Electricity and Directed Technological Change: Evidence from U.S. Rural Electrification, 1910-1950*

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Abstract

This paper investigates the impact of rural electrification on agricultural innovation between 1910 and 1950. We combine cross-county variation in access to the closest hydro-power plant and cross-crop variation in energy intensity before the arrival of electricity to identify the effect of electrification on the number of electric patents related to each of these crops. We find evidence that agricultural innovation responded to local incentives. These new electric patents are relevant and widely cited in the future, and are mainly attributed to a new generation of inventors. This would be consistent with theories of endogenous technological change where inventions respond to local relative factor prices. As further indication of this, we find larger impacts in counties with labour shortages and counties with larger market size.

1 Introduction

Electricity was one of the major technological changes in the modern era, which had long-lasting effects and changed almost every aspect of the human existence. David (1990) argues that the slow impact of electricity on productivity was due to the costly adjustments that were needed to properly benefit from electricity, including related innovations. Fiszbein et al. (2020), on the contrary, finds that when electricity was available at a sufficiently low price, productivity gains were visible relatively quickly suggesting that local access was key. This paper tries to formally test whether agricultural innovation in the 1900s depended on having access to cheaper power due to the electrification in rural areas. Examples of agricultural innovations that could have been driven by local availability of cheaper electricity are electric bale throwers, electric grape harvesters, cotton picker with an electric fan, etc.

In this context, electricity was first used in the U.S. in 1882 by Thomas Edison, however the spread of electrification was slow and happened even later in rural areas. By 1930, larger cities were mostly electrified, but less than 10 percent of farms had access to electricity (Lewis and Severnini, 2017). Related to David (1990)'s argument, this was mainly due to the high cost of infrastructure investment in relation to the small number of customers that could be served in rural areas compared to more populated areas. On average, a mile of distribution line could serve between 50 to 200 customers in a city; whilst in the countryside this was around 3. Therefore, it was not until 1930 that rural areas could benefit from it, when the government started implementing programs to increase rural electrification. [1] This meant that we can use the slow arrival of electricity across rural counties from 1910 until 1935 as a source of variation that may have influenced inventors.

This paper aims to bridge the gap between the effects of the invention of electricity as a large technological change on rural innovation, expanding the variety of production inputs in the agricultural sector. Much has been said about the effects of the invention of electricity on the rural labour market, but the mechanism that might explain these effects is likely to be associated to endogenous technological change theories. We believe there were counties and crops that had more incentives to innovate and make use of this new technology - due to market size and price effects. Therefore, we estimate the effect of local availability of cheaper electricity

[1] Tennessee Valley Authority in 1933, the Rural Electrification Administration 1935, the Bonneville dam power plant, etc.

on innovative agricultural production inputs using the total number of patents associated to the harvesting of specific crops and the differential impact on electric innovations. To do so, we build on the method implemented by Rajan and Zingales (1998), but use variation across counties and crops. Thus, this study documents, for the first time, the causal impact of local availability of electricity on the direction of the technological change in the agricultural sector - issue that has not been addressed before due to the endogenous nature of the problem.

We study whether accessibility to cheap electricity induced innovations in the context of agricultural sectors that could benefit from it more widely. We do this by exploiting the variation in local access to electricity across geographical regions, but we fear that earlier access to electricity for some counties could have been demand-driven - that is, electricity would had arrived earlier to zones where there was more demand for it. Hence, we cannot just compare counties with and without cheaper electricity access. At the same time, the use of electricity in certain agricultural sectors is also endogenous. Certain types of crops had more incentives to improve their production inputs due to the lower cost of energy generated by electricity - especially the energy-intensive crops. Thus, we cannot just compare differences on electricity use across crops. To solve this problem, we combine these two sources of variation: differences in electricity access across counties with differences in energy intensity - as a predictor of later electricity use - across crops. We argue, like in Fiszbein et al. (2020) did for manufacturing, that industries (crops) within agriculture that had the highest energy needs pre-electrification would be the ones that would benefit most from electrification. We thus compare high-energy crops to low-energy crops in a county with easier hydroelectric power access to the same difference in a county without access.

Using these two sources of variation, we estimate a difference-in-difference estimator to measure the effect of local availability of electricity on the agricultural innovation in rural counties in the U.S. We see that on average, having access to electricity increases electric based patents for crops that were more energy-intensive compared to those that were less by about 0.2 patents for each county-crop, every 5 years. This corresponds to a 290% increase compared to the initial 0.0009 electric patents by county-crop in 1890-1895, and 17 times the average number of electric patents by county-crop during 1910-1950. At the national level, this corresponds to an increase of almost 32 additional electric patents every 5 years due to the access to cheaper electricity during 1920-1950. Furthermore, we see a decrease in the total number of non-electric patents, suggesting in part substitution. Therefore, local availability of electricity in the early 1900s had an impact on agricultural innovation, and directed the technological change by increasing the number of crop-specific innovations that incorporated electricity - substituting patents that were not electric-based.

The invention of electricity was one of the major technological changes in the twentieth century, however, innovation, technology adoption and economic growth are not independent from one another - the larger is the value of a market, the higher are the incentives to invent new technologies and adopt them. Endogenous technological change theories (Romer, 1990) maintain that technology innovations expand the variety of inputs or machines used in production, increasing the division of labour and a better reallocation of resources. However, the adoption of these technological innovations are endogenous because they are likely to occur due to shifts in the supply of inputs that end up influencing the direction of the technological change (Hicks, 1932; Acemoglu, 2002a). Despite its wide use theoretically, Hanlon (2015) provides one of the few empirical test of the hypothesis by estimating the impact of a crop-specific exogenous shock to the supplies of cotton in the United Kingdom caused by the U.S Civil War on the technological innovations in the cotton industry in the same country. The war increased the cost of supplying U.S cotton, forcing British producers to move towards Indian suppliers - which were producing a different type of cotton. This change in the supply of inputs, led to a reorganization of the industry and investment of capital to create new technologies that would work with these new inputs. Similarly, San (2021) also studies the effect of the termination of a immigration program - that reduced the agricultural labour supply - on agricultural innovation, and demonstrates that after this shock, innovation is directed towards labour-intensive tasks. Calel and Dechezlepretre (2016) study a similar shock but in a complete different market. They demonstrate that the introduction of the European Union Emissions Trading System (EU ETS) increases in 1% low carbon patents from firms that are part of the European Carbon Market. Again, this specific study empirically demonstrates the directed technological change theory after a specific shock to a specific market. On the other hand, we see our paper as a more general test of this hypothesis using the whole agricultural sector- using all crops instead of just cotton - in response to a long-lasting general purpose technology instead of a short-term trade barrier.

There is a large literature on the economic impact of electrification, and how it increases the economic welfare of people that have access to it. Electrification enhances productivity and economic outcomes (Kitchens and Fishback, 2015), and improves households' welfare by improving living conditions (WorldBank, 2008) and increasing household per capita expenditure (Olanrele, 2020). Furthermore, it may trigger a rise in female labour force participation (Vidart, 2021). Nevertheless, these changes in the labour market usually come with a cost due to the destruction of certain types of jobs, sometimes leading to an overall negative effect on the labour market (Acemoglu and Restrepo, 2019). Fiszbein et al. (2020) demonstrate that electricity adoption in the U.S. induced rapid productivity improvement and change in the organization of production. However, employment effects were heterogeneous and dependant on a city/industry's market structure.

As opposed to cities and more developed areas, the effect of electricity on the rural labour market is not as polarised as in larger cities. Lewis and Severnini (2017) argue that early rural electrification increased agricultural employment and did not have an impact on the non-agricultural economy, leading rural counties to a persistent economic growth driven by the expansion of their agricultural sector. Capital deepening did not hollow out the skill distribution and electrification therefore created more jobs. Recent studies on the effects of rural electrification in developing countries show that the effects are not always the same as those of rural electrification in the 20th century. On the one hand, Dinkelman (2011) find that the labour market effects of the rural electrification in South Africa in 2001 are similar to Vidart (2021), leading to rising female employment and increasing overall hours of work. On the other, Lee et al. (2020); Burlig and Preonas (2021) find that rural electrification programs - in Kenya in 2013, and India in 2005, respectively - have limited medium-run economic impacts. In these cases, the economic mechanism to understand how electricity impacts economic outcomes is likely to differ from the mechanism in the 1900s. Nowadays, electric agricultural innovations are already patented, and thus estimating the economic impact of electricity arrival in developing countries respond to a slightly different question. While the effects of electrification on rural economic outcomes have been widely studied, not much has been said about the effects of electricity on agricultural innovation and how this could have improved the agricultural sector productivity, leading to a better reallocation of labour and economic growth.

Furthermore, to gain a deeper understanding of the impact of electricity on innovation, it is essential to explore the mechanisms that drive this relationship. Previous research, such as Gebauer et al. (2007) emphasizes the importance of local innovation networks and government agencies in driving innovation and technological change in German regions. Similarly, Brown and Duguid (2002) highlights the increasing significance of local knowledge in driving innovation and competitiveness in the networked age. However, while these studies suggest that innovation is influenced by local incentives, such as policies, worker characteristics, and local innovation networks, there is still a lack of clear and consistent evidence on these mechanisms. In this context, this study aims to fill the gap in the literature by providing a causal estimation of the impact of electricity on rural agricultural innovation, while also empirically testing the theory of endogenous technological change. In doing so, we shed light on the mechanisms underlying the relationship between electricity and innovation, and our findings suggest that rural agricultural innovation in the U.S. in the 1900s is influenced by local incentives and economic characteristics.

The paper is structured as follows. Section 2 describes the theoretical model behind endogenous technological change theories. Section 3 presents the empirical strategy, and section 4 describes the different data sources we use. Section 5 presents the results and analysis. Section 6 explores the mechanism and describe these new electric patents. Section 7 carries out robustness checks and, Section 8 analyses different sources of heterogeneity and the link with the theoretical framework. Finally, the last section concludes.

2 Theoretical Framework

This section presents the theoretical framework for this study, which is mainly based on endogenous technological change theories formalised by Acemoglu (2002b). The model endogenizes the direction and bias of the new technologies that are developed based on the elasticity of substitution between the production factors.

For the purpose of this study, we have two factors of production L (labour) and E (energy, kilowatts) to harvest different types of crops, that are used in different proportions depending on the type of crop. At the same time, there are factor-specific technologies that complement either one or the other factor, increasing their productivity. In this context, the technologies to be developed will be electric machines, that are complementary with the energy production factor, and their development will depend on their profitability. Under general conditions, an increase in the relative supply of a factor - in this case, the cheaper access to electricity increases the supply of energy - will always induce technological change that is biased in favour of this factor. This means that innovations will go towards energy-based inputs, such as electric-based machines.

This happens when the market size effect is usually larger than the price effect. In this specific context, agricultural outputs can be seen as commodities as they can be easily transported and traded anywhere within the same country. Thus, there are no limits to their market size, and if production costs are cheaper, there is always a new market where these agricultural commodities can be sold. Because of the same reason, agricultural producers are price takers, hence the price effect due to an increase in the supply is almost zero. Therefore, the increase in the production of crops that are energy intensive due to cheaper electricity, will dominate the decrease in prices due to this higher production. Hence, it will be profitable to develop technologies that are energy-related and thus the development of energy-based machines that use electricity increases. This model will also be useful to understand the possible sources of heterogeneity depending on the dominant effect for certain counties and crops.

Suppose the following relative demand curve for factors of production:

$$\frac{w_E}{w_L} = D(\frac{E}{L}, A)$$

where A corresponds to technology, E, L are the factors of production - energy-based machines and labour -, and w_E/w_L corresponds to the relative price of the factors of production. If D is increasing in A, then a higher RFP increases the demand for energy-based machines relative to labour - and the demand is always decreasing in the relative quantity of inputs, there will be an equilibrium bias if $A(E/L)$ is increasing in E/L. Hence, the technological change is biased towards the factor that becomes more abundant and profitable - which happens if the market size effect is larger than the price effect. In this context, the factor that becomes more profitable and abundant is energy relative to labour due to the local availability of cheaper access to electricity. Thus, we would expect to see a technological change biased towards energy and electric machines. However, to causally estimate the impact of local availability of cheaper electricity on innovation we cannot just exploit the variation in local access to electricity across geographical regions since the choice of the location of the power plant may be endogenous due to demand driving factors. Therefore, we implement an empirical strategy that will allow us to identify this effect.

3 Empirical Strategy

Following Rajan and Zingales (1998) we will use the crop-county as the unit of analysis – instead of industry-country - to estimate a difference-in-difference estimator that exploits the variation in electricity access for each type of crop depending on the county in which it is patented, and the variation in the energy needs between different crops – depending on their energy intensity between 1800-1850. Electricity adoption is influenced by these two sources of variation, and we therefore use the interaction between them to study the causal effects of having access to cheaper electricity on rural innovation.

We will estimate the following equation:

$$\Delta(y)_{ict} = \gamma_t \cdot EP_{i,0} \cdot Prox_c + \theta_{it} + \theta_{ct} + \epsilon_{ict} \tag{1}$$

where i denotes a crop and c a county. We control for fixed effects by crop θ_{it} and by county θ_{ct}. $Prox_c$ is dummy variable if the county is less than 70 km away from the nearest power plant or the inverse of the distance of each county to the nearest power plant. $EP_{i,0}$ measures the crop-specific initial share of patents that mentioned energy in 1850-1905. $\Delta(y)_{ict}$ corresponds to the change in the total number of non-electric patents' applications or change in the total number of electric patents between t relative to 1890-1895 [2]. Because we use the difference over time, we basically allow for county-specific trends and crop-specific trends through our fixed effects. γ_t measures the differential impact of the local availability to cheaper electricity on the agricultural innovation of crops that were more energy intensive. Given that the treatment is arguably at the county level, and there could be within-county correlations across crops, ϵ_{ict} corresponds to clustered standard errors at the county level. We estimate this period by period t and thus look for whether this relationship evolved over time in a way that would be consistent with time lags behind the invention process.

Similarly to Fiszbein et al. (2020), we thus compare crops with high versus low electricity potential before the widespread adoption of electricity – which is likely to be a good predictor of electricity adoption. We will also run regressions for different 5-years periods to distinguish the effect from early electrification and the late electrification that mainly affected rural areas. We expect to see a much larger effect after all the government interventions around 1930.

We can then estimate a triple-difference estimation, to measure the differential effect on electric innovations relative to non-electric innovations. In this case our unit of analysis corresponds

[2] We choose this 5-years period as the base comparison, since it was just 10 years after electricity was invented, hence it was still not widespread throughout rural counties, and at the same time, it is not that far away from the period of interest. By choosing further periods, we may be including overall increases in the total number of patents driven by other previous crop-county factors as well.

to county-crop-type of patent, and we estimate the effect using the following equation:

$$\Delta(y)_{icet} = \gamma_t \cdot EP_{i,0} \cdot Prox_c \cdot Electric_e + \theta_{it} + \theta_{ct} + \theta_{et} + \epsilon_{icte} \tag{2}$$

where $Electric_e$ is a dummy that denotes if the patents are electric or not. We also add fixed effects by electric patents θ_{et} and $\Delta(y)_{icet}$ corresponds to the change in the total number of electric/non-electric patents' applications between each 5-years period relative to 1890-1895 in each country and for each crop. γ_t measures the differential impact of having access to cheaper electricity on electric agricultural innovation compared to non-electric innovations for a specific crop given its location.

4 Data

We combine data at the county-crop level to run these specifications, and estimate the impact of local availability of cheaper electricity on patenting at a 5-yearly frequency for the period 1910-1950.

Most of the data used in this paper are collected from United States Patents and Trademark Office (USTPO) data through Google Patents. We also combine this main source of data with the patents' location in the HistPat dataset (Petralia et al., 2016), the distance to the nearest power plants in 1912 (Fiszbein et al., 2020) and 1935 (Kitchens and Fishback, 2015) and Haines ICPSR datasets of the Census. Thus, we build a balanced panel for all the county-crops that at least had one patent during the whole 1850-1950 period.

4.1 Agricultural Innovation Measure

The outcome variable is the agricultural innovation at the county-crop level, measured by the number of agricultural patents for each country-crop in a 5-years period.

Following San (2021), we use USTPO data from Google Patents and focus on technological innovations related to harvesting and mowing (CPC class A01D). Since we are concerned about agricultural innovation and not just harvesting, we also include patents within agriculture and forestry, planting, sowing, fertilizing, horticulture, plant reproduction and animal husbandry (CPC classes A01B, A01C, A01G, A01H, A01K). We treat animal husbandry as a separate crop. Patents are allocated to crops by searching the name of the crops in the patent's text.

When the name of more than one crop appears in the text, we allocate it to the crop that appears more times. The patents are also allocated to electricity innovations by searching the word "electr" in the patent's text. When the string is found, we classify the patent as electric. [3] Finally, we eliminate all the patents with kind code equal to E, since they are re-examinations.

The invention's location is retrieved from the HisPat dataset, where the invention is allocated to the county in which the inventor was based. We restrict our sample to agricultural inventions in rural counties to avoid the influence of power plants and electric innovations developed in large urban centres. Thus, we exclude all the counties that had no rural population and the ones that had a population at least 5 times higher than the average population in 1935. At the same time, we make use of Fiszbein et al. (2020) county matching procedure, to ensure consistent boundaries in geographical entities over time. By doing this, we address the issue of counties splitting, merging with other counties or changing their name.

Almost all the patents related to agricultural innovations during the period of interest are located in rural counties, but innovation is highly concentrated in a few ones. From the 2400 rural counties we have in our sample, on average, there are around 826 rural counties that develop agricultural patents in each of the 5-years period. For all these rural counties, there were a total of 2305 patents from which just 13 were electric between 1890-1895, whilst for the period 1930-1935, the same rural counties developed 2111 patents from which 161 were electric.

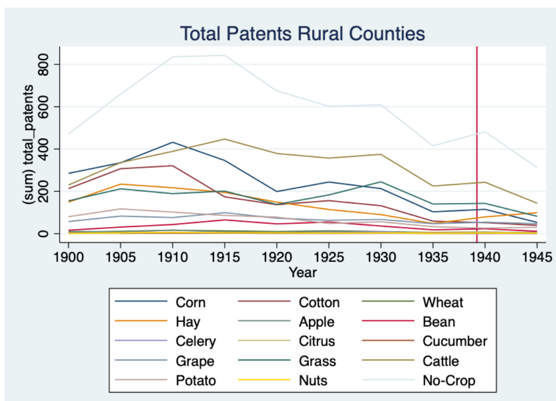
Figure 1 shows how the total number of patents are distributed between crops. There are many patents that are not associated to crops, because they are used in general agricultural tasks as mowing and other non-specific tasks within the non-harvesting classes (A01B, A01C, A01G, A01H). Without considering the non-crop patents, corn, hay, wheat, cotton and cattle are the most predominant crops. When we look at these figures by county, we see that on average, there are patents related to 1.6 types of crops per county, with just a few exceptions of counties innovating in more than 4 types of crops. Thus, the few rural counties that develop agricultural innovations are at the same time specialised in a certain type of crop.

Additionally, we can see that agricultural electrical innovation takes place at a slower pace compared to the manufacturing sector - by 1895 almost a 10% of the total manufacturing

[3] We selected random patents for different classifications and tested if the algorithm was correctly classifying them. We found that all the randomly chosen patents were correctly classified, except for the crop *corn*. The algorithm was considering all the patents that included the word *corner* as *corn* patents. To deal with this, we classified them as *corn* patents just if the *corn* count was greater than the *corner* one, and finally manually checking random patents.

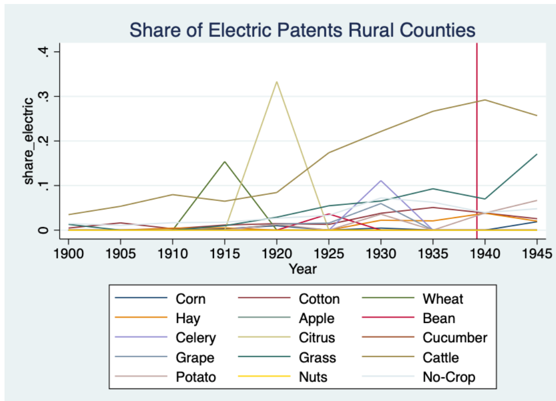
innovation was electric, whilst in the agricultural sector, 35 years later, only 2.4% of all patents were electric. In terms of share electric patents, animal husbandry is the one that has the largest share of electric patents, specially after 1920, as shown in Figure 2. Within the agricultural crops, and without considering the non-crop and grass patents, the most electrified patents by crops are cotton, hay and potato. On average for the period 1920-1950, each county crop had 0.24 and 0.015 total and electric patents per county-crop, respectively. For the period 1890-1895 only, our base period of comparison, there were 0.21 and 0.0009 total and electric patents per county-crop - which means that before 1900, the electricity innovation rate per county-crop was almost 0.

Figure 1: Total Patents by Crop in Rural Counties



Note: This graph groups the total number of patents per crop every 5-years. The x-axis corresponds to the first year of each of the 5-years period.

Figure 2: Share of Electric Patents by Crop in Rural Counties



Note: This graph shows the total number of patents per crop every 5-years as a proportion of the total number of patents in all rural counties. The x-axis corresponds to the first year of each of the 5-years period.

4.2 Energy Needs

Our empirical strategy requires a measure of which crops could benefit more from the arrival of electricity. Crop variation in energy-intensity in 1850-1905 - before electricity was invented and widespread - is used as a predictor of electricity adoption in the 1900s. Using the same Google Patents data, we search for the word "horsepower" and "steam" to construct a proxy of pre-electricity energy intensity by calculating the share of patents by crop that required energy - under our classification by word search - in 1850-1905. Table 1 presents the energy-use ranking obtained. High energy crops are oats, cattle, strawberry, apple and tobacco, nuts and wheat, while the crops classified as low energy crops are onion, lettuce, citrus, sugarcane, rye, tomato, asparagus, melon, cucumber, celery and sugarbeet.

The share of patents that used energy in each crop before electricity was widespread is a strong predictor of electricity adoption in future innovations for these crops. The energy intensity for each crop before the expansion of electricity predicts electricity adoption, since it means that those crops required more horsepower, and probably machines which are more likely to use electricity once there is easy access to it.

Table 1: Ranking of crops the highest energy needs in 1850-1905

Crop	Proportion of Patents in 1945	**Main Energy Need Measure**	**Alternative Measures for Energy Needs**		
		Share Energy 2 1850-1905	*Share Energy 2 1850-1890*	*Share Energy 1850-1870*	*Share Energy 2 1850-1890*
Oats	0.5%	0.101	0.081	0.030	0.172
Cattle	16.8%	0.086	0.053	0.006	0.136
No Crop	34.4%	0.051	0.039	0.018	0.256
Strawberry	0.11%	0.047	0.031	0	0.078
Apple	0.6%	0.033	0.013	0.013	0.078
Tobacco	0.5%	0.029	0.014	0	0.043
Nuts	0.8%	0.029	0	0	0.229
Wheat	1.1%	0.023	0.023	0.008	0.135
Rice	1.1%	0.020	0.015	0.003	0.099
Grape	0.3%	0.014	0	0	0.041
Grass	9.1%	0.013	0.007	0.003	0.127
Bean	2.8%	0.010	0.007	0.005	0.069
Cotton	7.1 %	0.008	0.005	0.002	0.052
Potato	3.4%	0.005	0.002	0.001	0.072
Hay	7.2 %	0.004	0.003	0.001	0.114
Corn	12.6%	0.003	0.003	0.001	0.058
Cucumber	0.1 %	0	0	0	0.111
Rye	0.3 %	0	0	0	0.042
Asparagus	0.2%	0	0	0	0
Melon	0.1%	0	0	0	0
Sugarbeet	0.0%	0	0	0	0
Tomato	0.2%	0	0	0	0.125
Sugarcane	0.0%	0	0	0	0.190
Lettuce	0.1%	0	0	0	0
Citrus	0.2%	0	0	0	0
Onion	0.5%	0	0	0	0.026

Note: The measure Share Energy 2 corresponds to the number of patents by crop - between the periods stated above - that mentioned at least one of the following words: horsepower and/or steam over the total number of patents by crop during those years. The measure Share Energy 1 is the same but also considers the words power and engine.

In the next columns of Table 1, we show that the ranking would remain very similar if we were to restrict our attention to periods even more distanced from the development of electricity. Finally, we also add additional words such as power and engine, which we had not included in our first measure because those two words may directly measure electrical inventions. We observe that while there are some differences between both measures, the ranking across crops is broadly consistent across the two measures.

4.3 Access to Electricity

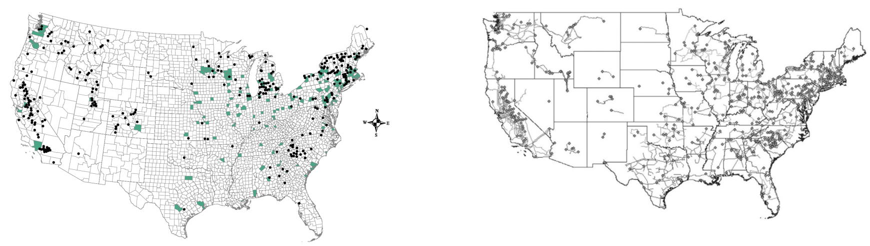
Our empirical strategy also requires a measure of access to cheaper electricity. A common measure used in the literature to identify the county's electricity access is the distance to the nearest power plant (Kitchens and Fishback, 2015; Fiszbein et al., 2020; Lewis and Severnini, 2017). The proximity to the nearest power plant was an important determinant of rural electricity access since it was not feasible to transport electricity far from the generation site before the late 1920s (Vidart; Cassaza, 2004) and, if it was feasible, electricity was considerably more expensive if the nearest power plant was far. At the same time, it is unlikely that the location of the plants was influenced by rural demand for electricity since it was still too low by 1935. In this context, we consider a county close enough to a power plant, and hence, having access to cheaper electricity, if the county's centroid distance to the nearest hydro power plant was within a radius of 70 kilometres. This is based on the fact that Fiszbein et al. (2020) find lower prices until this precise cut-off.

Using Kitchens and Fishback (2015) data on the state of the location of the electric transmission grid and electric generation plants in 1935 - built from the Federal Power Commission National Power Survey Interim Report Power Series No. 1 digitized using ArcGIS - we obtain a measure of each county's proximity to the nearest electric generation and/or transmission infrastructure for that year. We also identify early electricity access using Fiszbein et al. (2020) data on access to early hydro-power using the Census of Central Electric Light and Power Stations and Street and Electric Railways of 1912. In 1935-1940, 62% of counties were close to a power plant, whilst in 1910-1915, there were only 32% of rural counties that were close to a generation site. However, there were some plant closures, increasing the distance to the nearest power plant for some counties. Figure 3 shows the two maps with the location of the power plants in both years - 1912 and 1935. In our main specification, we will employ both sources of variation and not the change between the two periods.

In order to ensure the robustness of our findings, we employ an additional measure of access to electricity in rural counties by utilizing data on electrical capacity within a 50-mile radius of each county in 1911 and 1919. Vidart derived this data from the "Central Station Directory: A Complete List of Electric Light and Power Companies with Data" published by McGraw which contains information on plant power generation and location.

Figure 3: Location of Power Plants in the U.S in 1912 and 1935

(a) Location of Power Plants in 1912 (b) Location of Power Plants in 1935



Note: The top graph is constructed by Fiszbein et al. (2020), and the black dot shows the location of hydro-power plants with 1,000 or more horsepower in 1912 whilst the green counties correspond to the ones included in their sample sample. The bottom graph is constructed by Kitchens and Fishback (2015) and the diamonds represents the power plants, whilst the lines represent the electric transmission lines with at least 12 Kilovots of capacity

5 Results

5.1 Crop and County predictors of adoption of electricity

Our main variable of interest in our identification strategy is the interaction between the variation in the county's electricity access and the variation in the crop's energy intensity - that can be interpreted as crops that were more energy-intensive in counties that electricity was more accessible were more likely to innovate and improve their production inputs. In order to do so, we use two measures that predict the county's access to cheap electricity and the crop's energy intensity as a predictor of the crop's electricity adoption.

The first column in Table 2 shows the correlation between the crop electricity adoption predictor with the actual crop electricity adoption, by estimating the specification presented below:

$$EP_{ict} = \beta_i energy_i + \theta_c + \epsilon_{ict} \tag{3}$$

Where EP_{ict} corresponds to the share of electric patents for each county-crop in each of the 5-years periods from 1910 until 1950, $energy_i$ is the crop energy intensity in 1850-1905, θ_c is a county fixed effect and ϵ_{ict} are clustered standard errors at the county level. Thus, β_i measures the correlation between the crop energy intensity with the share of electric patents for each crop, taking as fixed everything that is constant at the county level.

We see that the share of patents by county-crop that used energy in 1850-1905 is positively and significantly correlated with the share of electric patents for each crop in the 1900s. This means the share of energy patents pre-electricity is a good predictor of electricity adoption by crop in the future. We can see that this relationships stays even when changing the energy intensity definition (see Appendix A.1)

On the other hand, column (2) and column (3) in Table 2 show the correlation between the county electricity adoption predictor with the actual county electricity adoption, by estimating the following specification.

$$EP_{ict} = \beta_c dummy\_close_c + \theta_i + \epsilon_{ict} \tag{4}$$

Where EP_{ict} corresponds to the share of electric patents in each county-crop for each 5-years period from 1910 until 1950 and $dummy\_close_c$ is a dummy that takes the value one if the the nearest power plant is not further than 70km - we run two specifications one using the distance in 1912 and the other using the distance in 1935. θ_i are crop fixed effects and ϵ_{ict} are clustered standard errors at the county level. Thus, β_c measures the correlation between the county's closeness to the nearest power plant with the share of electric patents for each county.

We see that being closer than 70km to the nearest power plant in 1912 and 1935 are positively and significantly correlated with the share of electric patents by county for different 5-years periods after 1910. Appendix A.2 shows this same correlation, but with a continuous measure of distance to predict electricity adoption by county. We use the logarithm of the inverse of distance and we see that the positive and significant correlation maintains.

Table 3 shows how the share of energy in 1850-1905 and the closeness to the nearest power plant in 1912 and 1935 predict the share of energy patents in each of 5-year period. We see that the energy intensity is positive and significant for all periods, whilst the distance remains positive for periods after 1920, but not always significant.

Table 2: Share Energy, Closeness to nearest power plant as predictors of crop electricity adoption and county electricity access

	% Electric Patents	% Electric Patents	% Electric Patents
	(1)	(2)	(3)
Crop Energy Intensity 1850-1905	1.430		
	(0.109)		
County with close plant in 1912		0.014	
		(0.005)	
County with close plant in 1935			0.014
			(0.005)
N	8237	8752	8752
Crop FE	NO	YES	YES
County FE	YES	NO	NO
Year FE	YES	YES	YES

Note: The table shows pooled OLS regressions for all the 5-years periods between 1910-1950. Column (1) shows the pooled OLS estimates from specification (3), whilst column (2) and (3) presents the pooled OLS results from specification (4). The data is collected at the county-crop-year bin level. It shows the correlation between the crop energy intensity in 1850-1905, and the dummies indicating those counties that were less than 70km away from the nearest power plant - in 1912 and 1935 - with the share of electric patents for those county-crops. Clustered standard errors by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Share energy, closeness to nearest power plant as predictors of crop electricity adoption and county electricity access by year

	1910-1920 (1)	1915-1920 (2)	1920-1925 (3)	1925-1930 (4)	1930-1935 (5)	1935-1940 (6)	1940-1945 (7)	1945-1950 (8)
				Panel A: By energy intensity of crop				
Energy Intensity	0.807	0.739	0.708	1.159	2.017	2.239	2.502	1.910
	(0.807)	(0.200)	(0.245)	(0.283)	(0.423)	(0.549)	(0.553)	(0.724)
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Crop FE	NO	NO	NO	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1387	1284	952	945	792	455	491	306
				Panel B: By whether the county had a power plant within 70km in 1912				
Plant within 70km in 1912	-0.001	0.005	0.010	0.021	0.023	0.031	-0.006	0.018
	(0.006)	(0.006)	(0.009)	(0.011)	(0.015)	(0.018)	(0.017)	(0.023)
				Panel C: By whether the county had a power plant within 70km in 1935				
Plant within 70km in 1935	0.007	-0.009	0.014	0.025	0.028	0.039	0.037	-0.017
	(0.005)	(0.007)	(0.007)	(0.010)	(0.014)	(0.016)	(0.016)	(0.025)
County FE	NO	NO	NO	NO	NO	NO	NO	NO
Crop FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2091	1946	1565	1499	1304	867	915	638

Note: The table shows OLS regressions for each of the cross-sections of 5-years periods between 1910-1950. Panel A shows the estimates from specification (3), whilst Panel B uses specification (4). The data is collected at the county-crop-year bin level. They show the correlation between the crop energy use in 1850-1905, and the dummies indicating those counties that were less than 70km away from the nearest power plant - in 1912 and 1935 - with the share of electric patents for those county-crops in each period. County clustered standard errors in parentheses.

5.2 Directed technological change effect

The following section presents the results from the main specification in (1). For each of the 5-years periods between 1910 and 1950 we estimate the coefficient of interest using the dummy that indicates if a county is less than 70km away from the nearest power plant - for both measures in 1912 and 1935. Figures B.1 and B.2 show the same specification with the continuous measure of distance, using the logarithm of the inverse of the distance for both years. The estimates are presented in Figure 4 and 5 with their respective 90% confidence interval and the standard errors clustered at the county-crop level.

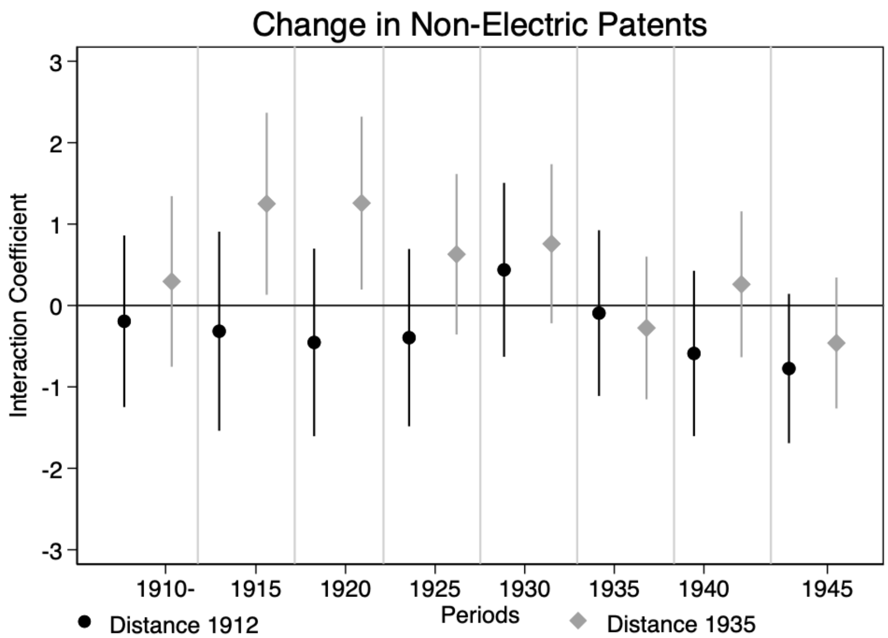
Figure 4 shows the effect of local availability of electricity on the total number of non-electric patents. Each estimate corresponds to the effect in each of the 5-years period between 1910 and 1950. The estimates on the left are obtained using the distance in 1912, whilst the ones on the right use the distance in 1935. We see that there are no significant effects if not a slight decrease in the total number of patents. This means that having easier access to electricity did not increase non-electric innovation in rural counties, and in fact may have induced a decrease in this type of innovation.

Conversely, when we look at the change on the number of electric patents on Figure 5, we see that a 1% increase in the crop energy intensity increases the number of electric patents by around 0.25 patents if the patenting of these crops happens in counties that are close to a power plant. The estimates are more precise compared to the total number of patents and significant at the 90% confidence, for both measures and most of the periods after 1920 - except for 1930-1935. Based on these estimates, in 1940, in a county with access to cheaper electricity, there would be 5 extra electric patents related to oats (10% energy intensive) compared to those related to onions (0% energy intensive) This means that electricity availability has a significant impact on directing the technological change in the agricultural sector in the U.S., and not by increasing overall innovation, but by re-directing innovation towards technologies that would incorporate electricity and save energy costs. The estimates that are dashed show that there are no pre-trends as there is no significant effect for electric patents before 1910, with the exception of 1905 for the distance to 1912 power plants, since very few rural countries had access to electricity before this year.

The estimates using the distance in 1935 are similar to the ones using the distance in 1912, but each of them are more precise for the periods where each of the distance measure was more accurate. Thus, from 1910-1930, the distance in 1912 works better, whilst for 1930-1950 the distance in 1935 is more precise. For both cases, the estimate increases with time, which could be indicating, as David (1990) argues, that the effects of having easier access to electricity on innovation were not immediate.

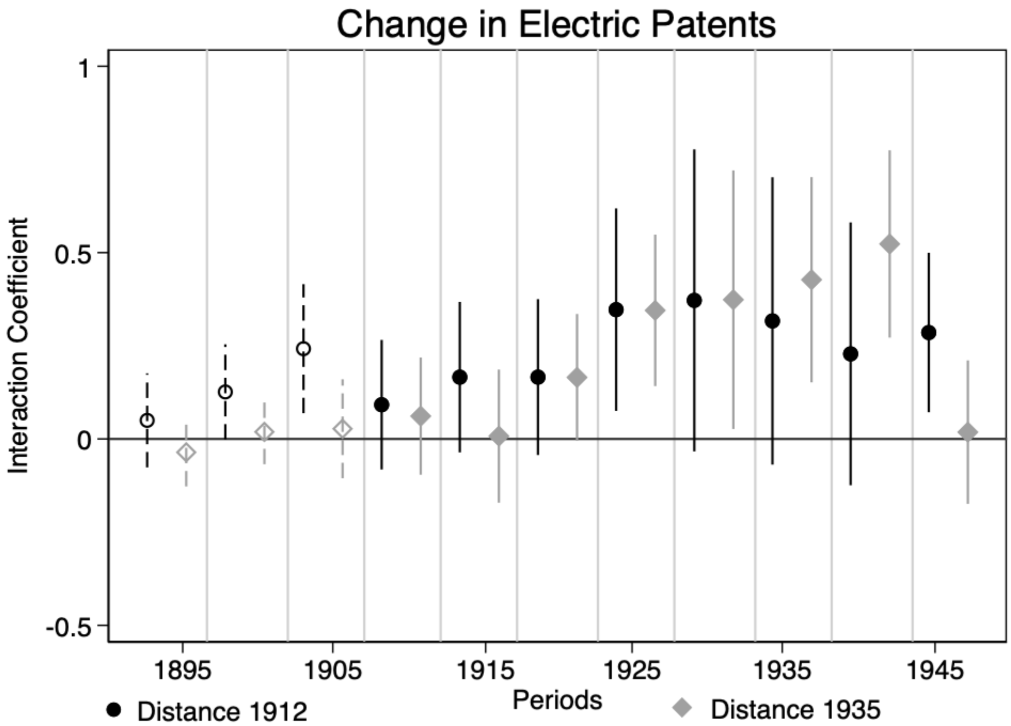
Figure 6 shows the change in total number of electric patents obtained from utilizing the county's electrical capacity data from Vidart. The results are consistent, with similar levels observed across the different time periods studied. Moreover, these estimates are more significant when using a later measure of access to electricity, which is in line with the fact that rural electrification started later. Furthermore, we observe that counties with higher energy capacity in 1910 appear to have experienced a more substantial impact, indicating a potential relationship between initial access to electricity and the subsequent effects on economic development.

Figure 4: Effect of electricity local availability on agricultural innovation in rural counties - distance to power plant



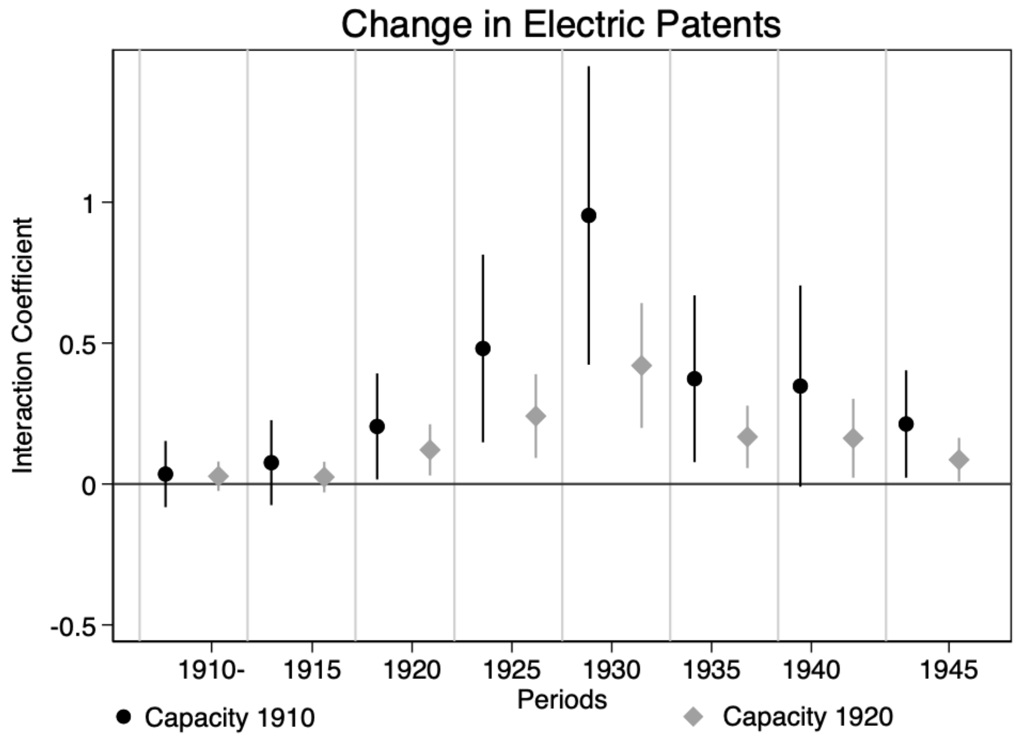
These figures present the coefficient of the interaction term in specification (1) using the change in the total number of patents compared to the total number of patents in 1890-1895 for each county-crop for each of the cross-sections of 5-years periods between 1910-1950. The data is collected at the county-crop-year bin level. The black circles are showing the coefficients from the specification using the distance to the nearest power plant in 1912, whilst the grey diamonds use the distance in 1935 for all the periods. The lines show the 90% confidence interval. The x-axis corresponds to the first year of each of the 5-years period.

Figure 5: Effect of electricity local availability on agricultural electric innovations in rural counties - distance to power plant



These figures present the coefficient of the interaction term in specification (1) using the change in the total number of electric patents compared to the total number of electric patents in 1890-1895 for each county-crop for each of the cross-sections of 5-years periods between 1910-1950. The data is collected at the county-crop-year bin level. The black circles are showing the coefficients from the specification using the distance to the nearest power plant in 1912, whilst the grey diamonds use the distance in 1935 for all the periods. The dashed coefficients show the pre-trends. The lines show the 90% confidence interval. The x-axis corresponds to the first year of each of the 5-years period.

Figure 6: Effect of electricity local availability on agricultural innovation in rural counties - electrical capacity



These figures present the coefficient of the interaction term in specification (1) using the change in the total number of patents compared to the total number of patents in 1890-1895 for each county-crop for each of the cross-sections of 5-years periods between 1910-1950. The data is collected at the county-crop-year bin level. The black circles are showing the coefficients from the specification using the distance to Vidart's electrical capacity in 1911, whilst the grey diamonds use the capacity in 1935 for all the periods. The lines show the 90% confidence interval. The x-axis corresponds to the first year of each of the 5-years period.

5.3 Pooled OLS with clustered standard errors

In this section, we use the specification presented in (1) to compute an average effect of local availability to electricity on agricultural innovation by estimating pooled OLS with clustered standard errors, and county, crop and year fixed effects. We use the change in the number of patents for each crop-county for all the 5-years periods from 1920 to 1950 compared to the number of patents in 1890-1895. We exclude the two 5-years periods before 1920, since we see that there are no significant effects on electric patents. This goes along with the fact that just a few percent of farms were electrified by 1910, hence, we should not expect a large effect for these initial years.

For all the 5-year periods before 1935, we use the dummy that indicates the closeness to the nearest power plant in 1912, whilst for all the 5-year periods between 1935 and 1950 we use the dummy using the distance in 1935. There are some counties in which the distance to the nearest power plant increases from 1912 to 1935. This is due to the closing of certain power plants - which is likely to be due to the construction of other upstream power plants. For all crops we use the share of mention of energy words in patents between 1850-1905 as the other ingredient in our difference-in-difference specification.

Table 4 shows that, on average, having access to cheaper electricity has a positive and significant effect on electric agricultural innovation in the 1900s in the U.S. - a 1% increase on the crop energy-intensity increases the total number of electric patents on 0.25 patents if the crop is harvested in a county that has cheaper access to electricity. This change corresponds to almost a 290% increase compared to the 0.0009 average electric patents per county-crop in 1890-1895, and 17 times the average number of electric patents by county-crop every 5 years during the period 1920-1950. Overall, considering all county-crops patented in counties with no electricity availability and their respective energy intensity, we see an average increase of 1.4 patents every 5 years. Conversely, the total increase in electric patents for those county-crops in counties with access to cheaper electricity is 33 patents every 5 years. Therefore, local availability of cheaper electricity led to the creation of 31.6 electric patents every 5 years between 1920-1950 - which translates into a total of 190 patents in 30 years. On the other hand, there is a decrease in the total number of non-electric patents, which suggests that the increase in electric patents was probably a substitution from non-electric innovation - a 1% increase on the crop energy-intensity decreases the total number of non-electric patents by 0.36 patents

Columns (3) and (4) estimate the effect of higher exposure to electricity by using a continuous measure of distance to the nearest power plant - measured as the inverse of the distance. We see that for crops that have the same energy-intensity, being patented in a county that is 1 km closer to a power plant increases the number of electric patents in around 0.17 patents while non-electric patents do not change.

Columns (5) and (6) estimate the impact of local availability of cheaper electricity by utilizing the county's electrical capacity data Vidart as a measure of this variable. We find that the results are consistent with those obtained from using distance as a proxy of access to electricity for electric patents. However, the negative effect on non-electric patents is now a positive but not statistically significant effect.

These results are consistent with endogenous technological change theories, that hypothesize that the direction of the innovations is influenced by external shocks to the inputs supply. In this case, the shock corresponds to the invention and spread of electricity that considerably reduced the cost of energy - altering the relative input cost of crops that were energy-intensive, and creating incentives to invest in electric-based technologies. In this context, we have shown that local availability of electricity had a causal impact on directing agricultural innovation in the U.S, by substituting non-electrical innovation efforts towards electric innovations in rural counties.

Table 4: Change in number of patents by 5-year periods relative to 1890-1895

	(1) Electric	(2) Non-Electric	(3) Electric	(4) Non-Electric	(5) Electric	(6) Non-Electric
Within 70km of a plant*Energy intensity	0.251	-0.359				
	(0.072)	(0.353)				
Log Inv. Dist. to nearest plant*Energy intensity			0.167	0.013		
			(0.047)	(0.209)		
Electrical capacity* Energy intensity					0.200	0.154
					(0.046)	(0.160)
Mean change for counties less than 70km away	0.005	-0.055	0.005	-0.055	0.005	-0.055
Crop FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	63588	63588	63588	63588	63588	63588

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950. It shows the coefficient of the interaction term in specification (1) run as pooled OLS. The data is collected at the county-crop-year bin level. The dummy close and inverse distance uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950. The inverse distance corresponds to the logarithm of the inverse of the distance in each respective period. Energy capacity corresponds to the county's electrical capacity. Clustered standard errors in parentheses.

5.4 Differential Effect on Electric Patents

The results indicate that there is a significant effect of having cheaper access to electricity on innovations that are related to electricity, whilst there is a non-significant decrease in the total number of non-electric patents. This suggests that local availability of electricity should have a differential impact on electric-based patents relative to non-electric-based patents, supporting directed technological theories. Electricity is complementary with production inputs such as energy and thus energy-based machines. Energy use became cheaper due to the easier access to electricity, which probably increased the use of this production factor. Therefore, there were more incentives to innovate and incorporate electricity in energy-based machines, instead of innovating on machines that did not incorporated electricity.

Table 5 shows the results of the specification presented in (2), where the coefficient of the interaction captures the differential impact of easier electricity access on electric agricultural innovation relative to non-electric innovations. We find that the effect is positive and significant for both measures of distance to the nearest power plant. On average, a 1% increase on the crop energy-intensity, increases electric innovations by 0.59 patents more compared to innovations that are not electric for each crop that is harvested in a county that is less than 70km away from the nearest power plant. This is consistent with our previous findings - where electric patents increased on 0.24, whilst non-electric patents decrease on 0.35. At the same time, crops that have the same energy-intensity but are patented in counties that are 1km closer to the generation plant, increase their number of electric patents relative to non- electric patents in around 0.15 patents but this is now far from being significant. The results are even weaker when using the county's electrical capacity instead of the distance as a measure of access to electricity - an increase of 1000 megawatts of electrical capacity increases the county's electric patents in 0.09 compared to those with lower capacity. Therefore, local availability of electricity directs rural agricultural technological change towards electric innovations.

Table 5: Differential effect on electric patents

	$\Delta(Patents)$ (1)	$\Delta(Patents)$ (2)	$\Delta(Patents)$ (5)
Within 70km of power plant *Energy Intensity*Electric	0.595		
	(0.334)		
Inverse Distance to plant *Energy Intensity*Electric		0.154	
		(0.192)	
Energy Capacity *Energy Intensity*Electric			0.09
			(0.143)
Mean change for counties less than 70km away	-0.025	-0.025	-0.025
N	127176	127176	127176

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950. It shows the coefficient of the interaction term in specification (2) run as pooled OLS. The data is collected at the county-crop-electric-year bin level. The dummy close and inverse distance uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950. The inverse distance corresponds to the logarithm of the inverse of the distance in each respective period. Energy capacity corresponds to the county's electrical capacity. The outcome variable corresponds to the difference the total patents in each of the 5-years periods and the total patents in 1890-1895 at the county-crop-electric-year bin. Clustered standard errors in parentheses.

6 Robustness Checks

In this section, we explore whether the results are driven by certain type of counties or crops. Table 6 presents the estimated effect of local availability of electricity on rural agricultural innovation under specification (1), and for different robustness checks.

Panel A shows that the results are consistent when we eliminate counties that have a large amount of patents relative to the average number of patents per county. Counties that are more likely to innovate may be a sort of "rural technological hubs" and could be inducing bias and driving the results. Since innovation is likely to take place is these counties it could be the case that these are also more likely to adopt new technologies. Nevertheless, we see that the effect is slightly lower when eliminating these counties, but it is still significant and economically important - the electric patents increase in 0.203 instead of 0.26. Panel B estimates the effect using the same specification, but using a different base period of comparison. In this case, we ran the specification using the change in electric patents in each period after 1920 compared to the electric patents in 1850-1855 instead of 1890-1895. The results show that effect is consistent and does not change. Figure C.1 shows that also the cross-section estimations are robust to this change.

We also estimate the effect, but excluding the four crops that have the most patents in each 5-years period. Panel C shows that the results remain robust and consistent to this change. In Panel D, we exclude counties that are extremely close to the nearest power plant - this is counties that are less than 30km away from the nearest plant. Being less than 30km away means that a power plant is likely to be in the same county, and thus there could be more endogenous demand-driven incentives to construct a power plant in this county. Nevertheless, we see that the effect is robust if we do not consider these counties. Panel E runs the specification controlling by the base year, Panel F and G use an alternative measure of energy intensity and Panel H clusters the standard errors at the county-crop level instead of county. Results are robust to all these changes.

Finally, Panel I estimates the same specification, but looking at the effect on the total number of water-related patents. Hydro-power plants may have established in these counties due to the higher presence of water relative to the others, and therefore incentives to innovate might have been driven by this. In this context, we would expect to see an increase in water-related patents as well. Results show that there is not a significant impact on the total number of water-related patents, and therefore the effect is unlikely to be driven by the existence of water in these counties.

Table 6: Robustness Checks

	Δ Electric Patents
Panel A: County Outliers	
Within 70km of plant * Energy Intensity	0.247
	(0.071)
N	62735
Panel B: Change Base Period	
Within 70km of plant * Energy Intensity	0.263
	(0.072)
N	63585
Panel C: Crop Outliers	
Within 70km of plant * Energy Intensity	0.248
	(0.073)
N	61764
Panel D: Extremely Close Counties	
Within 70km of plant * Energy Intensity	0.228
	(0.088)
N	50445
Panel E: Base year as control	
Within 70km of power plant *Energy Intensity	0.279
	(0.070)
N	63585
Panel F: Share Energy 2 1850-1870	
Within 70km of plant * Energy Intensity	0.433
	(0.204)
N	63585
Panel G: Share Energy 1 1850-1890	
Within 70km of plant * Energy Intensity	0.054
	(0.020)
N	63585
Panel H: County-crop clusters	
Within 70km of plant * Energy Intensity	0.251
	(0.067)
N	63585
Panel I: Water Patents	
Within 70km of plant * Energy Intensity	-0.040
	(0.169)
N	63585

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950. It shows the coefficient of the interaction term in specification (1) run as pooled OLS. The outcome variable is the change in electric patents relative to 1890-1895 - except for Panel C that changes the base period to 1850-1855. The data is collected at the county-crop-year bin level. The dummy close uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950. Clustered standard errors by county in parentheses.

7 Detailing the Electric Patenting Process

The long-term economic impact of these new electric patents replacing non-electric innovations depends on the relevance of these, and how the inventor's composition change once counties have access to cheaper electricity. As a measure of relevance, we use the future number of citations of the specific patent to proxy how this invention influenced future innovations. To understand the change in the inventor's composition, and thus who is driving this technological change, we look at the change in the number of patents that have at least one new inventor, and the change in the number of patents that were registered by existing inventors.

Table 7 shows the average results for the change in the number of patents with more than 10 cites for all the 5-years period compared to the base period. Overall, electric patents that were widely cited in the future increased in 0.12 patents per county-crop, representing a 40% of the average total increase in electric patents due to having access to cheaper electricity. Therefore, cheaper electricity induced a substitution between electric and non-electric patents, where almost the half of these new electric patents were important and influenced future innovations.

On the other hand, whilst the overall number of non-electric patents decreased, there is an increase on the importance of the non-electric innovations that were still taking place. Thus, non-electric patents that were replaced by electric ones were not as relevant - increasing the average importance of non-electric innovations once electricity arrived to rural counties.

Table 7: Change in the number of patents with more than 10 cites

	(1) Electric	(2) Non-Electric	(3) Electric	(4) Non-Electric
Within 70km of power plant *Energy Intensity	0.116	0.313		
	(0.028)	(0.083)		
Log Inverse Distance to plant*Energy Intensity			0.082	0.218
			(0.020)	(0.058)
Mean change for counties less than 70km away	0.002	0.018		
Crop FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	63588	63588	63588	63588

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950 for electric and non-electric innovations. It shows the coefficient of the interaction term in specification (1) run as pooled OLS. The data is collected at the county-crop-yearbin level. The dummy close and inverse distance uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950. The inverse distance corresponds to the logarithm of the inverse of the distance in each respective period.

We have evidenced that the electric patents substitution due to having access to cheaper electricity is relevant, and thus it is likely to influence future economic outcomes through the creation of related innovations. Directed technological change theories explain that there are economic incentives to adopt these new technologies. The question then is: who are the actors that understand these incentives and drive the technological change? Is it new inventors coming in and bringing innovative ideas? Is it old inventors modifying their old technologies? Are companies getting involved in this process?

First, we contribute to the literature by improving the inventors data, filling in the gaps for those patents where Google Patents was unable to identify the inventor. Then, we run the same specification in (1) to understand the change in the composition of inventors in the rural agricultural sector, but using the change in the number of patents that had at least one inventor as the outcome variable. Table 8 shows the results for electric patents - columns (1) and (2) corresponds to the change in the number of patents with just old inventors, and the change in the number of patents with at least one new inventor, respectively. Overall, 66% of the new electric patents were developed by new inventors, and thus the pool of inventors also changed due to having access to cheaper electricity. We also see that the main source of decrease in non-electric patents come from fewer patents by new inventors, thus suggesting a reorientation of the work of inventors when provided with cheaper electricity.

Table 9 shows the change on the number of assigned patents - innovations commissioned by businesses - due to having access to cheaper electricity. In 1915, only about 10% of electric patents were assigned by businesses. However, over the following decades, there was a substantial increase in the utilization of this method of patenting. Our results show that almost 32% of the new electric patents developed due to having access to cheaper electricity were assigned to inventors by companies. Thus, the local availability not only triggered a different type of innovation from a different pool of inventors, but also created incentives for companies to start taking part in this process as well. Assigned patents that were non-electric also grew suggesting a professionalization of invention in those counties, even for non-electric patents.

Table 8: Change in the number of patents by longevity of the inventor

	(1) Electric Old	(2) Electric New	(3) Non-Elec. Old	(4) Non-Elec. New
Within 70km of power plant *Energy Intensity	0.069	0.171	-0.032	-0.533
	(0.031)	(0.056)	(0.183)	(0.261)
Mean change for counties less than 70km away	0.001	0.004	-0.006	-0.049
Crop FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	63588	63588	63588	63588

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950 for electric and non-electric innovations. It shows the coefficient of the interaction term in specification (1) run as pooled OLS. The data is collected at the county-crop-yearbin level. The dummy close uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950.

Table 9: Change in the number of assigned patents

	(1) Electric	(2) Non-Electric	(3) Electric	(4) Non-Electric
Within 70km of power plant *Energy Intensity	0.090	0.390		
	(0.032)	(0.133)		
Log Inverse Distance to plant*Energy Intensity			0.072	0.326
			(0.027)	(0.085)
Mean change for counties less than 70km away	0.001	0.030		
Crop FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	63588	63588	63588	63588

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950 for electric and non-electric innovations. It shows the coefficient of the interaction term in specification (1) run as pooled OLS. The data is collected at the county-crop-yearbin level. The dummy close uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950.

Table 10: Change in the number of patents by agricultural steps

	(1) Electric Pre-Harvest	(2) Electric Post-Harvest	(3) Electric No Step	(4) Non-Elec. Pre-Harvest	(5) Non-Elec. Post-Harvest	(6) Non-Elec. No Step
Within 70km of power plant *Energy Intensity	0.010	0.011	0.229	-0.042	0.039	-0.340
	(0.007)	(0.012)	(0.068)	(0.040)	(0.062)	(0.332)
Mean change for counties less than 70km away	0.000	0.000	0.030	-0.018	0.000	-0.037
Crop FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	63588	63588	63588	63588	63588	63588

Note: The table shows pooled OLS regressions for all the 5-years periods between 1920-1950 for electric and non-electric innovations. It shows the coefficient of the interaction term in specification (1) run as pooled OLS. The data is collected at the county-crop-yearbin level. The dummy close uses the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950.

Finally, we classify patents by their purpose and stage of the agricultural process where these new inventions will be adopted as: pre-harvesting, post-harvesting and no specific purpose. Pre-harvesting processes correspond to plowing, harrowing, irrigating, fertilizing, sowing and mowing, while post-harvesting includes harvesting, storage, threshing and winnowing. We run the main specification to estimate the effect on the total number of electric and non-electric patents by different agricultural steps. Table 10 shows that the majority of these new electric patents generated due to having access to cheaper electricity did not have a specific purpose, and therefore electricity was mainly adopted in general agricultural processes. We cannot exclude, however, that our classification based on word search within patents also prevent us from understanding the main role that each patent played in the agricultural process.

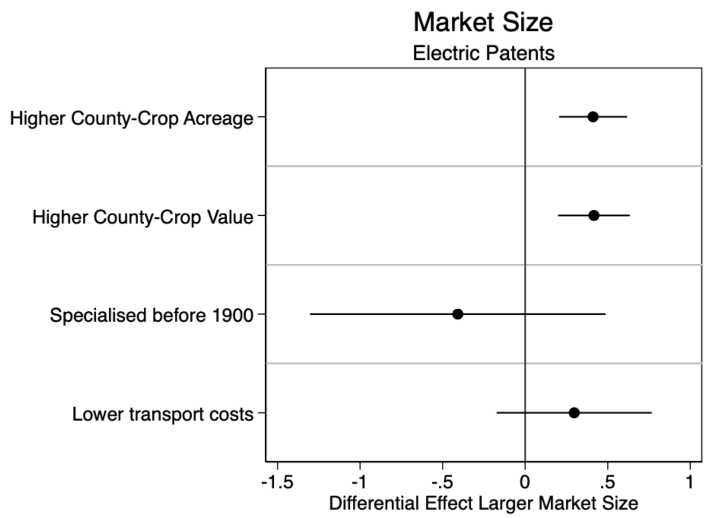
8 Link to Directed Technological Change

Based on endogenous technological theories, we suspect there might be some counties where the effect of local availability of electricity on electric innovations is larger than others due to existence of stronger incentives. Under the theoretical framework presented in Section 2, some county-crops may have larger incentives to bias their innovation towards electric patents due to either: (1) a larger initial market size in their respective counties or (2) due to a larger increase in the relative supply of the production factors (E/L) - enabling them to expand their production. Therefore, following what was presented in our theoretical framework, we expect to see a larger impact in counties that have a larger crop market size and larger agricultural labour shortages. First, because counties with a higher market size has a larger demand for the additional production, and secondly, the increase in the relative supply of energy over labour is larger in counties with larger agricultural labour shortages, and thus the decrease on the relative price of inputs is greater - inducing a technological change that is more biased towards energy in these counties.

First, we look at heterogeneous effects in counties that have a larger market size in 1935. We believe there might be incentives to innovate more in these counties because they have a larger market to sell the additional production due to lower costs. However, this is not clear since agricultural outputs can be seen as commodities and thus traded everywhere, and not necessarily in the same county. We use data from the 1930 U.S. Agricultural Census to understand county-crop specialisation and the county's market value. First, we compare counties that are specialised in a specific type of crop, with those that are not. This specialisation may be suggesting a larger demand for those specific crops in those counties. To determine specialised counties, we compare county-crops that have more than 40% of total county's farm acreage to those that have not. We also use the value of each county-crop over the county's total crop value as a proxy of county specialisation - we compare those county-crop that have a value larger than the average to those are below the average. Specialised counties may have a larger market size for those specialised crops, and thus a larger market size effect under our theoretical framework. At the county level, we compare those counties where their crop value per capita is larger than the average, with those that are below the average. Higher crop value per capita could be seen as a proxy of larger market size. Again, under directed technological theories this could create more incentives to invest in new electricity related technologies. Finally, we look at counties with low transportation costs, as it may be easier for these counties to reach a larger market by selling their agricultural products outside their own county.

Figure 7 presents the estimates on the change of electric patents for all the comparisons mentioned above. We see that specialised counties have 0.4 more electric patents than those that are not, whilst counties with crop value per capita above the average and counties with low transportation costs do not see differences. This suggests that there might be stronger incentives to invest in new technologies and increase production in those counties with larger specialised market size, where they can invest in crop specific electric innovations. On the other hand, counties with higher crop value per capita could be indicating (1) higher prices or (2) higher non-specialised production - which does not necessarily mean large crop specific market sizes. In terms of counties with low transportation costs, (1) there might not be enough variation in terms of transports costs - almost 95% of counties have transportation costs between 0.07 and 0.1 - or (2) counties with lower transport costs may be less rural and therefore have a smaller agricultural market. In any case, we see that the commodity nature of the agricultural outputs is not strong enough to offset the market size effect.

Figure 7: Change in Electric Patents under Market Size Sources of Heterogeneity



Note: These estimates are obtained by running pooled OLS using a triple difference specification, where the interaction between the county's distance and the crop energy-use is also interacted with the possible source of heterogeneity. For all the groups, we use all the 5-years periods between 1920-1950. The outcome variable is the change in electric patents relative to 1890-1895. The data is collected at the county-crop-yearbin level. We use the dummy close as the independent variable, using the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950.

We then compare counties with different production input structure to understand the effects of a reduction on the relative price of energy due to having access to cheaper electricity. We analyse labour markets to understand whether there are labour shortages in the agricultural sector, and counties with alternative sources of energy such as coal. Counties with a lower agricultural labour availability or without any other source of energy available have a larger increase in the relative supply of energy over labour when electricity becomes easily accessible compared to those counties where labour is not scarce or have a high coal production. Under the theoretical framework presented in Section 2, a larger increase in the relative supply of factors leads to a technological change more biased towards a higher electric mechanisation due to the cheaper cost of electricity relative to the cost of labour. When labour is scarce, and electricity is cheaper, producing with energy is cheaper than doing it with labour, and thus there are more incentives to create machines that incorporate this cheaper input. When energy is scarce, access to electricity should decrease the relative price of energy more than in those counties where energy is easily accessible.

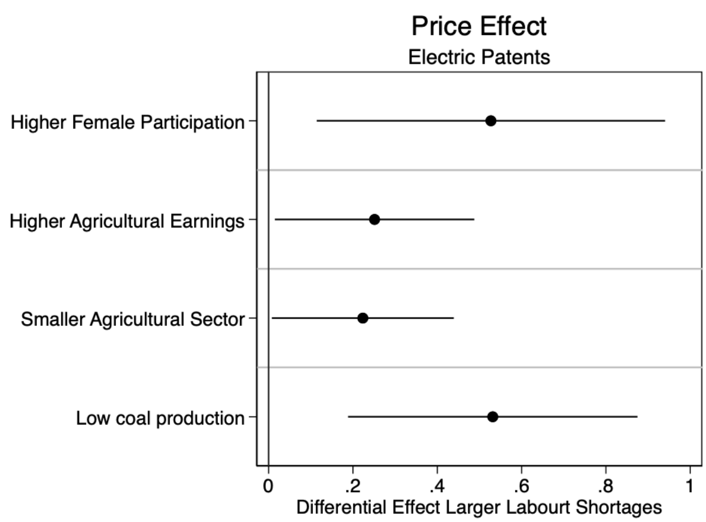
We use the 1930 U.S. Agricultural Census to understand each county's agricultural labour market, in order to understand differences in agricultural labour shortages across counties. First, we compare counties where earnings per employee in the agricultural sector are larger than the average with those that have lower earnings per employee. In counties where the employees earnings per capita are higher, ie where the cost of labour is higher, it may be more worth to substitute energy-based machines for labour when energy becomes cheaper. Thus, counties with high earnings per employee, also have more incentives to innovate and invest in new electric machines. Furthermore, we compare the effect in counties that have an agricultural sector that employs more than 40% of the county's labour force relative to those that have a smaller agricultural labour market. The latter could indicate a lower supply of agricultural labour force, hence the agricultural wages are probably higher. Again, a higher price of labour would create incentives to substitute labour for energy-based machines, and thus electrify certain processes due to cheaper cost of energy. Finally, we see that a higher female labour force participation is negatively correlated with the size of the agricultural labour market. Thus, counties with a higher female labour force participation, should have higher agricultural labour shortages because women tend to not work in the agricultural sector in those counties. Therefore, we look at counties that have a larger female labour force participation - counties that have more than 30% of female labour over their labour force compared to counties that have less than 30%. In terms of alternative energy sources, counties with a carbon production lower than 200,000 tons, are likely to have access to more expensive energy sources. Therefore, a reduction on the price of energy due to having access to cheaper electricity, should have a larger effect on the reduction of the relative price of energy as this was initially higher than in those counties with a high coal production.

Figure 8 presents estimates of the change in electric patents for counties with greater relative input price change, either due to labor shortages or not having access to alternative energy sources. We see that even though some of the differences are larger than others, the effect is more likely to be heterogeneous and larger for counties with greater labour shortages in the agricultural sector or lack of access to other energy sources. The effect in counties with higher female labour force participation is statistically larger than counties with low female participation at the 90% confidence interval. Oats innovation compared to onion in a county that has access to electricity, and a higher female labour force participation increases in almost

8 electric patents, whilst in a county that also has access to cheaper electricity, but with a lower female labour participation, increases in just 2. Counties with higher agricultural wages and a smaller agricultural sector also present higher estimates as predicted, but smaller in magnitude - where the increase on the effect varies around 2 patents. Counties producing less than 200,000 tons of coal have a differential effect of 0.5 patents if they have access to cheaper electricity. These results confirm that having a smaller agricultural labour market - and thus a higher agricultural labour shortage - or lack of access to other energy sources leads to a larger impact of having cheaper access to electricity since these counties have more incentives to mechanise their production due to a larger reduction in the price of energy relative to labour.

Finally, we also examined counties with higher banking penetration and higher capital stock to understand whether these effects were somehow driven by better access to finance or because they were already mechanized. However, results are not significant and therefore we found no evidence that these mechanisms occurred.

Figure 8: Change in Electric Patents under Labour Shortages Sources of Heterogeneity



These estimates are obtained by running pooled OLS using a triple difference specification, where the interaction between the county's distance and the crop energy-use is also interacted with the possible source of heterogeneity. For all the groups, we use all the 5-years periods between 1920-1950. The outcome variable is the change in electric patents relative to 1890-1895. The data is collected at the county-crop-yearbin level. We use the dummy close as the independent variable, using the distance in 1912 for all the 5-years period from 1920-1935 and the distance in 1935 for all the 5-years period between 1935-1950.

9 Conclusion

The impact of electricity on economic outcomes has argued to be needing time to happen, in particular because of the need to generate complementary innovations. New arguments (Fiszbein et al., 2020) suggest that it may simply be that not all geographical areas got access to cheap electricity at the same time. This paper shows that not only productivity but also innovations responded to local access to cheaper electricity. Using a novel approach, we find that innovation for energy-intensive crops in counties with easier - hence, cheaper - access to electricity was larger. Following directed technological theories (Acemoglu, 2002b), this innovation was biased towards electric technologies due to the cheaper cost of energy, and thus the larger market size of the agricultural commodities. We also find a positive differential effect of electricity access on electric patents relative to non-electric patents - suggesting a substitution of electric for non-electric innovation.

These new electric patents are important and widely cited - almost half of the new patents have more than 10 cites in the future - whilst non-electric based patents that stopped being developed were not as important. Furthermore, we see a new and knowledgeable wave of inventors that comes in to develop these patents incorporating electricity, and companies also getting involved in the process and commissioning these types of patents. In terms of heterogeneous effects, we show that the effect is larger for counties with larger market sizes and a greater drop in the relative price of energy due to either larger labour shortages or not having access to other sources of energy such as coal.

Our main conclusion is that electricity did have an impact on directing the technologies that were developed in the agricultural sector, and thus in its future labour market structure and economic growth. Innovation responded to local incentives as more energy-intensive crops, which are likely to be capital-intensive crops, increased their electric innovations deferentially if they were patented in counties with cheaper access to electricity. We find larger effects in counties with larger market sizes, greater labour shortages and lack of alternative energy sources. This suggests that the magnitude of the increase in the relative supply of inputs has a direct impact on the magnitude of the innovation effect. Depending on the crop's labour complementary with the capital, this could impact differently the labour market structure. These complementarities can be explored in future research, in order to directly link the results from this study with the rural agricultural labour market results ((Vidart, 2021; Kitchens and Fishback, 2015; Lewis and

Severnini, 2017).

References

D. Acemoglu. Technical change, inequality and the labour market. *Journal of Economic Literature*, 40(171):7–72, 2002a.

D. Acemoglu. Directed technical change. *The Review of Economic Studies*, 69(4):781–809, 2002b.

D. Acemoglu and P. Restrepo. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30, 2019.

J. S. Brown and P. a. Duguid. Local knowledge: Innovation in the networked age. *Management Learning*, 33(4):427–437, 2002.

F. Burlig and L. Preonas. Out of the darkness and into the light? development effects of rural electrification. *Energy Institute WP*, 268R, 2021.

R. Calel and A. Dechezlepretre. Environmental policy and directed technological change: Evidence from the european carbon market. *The Review of Economics and Statistics*, 98(1): 173–191, 2016.

J. Cassaza. The development of electric power transmission. *The Institute of Electrical and Electronics Engineers, Inc., New York*, 2004.

P. David. The dynamo and the computer: An historical perspective on the modern productivity paradox. *The Economic Review*, 80(2):335–361, 1990.

T. Dinkelman. The effects of rural electrification on employment: New evidence from south africa. *American Economic Review*, 101(7):3078–3108, 2011.

M. Fiszbein, J. Lafortune, E. Lewis, and J. Tessada. New technologies, productivity, and jobs: the (heterogeneous) effects of electrification on us manufacturing. *Working Paper*, 2020.

A. Gebauer, C. Woon Nam, and R. Parsche. Regional technology policy and factors shaping local innovation networks in small german cities. *European Planning Studies*, 13(5):661–683, 2007.

W. Hanlon. Necessity is the mother of invention: Input supplies and directed technical change. *Econometrica*, 83(1):67–100, 2015.

J. Hicks. The theory of wages. *The Economic Journal*, 43(171):460–472, 1932.

C. Kitchens and P. Fishback. Flip the switch: The impact of the rural electrification administration 1935-1940. *The Journal of Economic History*, 75(4):1161–1195, 2015.

K. Lee, E. Miguel, and C. Wolfram. Experimental evidence on the economics of rural electrification. *Journal of Political Economy*, 128(4), 2020.

J. Lewis and E. Severnini. Short- and long-run impacts of rural electrification: Evidence from the historical rollout of the u.s. power grid. *IZA DP*, 11243, 2017.

I. Olanrele. Assesing the effects of rural electrification on household welfare in nigeria. *Journal of Infrastructure Development*, 12(1):7–24, 2020.

S. Petralia, P.-A. Balland, and D. Rigby. HistPat Dataset, 2016. URL https://doi.org/10.7910/DVN/BPC15W.

R. Rajan and L. Zingales. Financial dependence and growth. *The American Economic Review*, 88(3):559–586, 1998.

P. Romer. Endogenous technological change. *Journal of Political Economy*, 98(5):71–102, 1990.

S. San. Labor supply and directed technical change: Evidence from the termination of the bracero program in 1964. *Working Paper, Applied Economics*, 2021.

D. Vidart. Human capital, female employment, and electricity: Evidence from the early 20th-century united states. *Review of Economic Studies*, forthcoming.

D. Vidart. Human capital, female employment, and electricity: Evidence from the early 20th century united states. *Working Paper*, 2021.

WorldBank. Independent evaluation group. the welfare impact of rural electrification: A reassessment of the costs and benefits. 2008.

A Alternative measures for first stage

A.1 Alternative measures of energy use previous to the rural electricity widespread as a predictor of electricity adoption by crop

	(1) Electric Patents	(2) Electric Patents	(3) Electric Patents	(4) Electric Patents	(5) Electric Patents	(6) Electric Patents
Crop Energy Intensity	0.169					
1850-1905*	(0.0224)					
Crop Energy Intensity		0.182				
1850-1890*		(0.0319)				
Crop Energy Intensity			-0.193			
1850-1870*			(0.104)			
Crop Energy Intensity				1.453		
1850-1905**				(0.111)		
Crop Energy Intensity					2.061	
1850-1890**					(0.159)	
Crop Energy Intensity						1.822
1850-1870**						(0.354)
N	8237	8237	8237	8237	8237	8237
Crop FE	NO	NO	NO	NO	NO	NO
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: The measure Share Energy 1 corresponds to the proportion of patents by crop - between the periods stated above - that mentioned at least one of the following words: horsepower, power, steam and/or engine. Share Energy 2 corresponds to the proportion of patents by crop between the periods stated above - that mentioned at least one of the following words: horsepower, and/or steam.
* Includes: power, horsepower, engine and steam.
** Includes: horsepower and steam

A.2 Logarithm of inverse distance to the nearest power plant as a predictor of share of electric patents by county

	(1) Share Electric	(2) Share Electric
Inverse Distance 1912	0.0058	
	(0.0023)	
Inverse Distance 1935		0.0103
		(0.0023)
N	8752	8752
Crop FE	YES	YES
County FE	NO	NO
Year FE	NO	NO

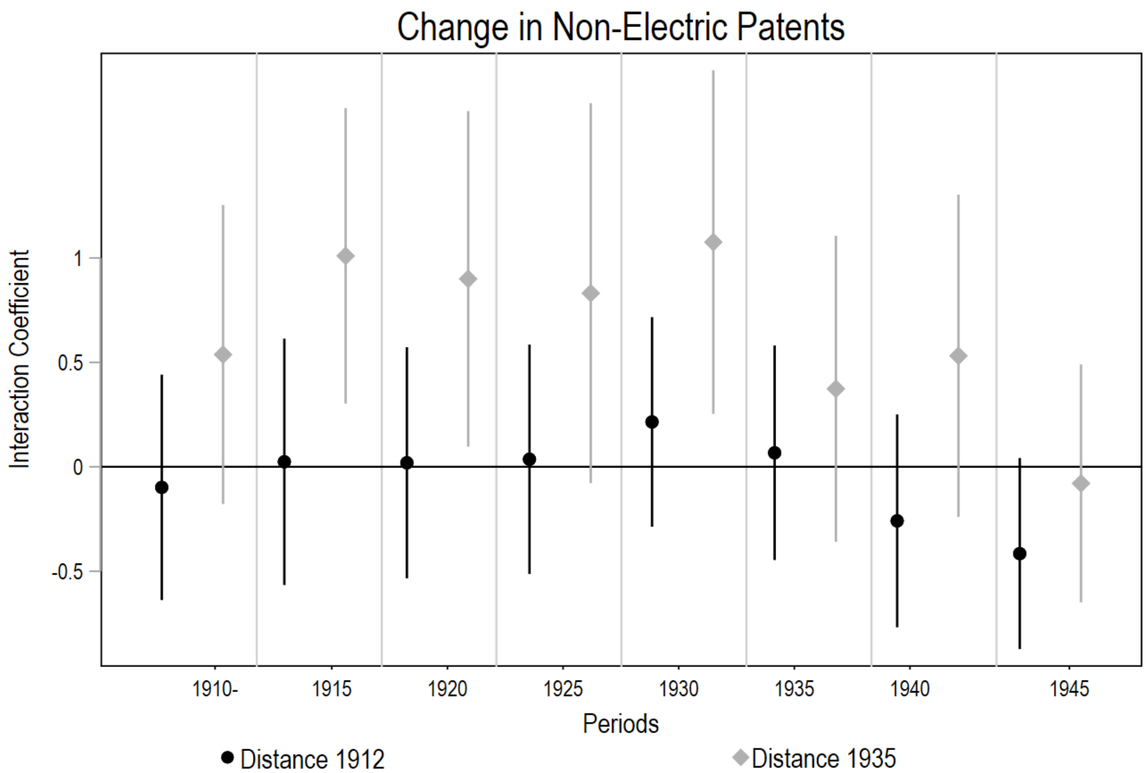
County clustered standard errors in parentheses

	(1)	(2)
	Share Electric	Share Electric
Inverse Distance 1912	0.0052	
	(0.0023)	
Inverse Distance 1935		0.0091
		(0.0023)
N	8752	8752
Crop FE	YES	YES
County FE	NO	NO
Year FE	YES	YES

County clustered standard errors in parentheses

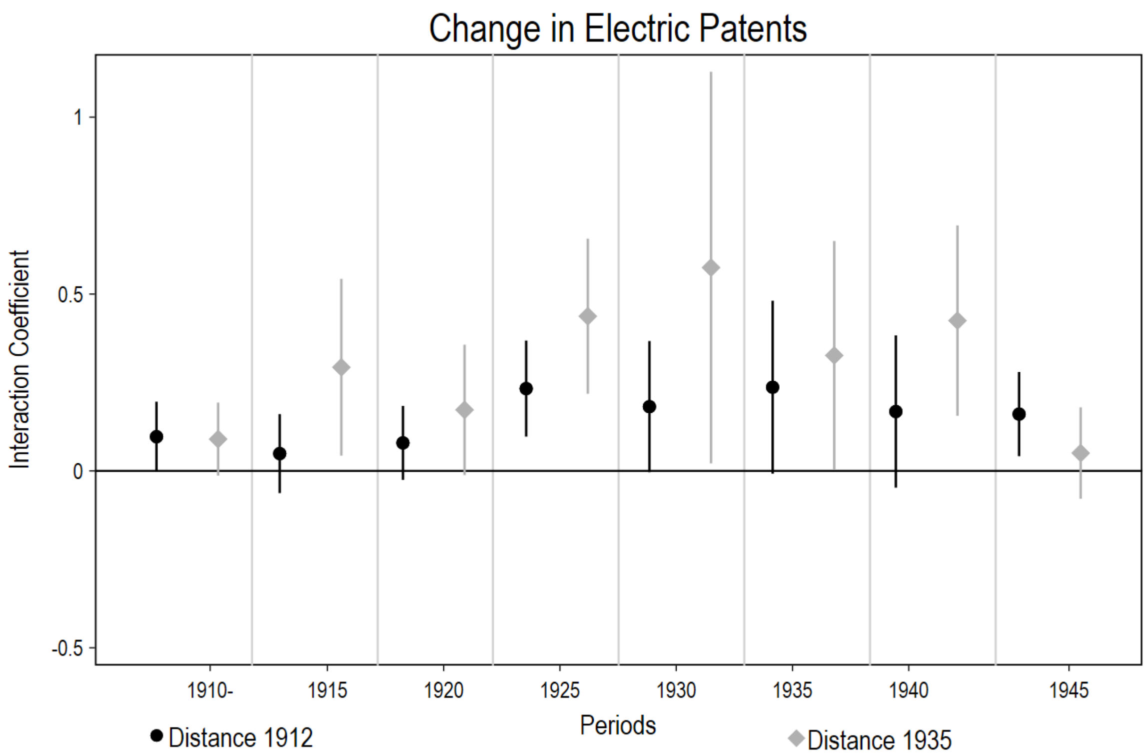
B Main Specification using alternative measures of distance

B.1 Change in Non-Electric Patents - using the inverse of the logarithm of the distance in 1912 and 1935



These figures present the coefficient of the interaction term in specification (2) using the change in the total number of non-electric patents compared to the total number of patents in 1890-1895 for each county-crop-electric for each of the cross-sections of 5-years periods between 1910-1950. The data is collected at the county-crop-yearbin level. The black circles are showing the coefficients from the specification using the distance to the nearest power plant in 1912, whilst the grey diamonds use the distance in 1935 for all the periods. The lines show the 90% confidence interval. The x-axis corresponds to the first year of each of the 5-years period.

B.2 Change in Electric Patents - using the inverse of the logarithm of the distance in 1912 and 1935



These figures present the coefficient of the interaction term in specification (2) using the change in the total number of electric patents compared to the total number of electric patents in 1890-1895 for each county-crop-electric for each of the cross-sections of 5-years periods between 1910-1950. The data is collected at the county-crop-yearbin level. The black circles are showing the coefficients from the specification using the distance to the nearest power plant in 1912, whilst the grey diamonds use the distance in 1935 for all the periods. The lines show the 90% confidence interval. The x-axis corresponds to the first year of each of the 5-years period.