

# Papers in Evolutionary Economic Geography

# 20.33

## **GPTs and Growth: Evidence on the Technological Adoption of Electrical & Electronic Technologies in the 1920s**

Sergio Petralia



Utrecht University

Human Geography and Planning

# GPTs and Growth: Evidence on the Technological Adoption of Electrical & Electronic Technologies in the 1920s

Sergio Petralia\*

August 12, 2020

## Abstract

The pervasive diffusion of electricity-related technologies at the beginning of the 20<sup>th</sup> century has been studied extensively to understand the transformative potential of General Purpose Technologies (GPTs). Most of what we know, however, has been investigated in relation to the diffusion of their use. This article provides evidence on the county-level economic impact of the technological adoption of Electrical & Electronic (E&E) technologies in the 1920s in the United States (US). Thus focusing on the impact of a GPT on technological adopters, i.e. those who are able to develop, transform and complement it. It is shown that places with patenting activity in E&E

---

\*Department of Economic Geography, Utrecht University, Utrecht, The Netherlands. Email: s.g.petralia@uu.nl. I would like to thank all the participants at the Harvard Kennedy School CID Growth Lab seminar, US Census Bureau seminar, University of Barcelona AQR seminar, the RSA 2017 conference, the Technical University of Eindhoven seminar, and the RIDGE Forum at the University of Buenos Aires for their useful comments. Additionally, I profited greatly from the comments of and interactions with V. Arza, P.A. Balland, R. Boschma, C. Esposito, A. Morrison, P. Moser, S. Perez, and M. Svarc. This research received financial support from the VIDI project number 452-11-013 (NWO).

technologies grew faster and paid higher wages than others between 1920 and 1930. This analysis required constructing a novel database identifying detailed geographical information for historical patent documents in the US since 1836, as well as developing a text-mining algorithm to identify E&E patents based on patent descriptions.

Keywords: Disruptive Technological Change, Historical Patent Documents, Technological Adoption, General Purpose Technologies.

JEL Classification: O33, O31, O30.

# 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 acceleration episodes are driven by particular technologies, that given their revolutionary nature, have the power to change the pace and direction of economic progress, as well as to transform the social and political structures surrounding them. These technologies are often referred to as “General Purpose Technologies” (GPTs) and widely known examples are the steam engine, the electricity, and more recently Information and communication technologies (ICTs).

Most of the literature studying the economic consequences of the spatial diffusion of these particularly influential technologies have mostly, if not exclusively, focused on measures of their usage. For instance, historical studies on the diffusion of steam engines have usually relied on measuring the number of steam engines per county in the eighteenth and nineteenth century in Great Britain (Nuvolari, Verspagen, and von Tunzelmann 2011; Crafts and Mills, 2004; Crafts, 2004) or in the nineteenth century in the United States (US) (Rosenberg and Trajtenberg, 2004).

When it comes to quantifying the impact of electricity, Dinkelman (2011) provides estimates of the positive effect of electrification on employment growth by analyzing South Africa’s mass diffusion of electricity to rural households. In the US rural context, Kitchens and Fishback (2015) shows that electrification in rural areas in the 1930s contributed to increases in crop output, crop productivity, and land values while Lewis and Severnini (2020) show how this early rural electrification fostered counties’ long term growth and increased employment, population, and property values in the short term. In addition, Gaggl, Gray, Marinescu, and Morin (2019) find that the expansion of high-voltage transmission lines between 1910 and 1940 was a key driver of structural transformation in the US economy.

This apparent consensus about the benefits of the geographical diffusion of these technologies contrasts with the lack of agreement in macro-level studies. For instance, while Alexopoulos and Cohen (2016) find that electrical innovations raised aggregated productiv-

ity, employment, and labor turnover, [Ristuccia and Solomou \(2014\)](#) argue that there was no generalized productivity boost from electrical power diffusion after developing and analyzing a comparative dataset on the usage of electricity in the manufacturing sectors of the US, Britain, France, Germany, and Japan. They find that the power of electricity to predict aggregate or sector growth is limited. In addition, [Crafts \(2004\)](#) casts doubts on the contribution of steam to the British economic growth in the nineteenth century. As a result, scholars have called into question the relevance and usefulness of the notion of GPTs ([Field, 2008](#); [Ristuccia and Solomou \(2014\)](#)).

What all these empirical studies have in common is that they have taken an usage-focus approach when testing the impact of the diffusion of electrical or steam technologies. This approach diverges from the way theoretical models have been constructed, as theory have placed considerable emphasis on the importance of those who are able to create and improve the GPT and on those who are able to develop other technologies that complement to it ([Bresnahan and Trajtenberg, 1995](#); [Helpman and Trajtenberg, 1998b](#) a [Aghion and Howitt, 2000](#))<sup>1</sup>.

Theoretical models have characterized the diffusion and impact of GPTs from the supply side, where the rate of adoption is measured considering the number of productive sectors that adopt the technology and the number of new complementary components that are developed. For instance, [Helpman and Trajtenberg \(1998a\)](#) discuss the evolution of the semiconductor industry and show that its success relied heavily on technological improvements made in the manufacturing and performance of transistors on the one hand, and on the invention of the integrated circuit and the microprocessor on the other. This approach is

---

<sup>1</sup>GPTs are characterized as possessing a wide scope for continuous improvement and elaboration, on the one hand, and high complementarity, on the other. The latter means that a GPT should be able to diffuse widely not only because it is used as an input in many different products and processes (wide pervasiveness), but also because it is a technological complement of existing and new technologies (high innovation complementarity). These characteristics are what make GPTs “engines of growth” ([Bresnahan and Trajtenberg, 1995](#)).

also present in empirical studies seeking to identify GPTs in data, which relied on technological production rather than usage. For instance, [Hall, Trajtenberg, et al. \(2006\)](#) discuss how to characterize GPTs with patent data studying the case of Information & Communication Technologies (ICTs), while [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 1920s. Also using patent data, [Feldman and Yoon \(2012\)](#) argue that technologies of genetic material recombination exhibit some of the characteristics of a GPT.

A crucial yet unsettled aspect about the diffusion of these disruptive and transformative technologies is the extent of the impact for those that are able to produce, transform, and actively engage with them. What portion of the benefits are kept by those who are able to produce, transform, and develop these type of technologies? How does this benefit compare to what users receive? What is the dynamic over time? Who benefits first? Who benefits most?

This article seeks to provide empirical evidence about the very first of these questions by studying the county-level economic impact of the adoption of Electrical & Electronic (E&E) technologies on manufacturing output and wages at the beginning of the 20<sup>th</sup> century in the US. Thus departing from existing studies by relying on patenting activity instead of a more passive measure of adoption like electricity consumption. In particular, the analysis is carried out using an extensive measure of technological adoption, i.e. whether counties have E&E patents or not. Doing so required developing a novel database identifying the geographical information of historical patent documents granted at the United States Patent and Trademark Office (USPTO) dating back to 1836, in combination with demographic and economic data from the US Census Bureau. It is shown that places with patenting activity in E&E technologies grew faster and paid higher wages than others in the manufacturing sector between 1920 and 1930.

The empirical identification strategy relies on using measures of the adoption of E&E technologies prior the 1870s as an instrument to predict the adoption of E&E technologies

between 1920 and 1930. It assumes that the early adoption of E&E technologies (prior to the invention of the electric light-bulb or the establishment of the first power plant) were determinant to the inventive structure of places 50 years later while not being correlated with the idiosyncratic events that will determine growth and wages between 1920 and 1930.

These results are robust to changes in the way E&E technologies are identified. In addition to the usual technological classification provided by the USPTO, this article develops an identifier of E&E technologies based on a text mining algorithm that searches for E&E-Related vocabulary on all patent descriptions. Even though this procedure identifies a considerably different subset of patents than the USPTO classification, results barely change.

Since this is a period characterized by the rapid diffusion of the electrical infrastructure in the US, and given the empirical evidence on its economic impact (Kitchens and Fishback, 2015; Lewis and Severnini, 2020; Gaggl, Gray, Marinescu, and Morin, 2019), an additional robustness check is carried out using counties that were likely not to be reached by the electrical grid. This exploits the fact that by 1930 only 10.4% of rural areas had access to electricity (Lewis and Severnini, 2020; Bureau, 1976). It is shown that results barely change if only rural areas are considered.

In addition, two falsification tests are carried out. On the one hand, results do not hold if misclassified E&E patents are considered. The information contained in patent descriptions is exploited to identify patents that are likely to be misclassified. On the other hand, results do not hold if an earlier period is considered, which is in line with the historical and anecdotal evidence stating that the transformative effect of E&E technologies took place only after 1914 (David, 1990; Goldfarb, 2005; Lipsey, Carlaw, and Bekar, 2005).

This evidence can be seen as an initial step to better understand how the production of these key technologies affect places and whether there exist disparate economic benefits between those who produce and those who use them. It also contributes to the literature of GPTs, by providing complementary evidence to the discussion of whether electricity fulfill the GPT criteria (Moser and Nicholas, 2004; Petralia, 2020).

Moreover, the new data sources this article describes represents an exceptional oppor-

tunity to study the multiple dimensions in which the diffusion of disruptive technologies, such as E&E in the 1920s, can transform the organization of production, the institutional environment, or any other aspect of the organization of a society, and vice versa<sup>2</sup>.

Because this article relies heavily on novel data initiatives, the next section starts by describing the different data sources, focusing on providing a comprehensive description of the nature and scope of the database on historical patent documents. Section 3 develops and evaluates an empirical strategy devoted to estimate the economic impact on manufacturing output and wages of the adoption of E&E technologies in the early 20<sup>th</sup> century. Section 4 concludes.

---

<sup>2</sup>It has been argued, for instance, that the “unit drive” electric motor allowed the re-arrangement of machines in the factory to coincide with the flow of production, thus establishing the conditions to create the assembly line (Lipsey, Carlaw, and Bekar, 2005).

## 2 Data Sources

This section describes the different sources of data used in this study, which when combined allow for a comprehensive overview of the emergence, evolution, development, and adoption of E&E technologies in their historical context. Empirical studies on the evolution of technologies are often limited in quantity and scope by the availability of data and the nature of the object of study. After all, the adoption of technologies takes decades, and the most interesting cases occurred long before data began to be collected systematically. For instance, the Corliss steam engine discussed in [Rosenberg and Trajtenberg \(2004\)](#) was patented in 1849<sup>3</sup>, while Edison’s carbon filament incandescent lamp mentioned in [David \(1990\)](#) dates back to 1880<sup>4</sup>. This is also true for the invention of integrated circuits, allegedly the engine of the ICT revolution, which can be traced back in the US to 1959<sup>5</sup>. These data limitations are overcome by merging several independently developed databases, which contain information about the technological and geographical attributes of patented inventions in the US, as well as county-level economic and demographic data from 1860 to 1930. Thus covering the emergence, development, and adoption of E&E technologies ([David, 1990](#); [Lipsey, Carlaw, and Bekar, 2005](#); [Greenwood, 1997](#); [Goldfarb, 2005](#)).

On the one hand, information about the technological class of all patented inventions since 1836 is made available by the USPTO<sup>6</sup>. Patents are classified into technological classes according to the type of invention to which they claim rights. There are currently more than 400 different technological classes in use, and whenever a new class is created, or an existing one re-defined, all available patents are re-classified to maintain temporal consistency. Furthermore, patents can be grouped into broad economically relevant categories (Chemical, Computer and Communications (C&C), Drugs and Medical (D&M), Electrical and Elec-

---

<sup>3</sup>See <https://www.google.com/patents/US6162>

<sup>4</sup>See <https://www.google.com/patents/US223898>

<sup>5</sup>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>).

<sup>6</sup><http://www.uspto.gov/learning-and-resources/electronic-bulk-data-products>

tronics (E&E), Mechanical, and Others<sup>7</sup>. During the period considered C&C and D&M technologies represent approximately 1% of total patenting activity and are not treated as separate categories but placed within the category Others<sup>8</sup>. Table I below shows the share occupied by each broad category over time<sup>9</sup>.

Table I: Distribution of Patenting Activity (in Percentages)

Decade	Chemical	E&E	Mechanical	Others
1850	10.50	1.90	39.60	48.00
1860	10.60	1.80	34.70	52.80
1870	8.60	2.10	34.30	55.00
1880	7.70	5.00	36.30	50.90
1890	7.50	6.50	38.10	47.90
1900	8.10	6.50	38.70	46.70
1920	10.00	9.60	37.10	43.40
1930	15.30	11.30	32.40	41.00

There are considerable differences among categories. Mechanical and Chemical technologies are among the most abundant types, which is a consequence of them being at a more advanced stage of maturity. Note that while Mechanical, Chemical, and Others exhibited stagnant or decreasing participation rates over this period E&E technologies exhibited a 5-fold increase, going from representing 2% of all inventive activity to more than 10%.

Even though the continuous technological reclassification of patents made by the USPTO ensures temporal consistency, it may be the case that this semi-automated process misplaces patents into wrong or unfit technological classes (particularly for old patents). Note that one

<sup>7</sup>See Hall, Jaffe, and Trajtenberg (2001) for details. The concordance is available at <http://www.nber.org/patents/>.

<sup>8</sup>All results do not differ if they are considered as separate categories.

<sup>9</sup>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.

could take advantage of the wealth of information contained in patent documents to provide a characterization of E&E technologies that gets around this issue.

In particular, patent descriptions can be scanned to identify key-words related the use of electronic and electrical components, notions, or principles and use the presence of this technical vocabulary to flag “E&E-Related” patents. This set of patents will typically include inventions that rely on electricity-related components, notions, or principles regardless of whether they produce any particular technological improvement in that area or not. This implies that patents could be classified as “E&E-Related” independently of its USPTO technological classification.<sup>10</sup> In fact, Table II shows that “E&E-Related” patents are found throughout the entire technological space during the period.

Two aspects of Table II are worth highlighting. First, the steady growth of E&E-Related vocabulary in Chemical, Mechanical and Others, which appeared in approximately 1% of the patents at the beginning of the sample and increased to approximately 20% by the end of it. In addition, note there is a considerable portion of patents that belong to the category E&E according to the USPTO classification but that do not contain any E&E-Related vocabulary, especially at early stages. This aspect will be exploited later to create a placebo test containing potentially misclassified patents to show that results do not hold if only this patents are considered. Please refer to the Appendix to see a detailed list of the key-words used to identify “E&E-Related” patents.

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<sup>11</sup>

---

<sup>10</sup>The list of “E&E-related” keywords was obtained by extracting all words containing “electri” or “electro” from the English dictionary. Although this procedure leaves out some potentially useful set of words that are strongly associated to E&E technologies (such as the word “circuit”), it aims to minimize the number of false positives identified by the algorithm. For a detailed list of the words used please refer to the Appendix.

<sup>11</sup>It is estimated that the last version of HistPat covers now approximately 99.3% of all patents to US residents in the period 1836-1975. The last version of this dataset can be downloaded at

Table II: Percentage of Patents Containing E&amp;E Related Vocabulary

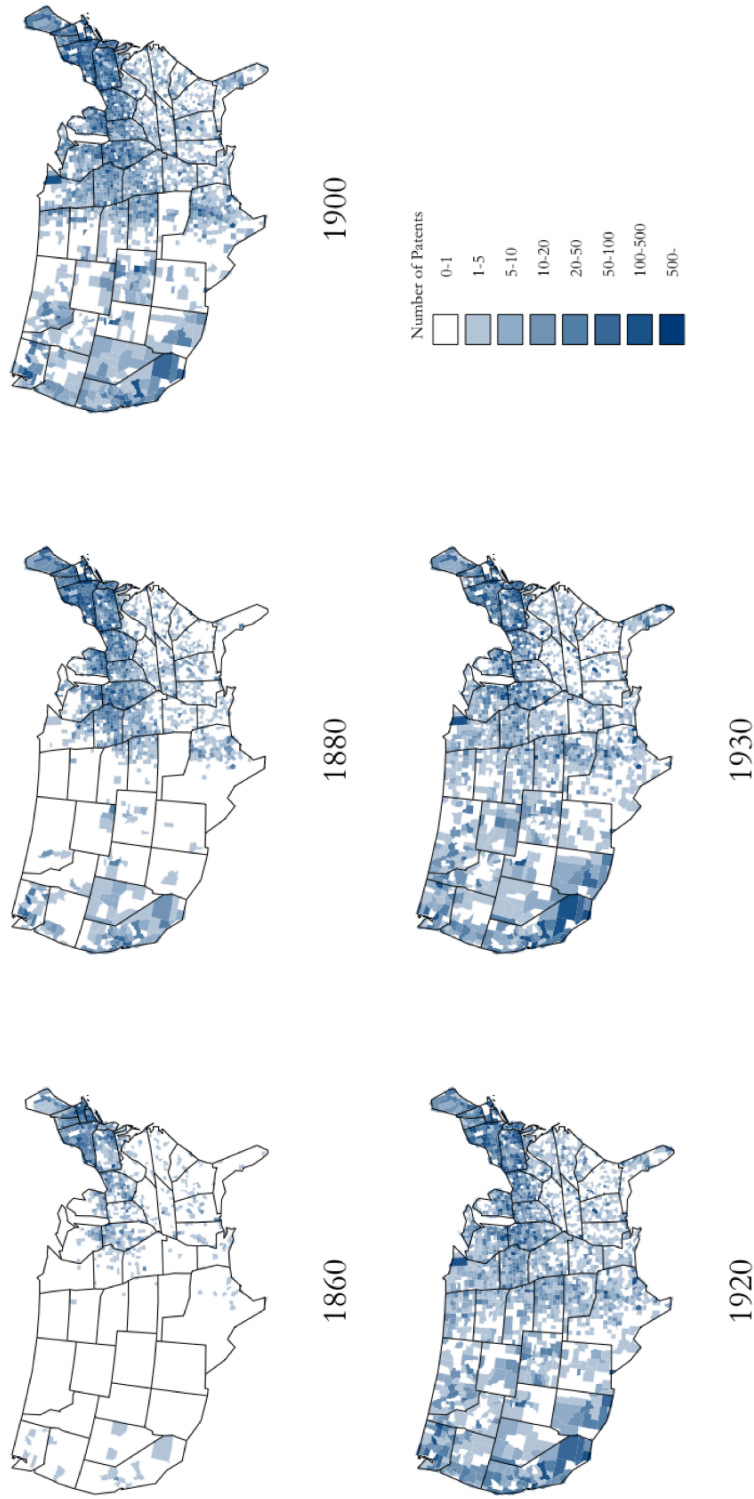
Decade	Chemical	E&E	Mechanical	Others
1850	1.19	16.23	0.45	1.23
1860	1.57	14.10	0.56	0.70
1870	1.90	25.45	0.74	1.51
1880	4.57	70.04	3.04	3.97
1890	7.68	78.89	7.32	5.59
1900	10.48	76.73	9.26	6.70
1920	14.23	75.59	11.77	11.90
1930	17.69	83.84	20.15	19.33

Given that the main purpose of this study is to relate inventive activity of places with their per capita growth and wages, one genuine concern may be that the amount of patenting or the degree of geographical dispersion of inventive activities is not enough to allow for a meaningful comparison across counties. Figure I describes graphically the diffusion of patenting activity over space and time, showing how widespread it was back then. Note how inventive activity first spread from the north-eastern states, where they were concentrated before the 1860s, toward the south-east to later reach the west coast by the 1880s. Patent activity closely followed the development of urban centers and migration (Ager and Brückner, 2013; Burchardi, Chaney, and Hassan, 2016). The central states joined the technological race by the turn of the century.

---

<https://dataverse.harvard.edu/dataverse/HistPat>. Petralia, Balland, and Rigby (2016) contains a detailed description of the machine learning methodology used to create it and a set of tests to discard the existence of potential biases using manually collected data.

Figure 1: The Geography of Patenting Activity Through the Years



Source: Own elaboration based on HistPat

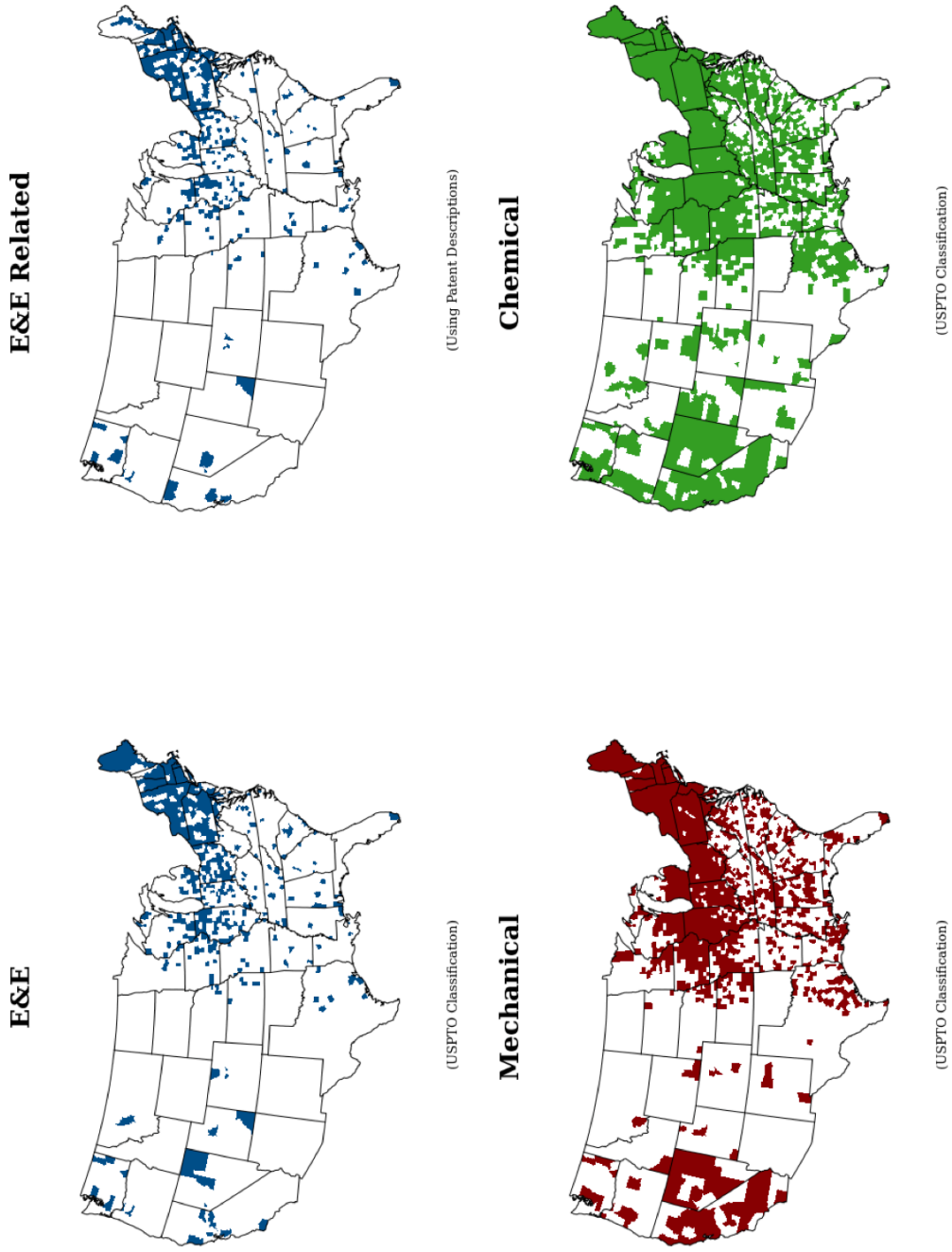
The geographical diffusion of inventive activities was quite heterogeneous across technologies, as shown in Table III. This table displays the correlation of patenting activity across different categories throughout the entire period, where each vector takes value one whenever patenting activity in a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

Table III: Geographical Correlation in Patenting Activity

	Chemical	E&E	Mechanical	Others	E&E Related
Chemical	1	0.376	0.177	0.209	0.416
E&E	0.376	1	0.159	0.149	0.613
Mechanical	0.177	0.159	1	0.086	0.205
Others	0.209	0.149	0.086	1	0.177
E&E Related	0.416	0.613	0.205	0.177	1

This geographical heterogeneity is even more pronounced at early stages. Figure II maps counties' technological production by type of technology prior 1880. Note that most of the production of E&E technologies, using either the USPTO classification or the patent content analysis, is concentrated in the northeastern states. More mature technologies, such as Chemical or Mechanical are more spatially spread.

Figure II: Patenting Activity by Technological Category Prior 1880



Source: Own elaboration based on HistPat

Information about the technological development of counties can be combined with economic and demographic data made available by the US Census Bureau and IPUMS. In particular, this paper relies on the database provided by the Inter-University Consortium for Political and Social Research (ICPSR) containing detailed decennial county-level data on demographic, economic, and social variables that were collected by the US Census Bureau<sup>12</sup>. Data on occupations come from IPUMS<sup>13</sup>.

Table IV below shows the evolution of the main economic and demographic variables in the sample. This is a period of rapid and continuous growth in population, which had quadrupled since 1860, with immigration being one of the main explanatory factors. By 1880, more than 10% of the population was foreign-born, with this number rising to 20% if second-generation immigrants are included (Burchardi, Chaney, and Hassan 2016). Migration was mostly unregulated until World War I. After that, a series of restrictions were incorporated, ultimately resulting in the establishment of a quota system in 1921<sup>14</sup>.

The remarkable increase in manufacturing production during this period was crucial for the positioning of the US as a world leader, which was realized after the 1900s when the US 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 1920s, manufacturing alone explained more than 80% of total factor productivity (TFP) growth.

There are many factors that are considered crucial in this remarkable success. Wright (1990) argues that growth in this period relied greatly on the exploitation of the geological potential of the US. In order to take into account for this possible source of growth, we include information about the number of working mineral deposits within counties from the United States Geological Survey (USGS)<sup>15</sup> and the use of primary inputs in manufacturing

---

<sup>12</sup>Available at <https://www.icpsr.umich.edu/icpsrweb/>

<sup>13</sup>See <https://usa.ipums.org/usa/intro.shtml>

<sup>14</sup>Daniels (1990) provides a detailed description of the nature and composition of immigration flows during this period.

<sup>15</sup>Available at: <https://mrdata.usgs.gov/mrds/about.php>

Table IV: 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 refers to output in manufactures. Wages are expressed as a share of the total output, while Labor Force counts hands employed in manufacture. All economic magnitudes are expressed at 1850's constant prices using Consumer Price Indexes from the Handbook of Labor Statistics.

by county from the census. In addition, since the impact of immigration on growth, wages and employment is very well documented in general (Ottaviano and Peri, 2005, 2008) and also during this period in particular (Ager and Brückner, 2013), information about the share of migrants per county is included.

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. We follow them and include the number of post offices per county to proxy for state presence<sup>16</sup>, which we also complement with measures of the amount of public employees in the county using IPUMS data. In addition, it has been argued that the shift from rural to a more efficient urban manufacturing organization could partially explain growth acceleration. Atack and Bateman (1999) and Kim (2005) find a simultaneous increase of manufacturing and urban population in the second half of the nineteenth century, with the share of manufacturing labor force and the share of urban population doubling between 1850 and

<sup>16</sup>This data was collected using original records which are available at: <https://catalog.hathitrust.org/Record/002137107>

1880 (from 10% to 20% and 15% to 30%, respectively). We use data on the share of urban population in a county from the census to take into account for that possibility.

It is also argued that railroads were crucial to the development of the US economy in the late nineteenth and early 20th century, since railroads became the dominant form of freight transportation and areas around railroad lines prospered. [Donaldson and Hornbeck \(2016\)](#) find that railroads were critical to the agricultural sector in 1890 and show that without them agricultural land values would have decreased by 60%. Their measures of counties' market access are included as a robustness check to take into account the importance of the railroad network in the development of the US manufacturing sector.

Finally, it has been shown that the presence of a college in a city has a considerable impact on the average wage and the technological capabilities of places. For instance, [Moretti \(2004\)](#) shows that a percentage point increase in the supply of college graduates raises high school drop-outs' wages by 1.9%, high school graduates' wages by 1.6%, and college graduates wages by 0.4%. Also, [Abramovsky, Harrison, and Simpson \(2007\)](#) provides evidence on the extent to which R&D activity locates near high quality university research departments in Great Britain. Following [Moretti \(2004\)](#), we include information about the presence of a land-grant college in a county to account for this factor.

### 3 Electricity: A GPT at Work

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

An empirical evaluation of these predictions should incorporate two widely documented characteristics of technological adoption. First, technological change can take several decades to spread (Griliches, 1957), even in the case of revolutionary technologies (David, 1990). Second, processes of technological adoption tend to be highly dependent on geography, as physical proximity and collocation are crucial in the dynamics of innovative processes (Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; Feldman and Kogler, 2010; Feldman and Yoon, 2012; Balland and Rigby, 2017; Nuvolari and Vasta, 2017). This effect is expected to be stronger for relatively new and unfamiliar technologies (Feldman and Kogler, 2010) as well as for complex technologies (Balland, Jara-Figueroa, Petralia, Steijn, Rigby, and Hidalgo, 2020; Petralia, Balland, and Morrison, 2017), such as E&E technologies at the beginning of the 20<sup>th</sup> century.

Even though theoretical models characterize the adoption of a GPT in a geographically-deprived setup, one can profit from the uneven geographical spread of different technologies when empirically assessing their worth. The unique place and time footprint left behind in patent documents provides an exceptional opportunity to exploit time-place variation in the adoption of technologies, to determine whether places producing E&E technologies grew more than the rest.

This study traces the adoption of different technologies over space and time using patenting activity within counties, assuming that the patenting activity of a place can be used as a suitable empirical counterpart of its capabilities to produce any given type of technology. Patents are a good indicator of technological adoption because they identify a very active engagement of people and places with any given technology, as they single out people and

companies that possess the ability to produce and recombine these technologies. Note that patent statistics have been used as an index of inventive output at least since [Schmookler \(1952\)](#), who used them to explain the aggregate efficiency of the US economy. Patenting activity can be seen as a good proxy to flag places that have reached the component-finding stage of the [Helpman and Trajtenberg \(1998a\)](#) model or the discovery phase in [Aghion and Howitt \(2000\)](#).

The main concern when evaluating the impact of technological adoption on economic outputs lies in the possibility that there may have reinforcing effects. If such feedback exist, Ordinary Least Squares (OLS) or Fixed Effects (FE) estimation methods would yield biased estimates, as the error term will be correlated with the regressor(s). This is likely to be the case for E&E technologies, which required considerable initial investments and complementary infrastructure to work. In fact, [Kitchens and Fishback \(2015\)](#); [Lewis and Severini \(2020\)](#); [Gaggl, Gray, Marinescu, and Morin \(2019\)](#) show this is a period characterized by the rapid diffusion of the electrical infrastructure in the US, which had considerable short and long run consequences for the well being of places.<sup>17</sup>

The empirical strategy adopted in this paper relies on using measures of the adoption of E&E technologies prior to the 1870s as an instrument to predict the adoption of E&E technologies between 1920 and 1930, to later evaluate its impact on manufacturing output and wages. This assumes that early adoption of E&E technologies (prior to the invention of the electric light-bulb or the establishment of the first power plant) was crucial to the inventive structure of places 50 years later while not being correlated with the contemporaneous determinants of growth and wages between 1920 and 1930. Non-contemporary patents have the potential to act as suitable instruments to track knowledge adoption since they provide a very detailed characterization of the technological profile of places without having any direct economic impact on them, as their granting periods are already expired and exceptional

---

<sup>17</sup>Transportation infrastructure can also have a positive impact regional economies by facilitating knowledge diffusion and spillovers [Agrawal, Galasso, and Oettl \(2017\)](#).

rents exhausted. <sup>18</sup>

Using the early adoption of E&E technologies as an instrument relies on three assumptions. First, it is assumed that early adoption of E&E technologies (prior to the 1870s) was not occurring because inventors expected those places to grow the most after the 1920s, or because they expected those places to be the most suitable to market their inventions in the future. This can be justified by noting that prior to the 1870s it was nearly impossible to predict which future markets would be the most appropriate for E&E technologies, as they were in a very exploratory phase, such that their possible range of application 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. These inventions included arc-lighting systems<sup>19</sup> dynamos<sup>20</sup>, and systems for electric distribution<sup>21</sup> among others. More than three decades after Elihu Thomson left his position (1880) as a 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 played a vital role in the construction of the Panama canal, which was completed in 1914. General Electric (GE), created in 1892 through the merger of the Edison General Electric Company and Thomson-Houston Electric Company, supplied approximately 1500 electric motors and electro-mechanical control boards that not only operated 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 (where the Thomson-Houston Electric Company was born) played an important role in the construction of the Panama

---

<sup>18</sup>It can be the case that old patenting activity is actually capturing some particular characteristic of places that remain relevant for decades. This would invalidate its validity as a suitable instrument. This specific concern will be addressed thoroughly during the econometric strategy.

<sup>19</sup>See <https://www.google.com/patents/US261790>

<sup>20</sup><https://www.google.com/patents/US302963>

<sup>21</sup><https://www.google.com/patents/US335159>

canal, a role that could not have been envisioned at the time of the company's founding<sup>22</sup>. 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) and 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 decisions of pioneering electrical entrepreneurs. Otherwise, infrastructure-led growth may have been the responsible factor behind the well-being of places, rather than the early adoption of any particular technology. Note, however, that electricity-related infrastructure was almost non-existent prior to the 1870s.<sup>23</sup> In fact, Pearl Street Station (in Manhattan, New York) was the first central power plant in the US, it opened in 1882 and served only 82 customers (Orrok, 1930). Even the possibility of electrical illumination was uncertain at the end of the 1870s, as early experiments by Thomas Edison in 1879 produced light bulbs that lasted only 13.5 hours (Israel and Edison, 1998).

The third assumption requires that early developments of a particular technology can be used to predict future adoption. Therefore, the persistence over time and space of technological capabilities is essential. In this regard, there is a well-established literature demonstrating that processes of technological adoption tend to be highly dependent on geography, as physical proximity and collocation are crucial in the dynamics of innovative processes (Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; Feldman and Kogler, 2010; Feldman and Yoon, 2012; Balland and Rigby, 2017). This effect is expected to be stronger for relatively new and unfamiliar technologies. At early stages, technological adoption is characterized by the importance of tacit knowledge; only when knowledge becomes standardized does geographical dispersion tends to occur (Feldman and Kogler, 2010).

---

<sup>22</sup>In fact, the importance of this initial venture persists into the present, as the factory remains an essential part of GE, producing helicopter and jet engines, among other things, and employing approximately 45,000 people

<sup>23</sup>The importance of other types of infrastructure is discussed later in the article

Following [Bresnahan and Trajtenberg \(1995\)](#), [Helpman and Trajtenberg \(1998b\)](#), [Helpman and Trajtenberg \(1998a\)](#), and [Aghion and Howitt \(2000\)](#), per capita output growth is used to measure the economic impact of a GPT and  $\Delta y_{c,t}$  is computed as the log difference in per capita output in manufactures for each county. On the other hand, technological adoption is captured by a set of dummies that take value one whenever a county has positive patenting activity in a particular technology in the five years prior to the census year<sup>24</sup>. Therefore, in this specification technological adoption is portrayed at the extensive margin, focusing on whether or not a particular technological competence is present in a county without considering the intensity at which it is being produced. However, robustness checks include alternative specifications that take into account the intensive margin of adoption. Please refer to Appendix [5.2](#) for details.

This implies that the entire technological profile of a county is characterized by a set of four dummy variables ( $E\&E_{c,t}$ ,  $Mechanical_{c,t}$ ,  $Chemical_{c,t}$ , and  $Others_{c,t}$ ) that take value one if there was patenting activity in the county in the previous five years, and zero otherwise<sup>25</sup>.

Then the estimating equation can be summarized as follows:

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

Where DV (the dependent variable) will be either the *per capita Growth* ( $\Delta y_{c,t}$ ) or the *Average Wage Growth* ( $\Delta w_{c,t}$ ).  $T_{c,t}$  represents a vector of technological variables, which includes the full set of dummy variables described above ( $E\&E_{c,t}$ ,  $Mechanical_{c,t}$ ,  $Chemical_{c,t}$ , and  $Others_{c,t}$ ).<sup>26</sup> Whenever the custom definition of E&E technologies is used, the USPTO classification scheme will be abandoned and  $T_{c,t}$  will only include a dummy that identifies

---

<sup>24</sup>It is common in empirical studies using patenting activity to use a window of years instead of a particular year, this is because patenting activity fluctuates greatly from year to year. Please see [Hall, Jaffe, and Trajtenberg \(2001\)](#) for a detailed discussion

<sup>25</sup>In the Appendix [5.3](#) it is shown that results are not sensitive to variations in the threshold used.

<sup>26</sup>An additional cleaning process has been made to the USPTO classification data, taking advantage of the text mining algorithm that identifies E&E vocabulary in patent descriptions. If a county has E&E

“E&E-Related” activity on places based on what is found in patent descriptions. This is because this custom definition will typically span above and beyond the boundaries of the usual USPTO classification.

$X_{c,t}$  comprises a set of control variables that could be crucial in determining  $\Delta y_{c,t}$  and  $\Delta w_{c,t}$ . This includes the share of the foreign population within counties (*Foreign*), as there is evidence of the importance of cultural diversity and immigration for growth (Ager and Brückner, 2013; Burchardi, Chaney, and Hassan, 2016). Furthermore, it includes two variables related to the availability and exploitation of natural resources, the share of primary inputs used in manufacturing (*Primary Inputs*) and the number of mineral deposits in activity (*Working Deposits*)<sup>27</sup>. The effect of natural resource exploitation during this period are discussed in detail by Wright (1990). Additionally,  $X_{c,t}$  contains a set of variables related to state presence at the 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). On the one hand, it includes the share over population of federal, state, and local public employees (*Public Employment*), and secondly, the number of post offices per county (*PO*) as a proxy for the state’s capacity on places (Acemoglu, Moscona, and Robinson, 2016).

Transportation infrastructure may impact regional economies not only through their effect on employment and investment but also by facilitating knowledge diffusion and spillovers. In fact, Agrawal, Galasso, and Oettl (2017) show that transportation infrastructure can foster regional growth by facilitating local knowledge flows, increasing the likelihood that innovators access knowledge inputs from neighboring places. In addition, Michaels (2008) find that highway access in the US lead to an increase in trade-related activities in places, raising the relative demand for skilled manufacturing workers in skill-abundant counties and

---

patenting activity according to the USPTO classification but none of the patents contain any E&E-Related vocabulary, then this county is not consider as an E&E adopter. This procedures ensures that counties with few E&E missclassified patents are not considered E&E producers.

<sup>27</sup>This variable was created by geolocating all mineral deposits within counties’ boundaries. Data on geo-located mineral deposits, including their operational status, can be found at <https://www.usgs.gov>

reducing it elsewhere. Counties' market access in 1890 (*MA 1890*), taken from Donaldson and Hornbeck (2016), is included to take into account the economic impact of access to the railroad network and the navigable waterways.

Because the shift from rural to a more efficient urban manufacturing organization could partially explain growth acceleration in this period,  $X_{c,t}$  also includes two variables aimed at capturing the urban and manufacturing structure of places. *Urban Population* and *Establishments per capita* measure the share of urban population<sup>28</sup> and the number of manufacturing establishments per capita within a county. Finally, *LGU* is a dummy variable that indicates the presence of a land-grant university in the county (Moretti, 2004). A lagged dependent variable is always included in the estimation ( $y_{c,t-1}$ ). Depending on the specification,  $X_{c,t}$  will include county, state, and year dummies.

Before describing the construction of the instrument, which by definition will be time invariant, it is worth evaluating how the adoption of E&E technologies relates to growth using the full span of available data (1860-1930). Table V reports a set of regressions that evaluate how technological adoption relates to growth ( $\Delta y_{c,t}$ ), they include year and county fixed effects and standard errors clustered at the same level according to Cameron, Gelbach, and Miller (2012). The difference between Column (1) and (2) is that the former uses the usual USPTO classification while the latter identifies E&E technological based on the information extracted from patent descriptions based on the text mining algorithm described in Section 2. Since this definition spans over the entire technological space and across USPTO technological boundaries, column (2) does not include technological variables based on the USPTO classification.

---

<sup>28</sup>A place is considered urban if it has more than 25.000 inhabitants according to the US Census bureau definition.

Table V: Adoption of E&amp;E Technologies and Growth

	<i>Growth</i> ( $\Delta y_{c,t}$ )	
	(FE)	(FE)
	(1)	(2)
E&E	0.188*** (0.062)	
E&E Related		0.171*** (0.058)
Mechanic	0.058** (0.027)	
Chemical	0.043* (0.024)	
Others	0.048** (0.021)	
Foreign (Share)	0.002*** (0.001)	0.002*** (0.001)
Establishments per Capita (in logs)	0.748*** (0.040)	0.751*** (0.040)
Primary Inputs	1.361*** (0.178)	1.362*** (0.179)
Working Deposits (in logs)	0.042 (0.034)	0.048 (0.034)
Public Employment	-0.001 (0.001)	-0.001 (0.001)
PO (in logs)	-0.003 (0.067)	0.016 (0.067)
Urban Population (Share)	0.513*** (0.094)	0.539*** (0.099)
$y_{c,t}$	-0.816*** (0.073)	-0.813*** (0.073)
Period	1860-1930	1860-1930
County & Year FE	Yes	Yes
Observations	14,865	14,865
Adjusted R <sup>2</sup>	0.574	0.573

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Note that all technological variables are positively related to per capita growth, with the coefficient of E&E adoption being higher than the rest (column 1). Column (2) also shows that there exist a significant positive correlation between the presence of E&E-Related capabilities and the per capita growth of places. The share of foreign immigration (*Foreign*) in a county is positively related to the output growth of counties. This is consistent with previous findings; see for instance, [Ager and Brückner \(2013\)](#) and [Hatton and Williamson \(2008\)](#). The intensity of the use of primary inputs (*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 US manufacturing ([Wright, 1990](#)). The role of the state's presence, captured by the number of post offices (*PO in logs*) and the share of public employment over population (*Public Employment*), doesn't seem to be have clear influence on growth. As suggested by [Atack and Bateman \(1999\)](#) and [Kim \(2005\)](#), places with a higher percentage of urban population (*Urban Population*) grew faster. In addition, places with a more manufacture-oriented production structure (*Establishments per Capita*) enjoyed higher growth.

Now consider the following instruments for E&E adoption:

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

and

$$E\&E \text{ Related}_{c,1870} = 1 \quad \text{if} \quad \sum_{1866}^{1875} Patents_{E\&E \text{ Related}} > 0, \text{ and zero otherwise}$$

Table [VI](#) reports the first stage regression using the instruments mentioned above and shows that they are strongly correlated with E&E adoption between 1920 and 1930. The coefficients for  $E\&E_{c,1870}$ ,  $E\&E \text{ Related}_{c,1870}$  are both individually and jointly statistically significant and they explain a significant fraction of the likelihood of E&E adoption between 1920 and 1930.

Not surprisingly, the adoption of E&E and E&E-Related technologies is strongly correlated with the adoption of other technologies, which reflects the fact that innovative places tend to be diversified and that technologies are highly complementary (GPTs in particular). Additionally, it is worth pointing out that places with higher share of migrants, higher manufacturing capabilities, and higher urban populations were more likely to adopt E&E technologies. However, these correlations are also likely to hold for other technologies. Note that the amount of post offices per county is also positively correlated with the likelihood of E&E adoption, since post offices were a crucial component of the US patent system. Patent applications could be sent by post free of charge and the availability of a post office nearby drastically reduced application costs (especially time-wise).

Table VI: 2SLS First Stage

	E&E (OLS)	E&E Related (OLS)
	(1)	(2)
$E \& E_{1870}$	0.113*** (0.017)	0.143*** (0.021)
$E \& E \text{ Related}_{1870}$	0.049** (0.019)	0.042* (0.024)
Mechanic	0.038*** (0.011)	
Chemical	0.157*** (0.010)	
Others	0.025** (0.011)	
Foreign (Share)	0.0003*** (0.0001)	0.0003** (0.0001)
Establishments per Capita (in logs)	-0.002 (0.009)	0.004 (0.012)
Primary Inputs	-0.028 (0.029)	-0.016 (0.036)
Working Deposits (in logs)	0.001 (0.005)	0.010 (0.007)
Public Employment	0.001** (0.0002)	0.001*** (0.0003)
PO (in logs)	0.061*** (0.008)	0.078*** (0.010)
Urban Population (Share)	0.570*** (0.026)	0.529*** (0.033)
LGU	0.085*** (0.026)	0.171*** (0.033)
$y_{c,t-1}$	0.031*** (0.005)	0.065*** (0.006)
Period	1920-1930	1920-1930
State & Year FE	Yes	Yes
Observations	5,078	5,078
Adjusted R <sup>2</sup>	0.481	0.356

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

Columns (1) and (2) in Table VII reports 2SLS estimates that evaluate how E&E adoption relates to  $\Delta y_{c,t}$ . The number of land-grant universities per county (*LGU*) is included in addition to the variables already present in Table V, which is time invariant. Results show a strong and positive relationship between the technological adoption of E&E technologies and the per capita growth of places, regardless of the measure of E&E considered. In addition, the estimates of the coefficients accompanying all control variables show very similar magnitudes with respect to the FE specification of Table V. The intensity of the use of primary inputs (*Primary Inputs*) and the number of manufacturing establishments in a place (*Establishments per Capita*) are positively related to growth as in Table V. The strong relationship between the share of urban population (*Urban Population*) and growth doesn't carry over to this specification.

Note that the instruments are highly correlated with E&E and E&E-Related adoption, as the F-test on the joint significance clearly rejects the null hypothesis. Additionally, as the 2SLS estimates are over-identified, the Sargan test of over-identified restrictions is reported at the bottom of the table. This test does not reject the null hypothesis of the instrument being orthogonal to the error term. As before, most technological variables are positively related to per capita growth, with the coefficient of E&E adoption being higher than the rest.

Table VII: Adoption of E&E Technologies & Growth

	<i>Growth</i> ( $\Delta y_{c,t}$ )			
	(2SLS)	(2SLS)	(2SLS)	(2SLS)
	(1)	(2)	(3)	(4)
E&E	0.711*** (0.270)		0.456** (0.226)	
E&E Related		0.903*** (0.230)		0.573*** (0.172)
Mechanic	0.134*** (0.030)		0.110*** (0.034)	
Chemical	0.058 (0.051)		0.059 (0.050)	
Others	0.100*** (0.031)		0.113*** (0.034)	
Foreign (Share)	0.0001 (0.0003)	0.0001 (0.0003)	0.0003 (0.0003)	0.0004 (0.0003)
Establishments per Capita (in logs)	0.698*** (0.030)	0.684*** (0.031)	0.591*** (0.035)	0.583*** (0.036)
Primary Inputs	1.246*** (0.082)	1.298*** (0.085)	0.916*** (0.099)	0.953*** (0.100)
Working Deposits (in logs)	-0.026* (0.014)	-0.028* (0.015)	-0.008 (0.015)	-0.007 (0.016)
Public Employment	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
PO (in logs)	0.038 (0.027)	0.049* (0.029)	0.034 (0.029)	0.045 (0.028)
Urban Population (Share)	-0.105 (0.178)	-0.084 (0.146)	-0.058 (0.138)	-0.029 (0.102)
LGU	0.006 (0.062)	-0.032 (0.074)	0.047 (0.053)	0.040 (0.056)
$y_{c,t-1}$	-0.379*** (0.017)	-0.379*** (0.021)	-0.307*** (0.019)	-0.298*** (0.021)
MA 1890 (in logs)			0.109* (0.062)	0.133** (0.064)
$y_{c,1870}$			-0.003 (0.027)	-0.001 (0.028)
$k_{c,1870}$			0.032 (0.027)	0.030 (0.028)
Period	1920-1930	1920-1930	1920-1930	1920-1930
State and Year FE	Yes	Yes	Yes	Yes
Sargan Test (p-value)	0.401	0.661	0.673	0.757
Weak Instruments E&E (F-statistic)	15.987	12.112	21.152	20.413
Observations	5,078	5,078	3,793	3,793
Adjusted R <sup>2</sup>	0.240	0.172	0.222	0.201

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

As in virtually all empirical studies using instrumental variables, the particular choice of the instrument is not exempt of potential threats. There are a few threats to the identification strategy that should be taken into account. First, it is possible that lagged values of E&E adoption may actually be capturing “initial conditions” of places, conditions that remain relevant 50 years later. For instance, early E&E adoption may be correlated with higher levels of development, better infrastructure, or better institutions, which can have a long-lasting effects on growth rates. More generally, this concern relates to the fact that the success of the empirical strategy relies on the maintained assumption that county-specific characteristics, included in the error term in the 2SLS specification, are not correlated with the instrument.

This issue is addressed in columns (3) and (4) of Table VII which includes additional regressors that control for initial county-specific characteristics of places, i.e. the per capita value of output ( $y_{c,1870}$ ) and capital ( $k_{c,1870}$ ) in manufactures in 1870<sup>29</sup>. The addition of these variables is based on the idea that they constitute a good proxy for initial levels of development and infrastructure. Using 1870’s per capita output and capital as additional regressors requires constraining the sample to include places that were covered by the 1870 census. Note that columns (3) and (4) also includes counties’ market access in 1890 ( $MA_{1890}$ ) in order to control for pre-existing infrastructure and access to the railroad network and the navigable waterways.

Results are robust to the sub-setting of the sample and the inclusion of proxies for the initial condition and infrastructure of places. Even though there is a considerable drop in the number of observations, results are similar when compared to those in columns (1) and (2), which use the full sample. Additionally, note that the F-test of joint significance always rejects the null hypothesis, while the Sargan test of over-identified restrictions does not reject the null.

Another important threat to the identification strategy relates to the fact that the baseline estimates of Table VII don’t take into account the expansion of the electrical grid in this

---

<sup>29</sup>Unfortunately, value of capital in manufactures is only available before the 1900s.

period, a factor that has been shown to be of great importance (Lewis and Severnini, 2020; Kitchens and Fishback, 2015; Gaggl, Gray, Marinescu, and Morin, 2019). Note that the percentage of electrified non-farm households increased from 5% in 1900 to approximately 85% in 1930 (Lewis and Severnini, 2020). This issue can be addressed, however, by exploiting the fact that by 1930 only 10.4% of rural areas had access to electricity (Lewis and Severnini, 2020; Bureau, 1976). The Appendix 5.5 includes a set of regressions that test whether estimates are actually driven by the expansion of the electrical grid, there it is shown that results barely change if only non-urban areas, where the electrical grid was barely diffused by 1930, are considered.

Although the inclusion of initial levels of capital and output can be helpful to reduce the possibility that results are driven by initial characteristics of places, it doesn't allow to control for the fact that results may actually be driven by faster initial growth rates. If early technological E&E adoption is correlated with higher growth rates and those growth rates are maintained during the entire period, the above-average performance of E&E patenting counties may be spurious. One can exploit anecdotal and historical evidence on the impact of E&E technologies to create a falsification test that takes into account this potentially relevant issue. Note that the literature of GPTs has argued that the transformative effect of E&E technologies only took place after 1914 (David, 1990; Lipsey, Carlaw, and Bekar, 2005). If the historical evidence is correct and results are not influenced by initial growth rates, then we should see that results do not hold for the period before 1914. In the Appendix 5.2 and 5.6 it is shown that that results are not significant for both measures of E&E adoption prior 1914.

An alternative way of testing whether results are actually driven by unobservables that were not appropriately controlled for consists of artificially exposing geographical units that are seemingly indistinguishable from the units of interest but that are actually not treated (i.e. they do not actually have or had E&E capabilities). Note that, if the presence of E&E capabilities is the main channel through which the effect takes place, we shouldn't see any effect if we consider only missclassified or unfit E&E patents. One could exploit the

wealth of information contained in patent descriptions to create a flag for patents that were classified as E&E by the USPTO but that do not contain any E&E-Related vocabulary and that are therefore likely to be misclassified patents. In the Appendix [5.7](#) it is shown that results do not hold if the specification used in Table [V](#) is implemented using only potentially misclassified E&E patents, i.e. that belong to E&E according to the USPTO classification system but that do not contain any E&E-Related vocabulary in it.

Another valid concern regarding the empirical strategy is based on the possibility that when properly estimated, the effect of adopting other technologies are higher than those of E&E technologies. If that is the case, the proposed 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 alone. For instance, because Chemical and Mechanical technologies were already mature technologies prior to the 1870s, their early adoption may be correlated with characteristics of the place that remain relevant years later. In the case of chemical technologies, their adoption may be correlated with the availability of natural resources, which are likely to have had long-lasting implications for growth ([Wright, 1990](#)).

One possible approach to this issue would be to use lagged values of technological adoption as instruments for the rest of the technological variables, based on the assumption that the time lag in the instrument makes it unlikely to be correlated with the error term in the main equation. In the Appendix [5.8](#) it is shown that results on the effect of E&E adoption on growth barely change after treating *Mechanical* technologies as endogenous.

Estimating a growth equation with OLS could yield biased estimates of the effect of E&E on growth. For instance, [Nickell \(1981\)](#) shows that using the within effect estimator will produce inconsistent estimates of the effect of the lagged dependent variable in dynamic models. If  $y_{c,t-1}$  is correlated with other regressors, the estimated coefficients could be biased even if they are exogenous. This means that the results of Table [VII](#) could be the reflection of the underlying correlation structure between the variables measuring technological adoption and  $y_{c,t-1}$ . To address this issue, the baseline results are compared to an alternative specification

in which  $y_{c,t-1}$  is instrumented with its own lagged values. Please refer to the Appendix [5.9](#) for more details.

In all specifications the effect of E&E adoption on growth is higher than the corresponding OLS estimates. The downward bias in the OLS estimates is likely to be the result of a simultaneity bias in the determination of technological adoption and the well being of places. In the absence of any omitted variable bias, the direction of the bias in the OLS estimates due to simultaneity depends on how the likelihood of E&E adoption responded to income changes during this period. Assuming that the baseline 2SLS estimates are correct, a downward bias in OLS estimates requires the likelihood of E&E adoption to have increased at least by 1.4% in response to a 1% increase in per capita output<sup>30</sup>. This hypothesis seems reasonable in the light of the available empirical evidence and considering the emerging state of E&E technologies during the period<sup>31</sup>. For instance, [Furman, Porter, and Stern \(2002\)](#) conduct an empirical examination of the determinants of country-level production of international patents (for 17 OECD countries and covering the period 1974-1996) and find that a 1% increase in GDP per capita could lead to 1.4% increase in international patenting (see Table 6, page 922). Additionally, [Sanyal and Jaffe \(2005\)](#) find that the number of patents granted at the UK patent office more than doubles in response to changes in GDP per capita of the source country (See Table 4B, page 234). Finally, [Verdolini and Galeotti \(2011\)](#) argues that a 1% increase in the ratio of a country GDP over the GDP of the US increases by 5% its probability of patenting in energy-related technologies at the USPTO<sup>32</sup>.

Finally, Appendix [5.10](#) provides an additional set of results which test the sensitivity of

---

<sup>30</sup>Consider the simplest simultaneous equation model, where  $Growth = \gamma_1 E\&E + u$  while  $E\&E = \gamma_2 Growth + e$ . Then the probability limit of the OLS estimator is  $\gamma_1^{OLS} = \gamma_1 + \frac{Cov(E\&E, u)}{Var(E\&E)}$ . If  $e$  and  $u$  are independent, then  $\gamma_1^{OLS} = \gamma_1 + \frac{\gamma_2}{1-\gamma_1\gamma_2} \frac{Var(u)}{Var(E\&E)}$ . If  $\gamma_1$  is replaced by 2SLS estimates, then then it is straightforward to find the minimum value of  $\gamma_2$  that makes the OLS estimates to be bias downward. Assuming  $\gamma_2$  is positive.

<sup>31</sup>The number of counties with positive E&E patenting activity was approximately 10 times higher in 1930 than in 1860

<sup>32</sup>[Levitt \(2002\)](#) and [Brückner \(2013\)](#) are clear examples of the extent of the bias simultaneity may cause.

the estimates to weakening the exclusion restriction assumption. It is based on the work of [Conley, Hansen, and Rossi \(2012\)](#), which proposes an estimation methodology that replace the exact exclusion restriction in an IV model with an assumption related to its support or distribution. Instead of assuming that the instruments are not correlated with the dependent variable, [Conley, Hansen, and Rossi \(2012\)](#) describe a procedure that allows the consistent estimation of the parameters of interest even when this correlation is different from zero, by allowing the researcher to specify a range of values it may take. These results suggest that estimates would become insignificant only at high levels of correlation between the instruments ( $E\&E_{c,1870}$  &  $E\&E\ Related_{c,1870}$ ) and  $\Delta y_{c,t}$ .

The virtuous effect of E&E adoption was not only limited to the per capita output of places. Table [VIII](#) reports a set of regressions that replicate the results presented in Table [VII](#) but that consider the effect of technological adoption on average wage growth in manufactures  $\Delta w_{c,t}$ . Columns (1) and (2) in Table [VIII](#) replicate the baseline estimation using  $\Delta w_{c,t}$  as a dependent variable, while columns (3) and (4) include additional regressors that control for initial county-specific characteristics of places, counties' per capita value of output ( $y_{c,1870}$ ) and capital ( $k_{c,1870}$ ) in manufactures in 1870 and their market access in 1890 ( $MA\ 1890$ ). Note that as before, the adoption of E&E technologies shows a positive effect on average wage growth across specifications.

Table VIII: Adoption of E&amp;E Technologies and Wages

	<i>Wage Growth</i> ( $\Delta w_{c,t}$ )			
	(2SLS)	(2SLS)	(2SLS)	(2SLS)
	(1)	(2)	(3)	(4)
E&E	0.293*** (0.098)		0.200** (0.095)	
E&E Related		0.315*** (0.075)		0.172*** (0.061)
Mechanic	0.060*** (0.010)		0.060*** (0.012)	
Chemical	-0.007 (0.018)		-0.003 (0.020)	
Others	0.049*** (0.010)		0.051*** (0.012)	
Foreign (Share)	0.0001 (0.0001)	0.0001 (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0001)
Establishments per Capita (in logs)	-0.050*** (0.009)	-0.053*** (0.010)	-0.060*** (0.010)	-0.058*** (0.011)
Primary Inputs	-0.179*** (0.025)	-0.152*** (0.026)	-0.209*** (0.032)	-0.186*** (0.032)
Working Deposits (in logs)	0.002 (0.004)	0.001 (0.005)	0.004 (0.005)	0.005 (0.005)
Public Employment	0.00004 (0.0002)	-0.0001 (0.0002)	0.0004 (0.0003)	0.0003 (0.0003)
PO (in logs)	-0.008 (0.009)	-0.001 (0.009)	0.007 (0.011)	0.018* (0.010)
Urban Population (Share)	0.004 (0.071)	0.036 (0.057)	0.050 (0.064)	0.105** (0.043)
LGU	-0.034 (0.025)	-0.042 (0.028)	-0.008 (0.025)	-0.0001 (0.025)
$w_{c,t-1}$	0.100*** (0.013)	0.101*** (0.014)	0.086*** (0.014)	0.093*** (0.015)
MA 1890 (in logs)			0.029* (0.018)	0.048** (0.019)
$y_{c,1870}$			-0.004 (0.009)	-0.004 (0.010)
$k_{c,1870}$			0.022** (0.009)	0.024** (0.010)
Period	1920-1930	1920-1930	1920-1930	1920-1930
State & Year FE	Yes	Yes	Yes	Yes
Sargan Test (p-value)	1	0.827	0.564	0.301
Weak Instruments E&E (F-statistic)	16.288	14.654	26.22	21.562
Observations	4,792	4,792	3,520	3,520
Adjusted R <sup>2</sup>	0.567	0.528	0.584	0.578

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

## 4 Concluding Remarks

This article provides evidence on the county-level economic impact of the technological adoption of E&E technologies in the 1920s in the US. It is shown that places with patenting activity in E&E technologies grew faster and paid higher wages than others between 1920 and 1930. Doing so required constructing a novel database identifying detailed geographical information for historical patent documents in the US since 1836, as well as developing a text-mining algorithm to identify E&E patents based on patent descriptions.

Although this article studies the impact of electricity from a different perspective results are in line with the existing literature, which has documented a positive impact of electrification on output and productivity. Note that the perspective used here could help disentangle why macro-level studies have struggled to provide clear evidence on the impact of GPTs, by providing another layer to be exploited. If there are differences in the timing of impact for GPT users and technological adopters, effects could be netting out in the aggregate. Establishing a clearer distinction between users and technological adopters can help identifying whether there are different dynamics between users and producers of GPTs, how these dynamics interact, whether they move along, and how they manifest in aggregated terms.

Moreover, the evidence provided here raises further questions. How does the the emergence of a GPT benefit active and passive adopters? What portion of the benefits are kept by those who are able to produce, transform, and develop these type of technologies? How does this benefit compare to what users receive? What is the dynamic over time? Who benefits first? Who benefits most? A potentially interesting line of research could concentrate on measuring the magnitude and differences of the economic benefits brought about by different types of adoption or diffusion. Even though theoretical models explicitly consider a more active type of adoption ([Bresnahan and Trajtenberg, 1995](#); [Helpman and Trajtenberg, 1998b](#); [Aghion and Howitt, 2000](#)), there is a generalized idea that the mere diffusion of a disruptive technology should have a significant impact on those who use it.

The availability of historical databases such as the one described here could be used to disentangle many aspects of the evolution of technologies that have been impossible to

address so far, as technological cycles usually develop and mature over very long periods of time.

## 5 Appendix

### 5.1 List of Key-Words Used to Identify E&E-Related Patents

The list of “E&E-related” keywords was obtained by extracting all words containing “electri” or “electro” from the English dictionary. This procedure leaves out some potentially useful set of words that are strongly associated to E&E technologies (such as the word “circuit”) but that could have another meaning and therefore induce errors in the automated process. Please find the entire list of key-words below:

- 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
- Electrocapillarity
- 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
- Electrosterereotype
- Electrotelegraphic
- Electrotelegraphy
- Electrotherapeutics
- Electrothermancy
- Electrotint
- Electrotonic
- Electrotonize
- Electrotonous
- Electrotonus
- Electrotyle
- Electrotyped
- Electrotyping
- Electrotyper
- Electrotypic
- Electrotypy
- Electrorevital
- Electrorevitalism
- Electrum
- Hydroelectric
- Idioelectric
- Magnetolectric
- Magnetolectrical
- Magnetolectricity
- Parelectronic
- Parelectronomy
- Photoelectric
- Photoelectrotypic
- Pyroelectric
- Pyroelectricity
- Resinoelectric
- Stereoelectric
- Thermolectric
- Thermolectricity
- Thermolectrometer
- Voltaelectric
- Voltaelectrometer

## 5.2 Alternative Estimates Using the Number of Patents

In Section 3 technological adoption is depicted at the extensive margin. This means that adoption variables capture whether or not a particular technological competence is present in a county without considering the intensity at which it is being produced. This subsection replicates the estimates of Table V (FE estimator) using a different set of technological variables that capture the intensive margin of technological adoption in a county, the number of patents (in logs).

As mentioned in Section 3 results do not vary significantly when a measure of the intensity of adoption is considered. Meaning that the estimated coefficients using the number of E&E patents in a county is higher in E&E than the rest. Unfortunately, the proposed

instruments used in the 2SLS strategy are not strong enough to replicate 2SLS estimates using the number of patents. This is because lagged values of previous patenting activity accurately predict whether a place will continue to produce that type of technology but perform poorly when it comes to predicting how many patents they will produce.

Table IX: Patenting of E&amp;E Technologies and Growth

	<i>Growth</i> ( $\Delta y_{c,t}$ )			
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
E&E	0.062*** (0.017)			
E&E (Year $\geq$ 1920)		0.079*** (0.018)		
E&E (Year <1920)		0.025 (0.020)		
E&E Related			0.092*** (0.028)	
E&E Related (Year $\geq$ 1920)				0.114*** (0.023)
E&E Related (Year <1920)				0.044 (0.032)
Mechanic	0.056*** (0.014)	0.056*** (0.014)		
Chemical	0.028** (0.013)	0.026* (0.014)		
Others	0.034* (0.019)	0.035* (0.019)		
Foreign (Share)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Establishments per Capita (in logs)	0.743*** (0.039)	0.748*** (0.039)	0.754*** (0.039)	0.759*** (0.040)
Primary Inputs	1.364*** (0.178)	1.360*** (0.177)	1.364*** (0.179)	1.358*** (0.177)
Working Deposits (in logs)	0.035 (0.033)	0.037 (0.033)	0.050 (0.034)	0.052 (0.034)
Public Employment	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
PO (in logs)	-0.017 (0.067)	-0.019 (0.067)	0.017 (0.068)	0.012 (0.068)
Urban Population (Share)	0.334*** (0.094)	0.293*** (0.085)	0.423*** (0.104)	0.378*** (0.100)
$y_{c,t-1}$	-0.823*** (0.074)	-0.821*** (0.073)	-0.812*** (0.073)	-0.811*** (0.073)
Period	1860-1930	1860-1930	1860-1930	1860-1930
County & Year FE	Yes	Yes	Yes	Yes
Observations	14,865	14,865	14,865	14,865
Adjusted R <sup>2</sup>	0.577	0.577	0.573	0.574

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

### 5.3 2SLS Estimates for Different Thresholds

This subsection evaluates the robustness of the results to the use of different thresholds to identify adopting counties. In Section 3 technological adoption variables were constructed identifying positive patenting activity in a county, for instance,

$$Chemical_{c,t} = 1 \quad \text{if} \quad \sum_{t-5}^t Patents_{Chem} > \mu \text{ and zero otherwise, with } \mu = 0.$$

Table X and XI reports how results change after considering different thresholds based on the number of patents per 100,000 inhabitants. Columns (2) and (5) reproduce the baseline estimates considering as adopters only those counties with more than 2 patents per 100,000 inhabitants. The last threshold considered is  $\mu = 5$  (in columns 3 and 6), which represents the average number of patents per 100,000 inhabitants in E&E technologies.

Results show little variation with respect to the baseline estimates. The most remarkable differences are that, when  $\mu = 5$ , instruments are better predictors in the first stage regressions and the goodness of fit of the main equations are higher.

Table X: Effect E&amp;E Adoption for Different Thresholds

	<i>Growth</i> ( $\Delta y_{c,t}$ )			<i>Wages</i> ( $\Delta w_{c,t}$ )		
	( $\mu > 0$ )	( $\mu > 2$ )	( $\mu > 5$ )	( $\mu > 0$ )	( $\mu > 2$ )	( $\mu > 5$ )
	(1)	(2)	(3)	(4)	(5)	(6)
E&E	0.711*** (0.270)	0.635** (0.250)	0.562** (0.239)	0.293*** (0.098)	0.278*** (0.091)	0.253*** (0.086)
Mechanic	0.134*** (0.030)	0.136*** (0.030)	0.137*** (0.029)	0.060*** (0.010)	0.061*** (0.010)	0.062*** (0.009)
Chemical	0.058 (0.051)	0.076 (0.046)	0.047 (0.044)	-0.007 (0.018)	-0.001 (0.016)	0.00004 (0.015)
Others	0.100*** (0.031)	0.103*** (0.030)	0.086*** (0.029)	0.049*** (0.010)	0.050*** (0.010)	0.051*** (0.009)
Foreign (Share)	0.0001 (0.0003)	0.0001 (0.0003)	0.0001 (0.0003)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Establishments per Capita (in logs)	0.698*** (0.030)	0.695*** (0.030)	0.688*** (0.030)	-0.050*** (0.009)	-0.050*** (0.009)	-0.048*** (0.009)
Primary Inputs	1.246*** (0.082)	1.248*** (0.082)	1.271*** (0.081)	-0.179*** (0.025)	-0.176*** (0.025)	-0.162*** (0.025)
Working Deposits (in logs)	-0.026* (0.014)	-0.024* (0.014)	-0.022 (0.014)	0.002 (0.004)	0.003 (0.004)	0.003 (0.004)
Public Employment (Share)	-0.001 (0.001)	-0.001 (0.001)	-0.0005 (0.001)	0.00004 (0.0002)	0.00004 (0.0002)	0.00004 (0.0002)
PO (in logs)	0.038 (0.027)	0.045* (0.026)	0.071*** (0.023)	-0.008 (0.009)	-0.006 (0.009)	0.003 (0.008)
Urban Population (Share)	-0.105 (0.178)	-0.041 (0.161)	0.048 (0.142)	0.004 (0.071)	0.021 (0.064)	0.060 (0.054)
LGU	0.006 (0.062)	0.014 (0.061)	0.055 (0.058)	-0.034 (0.025)	-0.033 (0.025)	-0.019 (0.024)
$y_{c,t-1}$	-0.379*** (0.017)	-0.376*** (0.017)	-0.356*** (0.015)			
$w_{c,t-1}$				0.100*** (0.013)	0.101*** (0.013)	0.114*** (0.013)
Period	1920-1930	1920-1930	1920-1930	1920-1930	1920-1930	1920-1930
Year & State FE	Yes	Yes	Yes	Yes	Yes	Yes
Weak Instruments (F-statistic)	15.987	17.253	19.003	16.288	17.571	19.137
Sargan Test (p-value)	0.401	0.236	0.118	1	0.689	0.499
Observations	5,078	5,078	5,078	4,792	4,792	4,792
Adjusted R <sup>2</sup>	0.240	0.251	0.248	0.567	0.571	0.573

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table XI: Effect E&E Adoption for Different Thresholds

	<i>Growth</i> ( $\Delta y_{c,t}$ )			<i>Wages</i> ( $\Delta w_{c,t}$ )		
	( $\mu > 0$ )	( $\mu > 2$ )	( $\mu > 5$ )	( $\mu > 0$ )	( $\mu > 2$ )	( $\mu > 5$ )
	(1)	(2)	(3)	(4)	(5)	(6)
E&E Related	0.903*** (0.230)	0.920*** (0.243)	0.817*** (0.221)	0.315*** (0.075)	0.332*** (0.080)	0.322*** (0.080)
Foreign (Share)	0.0001 (0.0003)	0.00003 (0.0003)	0.00000 (0.0003)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Establishments per Capita (in logs)	0.684*** (0.031)	0.680*** (0.031)	0.676*** (0.031)	-0.053*** (0.010)	-0.054*** (0.010)	-0.052*** (0.010)
Primary Inputs	1.298*** (0.085)	1.297*** (0.085)	1.318*** (0.085)	-0.152*** (0.026)	-0.153*** (0.026)	-0.138*** (0.026)
Working Deposits (in logs)	-0.028* (0.015)	-0.027* (0.015)	-0.027* (0.015)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)
Public Employment (Share)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.0001 (0.0002)	-0.0002 (0.0003)	-0.0001 (0.0002)
PO (in logs)	0.049* (0.029)	0.052* (0.029)	0.079*** (0.025)	-0.001 (0.009)	-0.0005 (0.009)	0.008 (0.008)
Urban Population (Share)	-0.084 (0.146)	-0.058 (0.144)	0.051 (0.123)	0.036 (0.057)	0.040 (0.058)	0.076 (0.051)
LGU	-0.032 (0.074)	-0.032 (0.075)	0.051 (0.064)	-0.042 (0.028)	-0.044 (0.029)	-0.014 (0.025)
$y_{c,t-1}$	-0.379*** (0.021)	-0.377*** (0.021)	-0.356*** (0.018)			
$w_{c,t-1}$				0.101*** (0.014)	0.102*** (0.014)	0.110*** (0.014)
Period	1920-1930	1920-1930	1920-1930	1920-1930	1920-1930	1920-1930
Year & State FE	Yes	Yes	Yes	Yes	Yes	Yes
Weak Instruments (F-statistic)	21.152	18.881	21.061	26.22	22.562	22.256
Sargan Test (p-value)	0.673	0.499	0.294	0.564	0.736	0.986
Observations	5,078	5,078	5,078	4,792	4,792	4,792
Adjusted R <sup>2</sup>	0.172	0.164	0.181	0.528	0.517	0.519

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

## **5.4 2SLS Estimates in Levels and Including State x Year FE**

This subsection test the robustness of the results to a change in the econometric specification. Columns (2) and (4) depart from the baseline specification by including State x Year fixed effects. Results barely change with respect to baseline estimates in columns (1) and (3). As before, results show a strong and positive impact of E&E technologies on output and wages.

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

	<i>Growth</i> ( $\Delta y_{c,t}$ )		<i>Wage Growth</i> ( $\Delta w_{c,t}$ )	
	(2SLS)	(2SLS)	(2SLS)	(2SLS)
	(1)	(2)	(3)	(4)
E&E	0.711*** (0.270)	0.692*** (0.264)	0.294*** (0.098)	0.321*** (0.094)
Mechanic	0.134*** (0.030)	0.133*** (0.029)	0.060*** (0.010)	0.059*** (0.010)
Chemical	0.058 (0.051)	0.056 (0.050)	-0.007 (0.018)	-0.016 (0.017)
Others	0.100*** (0.031)	0.090*** (0.030)	0.049*** (0.010)	0.042*** (0.010)
Foreign (Share)	0.0001 (0.0003)	0.0004 (0.0003)	0.0001 (0.0001)	0.0003*** (0.0001)
Establishments per Capita (in logs)	0.698*** (0.030)	0.715*** (0.030)	-0.050*** (0.009)	-0.034*** (0.009)
Primary Inputs	1.246*** (0.082)	1.254*** (0.082)	-0.179*** (0.025)	-0.173*** (0.024)
Working Deposits (in logs)	-0.026* (0.014)	-0.027* (0.014)	0.002 (0.004)	0.001 (0.004)
Public Employment (Share)	-0.001 (0.001)	-0.001 (0.001)	0.00004 (0.0002)	-0.0001 (0.0002)
PO (in logs)	0.038 (0.027)	0.032 (0.026)	-0.008 (0.009)	-0.013 (0.009)
Urban Population (Share)	-0.105 (0.178)	-0.145 (0.173)	0.004 (0.071)	-0.042 (0.068)
LGU	0.006 (0.062)	0.001 (0.059)	-0.034 (0.025)	-0.034 (0.025)
$y_{c,t-1}$	-0.379*** (0.017)	-0.365*** (0.017)		
$w_{c,t-1}$			0.100*** (0.013)	0.150*** (0.015)
Period	1920-1930	1920-1930	1920-1930	1920-1930
Year & State FE	Yes	No	Yes	No
Year x State FE	No	Yes	No	Yes
Weak Instruments (F-statistic)	15.987	15.986	16.296	17.014
Sargan Test (p-value)	0.401	0.363	1	0.749
Observations	5,078	5,078	4,793	4,793
Adjusted R <sup>2</sup>	0.240	0.267	0.567	0.591

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

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

	<i>Growth</i> ( $\Delta y_{c,t}$ )		<i>Wage Growth</i> ( $\Delta w_{c,t}$ )	
	(2SLS)	(2SLS)	(2SLS)	(2SLS)
	(1)	(2)	(3)	(4)
E&E Related	0.870*** (0.229)	0.846*** (0.223)	0.340*** (0.083)	0.354*** (0.080)
Foreign (Share)	0.00004 (0.0003)	0.0004 (0.0003)	0.0001 (0.0001)	0.0003*** (0.0001)
Establishments per Capita (in logs)	0.694*** (0.030)	0.711*** (0.030)	-0.047*** (0.009)	-0.030*** (0.009)
Primary Inputs	1.292*** (0.083)	1.298*** (0.083)	-0.151*** (0.025)	-0.148*** (0.024)
Working Deposits (in logs)	-0.023 (0.015)	-0.024* (0.014)	0.003 (0.004)	0.002 (0.004)
Public Employment (Share)	-0.001 (0.001)	-0.001 (0.001)	0.00002 (0.0002)	-0.0001 (0.0002)
PO (in logs)	0.049* (0.029)	0.042 (0.028)	-0.003 (0.010)	-0.009 (0.009)
Urban Population (Share)	-0.170 (0.174)	-0.209 (0.169)	-0.015 (0.072)	-0.058 (0.068)
LGU	0.018 (0.067)	0.013 (0.064)	-0.029 (0.027)	-0.030 (0.026)
$y_{c,t-1}$	-0.362*** (0.019)	-0.349*** (0.018)		
$w_{c,t-1}$			0.108*** (0.014)	0.158*** (0.015)
Period	1920-1930	1920-1930	1920-1930	1920-1930
Year & State FE	Yes	No	Yes	No
Year x State FE	No	Yes	No	Yes
Weak Instruments (F-statistic)	22.536	22.48	23.339	24.209
Sargan Test (p-value)	0.322	0.291	0.786	0.935
Observations	5,078	5,078	4,793	4,793
Adjusted R <sup>2</sup>	0.206	0.236	0.541	0.570

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

## 5.5 Analysis in Non-Urban Counties

One important threat to the identification strategy relates to the fact that the baseline estimates of Table VII don't take into account the expansion of the electrical grid in this period, a factor that has been shown to be of great importance (Lewis and Severnini, 2020; Kitchens and Fishback, 2015; Gaggl, Gray, Marinescu, and Morin, 2019). This subsection addresses this issue by exploiting the fact that by 1930 only 10.4% of rural areas had access to the electrical grid (Lewis and Severnini, 2020; Bureau, 1976). Tables XIV and XV replicate the set of regressions in Tables V and VII, respectively. They are intended to test whether estimates survive if only counties that barely had access to the electrical grid are considered (this means that only non-urban counties are included, identified as those with less than 5% of urban population). Results do not change significantly in comparison to baseline estimates (although they are smaller in magnitude), as they show a strong and positive relationship between the adoption of E&E technologies and growth. In addition, note that the Sargan test of over-identifying restrictions does not reject the null hypothesis that the error term is orthogonal to the instruments, and the F-test of joint significance strongly rejects the null hypothesis in all cases.

Table XIV: Adoption of E&E Technologies & Growth in Non-Urban Counties

	<i>Growth</i> ( $\Delta y_{c,t}$ )	
	(FE)	(FE)
	(1)	(2)
E&E	0.204** (0.058)	
E&E Related		0.174** (0.052)
Mechanic	0.055* (0.024)	
Chemical	0.037 (0.021)	
Others	0.046** (0.018)	
Foreign (Share)	0.002** (0.001)	0.002** (0.001)
Establishments per Capita (in logs)	0.765*** (0.035)	0.768*** (0.035)
Primary Inputs	1.386*** (0.159)	1.387*** (0.160)
Working Deposits (in logs)	0.058 (0.030)	0.064* (0.030)
Public Employment	-0.001 (0.001)	-0.001 (0.001)
PO (in logs)	0.018 (0.057)	0.037 (0.057)
$y_{c,t-1}$	-0.819*** (0.063)	-0.816*** (0.064)
Period	1860-1930	1860-1930
County & Year FE	Yes	Yes
Observations	13,983	13,983
Adjusted R <sup>2</sup>	0.578	0.577

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

Table XV: Adoption of E&E Technologies in Non-Urban Counties

	<i>Growth</i> ( $\Delta y_{c,t}$ )			
	(2SLS)	(2SLS)	(2SLS)	(2SLS)
	(1)	(2)	(3)	(4)
E&E	0.647*** (0.213)		0.389* (0.217)	
E&E Related		0.806*** (0.191)		0.543*** (0.174)
Mechanic	0.141*** (0.029)		0.117*** (0.034)	
Chemical	0.075* (0.041)		0.070 (0.046)	
Others	0.102*** (0.031)		0.118*** (0.034)	
Foreign (Share)	-0.00001 (0.0003)	0.00000 (0.0003)	0.0003 (0.0004)	0.0004 (0.0004)
Establishments per Capita (in logs)	0.732*** (0.031)	0.717*** (0.032)	0.611*** (0.035)	0.600*** (0.035)
Primary Inputs	1.274*** (0.083)	1.330*** (0.086)	0.936*** (0.102)	0.980*** (0.103)
Working Deposits (in logs)	-0.028* (0.015)	-0.029* (0.016)	-0.007 (0.016)	-0.006 (0.017)
Public Employment	-0.0003 (0.001)	-0.001 (0.001)	-0.0004 (0.001)	-0.001 (0.001)
PO (in logs)	0.060** (0.026)	0.077*** (0.028)	0.053* (0.030)	0.064** (0.030)
LGU	0.045 (0.070)	0.006 (0.079)	0.077 (0.060)	0.066 (0.064)
$y_{c,t-1}$	-0.388*** (0.016)	-0.381*** (0.019)	-0.309*** (0.019)	-0.298*** (0.021)
MA 1890 (in logs)			0.116* (0.064)	0.137** (0.067)
$y_{c,1870}$			-0.009 (0.028)	-0.005 (0.029)
$k_{c,1870}$			0.035 (0.028)	0.031 (0.029)
Period	1920-1930	1920-1930	1920-1930	1920-1930
State & Year FE	Yes	Yes	Yes	Yes
Sargan Test (p-value)	0.537	0.388	0.77	0.682
Weak Instruments E&E (F-statistic)	25.497	13.005	30.956	18.581
Observations	4,587	4,587	3,329	3,329
Adjusted R <sup>2</sup>	0.264	0.209	0.234	0.207

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

## 5.6 Analysis Falsification Test Using the Year 1900

Table [XVI](#) includes a set of 2SLS regressions analogous to those in columns (1) and (2) of Table [VII](#) but considering the census year 1900<sup>33</sup>. Note that results are not significant for both measures of E&E adoption, although in both cases the F-test of joint significance always rejects the null hypothesis, while the Sargan test of over-identified restrictions does not reject the null. This lack of results is consistent with the claim that initial growth rates are not the reason why the baseline results hold.

---

<sup>33</sup>Unfortunately the year 1910 is not available

Table XVI: Falsification Test

	<i>Growth</i> ( $\Delta y_{c,t}$ )	
	(2SLS)	(2SLS)
	(1)	(2)
E&E	0.161 (0.195)	
E&E Related		0.312 (0.206)
Mechanic	0.130*** (0.034)	
Chemical	0.105*** (0.035)	
Others	0.054 (0.038)	
Foreign (Share)	0.002*** (0.0003)	0.002*** (0.0003)
Establishments per Capita (in logs)	0.647*** (0.042)	0.672*** (0.044)
Primary Inputs	1.666*** (0.159)	1.692*** (0.164)
Working Deposits (in logs)	0.011 (0.021)	0.015 (0.021)
Public Employment	0.001 (0.002)	0.001 (0.002)
PO (in logs)	-0.016 (0.028)	0.011 (0.029)
Urban Population (Share)	0.191 (0.161)	0.138 (0.150)
LGU	-0.037 (0.061)	-0.010 (0.061)
$y_{c,t-1}$	-0.548*** (0.016)	-0.541*** (0.018)
Period	1900	1900
State FE	Yes	Yes
Sargan Test (p-value)	0.401	0.661
Weak Instruments E&E (F-statistic)	15.987	12.112
Observations	2,468	2,468
Adjusted R <sup>2</sup>	0.542	0.526

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

## 5.7 Falsification Test Using Potentially Miss-classified Patents

An alternative way of testing whether results are actually driven by unobservables that were not appropriately controlled for consists of artificially exposing geographical units that are seemingly indistinguishable from the units of interest but that are actually not treated (i.e. they do not actually have or had E&E capabilities). Note that, if the presence of E&E capabilities is the main channel through which the effect takes place, we shouldn't see any effect if we consider only miss-classified or unfit E&E patents. One could exploit the wealth of information contained in patent descriptions to create a flag for patents that were classified as E&E by the USPTO but that do not contain any E&E-Related vocabulary and that are therefore likely to be miss-classified patents.

Table [XVII](#) shows that results do not hold if the specification used in Table [V](#) is carried out using only potentially miss-classified E&E patents, i.e. that belong to E&E according to the USPTO classification system but that do not contain any E&E-Related vocabulary in it. Additionally, note that all remaining coefficients remain practically invariant with respect to the results reported in Table [V](#).

Table XVII: Falsification Test Using Potentially Miss-classified Patents

	<i>Growth</i> ( $\Delta y_{c,t}$ ) (FE)
E&E (miss-classified)	-0.016 (0.016)
Mechanic	0.056* (0.026)
Chemical	0.049* (0.023)
Others	0.045* (0.019)
Foreign (Share)	0.002** (0.001)
Establishments per Capita (in logs)	0.744*** (0.037)
Primary Inputs	1.365*** (0.158)
Working Deposits (in logs)	0.046 (0.030)
Public Employment	-0.001 (0.001)
PO (in logs)	-0.004 (0.059)
Urban Population (Share)	0.646*** (0.107)
log(Lag.Output.Pop)	-0.813*** (0.067)
Period	1860-1930
County & Year FE	Yes
Observations	14,865
Adjusted R <sup>2</sup>	0.571

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

## 5.8 Including Additional Endogenous Variables

It is possible that when properly estimated the impact of adopting other technologies is higher than those of E&E technologies. If this is the case, the alleged E&E differential would not exist.

The validity of the instruments used in the baseline estimation relies heavily on characteristics and historical features that are specific to E&E technologies. For instance, because Chemical and Mechanical technologies were already mature technologies prior to the 1870s, their early 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 the availability of natural resources, which is likely to have had long-lasting implications for growth. Even though using early adoption as an instrument may not be optimal for Mechanical technologies, this section tests the robustness of the results to treat it as an endogenous regressor.

Table [XVIII](#) shows how the baseline estimates of the effect of E&E adoption on growth and wages change, respectively, as other technologies are instrumented. Columns (1) and (3) replicate the results obtained in tables [VII](#) and [VIII](#), while columns (2) and (4) allow mechanical technologies to be treated as endogenous. In all cases, adoption after the 1920s is instrumented with early adoption (before 1870), as in the baseline case.

Note that the baseline results on the effect of E&E adoption on growth and wages barely change after treating mechanical technologies as endogenous. Additionally, the Sargan test of over-identifying restrictions does not reject the null hypothesis that the error term is orthogonal to the instruments, and the F-test of joint significance strongly rejects the null hypothesis in all cases.

If Chemical technologies are also treated as endogenous we observe a generalized loss of statistical significance for all estimates of technological adoption.

In summary, the baseline results are robust to treating the adoption of mechanical technologies as endogenous. They are robust in the sense that estimates of effect of E&E adoption are stable in magnitude after the inclusion of additional endogenous variables. However, their

statistical significance disappears if all technologies are instrumented.

Table XVIII: Allowing for Multiple Endogenous Variables

	<i>Growth</i> ( $\Delta y_{c,t}$ )		<i>Wages</i> ( $\Delta w_{c,t}$ )	
	(1)	(2)	(3)	(4)
E&E	0.711*** (0.270)	0.603** (0.285)	0.293*** (0.098)	0.300** (0.118)
Mechanic	0.134*** (0.030)	0.391 (0.527)	0.060*** (0.010)	0.025 (0.166)
Chemical	0.058 (0.051)	0.044 (0.053)	-0.007 (0.018)	-0.003 (0.018)
Others	0.100*** (0.031)	0.027 (0.155)	0.049*** (0.010)	0.060 (0.050)
Foreign (Share)	0.0001 (0.0003)	0.00005 (0.0003)	0.0001 (0.0001)	0.0001 (0.0001)
Establishments per Capita (in logs)	0.698*** (0.030)	0.696*** (0.030)	-0.050*** (0.009)	-0.049*** (0.010)
Primary Inputs	1.246*** (0.082)	1.227*** (0.090)	-0.179*** (0.025)	-0.174*** (0.032)
Working Deposits (in logs)	-0.026* (0.014)	-0.029* (0.016)	0.002 (0.004)	0.002 (0.005)
Public Employment (Share)	-0.001 (0.001)	-0.001 (0.001)	0.00004 (0.0002)	0.00002 (0.0002)
PO (in logs)	0.038 (0.027)	0.033 (0.027)	-0.008 (0.009)	-0.006 (0.009)
Urban Population (Share)	-0.105 (0.178)	-0.034 (0.190)	0.004 (0.071)	0.002 (0.076)
LGU	0.006 (0.062)	0.006 (0.059)	-0.034 (0.025)	-0.033 (0.024)
$y_{c,t-1}$	-0.379*** (0.017)	-0.390*** (0.028)		
$w_{c,t-1}$			0.100*** (0.013)	0.102*** (0.015)
Period	1920-1930	1920-1930	1920-1930	1920-1930
Year & State FE	Yes	Yes	Yes	Yes
Weak Instruments E&E (F-statistic)	15.987	14.567	16.288	18.602
Weak Instruments Mechanical (F-statistic)		8.653		12.884
Sargan (p-value)	0.401	0.729	1	0.939
Observations	5,078	5,078	4,792	4,792
Adjusted R <sup>2</sup>	0.240	0.241	0.567	0.563

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

## 5.9 Treating $y_{c,t-1}$ as Endogenous

As mentioned at the end of Section 3 estimating a growth equation with OLS could yield biased estimates of the effect of E&E on growth. Nickell (1981) shows that using the within effect estimator will produce inconsistent estimates of the effect of the lagged dependent variable in dynamic models. If  $y_{c,t-1}$  is correlated with other regressors, the estimated coefficients could be biased even if they are exogenous. This means that the results of Table VII could be the reflection of the underlying correlation structure between the variables measuring technological adoption and  $y_{c,t-1}$ .

Table XIX compares the baseline results of Table VII with an alternative specification in which  $y_{c,t-1}$  is instrumented with its own lagged values. This specification is analogous to that reported in column (1) of Table VII but treats  $y_{c,t-1}$  as endogenous and instruments it with  $y_{c,1880}$ . Note that results are also consistent with previous findings, showing a strong effect of E&E adoption on growth rates. The Sargan test of over-identifying restrictions does not reject the null hypothesis that the error term is orthogonal to the instruments, and the F-test of joint significance strongly rejects the null hypothesis for both first stages.

Table XIX: Adoption of E&amp;E Technologies

	<i>Growth</i> ( $\Delta y_{c,t}$ )			
	(2SLS)	(2SLS)	(2SLS)	(2SLS)
	(1)	(2)	(3)	(4)
E&E	0.711*** (0.270)	0.533** (0.268)		
E&E Related			0.903*** (0.268)	0.660** (0.269)
Mechanic	0.134*** (0.030)	0.086** (0.034)		
Chemical	0.058 (0.051)	0.021 (0.053)		
Others	0.100*** (0.031)	0.108*** (0.034)		
Foreign (Share)	0.0001 (0.0003)	-0.00003 (0.0003)	0.0001 (0.0003)	-0.00002 (0.0003)
Establishments per Capita (in logs)	0.698*** (0.030)	0.560*** (0.042)	0.684*** (0.025)	0.553*** (0.036)
Primary Inputs	1.246*** (0.082)	0.954*** (0.100)	1.298*** (0.075)	1.007*** (0.098)
Working Deposits (in logs)	-0.026* (0.014)	-0.013 (0.015)	-0.028* (0.014)	-0.013 (0.015)
Public Employment	-0.001 (0.001)	-0.0005 (0.001)	-0.001 (0.001)	-0.001 (0.001)
PO (in logs)	0.038 (0.027)	0.035 (0.029)	0.049 (0.030)	0.039 (0.032)
Urban Population (Share)	-0.105 (0.178)	-0.174 (0.166)	-0.084 (0.175)	-0.154 (0.151)
LGU	0.006 (0.062)	0.003 (0.056)	-0.032 (0.084)	-0.021 (0.076)
$y_{c,t-1}$	-0.379*** (0.017)	-0.220*** (0.047)	-0.379*** (0.022)	-0.223*** (0.052)
Period	1920-1930	1920-1930	1920-1930	1920-1930
State & Year FE	Yes	Yes	Yes	Yes
Sargan Test (p-value)	0.401	0.439	0.673	0.626
Weak Instruments E&E (F-statistic)	15.987	12.59	21.152	31.2
Weak Instruments $y_{c,t-1}$		107.648		134.615
Observations	5,078	4,248	5,078	4,248
Adjusted R <sup>2</sup>	0.240	0.214	0.172	0.181

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

## 5.10 IV Estimation Under Weaker Assumptions

This subsection provides an additional set of results which test the sensitivity of the estimates to weakening the assumptions required in the 2SLS estimation procedure. It is based on the work of [Conley, Hansen, and Rossi \(2012\)](#), which proposes an estimation methodology that replace the exact exclusion restriction in an IV model with an assumption related to its support or distribution.

Instead of assuming that the instruments are not correlated with the dependent variable, [Conley, Hansen, and Rossi \(2012\)](#) describe a procedure that allows the consistent estimation of the parameters of interest even when this correlation is different from zero, by allowing the researcher to specify a range of values it may take. This procedure also allows to specify a distributional assumption about the true value of the correlation, so one can place more or less weight on values that are perceived to be more or less likely.

In the particular setup of this article, this means one could test whether the baseline results are sensitive to departures from the 2SLS assumptions, by allowing the instruments ( $E\&E_{c,1870}$  &  $E\&E\ Related_{c,1870}$ ) to be correlated with  $\Delta y_{c,t}$ . For instance, one could hypothesize that these parameters represent a percentage of the baseline (contemporaneous) estimated parameters (columns (1) and (2) in [Table VII](#)). By doing so it is assumed that the instruments, which are lagged values of the instrumented variables, have still an effect (although weaker) on contemporaneous growth after 50 years. This subsection evaluates the sensitivity of the baseline estimates after allowing instruments to be correlated with growth (i.e. to function as explanatory variables in the main equation) with a coefficient value that ranges from zero (this is the assumption made in the classical 2SLS procedure) to 20% of the corresponding baseline estimate.

Therefore, the alternative estimating equation can be written as:

$$DV_{c,t} = \beta_0 + \beta_1 T_{c,t} + \beta_2 X_{c,t} + \gamma_1 E\&E_{c,1870} + \gamma_2 E\&E\ Related_{c,1870} + \epsilon_{c,t} \quad (2)$$

Equation [2](#) is the same as the baseline estimating equation [\(1\)](#) plus two additional terms. In the 2SLS procedure reported in [Table VII](#)  $\gamma_1$  and  $\gamma_2$  are assumed to be zero. [Table XX](#)

shows the result of estimating the "Local to Zero" procedure described in [Conley, Hansen, and Rossi \(2012\)](#) assuming that  $\gamma_1 \sim U[0, k_1 * \beta_{E\&E}]$  and  $\gamma_2 \sim U[0, k_2 * \beta_{E\&E\ Related}]$ , where  $k_1$  and  $k_2$  take the values 0.1 and 0.2 (10% and 20% of the corresponding baseline estimate).<sup>34</sup>

Table XX: Upper & Lower Bound Estimates of Baseline Results

Parameters ( $\gamma_s, k_s$ )	$\beta_{E\&E}$ (LB)	$\beta_{E\&E}$ (UB)	$\beta_{E\&E\ Related}$ (LB)	$\beta_{E\&E\ Related}$ (UB)
$\gamma_1 = 0 (k_1 = 0) \& \gamma_2 = 0 (k_2 = 0)$	0.201	1.211	0.463	1.343
$\gamma_1 = 0.07 (k_1 = 0.1) \& \gamma_2 = 0 (k_2 = 0)$	0.085	1.193	0.441	1.34
$\gamma_1 = 0.14 (k_1 = 0.2) \& \gamma_2 = 0 (k_2 = 0)$	0.069	1.15	0.415	1.32
$\gamma_1 = 0 (k_1 = 0) \& \gamma_2 = 0.09 (k_2 = 0.1)$	.125	1.178	0.417	1.273
$\gamma_1 = 0 (k_1 = 0) \& \gamma_2 = 0.18 (k_2 = 0.2)$	.0752	1.121	0.38	1.31

Note: This table displays Upper Bounds (UB). and Lower Bounds (LB) corresponding to the 95% confidence intervals associated with the parameters ( $\beta_s$ ).

In all cases the bounds produced for the endogenous variable of interest using 95% confidence intervals do not contain the zero, meaning that the estimated parameters are statistically different from zero at the specified confidence level. It is worth noting that these robustness checks provide more details on the limitations of the present study to failures in the assumptions that have been made. In particular, they show that results would not be significant if the instruments have a considerably high direct impact in the main estimating equation. However, note that the highest values assumed for the correlations ( $\gamma_s$ ) are higher than any other estimated correlation for any technological variable. This means that the

<sup>34</sup>[Clarke and Matta \(2018\)](#) show that different specifications in the procedure can lead to tighter or wider bounds, depending on the assumptions made by the researcher. For instance, by choosing a normal prior one would be placing greater weight on values closer to the specified mean. The uniform distribution assumes that every value in the specified interval can happen with equal probability.

maximum values used here exceed the estimated correlation between contemporaneous values of technological production and growth for any technology (Mechanical, Chemical and Others).

## References

- ABRAMOVSKY, L., R. HARRISON, AND H. SIMPSON (2007): “University research and the location of business R&D,” *The Economic Journal*, 117(519), C114–C141.
- ACEMOGLU, D., J. MOSCONA, AND J. A. ROBINSON (2016): “State Capacity and American Technology: Evidence from the Nineteenth Century,” *The American Economic Review*, 106(5), 61–67.
- AGER, P., AND M. BRÜCKNER (2013): “Cultural diversity and economic growth: Evidence from the US during the age of mass migration,” *European Economic Review*, 64, 76–97.
- AGHION, P., AND P. HOWITT (2000): “On the macroeconomic effects of major technological change,” in *The economics and econometrics of innovation*, pp. 31–53. Springer.
- AGRAWAL, A., A. GALASSO, AND A. OETTL (2017): “Roads and innovation,” *Review of Economics and Statistics*, 99(3), 417–434.
- ALEXOPOULOS, M., AND J. COHEN (2016): “The medium is the measure: Technical change and employment, 1909—1949,” *Review of economics and statistics*, 98(4), 792–810.
- ATAK, J., AND F. BATEMAN (1999): “Nineteenth-Century US Industrial Development through the Eyes of the Census of Manufactures a New Resource for Historical Research,” *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 32(4), 177–188.
- AUDRETSCH, D. B., AND M. P. FELDMAN (1996): “R&D spillovers and the geography of innovation and production,” *The American economic review*, 86(3), 630–640.
- BALLAND, P.-A., C. JARA-FIGUEROA, S. G. PETRALIA, M. P. STEIJN, D. L. RIGBY, AND C. A. HIDALGO (2020): “Complex economic activities concentrate in large cities,” *Nature Human Behaviour*, pp. 1–7.
- BALLAND, P.-A., AND D. RIGBY (2017): “The Geography of Complex Knowledge,” *Economic Geography*, 93(1), 1–23.

- BRESNAHAN, T. F., AND M. TRAJTENBERG (1995): “General purpose technologies ‘Engines of growth’?,” *Journal of econometrics*, 65(1), 83–108.
- BRÜCKNER, M. (2013): “On the simultaneity problem in the aid and growth debate,” *Journal of Applied Econometrics*, 28(1), 126–150.
- BURCHARDI, K., T. CHANEY, AND T. A. HASSAN (2016): “Migrants, Ancestors, and Foreign Investments,” .
- BUREAU, U. C. (1976): *The Statistical History of the United States, from Colonial Times to the Present*. Basic Books (AZ).
- CAMERON, A. C., J. B. GELBACH, AND D. L. MILLER (2012): “Robust inference with multiway clustering,” *Journal of Business & Economic Statistics*.
- CLARKE, D., AND B. MATTA (2018): “Practical considerations for questionable IVs,” *The Stata Journal*, 18(3), 663–691.
- CONLEY, T. G., C. B. HANSEN, AND P. E. ROSSI (2012): “Plausibly exogenous,” *Review of Economics and Statistics*, 94(1), 260–272.
- CRAFTS, N. (2004): “Steam as a general purpose technology: a growth accounting perspective,” *The Economic Journal*, 114(495), 338–351.
- CRAFTS, N., AND T. C. MILLS (2004): “Was 19th century British growth steam-powered?: the climacteric revisited,” *Explorations in Economic History*, 41(2), 156–171.
- DANIELS, R. (1990): *Coming to America*. Harper Collins Publishers.
- DAVID, P. A. (1990): “The dynamo and the computer: an historical perspective on the modern productivity paradox,” *The American Economic Review*, 80(2), 355–361.
- DINKELMAN, T. (2011): “The effects of rural electrification on employment: New evidence from South Africa,” *American Economic Review*, 101(7), 3078–3108.
- DONALDSON, D., AND R. HORNBECK (2016): “Railroads and American economic growth: A “market access” approach,” *The Quarterly Journal of Economics*, 131(2), 799–858.

- FELDMAN, M. P., AND D. F. KOGLER (2010): “Chapter 8 - Stylized Facts in the Geography of Innovation,” in *Handbook of The Economics of Innovation, Vol. 1*, ed. by B. H. Hall, and N. Rosenberg, vol. 1 of *Handbook of the Economics of Innovation*, pp. 381 – 410. North-Holland.
- FELDMAN, M. P., AND J. W. YOON (2012): “An empirical test for general purpose technology: an examination of the Cohen–Boyer rDNA technology,” *Industrial and Corporate Change*, 21(2), 249–275.
- FIELD, A. J. (2006): “Technological change and US productivity growth in the interwar years,” *The Journal of Economic History*, 66(01), 203–236.
- (2008): “Does Economic History Need GPTs?,” *Available at SSRN 1275023*.
- FURMAN, J. L., M. E. PORTER, AND S. STERN (2002): “The determinants of national innovative capacity,” *Research policy*, 31(6), 899–933.
- GAGGL, P., R. GRAY, I. MARINESCU, AND M. MORIN (2019): “Does Electricity Drive Structural Transformation? Evidence from the United States,” Discussion paper, National Bureau of Economic Research.
- GOLDFARB, B. (2005): “Diffusion of general-purpose technologies: understanding patterns in the electrification of US Manufacturing 1880–1930,” *Industrial and Corporate Change*, 14(5), 745–773.
- GREENWOOD, J. (1997): *The third industrial revolution: technology, productivity, and income inequality*, no. 435. American Enterprise Institute.
- GRILICHES, Z. (1957): “Hybrid Corn: An Exploration in the Economics of Technological Change,” *Econometrica*, 25(4), 501–522.
- HALL, B. H., A. B. JAFFE, AND M. TRAJTENBERG (2001): “The NBER patent citation data file: Lessons, insights and methodological tools,” Discussion paper, National Bureau of Economic Research.

- HALL, B. H., M. TRAJTENBERG, ET AL. (2006): “Uncovering general purpose technologies with patent data,” *Chapters*.
- HATTON, T. J., AND J. G. WILLIAMSON (2008): “The Impact of Immigration: Comparing Two Global Eras,” *World Development*, 36(3), 345 – 361.
- HELPMAN, E., AND M. TRAJTENBERG (1998a): “Diffusion of General Purpose Technologies,” in *General purpose technologies and economic growth*, ed. by E. Helpman, p. 85. MIT Press.
- (1998b): “A Time to Sow and a Time to Reap: Growth Based on General Purpose Technologies,” in *General purpose technologies and economic growth*, ed. by E. Helpman, p. 55. MIT Press.
- ISRAEL, P. B. E., AND A. EDISON (1998): “A Life of Invention,” .
- JAFFE, A. B., M. TRAJTENBERG, AND R. HENDERSON (1993): “Geographic localization of knowledge spillovers as evidenced by patent citations,” *the Quarterly journal of Economics*, 108(3), 577–598.
- KHAN, B. Z. (2005): *The Democratization of Invention: patents and copyrights in American economic development, 1790-1920*. Cambridge University Press.
- KIM, S. (2005): “Industrialization and urbanization: Did the steam engine contribute to the growth of cities in the United States?,” *Explorations in Economic History*, 42(4), 586–598.
- KITCHENS, C., AND P. FISHBACK (2015): “Flip the switch: the impact of the rural electrification administration 1935–1940,” *The Journal of Economic History*, 75(4), 1161–1195.
- LEVITT, S. D. (2002): “Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply,” *The American Economic Review*, 92(4), 1244–1250.
- LEWIS, J., AND E. SEVERNINI (2020): “Short-and long-run impacts of rural electrification: evidence from the historical rollout of the us power grid,” *Journal of Development Economics*, 143, 102412.

- LIPSEY, R. G., K. I. CARLAW, AND C. T. BEKAR (2005): *Economic transformations: general purpose technologies and long-term economic growth*. OUP Oxford.
- MICHAELS, G. (2008): “The effect of trade on the demand for skill: Evidence from the interstate highway system,” *The Review of Economics and Statistics*, 90(4), 683–701.
- MORETTI, E. (2004): “Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data,” *Journal of econometrics*, 121(1-2), 175–212.
- MOSER, P., AND T. NICHOLAS (2004): “Was Electricity a General Purpose Technology?,” in *The American Economic Review, Papers and Proceedings*, vol. 94, pp. 388–394.
- NEBEKER, F. (2009): *Dawn of the electronic age: Electrical technologies in the shaping of the modern world, 1914 to 1945*. John Wiley & Sons.
- NICKELL, S. (1981): “Biases in dynamic models with fixed effects,” *Econometrica: Journal of the Econometric Society*, pp. 1417–1426.
- NUVOLARI, A., AND M. VASTA (2017): “The geography of innovation in Italy, 1861–1913: evidence from patent data,” *European Review of Economic History*, 21(3), 326–356.
- NUVOLARI, A., B. VERSPAGEN, AND N. VON TUNZELMANN (2011): “The early diffusion of the steam engine in Britain, 1700–1800: a reappraisal,” *Cliometrica*, 5(3), 291–321.
- ORROK, G. A. (1930): “Pearl Street Station The First Central Station in the World,” *Transactions of the Newcomen Society*, 11(1), 98–108.
- OTTAVIANO, G. I., AND G. PERI (2005): “Rethinking the Gains from Immigration: Theory and Evidence from the U.S.,” Working Paper 11672, National Bureau of Economic Research.
- (2008): “Immigration and National Wages: Clarifying the Theory and the Empirics,” Working Paper 14188, National Bureau of Economic Research.
- PETRALIA, S. (2020): “Mapping general purpose technologies with patent data,” *Research*

- Policy*, 49(7), 104013.
- PETRALIA, S., P.-A. BALLAND, AND A. MORRISON (2017): “Climbing the ladder of technological development,” *Research Policy*, 46(5), 956–969.
- PETRALIA, S., P.-A. BALLAND, AND D. L. RIGBY (2016): “Unveiling the geography of historical patents in the United States from 1836 to 1975,” *Scientific Data*, 3.
- RISTUCCIA, C. A., AND S. SOLOMOU (2014): “Can general purpose technology theory explain economic growth? Electrical power as a case study,” *European Review of Economic History*, 18(3), 227–247.
- ROSENBERG, N., AND M. TRAJTENBERG (2004): “A general-purpose technology at work: The Corliss steam engine in the late-nineteenth-century United States,” *The Journal of Economic History*, 64(01), 61–99.
- SANYAL, P., AND A. B. JAFFE (2005): “Peanut Butter Patents versus the New Economy: Does the Increased Rate of Patenting Signal More Invention or Just Lower Standards?,” *Annales d’Économie et de Statistique*, pp. 211–240.
- SCHMOOKLER, J. (1952): “The changing efficiency of the American economy, 1869-1938,” *The review of economics and statistics*, pp. 214–231.
- SOKOLOFF, K. L. (1988): “Inventive activity in early industrial America: evidence from patent records, 1790-1846,” .
- VERDOLINI, E., AND M. GALEOTTI (2011): “At home and abroad: An empirical analysis of innovation and diffusion in energy technologies,” *Journal of Environmental Economics and Management*, 61(2), 119–134.
- WRIGHT, G. (1990): “The origins of American industrial success, 1879-1940,” *The American Economic Review*, pp. 651–668.