\Delta y_{c,t}$) (FE)	*Average Wage* ($W_{c,t}$) (FE)
	(1)	(2)
Electrical and Electronics	0.109**	45.903***
	(0.043)	(16.126)
Mechanic	0.048	27.974***
	(0.031)	(7.400)
Chemical	0.052*	15.069***
	(0.027)	(5.794)
Others	0.037*	10.473*
	(0.022)	(5.903)
Foreign (Share)	0.002***	−0.385*
	(0.001)	(0.207)
Establishments per Capita (in logs)	0.741***	−33.974
	(0.043)	(21.197)
Primary Inputs	1.376***	−56.063
	(0.178)	(36.628)
Working Deposits (in logs)	0.045	−8.226
	(0.034)	(15.904)
Federal Employment (Share)	−0.001	0.173
	(0.001)	(0.228)
State Employment (Share)	−0.001	0.699
	(0.003)	(0.675)
Local Employment (Share)	0.002	0.309
	(0.003)	(0.553)
PO (in logs)	−0.006	28.383*
	(0.067)	(15.190)
$y_{c,t-1}$	−0.807***	
	(0.075)	
Period	1860-1930	1860-1930
Year FE	Yes	Yes
County FE	Yes	Yes
Observations	14,866	16,762
Adjusted R^2	0.568	0.866

*p<0.1; **p<0.05; ***p<0.01

As discussed earlier, joint determination of economic outcomes and technological adoption as well as the omission of any relevant explanatory variable correlated with technological adoption would render biased OLS estimates. Table 5 below shows the result of estimating a 2SLS model using early adoption of E&E technologies as an excluded instrument to predict adoption of E&E technologies between 1900 and 1930. In particular, I construct two instruments:

$$E\&E_{c,1870} = 1 \qquad if \qquad \sum_{1866}^{1875} Patents_{E\&E} > 0,\ and\ zero\ otherwise,$$

and

$$E\&E_{c,1860} = 1 \qquad if \qquad \sum_{1856}^{1865} Patents_{E\&E} > 0,\ and\ zero\ otherwise$$

For comparison, the FE estimates of table 4 are reported jointly with the 2SLS estimates of each specification. 2SLS estimates of E&E adoption on both, wages and growth, are several times higher than the corresponding FE estimates. 2SLS estimates suggest that the adoption of E&E technologies during this period is associated with a higher steady-state level of income per capita. Additionally, places adopting E&E technologies paid, on average, higher wages too. Other coefficients have similar values when comparing FE with 2SLS estimates, provided that they are statistically significant in both cases.

Note that instruments are highly correlated with the adoption of E&E technologies, as the F-test on the joint significance strongly rejects the null hypothesis. For more details about the first stage of the 2SLS regression please refer to the appendix. Additionally, as the 2SLS estimates are over-identified, the Sargan test of over-identified restrictions is reported at the bottom of the table. In both cases, the test does not the reject the null hypothesis of the instrument being orthogonal to the error term.

Table 5: Effect of the Adoption of E&E Technologies

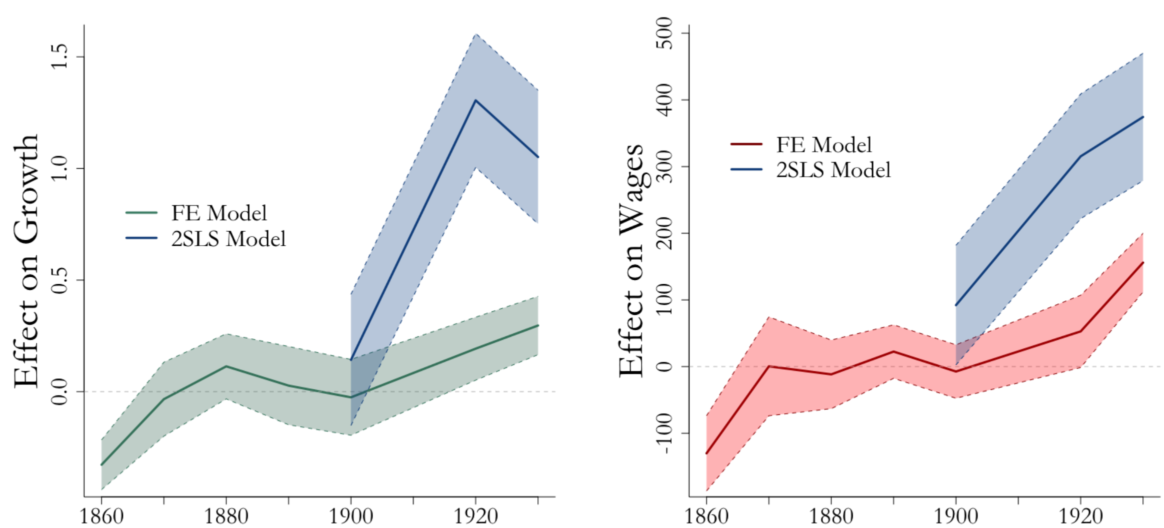
	Growth ($\Delta y_{c,t}$)		*Average Wage* ($W_{c,t}$)	
	(FE)	(2SLS)	(FE)	(2SLS)
	(1)	(2)	(3)	(4)
Electrical and Electronics	0.109**	0.816***	45.903***	293.907***
	(0.043)	(0.158)	(16.126)	(43.588)
Mechanic	0.048	0.092***	27.974***	26.378***
	(0.031)	(0.026)	(7.400)	(7.514)
Chemical	0.052*	0.014	15.069***	−16.381
	(0.027)	(0.038)	(5.794)	(11.980)
Others	0.037*	0.049*	10.473*	13.721*
	(0.022)	(0.028)	(5.903)	(7.632)
Foreign (Share)	0.002***	0.001***	−0.385*	−0.004
	(0.001)	(0.0002)	(0.207)	(0.060)
Establishments per Capita (in logs)	0.741***	0.644***	−33.974	−45.709***
	(0.043)	(0.025)	(21.197)	(6.423)
Primary Inputs	1.376***	1.392***	−56.063	−115.387***
	(0.178)	(0.074)	(36.628)	(19.906)
Working Deposits (in logs)	0.045	−0.013	−8.226	1.226
	(0.034)	(0.012)	(15.904)	(3.412)
Federal Employment (Share)	−0.001	−0.001	0.173	0.206
	(0.001)	(0.001)	(0.228)	(0.200)
State Employment (Share)	−0.001	0.001	0.699	1.722
	(0.003)	(0.004)	(0.675)	(1.377)
Local Employment (Share)	0.002	0.001	0.309	1.704***
	(0.003)	(0.002)	(0.553)	(0.572)
PO (in logs)	−0.006	−0.017	28.383*	1.135
	(0.067)	(0.020)	(15.190)	(4.748)
$y_{c,t-1}$	−0.807***	−0.465***		
	(0.075)	(0.015)		
Period	1860-1930	1900-1930	1860-1930	1900-1930
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No
State FE	No	Yes	No	Yes
Weak Instruments (F-statistic)		52.702		72.338
Sargan Test (p-value)		0.758		0.3
Observations	14,866	7,547	16,762	8,059
Adjusted R^2	0.568	0.272	0.866	0.725

*p<0.1; **p<0.05; ***p<0.01

According to theoretical models, the virtuous effect of adopting the new GPT should be the highest when enough complementarities have been developed. Historical evidence suggests that in the case of electricity this happened after the 1910's (David, 1990; Lipsey, Carlaw, and Bekar, 2005), which is consistent with the economy-wide diffusion of use and innovative complementarities reported in subsections 3.2 and 3.3. It is therefore worth exploring whether we see a similar pattern here.

Figure 6 shows the result of interacting the E&E variable with a dummy for each census year [28]. It corroborates what David (1990); Greenwood (1997); Lipsey, Carlaw, and Bekar (2005) and Field (2008) suggested, the impact of E&E technologies increased over time, and is significant only after the 1910's. This suggests that the economy-wide expansion in the number of E&E complementarities strengthen the effect on economic outcomes of adopting E&E technologies.

Figure 6: The Effect of E&E Adoption over Time



There are a few threats to the identification strategy that should be taken into account.

[28]The regression table can be found in the appendix.

First, it is possible that when properly estimated, the effect of adoption of other technologies are higher than those of E&E technologies. If that is the case, the alleged E&E differential would not exist.

The validity of the instrument used here relies heavily on characteristics and historical features that are particular to E&E technologies only. For instance, because chemical and mechanical technologies were already mature technologies prior the 1870's, its adoption may be correlated with characteristics of the place that remain relevant years later. In the case of chemical technologies, adoption may be correlated with availability of natural resources, which probably had long-lasting implications for growth.

To tackle this first issue I use lagged values of technological adoption as instruments for technologies other than E&E. In the appendix I show that results do not change in any significant way. Although the magnitud of the E&E coefficient doesn't change significantly after instrumenting for adoption of other technologies, its significance decrease.

Another potential theat has to do with the fact that using lagged variables of E&E adoption may be actually capturing characteristics of places that remain relevant 50 years later. For instance, early E&E adoption may be correlated with initial characteristics of places such as higher level of development, better infrastructure, or better institutions; which can have a long-lasting effect on growth rates and wages.

In order to control for initial characteristics of places, in the appendix I provide further results using lagged values of regressors and output levels as additional explanatory variables. Because the coverage of the census is more limited prior the 1870's, this implies loosing some observational units. As before, results do not change significantly.

Last but not least, estimating a growth equation using OLS or FE methods can potentially bias the coefficients of the technological variables. Nickell (1981) shows that using the within-effect estimator will produce inconsistent estimates of the lagged dependent variable in dynamic models. If $y_{c,t-1}$ is correlated with other regressors, estimated coefficients will be biased even if regressors are exogenous.

To adress this concern I use alternative GMM methods aimed at properly identifying the effect of $y_{c,t-1}$, such as those described in Blundell and Bond (1998). Using the proposed set of instruments, which also rely on lagged values of endogenous variables, I instrument both the adoption of E&E technologies and the effect of $y_{c,t-1}$. Additionally, and because exogeneity tests cast doubts about the validity of the GMM instruments, I provide an additional robustness check using lagged values of E&E adoption and $y_{c,t-1}$ as instruments in a 2SLS framework. In both cases results are consistent with previous findings.

5 Conclusions

This paper discusses, on the one hand, a simple way of characterizing GPTs using patent data. By relying on historical patents documents, it provides a comprehensive view of the emergence, evolution, development, and diffusion of E&E technologies in their historical context. It shows that the behaviour of E&E technologies between 1860 and 1930 is in line with what can be expected from a GPT, namely: Above-average growth rates in patenting activity, the development of a wide variety of innovation complementarities, and a high degree of pervasiveness in the U.S. inventive structure.

On the other hand, I present evidence that the adoption of E&E technologies between 1860 and 1930 is related to higher per capita growth and higher wages. Identification of the impact is achieved using 2SLS methods and instrumenting E&E adoption with lagged values of it. Even if potential threats to the identification strategy exist, as in any empirical endeavour, results are robust to changes in the model specification and to alternative adoption measures, among other things.

Having a simple and useful mean to characterize GPTs has considerable policy implications. It could be used, for instance, to identify technologies that are currently showing qualities of a GPT; which would be capable of fostering growth and generate spillovers. Additionally, results suggest that the uneven diffusion of revolutionary technologies may generate inequality across places in terms of growth and earnings.

It is important also to emphasize the limitations of this study. Because it relies solely on collecting the traces of information that have been left behind in patent documents, it is not possible to draw any general conclusion on the full extent of the effect of GPTs on the economy. In the case of E&E technologies, it is widely known that their impact went beyond and above what can be traced in patent documents. It had implications on the organization of factories, the transportation systems of cities, etc. Additionally, this study does not account for the benefits that mere adopters may have experienced.

A natural step forward would be to test whether the characterization of GPTs provided here portrays a similar pattern for ICTs after the 1970's. Focusing on a more recent period would give the opportunity to use more disaggregated and detailed data; which could be exploited to design better identification strategies and/or explore additional aspects of the GPT diffusion.

6 Appendix (Incomplete)

6.1 List of Words Used in Section 3.2

- Catelectrode
- Catelectrotonic
- Catelectrotonus
- Dielectric
- Dynamoelectric
- Electre
- Electrepeter
- Electress
- Electric
- Electrical
- Electrically
- Electricalness
- Electrician
- Electricities
- Electricity
- Electrifiable
- Electrification
- Electrified
- Electrifying
- Electrify
- Electrine
- Electrition
- Electrization
- Electrized
- Electrizing
- Electrize
- Electrizer
- Electro
- Electroballistic
- Electroballistics
- Electrobiologist
- Electrobiology
- Electrobioscopy
- Electrocapillarity
- Electrocapillary
- Electrochemical
- Electrochemistry
- Electrochronograph
- Electrochronographic
- Electrocute
- Electrode
- Electrodynamic
- Electrodynamical
- Electrodynamics
- Electrodynamometer
- Electroengraving
- Electroetching
- Electrogenesis
- Electrogenic
- Electrogeny
- Electrogilding
- Electrogilt
- Electrograph
- Electrokinetic
- Electrokinetics
- Electrolier
- Electrology
- Electrolysis
- Electrolyte
- Electrolytic
- Electrolytical
- Electrolyzable
- Electrolyzation
- Electrolyzed
- Electrolyzing
- Electrolyze
- Electromagnet
- Electromagnetic
- Electromagnetism
- Electrometallurgy
- Electrometer
- Electrometric
- Electrometrical
- Electromotion
- Electromotive
- Electromotor
- Electromuscular
- Electron
- Electronegative
- Electropathy
- Electrophone
- Electrophori
- Electrophorus
- Electrophysiological
- Electrophysiology
- Electroplating
- Electroplate
- Electroplater
- Electropolar
- Electropositive
- Electropuncturation
- Electropuncturing

- Electropuncture
- Electroscope
- Electroscopic
- Electrostatic
- Electrostatics
- Electrostereotype
- Electrotelegraphic
- Electrotelegraphy
- Electrotherapeutics
- Electrothermancy
- Electrotint
- Electrotonic
- Electrotonize
- Electrotonous
- Electrotonus
- Electrotype
- Electrotyped
- Electrotyping
- Electrotyper
- Electrotypic
- Electrotypy
- Electrovital
- Electrovitalism
- Electrum
- Hydroelectric
- Idioelectric
- Magnetoelectric
- Magnetoelectrical
- Magnetoelectricity
- Parelectronomic
- Parelectronomy
- Photoelectric
- Photoelectrotype
- Pyroelectric
- Pyroelectricity
- Resinoelectric
- Stereoelectric
- Thermoelectric
- Thermoelectricity
- Thermoelectrometer
- Voltaelectric
- Voltaelectrometer

6.2 Regression Table with Year Interaction

6.3 Controlling for Initial Characteristics of Places

One potential threat to the identification strategy has to do with the fact that using lagged variables of E&E adoption could be also capturing initial conditions of places. If these initial conditions were important enough to set up a virtuos path of long-lasting growth and wealth accumulation, then the instrument loses its validity. Early characteristics of places such as having higher levels of development, better infraestructure, or higher state's presence may have had long-lasting implications for the productive structure of places and their growth.

I use two additional variables to capture initial conditions of places: On the one hand, output per capita in 1870 ($y_{c,1870}$) to proxy for initial levels of delvelopment and infraestructure, and the number of post offices in 1870 to proxy for state presence ($PO_{c,1870}$) on the other.

Using 1870's per capita output as an additional regressor requires constraining the sample to include places that were censused by 1870. This may result in a non-trivial selection of the sample, biasing the results. Therefore, I approach the problem by checking the robustness of the results in two steps: First I compare two sets of FE estimates, with the only difference between them being the number of counties included in the sample. This is to check the effect that constraining the sample has on estimates independently of initial conditions, as FE estimates already control for that. Next, I include a $y_{c,1870}$ and $PO_{c,1870}$ as additional regressors on 2SLS estimates and check whether results change.

Columns (1) and (3) in Table 6 below present the baseline results of Table 4; while columns (2) and (4) replicate the procedure for the subset of counties that had output data by 1870. Results do not change significantly between specifications, specially for the variables capturing technological adoption.

Table 6: FE Estimates on the Restricted Sample

	Growth ($\Delta y_{c,t}$)		*Average Wage* ($W_{c,t}$)	
	(1)	(2)	(3)	(4)
Electrical and Electronics	0.109**	0.109**	45.903***	47.676***
	(0.043)	(0.048)	(16.126)	(18.198)
Mechanic	0.048	0.050	27.974***	23.826***
	(0.031)	(0.031)	(7.400)	(8.017)
Chemical	0.052*	0.050*	15.069***	12.183**
	(0.027)	(0.027)	(5.794)	(6.015)
Others	0.037*	0.036	10.473*	9.118
	(0.022)	(0.024)	(5.903)	(6.578)
Foreign (Share)	0.002***	0.001**	−0.385*	−0.331
	(0.001)	(0.001)	(0.207)	(0.216)
Establishments per Capita (in logs)	0.741***	0.735***	−33.974	−37.419*
	(0.043)	(0.048)	(21.197)	(20.796)
Primary Inputs	1.376***	1.276***	−56.063	−74.758**
	(0.178)	(0.174)	(36.628)	(33.394)
Working Deposits (in logs)	0.045	0.049	−8.226	−14.651
	(0.034)	(0.033)	(15.904)	(16.171)
Federal Employment (Share)	−0.001	−0.001	0.173	0.280
	(0.001)	(0.001)	(0.228)	(0.207)
State Employment (Share)	−0.001	0.0001	0.699	1.887***
	(0.003)	(0.003)	(0.675)	(0.565)
Local Employment (Share)	0.002	0.002	0.309	0.519
	(0.003)	(0.003)	(0.553)	(0.726)
PO (in logs)	−0.006	−0.005	28.383*	24.782
	(0.067)	(0.073)	(15.190)	(15.941)
$y_{c,t-1}$	−0.807***	−0.780***		
	(0.075)	(0.076)		
Period	1860-1930	1860-1930	1860-1930	1860-1930
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	14,866	12,917	16,762	13,775
Adjusted R^2	0.568	0.547	0.866	0.857

*p<0.1; **p<0.05; ***p<0.01

Table 7 below compares the 2SLS baseline estimates of Table 5, in columns (1) and (4), with two analogous ones: Columns (2) and (5) replicate baseline estimates but on the reduced sample; while columns (3) and (6) do the same but also include $y_{c,1870}$ and $PO_{c,1870}$ as additional regressors.

Results are robust to the subseting of the sample and the inclusion of proxies for initial conditions of places. They display the same consistent pattern across specifications, with instrumented adoption of E&E technologies showing a strong effect on wages and output. Additionally, note that both tests for the validity of the instruments also work on the alternative specifications: The F-test of joint significance always strongly rejects the null hypothesis while the Sargan test of over-indentified restrictions doesn't.

Table 7: 2SLS Estimates Proxying for Initial Conditions

	Growth ($\Delta y_{c,t}$)			*Average Wage* ($W_{c,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
Electrical and Electronics	0.816^{***}	0.756^{***}	0.658^{***}	293.901^{***}	306.323^{***}	312.954^{***}
	(0.158)	(0.171)	(0.182)	(43.429)	(49.693)	(56.627)
Mechanic	0.092^{***}	0.066^{**}	0.073^{**}	26.548^{***}	21.677^{**}	21.734^{**}
	(0.026)	(0.031)	(0.032)	(7.470)	(9.199)	(9.499)
Chemical	0.014	0.023	0.037	−16.352	−21.814	−23.463
	(0.038)	(0.041)	(0.042)	(11.942)	(13.588)	(14.407)
Others	0.049^{*}	0.063^{**}	0.067^{**}	14.265^{*}	18.016^{**}	17.725^{**}
	(0.028)	(0.031)	(0.031)	(7.538)	(8.425)	(8.515)
Foreign (Share)	0.001^{***}	0.001^{**}	0.001^{**}	−0.011	0.094	0.035
	(0.0002)	(0.0002)	(0.0002)	(0.059)	(0.077)	(0.080)
Establishments per Capita (in logs)	0.644^{***}	0.575^{***}	0.570^{***}	-44.850^{***}	-60.795^{***}	-62.043^{***}
	(0.025)	(0.029)	(0.029)	(6.337)	(7.293)	(7.215)
Primary Inputs	1.392^{***}	1.154^{***}	1.140^{***}	-113.816^{***}	-130.347^{***}	-127.800^{***}
	(0.074)	(0.089)	(0.088)	(19.620)	(23.920)	(23.853)
Working Deposits (in logs)	−0.013	−0.008	−0.011	1.115	−0.577	−0.001
	(0.012)	(0.013)	(0.013)	(3.404)	(3.911)	(3.968)
Federal Employment (Share)	−0.001	−0.001	−0.001	0.200	0.403	0.379
	(0.001)	(0.001)	(0.001)	(0.200)	(0.308)	(0.308)
State Employment (Share)	0.001	0.002	0.001	1.737	1.719	1.635
	(0.004)	(0.004)	(0.004)	(1.374)	(1.555)	(1.596)
Local Employment (Share)	0.001	0.003	0.003	1.569^{***}	2.166^{**}	1.933^{*}
	(0.002)	(0.003)	(0.003)	(0.562)	(1.003)	(1.008)
PO (in logs)	−0.017	−0.031	−0.035	1.298	4.796	17.945^{**}
	(0.020)	(0.023)	(0.025)	(4.709)	(6.200)	(7.092)
$y_{c,t-1}$	-0.465^{***}	-0.425^{***}	-0.425^{***}			
	(0.015)	(0.017)	(0.017)			
$y_{c,1870}$			0.024^{**}			8.131^{**}
			(0.012)			(3.926)
$PO_{c,1870}$ (in logs)			0.028			-24.454^{***}
			(0.021)			(6.146)
Period	1900-1930	1900-1930	1900-1930	1900-1930	1900-1930	1900-1930
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Weak Instruments (F-statistic)	52.702	41.556	35.087	72.917	56.26	43.797
Sargan Test (p-value)	0.758	0.56	0.566	0.295	0.304	0.343
Observations	7,547	5,893	5,893	8,129	5,983	5,983
Adjusted R^2	0.272	0.237	0.265	0.727	0.724	0.722

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

6.4 Robustness to Alternative Estimation Methods for Dynamic Panels

Table 8: GMM vs 2SLS Estimates

	Output per Capita ($y_{c,t}$)		
	(2SLS)	(GMM)	(2SLS)
	(1)	(2)	(3)
Electrical and Electronics	0.816***	0.918***	0.597***
	(0.180)	(0.095)	(0.213)
Mechanic	0.092***	0.058***	0.070***
	(0.027)	(0.022)	(0.027)
Chemical	0.014	0.018	0.024
	(0.041)	(0.023)	(0.041)
Others	0.049*	0.019	0.075***
	(0.027)	(0.023)	(0.027)
Foreign (Share)	0.001***	0.001***	0.0005**
	(0.0002)	(0.0001)	(0.0002)
Establishments per Capita (in logs)	0.644***	0.709***	0.548***
	(0.021)	(0.022)	(0.028)
Primary Inputs	1.392***	0.947***	1.168***
	(0.064)	(0.081)	(0.073)
Working Deposits (in logs)	−0.013	−0.011	−0.009
	(0.012)	(0.013)	(0.012)
Federal Employment (Share)	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
State Employment (Share)	0.001	0.001	0.004
	(0.004)	(0.005)	(0.004)
Local Employment (Share)	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)
PO (in logs)	−0.017	−0.022	−0.007
	(0.021)	(0.019)	(0.023)
$y_{c,t-1}$	0.535***	0.416***	0.641***
	(0.014)	(0.021)	(0.039)
Period	1900-1930	1860-1930	1900-1930
Weak Instruments E&E (F-statistic)	52.702		75.925
Weak Instruments $y_{c,t-1}$ (F-statistic)			315
Sargan Test (p-value)	0.758	0	0.725
Autocorrelation Test (1) (p-value)		0	
Autocorrelation Test (2) (p-value)		0.305	
Observations	7,547	3,021	6,607

*p<0.1; **p<0.05; ***p<0.01

6.5 More Endogenous Variables

Table 9: Allowing for Multiple Endogenous Variables

	Growth ($\Delta y_{c,t}$)		
	(1)	(2)	(3)
Electrical and Electronics	0.816***	0.760***	0.901
	(0.158)	(0.145)	(1.104)
Mechanic	0.092***	0.249	0.300
	(0.026)	(0.243)	(0.291)
Chemical	0.014	0.007	−0.164
	(0.038)	(0.033)	(1.027)
Others	0.049*	0.004	−0.001
	(0.028)	(0.075)	(0.078)
Foreign (Share)	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0003)
Establishments per Capita (in logs)	0.644***	0.641***	0.641***
	(0.025)	(0.025)	(0.027)
Primary Inputs	1.392***	1.383***	1.373***
	(0.074)	(0.075)	(0.090)
Working Deposits (in logs)	−0.013	−0.015	−0.014
	(0.012)	(0.013)	(0.018)
Federal Employment (Share)	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
State Employment (Share)	0.001	0.0002	0.0002
	(0.004)	(0.004)	(0.005)
Local Employment (Share)	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
PO (in logs)	−0.017	−0.022	−0.021
	(0.020)	(0.021)	(0.022)
$y_{c,t-1}$	−0.465***	−0.469***	−0.468***
	(0.015)	(0.015)	(0.017)
Period	1900-1930	1900-1930	1900-1930
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Weak Instruments E&E (F-statistic)	52.702	52.091	67.933
Weak Instruments Mechanical (F-statistic)		21.303	22.147
Weak Instruments Chemical (F-statistic)			88.65
Sargan (p-value)	0.758	0.722	0.796
Observations	7,547	7,547	7,547
Adjusted R^2	0.272	0.282	0.234

*p<0.1; **p<0.05; ***p<0.01

Table 10: Allowing for Multiple Endogenous Variables

	Average Wage ($W_{c,t}$)		
	(1)	(2)	(3)
Electrical and Electronics	293.901***	304.277***	482.037
	(43.429)	(43.694)	(426.726)
Mechanic	26.548***	−218.384***	−175.542*
	(7.470)	(76.826)	(106.440)
Chemical	−16.352	18.915*	−166.658
	(11.942)	(11.245)	(408.621)
Others	14.265*	97.711***	92.693***
	(7.538)	(24.492)	(27.892)
Foreign (Share)	−0.011	0.040	0.015
	(0.059)	(0.058)	(0.100)
Establishments per Capita (in logs)	−44.850***	−29.841***	−31.328***
	(6.337)	(7.253)	(8.647)
Primary Inputs	−113.816***	−80.500***	−90.671***
	(19.620)	(22.732)	(32.177)
Working Deposits (in logs)	1.115	4.547	6.808
	(3.404)	(3.843)	(7.232)
Federal Employment (Share)	0.200	0.150	0.293
	(0.200)	(0.241)	(0.395)
State Employment (Share)	1.737	2.928**	2.902*
	(1.374)	(1.468)	(1.635)
Local Employment (Share)	1.569***	1.803***	1.711**
	(0.562)	(0.604)	(0.706)
PO (in logs)	1.298	13.620**	13.457**
	(4.709)	(5.462)	(6.157)
Period	1900-1930	1900-1930	1900-1930
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Weak Instruments E&E (F-statistic)	72.917	69.996	95.788
Weak Instruments Mechanical (F-statistic)		26.496	35.377
Weak Instruments Chemical (F-statistic)			125.872
Sargan (p-value)	0.295	0.656	0.793
Observations	8,129	8,129	8,129
Adjusted R^2	0.727	0.669	0.567

*p<0.1; **p<0.05; ***p<0.01

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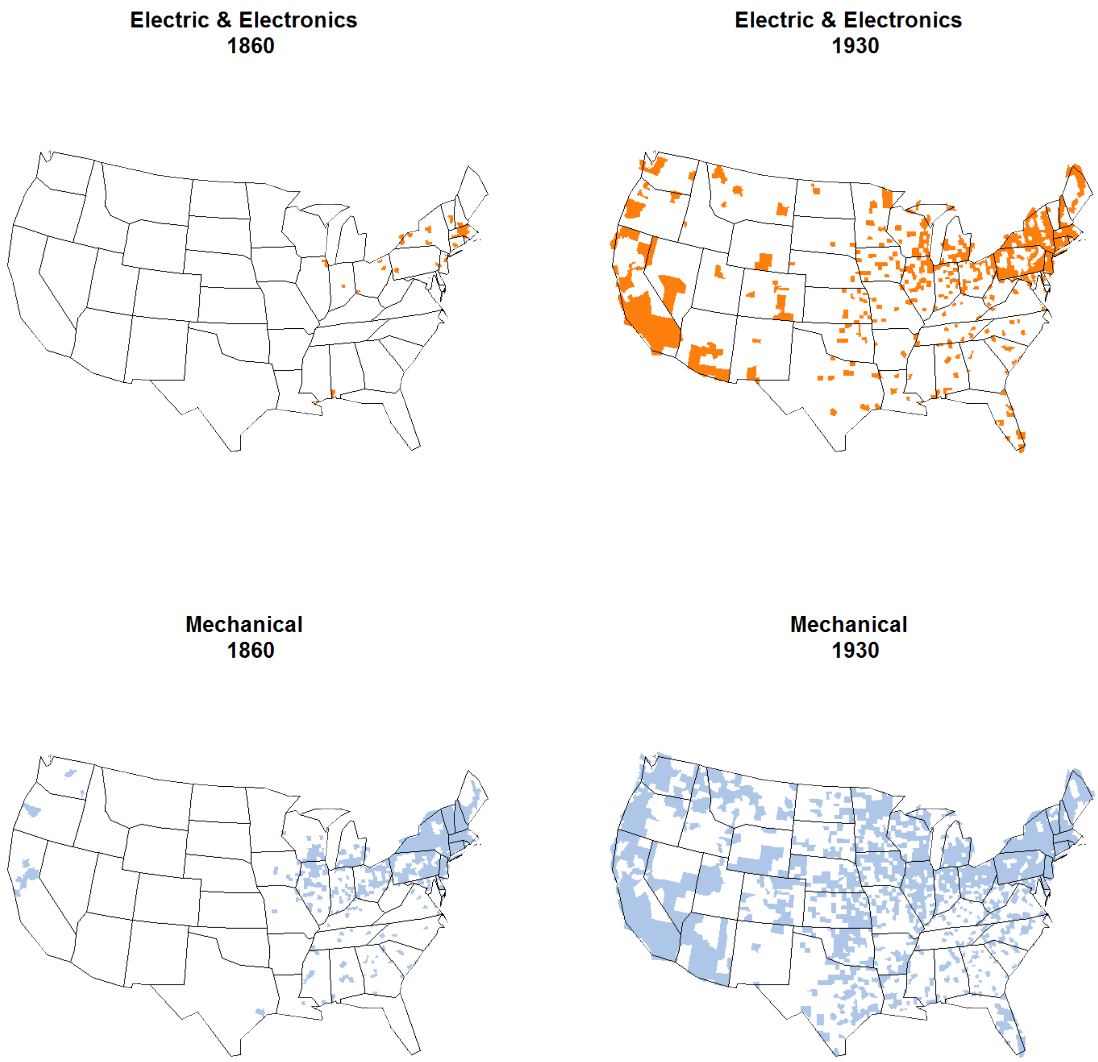
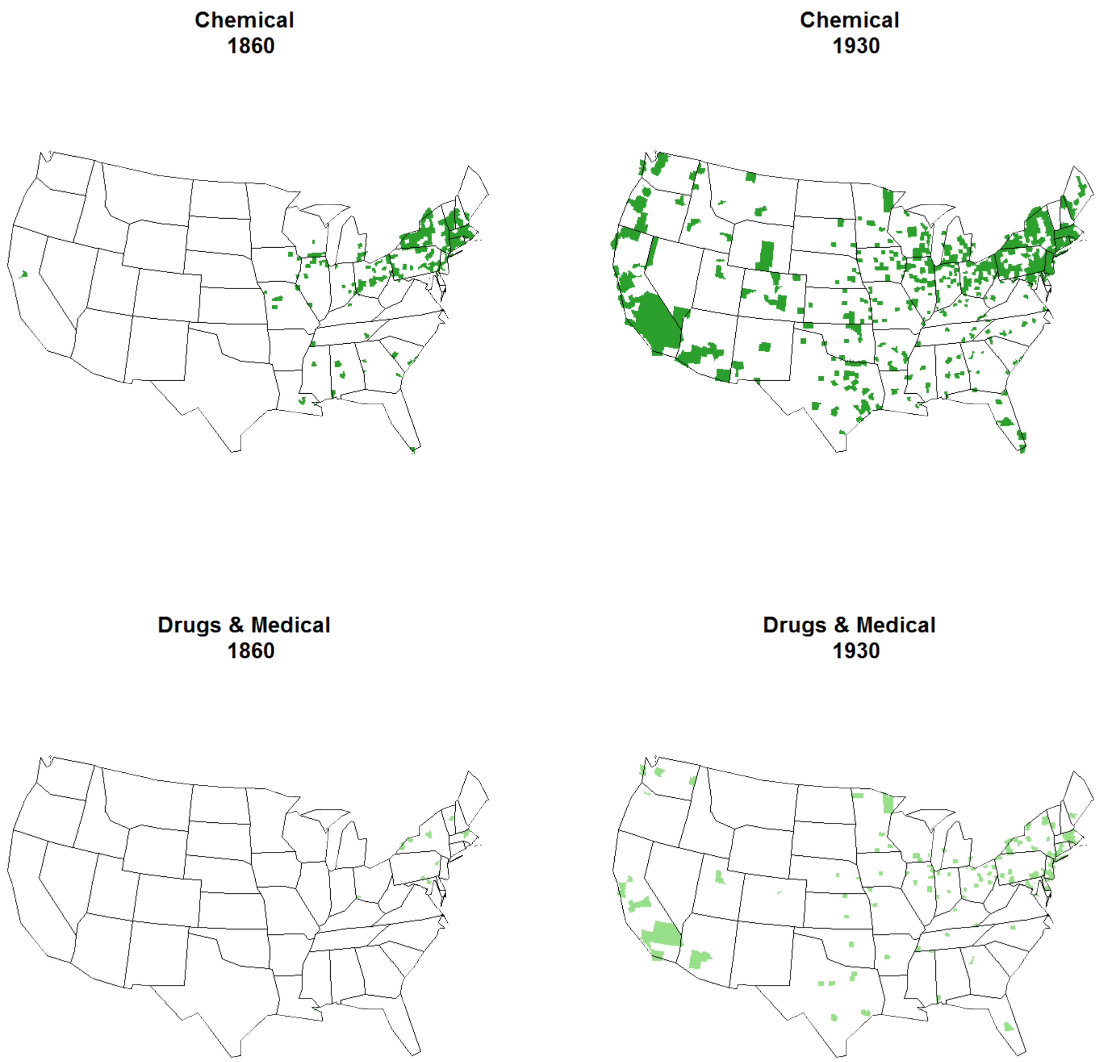
Figure 7: Geographical Diffusion of Technologies



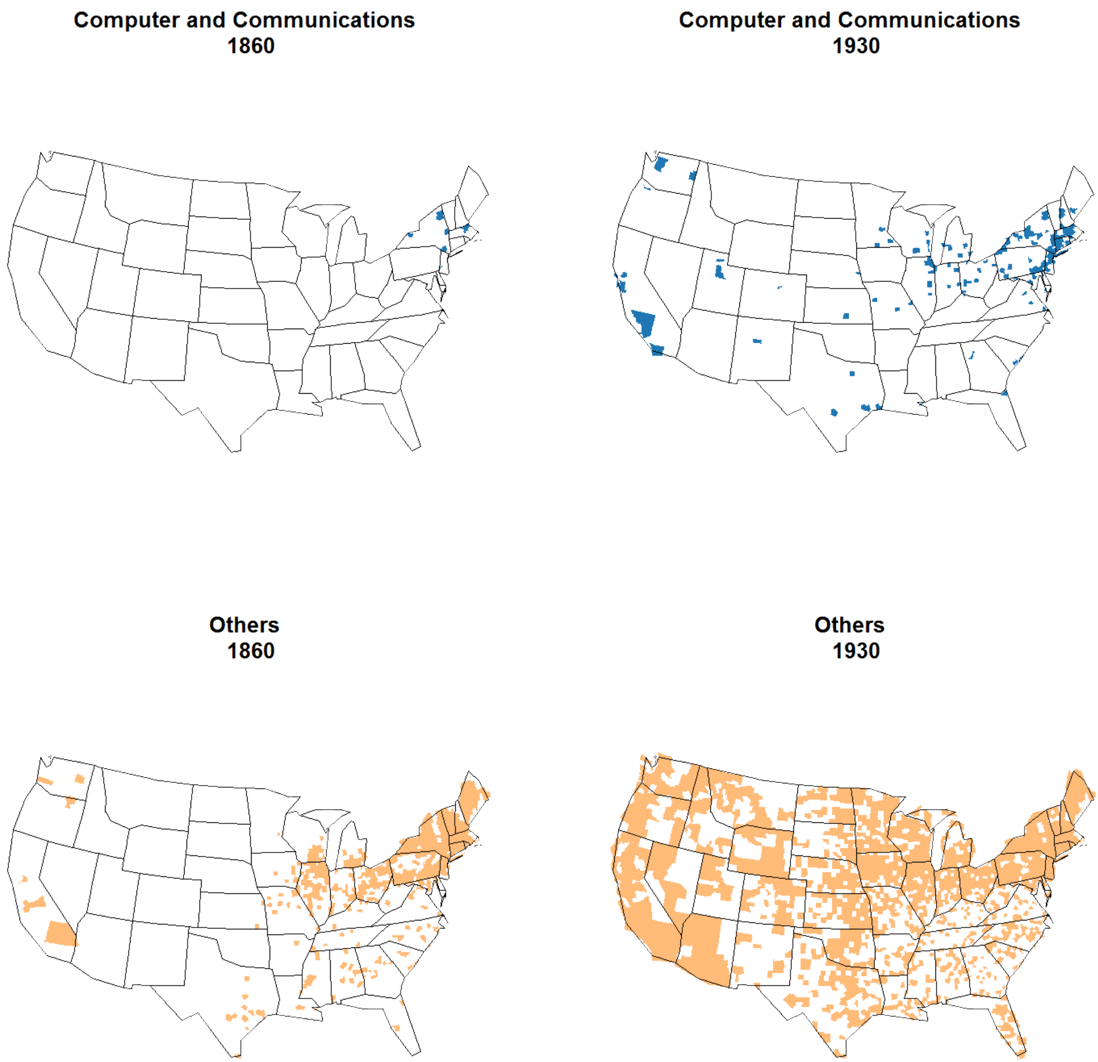
Source: Own elaboration based on USPTO and HistPat Patent Data

Figure 8: Geographical Diffusion of Technologies



Source: Own elaboration based on USPTO and HistPat Patent Data

Figure 9: Geographical Diffusion of Technologies



Source: Own elaboration based on USPTO and HistPat Patent Data