

Directed Technical Change: Evidence from U.S. Rural Electrification*

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Abstract

This paper examines the impact of rural electrification on agricultural productivity and innovations between 1910 and 1950. We set up a model of endogenous technological change with multiple outputs that differ in their requirements of two different inputs. We show that making an input more abundant leads to innovation in products that use this input more intensively, but not necessarily innovations complementing this. We combine variation across counties in proximity to hydro-power plants and variation across agricultural products in pre-electrification energy intensity. We find that local access to electric power induced an increase in the intensity of production and productivity for energy-intensive crops. In addition, electricity bolstered patenting activity in these products, including when focusing on more cited patents. A disproportionate fraction of these added patents were directly related to electricity or to activities where electricity was anticipated to be useful. Inventors who were new and individually-motivated and those in geographical zones that specialized already in energy-intensive crops were more likely to respond by generating electrically-related inventions.

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1 Introduction

Technological change is a key force in the process of growth and structural change, and a classic area of inquiry in macroeconomic analysis and development economics from Smith to Solow to endogenous growth theory. Understanding the drivers of technological change remains a central topic, on which empirical research—including history—can provide valuable insights that complement theoretical work. In this paper, we provide novel evidence on directed technological change at the local level in a setting where multiple inputs are used in the production of different products with different intensity.

An old literature introduces the notion of induced innovation, arguing that scarcity and bottlenecks drive innovation (Hicks, 1932; Hayami and Ruttan, 1971). A more formally expressed theory of directed technical change (e.g., Acemoglu, 2002b) lays out two relevant forces—market size effects and price effects—and shows that the force of “induced innovation” underscored in the old literature is a particular case in which the price effects is dominant, which is unlikely to hold in general. An empirical discussion of the path of agriculture in the U.S. provides reasons to be skeptical of this induced innovation view by underscoring supply-side considerations (such as Olmstead and Rhode, 1993). We provide rich, detailed evidence that supports the relevance of directed technological change in a setting where inputs and sectors are not a one-to-one match.

We study this topic in a setting that offers fine-grained variation in factor availability within a very important institutional and macroeconomic context: the diffusion of electricity. We examine the responses of local agricultural production and innovation to this transformation, leveraging the geographic variation in the diffusion of electricity, combined with differences in its local relevance depending on the output mix. Furthermore, the local aspect of factor availability raises new questions in the context of multiple inputs and outputs. Is technology more likely to be complementing factors that become more abundant for all outputs? Or is it likely to complement the production of outputs that make more use of that input?

In addition to the historical and economic importance of the factors driving this transformation, the responses of agriculture offer a window to understanding directed technical change. Classic studies on induced innovation were, interestingly, focused on agriculture (Hayami and Ruttan, 1971; Ruttan et al., 1980; Ruttan, 1977). Moreover, agricultural innovation has been shown to respond to local conditions (Griliches, 1957), making it more likely that the availability of local factors influences innovation in that sector than in others. Furthermore, during the early 20th century in the U.S., two-thirds of all agricultural patents were from rural counties. Agricultural inventors were mostly from rural areas, a large fraction were farmers themselves or local craftsmen.

A theoretical framework organizes our empirical analysis. In a model where multiple outputs are generated by using two inputs in different locations, an increase in the local abundance of one of the inputs will lead to an expansion of the production of the good that is more intensive in that factor. This is a typical result in a trade framework (Rybczynski, 1955). This reorganization of the product mix *in itself* will lead to more incentives to produce machines that increase the productivity

of that crop. We then show that within each product, there may be an additional incentive to focus on innovations that complement the now more abundant factor. Because prices of inputs are fixed, this will occur because in those sectors where the factor is used more intensively, innovation that is complementing it will produce more cost-reduction than in a sector where it is less intensively used. Finally, there should be heterogeneity by marginal cost of innovations: when the cost of producing innovations is lower, we should observe a larger response.

We thus turn to testing empirically the predictions of our model. Our empirical design leverages two sources of variation. First, we rely on the accessibility of electricity to rural counties in the first decades of the 20th century. This captures early access to electricity since, by 1930, while larger cities were mostly electrified, less than 10 percent of farms had access to electricity (Lewis and Severini, 2017).¹ Our period of analysis is thus mostly before the active government investment in rural electrification and less likely to be due to local demand pressures. The rural counties that get access do so because of their proximity to cities that wish to electrify. We show that this variation predicts well which farms had access to electricity and that more electric patents were generated in those locations. However, our theoretical framework emphasizes that we should observe differential impact across products, depending on their reliance on energy. We thus also exploit variation within counties, relying on variation in energy intensity across agricultural products. We show that this is robust to the way we measure energy-intensity and that it is highly predictive of electric patenting in those crops at the national level either contemporaneously or once electricity has fully diffused to all counties.

Our empirical strategy combines variation in energy intensity across crops (as a predictor of later electricity use) with the variation in electricity access across counties. We argue, like Fiszbein et al. (2020) did for manufacturing, that sectors (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 use a difference-in-differences estimator to measure the effect of local availability of electricity on agricultural choices and innovation, similar in spirit to Rajan and Zingales (1998), but using variation across counties and crops.

We begin by documenting that counties with access to hydropower plant become more specialized in energy-intensive crops relative to other counties. This suggests that the positive impacts of electrification on agricultural production and productivity, previously documented by Lewis and Severini (2017), were concentrated in specific crops. This proves our first model prediction and suggests that inventors may have seen a bigger potential local market for innovations that focused on those crops than others.

We then show how innovation responded to changes in local conditions. We show that total

¹This 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.

patenting increased in energy-intensive crops versus those that were less energy-intensive in counties that were closer to a power plant. A crop that was 10 percent more energy-intensive saw about 0.04 more patents in a location that was within 70 km of a power plant every 5 years. This is a substantial number given that the average number of electric patents by crop and county in a given period was only 0.006. It is robust to the way we define access to hydropower. We find the bias towards electricity is even more marked if we instead classify patents using action words and restrict our attention to those where electricity was anticipated to be useful. This suggests that there was more innovation in those localities and these crops and that this was particularly strong for innovations related to electricity. Results are robust to a variety of sensitivity checks and are visible even when focusing on patents that were more cited in the future.

We finally explore whether there is substantial heterogeneity in which counties or crops responded more to the arrival of electricity, which our model would relate to differences in the marginal cost of innovation. We find evidence that more electric patents arose in locations and products that were already specializing in these energy-intensive crops but not those that had a large patenting experience. We also find that while the additional general patents were assigned and registered by existing inventors, electric patents had a more substantial share of new and individually-motivated inventors, maybe indicating that the marginal cost of thinking about electric inventions required new skills and were not really conceived within large innovation firms. In simpler terms, the arrival of electricity may also focus potential inventors' attention on taking advantage of the new resource, an example of, as [Rosenberg \(1969\)](#) put it, "Technological imbalances leading to changes in complementary processes" (p. 10). Finally, we find limited role for experimental stations ([Kantor and Whalley, 2019](#)), for the presence of engineers ([Maloney and Caicedo, 2022](#)) or college graduates, suggesting limited complementarity between state investments or education. In accordance to our model, we find also limited roles for differences in initial wage levels.

Our work contributes to the literature on endogenous technological change. Theories in that optic ([Romer, 1990](#)) maintain that innovations expand the variety of inputs or machines used in production, increasing the division of labor 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, 2002b](#)). Our model expands the existing literature recognizing that multiple inputs and outputs may complicate predictions made about directed technological change ([Xu, 2001](#); [Burstein and Vogel, 2017](#)).

Empirical tests of these models are scarce. [Hanlon \(2015\)](#) shows that when the supply of American cotton to the United Kingdom was diminished by the U.S Civil War, there was a reorganization of the industry and investment of capital to create new technologies that favored Indian cotton. [San \(2023\)](#) shows that the termination of the Bracero program - that reduced the agricultural labor supply led to innovations directed towards labor-intensive tasks. [Calel and Dechezlepretre \(2016\)](#) 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. Our results emphasize

that sector-biased innovation responds and that factor-biased innovation occurs within the favored sectors. Moreover, we are the first paper to document responses to local incentives for innovation.

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 (Bank, 2008) and increasing household per capita expenditure (Olanrele, 2020). Furthermore, it may trigger a rise in female labor force participation (Vidart, 2024). Nevertheless, these changes in the labor market usually come with a cost due to the destruction of certain types of jobs, sometimes leading to an overall negative effect on the labor 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 in the manufacturing sector. 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. We add to this literature an emphasis that this may not have been equal across all crops with electrification favoring some more than others.

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 labor market effects of the rural electrification in South Africa in 2001 are similar to Vidart (2024), 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 labor 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.

The rest of the paper is structured as follows. Section 2 outlines a simple conceptual framework based on endogenous technological change theories and presents our empirical strategy. Section 3 describes the different data sources and measures we use. Section 4 presents the results on agricultural outcomes. Section 5 then presents the results on innovation, exploring robustness and heterogeneity. The last section concludes.

2 Conceptual Background and Empirical Strategy

2.1 Model

We first set up a model that can explain what types of innovations will be more likely to be developed in a model where, in contrast to [Acemoglu \(2002b\)](#), multiple goods are produced each with a different combinations of the same factors. The model is inspired by [Burstein and Vogel \(2017\)](#) who have multiple inputs and outputs and technological innovation that can be biased towards a factor. Our model is closest to [Xu \(2001\)](#) who uses a two-input, two-output, two-country model to study the impact of openness to trade on directed innovation.

Let us imagine that each county n produces j crops using a combination of labor L_{jn} and energy E_{jn} , facing local factor prices w_n and r_n respectively. There are multiple varieties of crop j that we will denote by ω_j and each variety is produced combining both factors in a CES production function as

$$q_n(\omega_j) = A_j (\alpha_j (\gamma_{Ej} E_j)^\sigma + (1 - \alpha_j) (\gamma_{Lj} L_j)^\sigma)^{1/\sigma}$$

where α_j represents the intensiveness of the product j in energy. γ_{Ej} and γ_{Lj} capture the factor-augmenting technology parameters while A_j is technology parameter that is factor-neutral. Finally, $\sigma \leq 1$ represents the elasticity of substitution between inputs in the production of each agricultural product. This unit cost will be given by

$$c(\omega_j) = \frac{1}{A_j} (\alpha_j (1/\gamma_{Ej} r_n)^{1-\rho} + (1 - \alpha_j) (1/\gamma_{Lj} w_n)^{1-\rho})^{\frac{1}{1-\rho}}$$

where $\rho = 1/1 - \sigma$.

Each customer has preferences across varieties that are characterized by the standard CES form, with an elasticity of substitution given by $\eta > 1$. These preferences generate a demand function for variety ω_j as a function of the price of that variety $p(\omega_j)$ that is given by

$$q(\omega_j) = E * P^{\eta-1} (p(\omega_j))^{-\eta}$$

where P is the price index of crop j

$$P = \left(\int_0^{M_j} p(\omega_j)^{1-\eta} d\omega_j \right)^{\frac{1}{1-\eta}}$$

if there are M_j varieties for crop j and E represents the total spending in the economy.

As in [Burstein and Vogel \(2017\)](#), given the fact that the production function displays constant returns to scale, each variety will be priced at its unit cost if firms compete a la Bertrand—that is by posting a price and selling all units demanded by consumers at that price if it is the lowest price on the market— and farms are initially identical.²

The total quantity of crop j produced in the county $Q_n(j)$ depends on the production of each variety aggregated through a constant elasticity of substitution factor η such that

$$Q_n(j) = \left[\int_0^1 q_n^\eta(\omega_j) d\omega_j \right]^{1/\eta}$$

The aggregate output j is traded competitively between counties.

Each county is endowed with a fixed amount of workers L_n and a fixed amount of energy E_n . Factors are priced competitively and thus the demand for energy and labor of all producers is equal to that endowment. We will model the arrival of electricity as an increase in the endowment of a county in terms of energy.

Proposition 1: Impact on crop choice. Assuming that productivity parameters are fixed and that we are in the cone of diversification, a county that obtains access to electricity will see $Q_n(j)$ increase for the products with the highest α_j and shrink for those with the smallest α_j .

Proof. See [Rybczynski \(1955\)](#). In order to be in equilibrium, factor demand must equal factor endowment at the county level. Factor demand for E_n could increase for each crop j if the factor price of E was to fall. If we are in the cone of diversification and factor prices are fixed, demand can increase by the expansion of crops that have the highest α_j . In order to maintain the equilibrium in the labor market, crops with the lowest α_j will shrink. This will allow factor prices to remain constant.

We now add the possibility of technological change. Assume that some farms can purchase a patent or invent a new machine over which they will have monopolistic power. Given that farms compete a la Bertrand, farms that can lower their unit cost through this investment would price their output just below that of the farms without the new technology and capture all the market. The extra profits they could obtain from purchasing that technology would thus be $(c_{old}(q_n(\omega_j)) - c_{new}(q_n(\omega_j))) * q_n(\omega_j)$. Thus, a farm would purchase a new technology whenever

$$(c_{old}(q_n(\omega_j)) - c_{new}(q_n(\omega_j))) * q_n(\omega_j) \geq p_{jn}$$

where p_{jn} represents the price of the new technology.

Inventors (or firms selling the new technology) are assumed to be monopolistic. They will produce new technologies for crop j in county n as long as they can extract a price p_{jn} for that technology is

²As an alternative, as in [Bustos \(2011\)](#), farms could have market power and maximize profits given the demand they face and with CES preferences, this would generate a constant mark-up over marginal cost which would replicate the results presented below.

higher than their marginal cost MC_{jn} . This leads us to our next proposition.

Proposition 2: Impact on sector-biased innovation Assuming that all innovations are equally costly to develop (same MC_{jn}) and can generate a similar decrease in the cost per unit produced (same $c_{old}(q_n(\omega_j)) - c_{new}(q_n(\omega_j))$), innovation will be more biased towards energy-intensive sectors (high α_i) after the arrival of electricity.

Proof. If all innovations have the same MC_{jn} , then firms would invest in those inventions that can obtain the largest p_{jn} . Based on the willingness to pay equation, innovation will target varieties that have a higher demand $q_n(\omega_j)$ if its impact on the unit cost is the same as well. With the arrival of electricity, we have already shown that crops that are more intensive in energy will expand more. This will imply that $q_n(\omega_j)$ will increase for crops in counties with electricity than those without. Incentives will thus become higher to develop new technologies in those crops in those counties than in others that do not receive electricity.

This is akin to the “market size” effect described in [Acemoglu \(2002a\)](#). In that work, incentives were higher for inventions that were more complementary to the productivity of the factor that became more abundant. However, sector and factor were a one-to-one match in that model. In our setting, sectors that are more intensive expand to absorb the local more abundant factor. There is no incentive to increase the productivity of energy in a sector that is shrinking because of the arrival of electricity.

Let us now detail how the nature of innovation may differ within a crop j and county n . Define the factor-biased productivity parameters such that the unit cost become

$$c(q_n(\omega_j)) = \frac{1}{A_j z(\omega_j)} \left(\alpha_j (z(\omega_j)^{-\theta/2} r_n)^{1-\rho} + (1 - \alpha_j) (z(\omega_j)^{\theta/2} w_n)^{1-\rho} \right)^{\frac{1}{1-\rho}}$$

$z(\omega_j)$ represents a technological parameter that improves the productivity of the energy input at the cost of that of labor. We also parametrize the intensity of the “energy-bias” in innovation through $\theta \in [-2, 2]$. When that number is positive, it is energy-biased or augmenting while when it is negative, the innovation is labor-biased.

Proposition 3: Factor-biasedness of new innovations. Innovation in sectors that are expanding will be more likely to be energy-biased innovation when $\alpha_j (z(\omega_j)^{-\theta/2} r_n)^{1-\rho} > (1 - \alpha_j) (z(\omega_j)^{\theta/2} w_n)^{1-\rho}$, for $\theta > 0$, that is when the sector is more intensive in energy and when the price of energy is lower than that of labor.

Proof. Investing in A_j lowers the unit cost by c/A_j . Investing in z reduces the unit cost by

$$\frac{c \left(1 + \frac{\theta}{2} \right) \alpha_j (z(\omega_j)^{-\theta/2} r_n)^{1-\rho} + \left(1 - \frac{\theta}{2} \right) (1 - \alpha_j) (z(\omega_j)^{\theta/2} w_n)^{1-\rho}}{z \left(\alpha_j (z(\omega_j)^{-\theta/2} r_n)^{1-\rho} + (1 - \alpha_j) (z(\omega_j)^{\theta/2} w_n)^{1-\rho} \right)}$$

The difference between the two depends on the second fraction of the expression above. For any $\theta > 0$, that expression will be larger than 1 whenever $\alpha_j(z(\omega_j)^{-\theta/2}r_n)^{1-\rho}$ is larger than $(1 - \alpha_j)(z(\omega_j)^{\theta/2}w_n)^{1-\rho}$. In counties where w_n is larger, the incentive to invest in energy-biased innovation will be lower than in counties where that cost is higher because the cost-reduction that can be achieved through that innovation is less than when energy is relatively more expensive.

Local innovation will thus increase in crops that are more energy-intensive compared to crops that are less so in counties where electricity becomes available compared to those where it does not. Whether that innovation will be energy-biased or not will depend on the relative cost of labor and energy *before* the arrival of electricity. For crops that have a higher α_j , it is more likely that innovation be energy-biased when faced with the same factor prices.

This is related to what [Acemoglu \(2002a\)](#) calls the “price effect”, by which there is less of an incentive to invest in a technology that complements a factor that is cheaper because the gains from doing so are lower. However, in our case, if we are in the cone of diversification, prices do not respond to the local availability of electricity and thus do not modify incentives for energy-biased innovation. Instead, innovation will always be biased towards crops that expand but the factor-bias will depend on the initial conditions that include prices.

So far, we have assumed that the cost of producing a new technology (MC_{jn}) is the same for all counties, crops and types of innovation. This is not necessarily true. [Kennedy \(1964\)](#) discusses that there may be limits to the “innovation production frontier”. We may think that this applies to local capacities of innovators as well. There are some tasks for which there may have been limited ways to improve productivity. Electric tractors, for example, were not useful because there was no way to keep them plugged while in the field. If gaining access to local electricity modifies the cost of producing machines that are electric because the knowledge about electricity diffuses or complementary innovations are developed, this could also influence the energy-bias of innovation in crops that are expanding. It may also influence who becomes an inventor if the arrival of electricity does not influence the cost of innovation in a similar way for all potential inventors.

Proposition 4: Heterogeneity of innovation effect by cost. Innovation in crops that are expanding will be more present when MC_{jn} is lower. It will be more energy-biased if MC_{jn} is lower for those innovations.

Proof. The marginal benefit of innovating in crops that are more energy-intensive will be higher in counties that get access to electricity than in those that do not (compared to less-energy intensive crops) because of the response in $q_n(\omega_j)$. When MC_{jn} is lower, this increased output will lead to even more innovation by firms selling the new technology. If MC_{jn} differs by type of technology, it will also change the factor bias of the innovations.

We will proxy for the marginal cost of innovations by using actions that were technologically easier to electrify. We will also look at the identity of inventors if first inventors or those working on their own have higher marginal costs of developing new technologies. Finally, we will also

Similar results can be obtained if one considers instead a partial equilibrium model in one isolated

county where the arrival of electricity lowers the price of that input. Marginal costs decrease more for crops that use energy more intensively, leading them to increase more output. This would increase the incentives to invest in technologies for that crop. There would be a price effect that would counter this but as in [Acemoglu \(2002a\)](#), this should be smaller than the market size effect.

Thus, the model predicts that the arrival of electricity in a county that is a small open economy will lead to more production and thus more incentives for innovation in energy-intensive crops compared to a county that does not receive electricity. Innovation may be general or skewed towards energy, depending on the relative factor prices and on the marginal cost of developing the new technology.

2.2 Empirical strategy

Our empirical strategy derives from the model presented above. It suggests that we should compare counties with and without electricity in crops that were more or less energy-intensive before the arrival of electricity and study whether there is a response in terms of (i) crop mix; (ii) total innovation efforts; and (iii) factor-bias of that innovation.

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 geographic variation in electricity access and the variation in the energy needs between different crops.

We will estimate the following equation:

$$\Delta(y)_{ict} = \gamma_t \cdot EP_{i,0} \cdot Prox_{ct} + \theta_i + \theta_c + \epsilon_{ict} \quad (1)$$

where i denotes a crop and c a county. We control for crop, θ_i , and county, θ_c , fixed effects, which capture, respectively, crop- and county- specific linear trends. (Our variation also allows us to control for unrestricted trends by county and crop, which we do in robustness checks.) $Prox_{ct}$ is variable measuring the proximity of county c to hydropower in period t . $EP_{i,0}$ measures the energy-intensity of crop i before the arrival of electricity. $\Delta(y)_{ict}$ corresponds to the change in an outcome between t relative to a base year. γ_t measures the differential impact of the local availability to cheaper electricity on the agricultural outcome 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. We then pool all post-1915 years in one regression to compute the average difference between counties with and without access to electricity in high-versus low-energy intensive crops.

3 Data

We combine data at the county-crop level to run these specifications, and estimate the impact of local availability of cheaper electricity the outcomes specified by our framework.

3.1 Agricultural inputs and outputs

Using the interaction between electricity access and crop energy-intensity, we test the first prediction of our model regarding the change in crop mix. We measure this through proxies of inputs and outputs per crop at the county level. These outcomes are found in the decennial (and intercensal for 1925 and 1935) Census of Agriculture between 1900 and 1940. We use the digitalized versions available from NHGIS when possible. We also use some variables that were digitalized by [Lafortune et al. \(2015\)](#). We digitalized some additional variables for the purpose of this research. We are able to use 23 numbers of different crops in this data. For these, we measure inputs as the acres planted for a crop when available. When the product is not planted by acres, we use the number of trees (for fruits and nuts) or the number of animal heads (for milk and animal husbandry). We see that for crops that are planted, corn and forage are the ones that use the most acres in our sample. Tobacco, rice and beans are the ones planted in the smallest surfaces. The fruit most commonly planted is by far apples with more than 50,000 trees on average per county. The amount of milk cows is about half of the rest of beef cattle and other animals are much more numerous.

Our baseline period for these outcomes is 1900 and post-periods are from 1910 to 1940. Data for 1890 are sparser.

To unify our different units of inputs, we estimate the expected output value for each input by employing the data of 1930. For that year, we have value of production and amount of inputs for each of almost all of the 23 crops, where we have to join all fruits and nuts into one category and all different animals into one as well. We thus run a regression for each crop of value of products against input at the county level. From that regression, we obtain an average value of product per input in 1930. We thus provided an estimated value of products for all counties and years using that “price” multiplied by the amount of inputs for that crop in that county in that year. The fact that we use 1930 as our reference year ensures that the difference across years is entirely due to change in input intensity and not in returns to those inputs. Products that have the highest value in our sample are hay and other forage, corn and animal husbandry.

3.2 Agricultural Innovation Efforts

We use as a proxy of efforts or incentives for innovations the number of patents for a given crop and county. Most of the data related to innovation are collected from United States Patents and Trademark Office (USTPO) data through Google Patents.

We build a balanced panel for all the county-crops that at least had one patent during the whole 1850-1950 period.³

Our outcome variable is the change in agricultural innovation at the county-crop level, measured by the number of agricultural patents for each country-crop in a 5-years period, using 1890-1895 as

³Put differently, if a county ever had a patent in a given county and crop between 1850 and 1950, we include that crop-county cell in all years of our data, including zeros. But the set of crops may differ by county.

a baseline.⁴ While patents are clearly not the universe of all innovations, they provide one possible way of measuring how much interest there was in finding and selling innovations to American farmers over this period.

Following San (2023), we use USPTO 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 and milk production as two separate crops. 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. A fraction of patents do not include the mention of any crops and are thus classified as “no-crop”. These are, in general, generic patents like a hoe or a cultivator that can be employed for many different crops and none are mentioned. 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.⁵ 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 centers. Thus, we exclude all the counties that had less than 30 percent of the population being rural in 1910 or in 1920. 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.

Two-thirds of the patents related to agricultural innovations during the period of interest are located in what we define as 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 3462 patents from which just 13 were electric between 1890-1895, whilst for the period 1930-1935, the same rural counties developed 2950 patents from which 150 were electric.

From the patent filing, we can recover the name of the inventor. Using this, we can classify whether an inventor is “new” or “old” in terms of this being the first patent where their name was mentioned. The patent filing also includes whether the patent is assigned or not. Assigned patent transfers the legal ownership of a patent from the inventor to another person or firm (assignee). This implies that the assignee now enjoys all the rights and benefits of the patent.

⁴We choose this 5-year period as the base comparison, since it was just 10 years after electricity was invented and electricity was still absent from rural US counties but not so far that there may be other technological changes at play.

⁵We 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.

We finally also matched inventors to the Censuses of 1880 to 1940. We used the Census year closest to that of the patent and matched the inventor based on their name (Jaro-Winkler score of 0.95 or better) and county of residence. We restrict our attention only to male inventors since the fraction of female inventors is extremely small. Out of the 32,172 agricultural patents in our database, we were able to find 12,823 inventors with a perfect or unique match (sample 1). We added about 2,000 more when adding those where the first-ranked match was different than the second instead of requiring perfectness (sample 2).

Appendix Table [A.1](#) first shows the characteristics of these inventors in all years. Using either samples, we document that inventors are around 44 years old, 12-13 percent are foreign born and around 31 percent are either foreign born or second-generation immigrants. About half do not live in the same state where they were born. More importantly for our argument that innovation is a local activity, 70 percent live in rural counties and almost 40 percent are farmers (owners, managers, laborers) and about 15 percent are craftsmen (including the local blacksmith, carpenter, butcher, etc). Less than 2 percent are engineers and a bit more than 10 percent of them are not fully literate. In 1940, the only year where we can measure years of education, inventors have on average 10 years of school, with a small fraction having attended college. This clearly points to innovators as being local and exposed to farming activity, which reinforces the idea that they could respond to local incentives relatively quickly.

3.3 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 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. Figure [1](#) displays graphically the energy-intensity measure obtained from this strategy. Appendix Table [A.2](#) reports the exact values the energy-use ranking produced. Based on our main measure which includes the mention of horsepower and steam in 1850-1905, we observe the gray bars indicating that milk production is substantially more energy-intensive than any other farm activity. At a lower level, animal husbandry, nuts, no-crop, strawberry, wheat and tobacco are also energy-intensive while the crops classified as low energy crops are most vegetables and fruits, sugarcane, bean, sugarbeet, rye and oats.

We next show that the ranking remains very similar when restricting our attention to earlier (large gray squares) or later periods (triangles). 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 with the small squares in Figure [1](#) that while there are some differences between both measures, the ranking across crops is broadly consistent across the two measures. All exact numbers are provided for these alternatives in Appendix Table [A.2](#).

Figure 1: Energy-intensity of crops by different measures

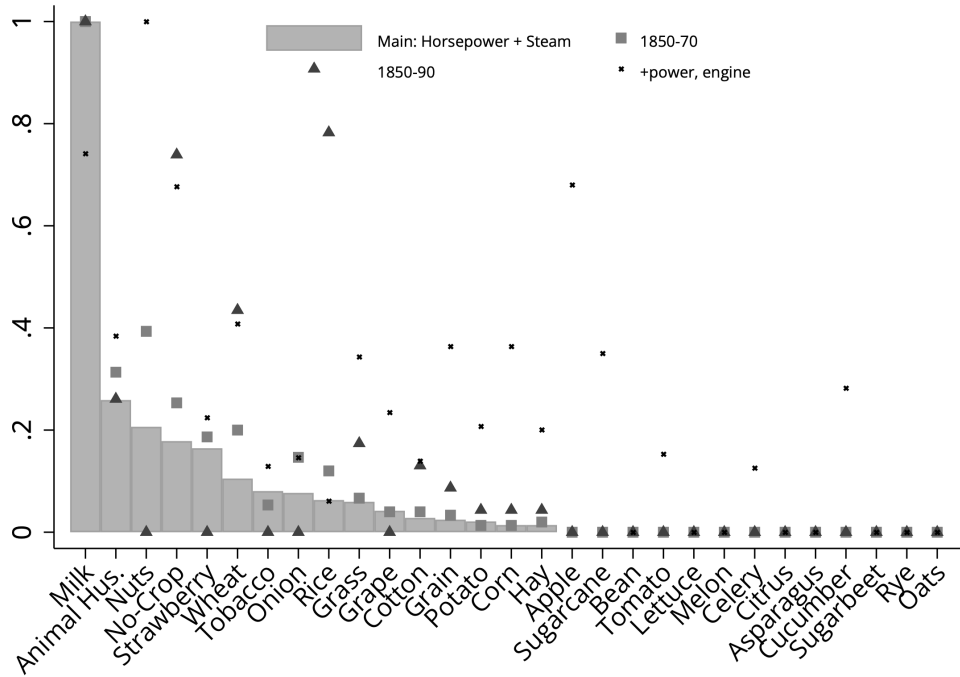
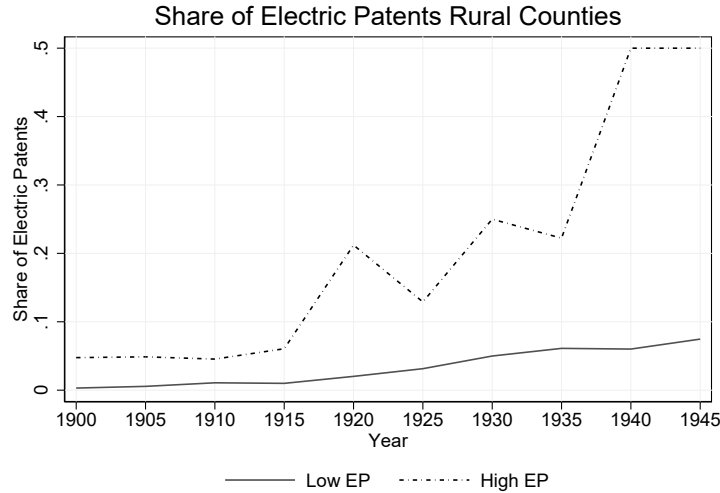


Figure 2 shows graphically how energy-intensity is correlated with electricity adoption by showing the fraction of patents mentioning the word “electr” for crops that are in the bottom and top half of the energy-intensity distribution. At the beginning of the twentieth century, very few patents were electricity-related, irrespective of the energy-intensity of the crop. As electricity spread to American farms, the fraction of patents that mentioned electricity remained very low for crops that were not very energy-intensive at the beginning of the period. However, for the most energy-intensive crops, the share increases steadily over the period, reaching 0.5 percentage points at the end of the period.

Figure 2: Share of electrical patents by Crop in Rural Counties



Note: This graph shows the share of patents in all rural counties by two groups of crops that mention the word “electr” every 5-years. The x-axis corresponds to the first year of each of the 5-years period.

We now formalize the link between energy-intensity and electricity-relevance. 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. We show this in Table 1 where we regress the fraction of patents at the national level that are electric for a given crop against our 1850-1905 energy-intensity measure. We use 1950-1970 since most American farms have been electrified by this period, implying that access to electricity is not driving these results but rather technical suitability. While this is a very simple regression where omitted variables could be a problem, we show that a crop that had one percent more mention of energy words before the arrival of electricity observed 0.2 to 0.3 percentage points higher use of the word electr in future agricultural patents. This suggests that our measure captures the technological likelihood that a crop will be able to benefit from electricity. We next use other versions of our energy-intensity measure changing either the type of words used or the time period over which the fraction of patents using them is computed. We find that the strong relationship continues irrespective of the way we measure energy intensity.

Table 1: Relationship between future electricity-intensity and past energy-intensity of a crop

	Fraction of patents electric		
	1950-1970 (1)	1950-1960 (2)	1960-1970 (3)
Energy intensity (horsepower and steam, 1850-1905)	0.284*** (0.085)	0.236*** (0.082)	0.319*** (0.097)
Energy intensity (adding power and engine, 1850-1905)	0.479** (0.190)	0.428** (0.177)	0.523** (0.218)
Energy intensity (horsepower and steam, 1850-1890)	2.792*** (0.683)	2.852*** (0.586)	2.971*** (0.805)
Energy intensity (horsepower and steam, 1850-1870)	9.172*** (3.975)	9.622*** (3.564)	9.225*** (4.608)
N	29	29	29

We next repeat this analysis, but using contemporaneous patents. However, because we are afraid of the geographic component we will use later being highly relevant, we will control for fixed effects by county in the following regression:

$$EP_{ict} = \beta energy_i + \theta_c + \theta_t + \epsilon_{ict} \quad (2)$$

Where EP_{ict} corresponds to the share of electrical 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 are county effects, θ_t are year effects. Standard errors are clustered at the county level. β measures the correlation between the crop energy intensity with the share of electrical patents for each crop, taking as fixed everything that is constant at the county level.

Table 2: Relationship between crop energy-intensity and the fraction of patents being electric

	Fraction of patents being electric		
	1850-1905 (1)	1850-1890 (2)	1850-1870 (3)
	Panel A: Horsepower and steam only		
Crop Energy Intensity	1.042*** (0.104)	1.736*** (0.164)	2.425*** (0.423)
	Panel B: Adding power and engine		
Crop Energy Intensity	0.253*** (0.038)	0.248*** (0.047)	-0.196 (0.123)
<i>N</i>	7457	7457	7457
Crop FE	No	No	No
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The table shows pooled OLS regressions for all the 5-years periods between 1910-1950 of specification (2). Each observation is a county-crop-year bin. It shows the correlation between the crop energy intensity (defined differently in each panel and using different years depending on the columns). Clustered standard errors by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 electrical patents for each crop from 1905-1950. A one percent higher use of energy words in patents for a given crop before the arrival of electricity leads to one more percent of patents being electric in that crop. This suggests that the share of energy patents pre-electricity is a good predictor of electricity adoption by crop once electricity arrives to American farms, even once controlling for elements that are specific to each location. We show that the correlation remains whether we use the full pre-electricity period or only some sub periods to calculate the energy-intensity of crops.

In Panel B, we use our broader definition of energy intensity, this time using also power and engine as words indicating energy. The coefficients fall as the range of this measure is wider than the one presented in Panel A. However, it continues to show a positive and significant correlation between crop energy intensity and the fraction of patents mentioning electricity when using the full pre-electricity period or at least 1850-1890. We do observe that the measure becomes weaker when using only the first 20 years of our dataset.

Panel A of Appendix Table A.3 shows that the relationship between crop energy intensity and the fraction of patents that are electric remains very significant over all 5-year periods of our analysis. In terms of magnitude, it is largest for 1940-1945 and then shrinks after that.

We see this as indicative that our measure of energy intensity properly captures differences across crops that were linked to the usefulness of electricity in the future.

3.4 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, 2024; 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 rural counties were close to a power plant, whilst in 1910-1915, only 32% of rural counties that were. 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 (2024) 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. 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 Kilovolts of capacity

We are able to show that proximity to power plants is correlated with more use of electricity on farms. To do so, we rely on the agricultural census data of 1930 which collected information on the use of electricity on American farms. We use the digitalized version of this dataset from Haines ICPSR data and in NHGIS. In [Table 3](#), we show that counties that are within 70km of a power plant have a higher fraction of farms reporting that they use electricity (around 6 percentage point) and that they have electric motors (2 percentage points). The fraction of farms reporting having motor trucks is also higher but by about 1 percentage point. Reassuringly, it is not correlated with all capital investments as the fraction of farms with tractors is smaller in counties that are within 70 km of a power plant. In panel B, we also show that counties closer to a power plant report a higher fraction of farm expenses on electricity by 0.5 percentage point, while the same is not true for other types of machines. We also find that counties that are close to a power plant have a higher number of electric motors and motor trucks per acre of farm land than those who are further away. However, we are careful in this interpretation because, without a control for county effects in these aggregate data, we cannot separate this effect from unobserved geographical conditions that could make hydropower more likely and also alter how agriculture is organized.

We repeat the suggestive evidence we presented by crop but this time differentiating between counties that are close and far from a power plant. We thus report the share of total patents in a group of crops (above and below the median in terms of energy intensity) and in a group of counties (within 70km of a power plant or not) that use the word “electr” in their text. We report this graphically in [Figure 4](#). The left-hand panel suggests that low energy-intensity crops have few patents being electric, irrespective of the location of the county relative to a power plant. However, for crops that have higher energy requirements, we observe, in the right-hand panel, that starting in 1915, a gap opens favoring counties that are closer to a power plant and remains until 1945. We use

Table 3: Correlation between proximity to a power plant and use of electricity on farms

	(1)	(2)	(3)	(4)
	Fraction of farms reporting...			
	Electricity	Electric motors	Motor trucks	Tractors
Within 70 km of power plant	0.058*** (0.005)	0.022*** (0.003)	0.014** (0.006)	-0.019** (0.008)
<i>N</i>	2595	2595	2595	2595
	Expenditure Share on		N. Machines by farm acre	
	Electricity	Machines	Electric motors	Motor trucks
Within 70 km of power plant	0.005*** (0.000)	-0.051*** (0.005)	0.424*** (0.038)	0.773*** (0.068)
<i>N</i>	2626	2626	2626	2626

Data from the Census of Agriculture 1930. Each observation is a county and the outcome is regressed on a dummy of whether the county is within 70km of a power plant in 1912.

the distance to 1935 power plants but similar results are obtained when using 1912.

Figure 4: Share of electric patents by energy-intensity and location

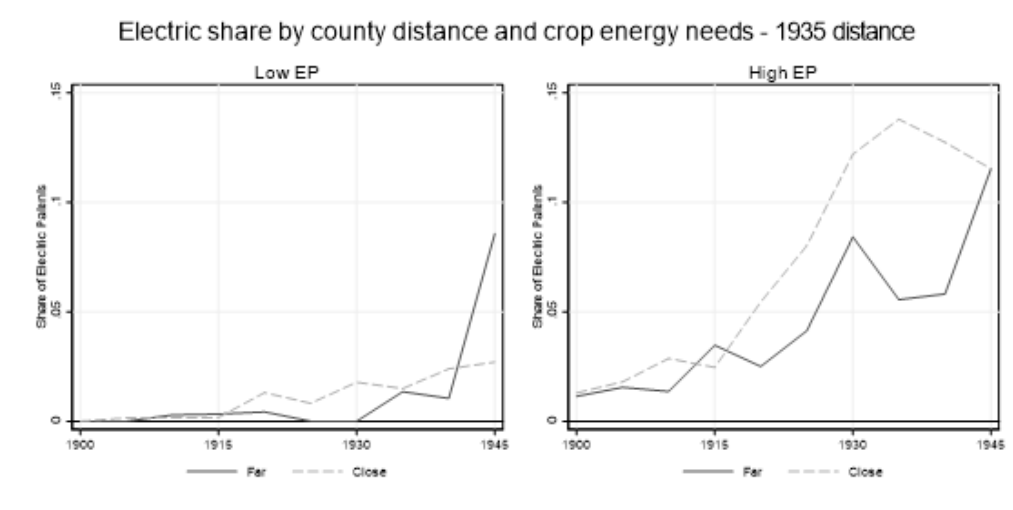


Figure 5: Note: Note: This graph shows the share of patents in all rural counties by two groups of crops that mention the word “electr” every 5-years by counties that are within 70km of a power plant in 1935 versus those that are further. The x-axis corresponds to the first year of each of the 5-years period.

We then ask more formally if counties that are closer to a power plant also see a higher fraction of their agricultural patents being electric. Columns (2) and (3) in Table 2 show the correlation between a dummy indicating the county being close to a power plant with the share of patents from

that county being electric, by estimating the following specification:

$$EP_{ict} = \beta dummy_close_c + \theta_i + \theta_t + \epsilon_{ict} \quad (3)$$

Where EP_{ict} corresponds to the share of electrical patents in each county-crop for each 5-year 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 effects and θ_t are year effects. Thus, β measures the correlation between the county’s closeness to the nearest power plant with the share of electrical patents for each county.

Table 4: Correlation between proximity to power plant and fraction of patents electric

	Share of patents that are electric					
	1912 (1)	1935 (2)	1912 (3)	1935 (4)	1910 (5)	1920 (6)
Within 70km of plant	0.014** (0.005)	0.015*** (0.005)				
Inverse Distance			0.004* (0.003)	0.008*** (0.003)		
Electric capacity					0.017*** (0.005)	0.009*** (0.002)
<i>N</i>	7971	7865	7971	7865	7971	7971
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table shows pooled OLS regressions for all the 5-years periods between 1910-1950 of specification (3). Each observation is a county-crop-year bin. It shows the correlation between the proximity to a power plant (defined differently and using different years depending on the columns). Clustered standard errors by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 electrical patents by county for different 5-year periods after 1910. Counties that are within 70km of a power plant in 1912 or in 1935 have 1 percentage point higher fraction of their patents being electric. Columns (3) and (4) 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 between proximity and electric patenting remains. The measure of electric capacity from Vidart (2024) shows a strong predictive power as well, whether measured in 1910 and 1920.

Panel B and C of Appendix Table A.3 explores the robustness of these correlations across the full period of analysis. We find that dividing the sample in separate years reduces substantially the statistical power that can be derived. Proximity to a power plant in 1912 or 1935 tends to be a good

predictor between 1920 and 1945 but is less accurate before and after those time periods.

Overall, we see this analysis as indicative that proximity to a power plant appears to properly identify counties in which farms were able to employ electricity.

4 Agricultural inputs, output and productivity

Having shown that there is a fruitful source of variation in energy intensity by crop and proximity to hydro power by county, we now turn to measuring the impact of having electricity on agricultural outcomes, as presented in our first proposition. According to this, we should observe that, in response to a higher availability of electricity in counties, crops that are more intensive in energy should see an increase in the inputs dedicated to them, higher production and finally, potentially higher productivity.

If all our crops were planted and sown, it would be simple to use crop acreage as a measure of intensity. However, this is not the case as some of our crops include cattle or fruit trees. We thus turn to an alternative method to measure how the intensity of production changed over time. In our first measure, we use the change between 1900 and later years in the raw acreage, number of trees planted or number of animals held in each county. Because this does not have a unit, we explore changes in percentage terms and in log terms instead.

However, to increase the comparability, we also derive a measure of predicted value of output based on the choice of inputs. This allows us to have a fixed unit which is dollars. We continue to use change in levels, percentage, and log terms to facilitate the comparison with the input based measures.

Table 5 shows in the top panel the impact of being close to a power plant and being a crop that is intensive in energy on the level of inputs used for that crop (acreage sown, trees planted or number of animals). Results indicate a very strong positive relationship between availability of electricity and expansion of crops that are more energy intensive. This is the case when we use the change in level, the change in percentage term and the change in logs. A one percentage point increase in energy intensity leads to 55 more acres/trees, etc, in counties that were close to a power plant than those that were not. This translates into a 166 percentage higher increase in inputs compared to 1900. Once we use the log approximation and include all the zeros, we find that crops that were 1 percentage point more energy intensive saw their inputs increase in 0.46 percentage points when they were close to a power plant than when they were not.

This panel has the problem that we do not have a common unit of measure between crops. Panel B replicates the same regression, but this time, the acreage, the number of trees, or the number of animals is transformed into a predicted value of products. Using that as a measure of inputs, we observe that crops that are more energy intensive saw their predicted output value grow more over this period when they were in a county that was close to a power plant. The difference is not small with a one percent higher energy intensity leading to USD 4,000 higher predicted output value or about 33 percent of the 1900 value.

Table 5: Impact of electricity availability on crop intensity and productivity

	(1)	(2)	(3)
	Δ level	$\Delta\%$	$\Delta \text{Log}(1+x)$
Panel A: Product Acreage / Trees / Animals			
Energy Intensity \times Proximity	5518.076***	166.817**	0.461***
	(1734.536)	(80.187)	(0.089)
Crop, Cnty, Yr FE	Yes	Yes	Yes
N	149777	104045	149777
Panel B: Estimated output value			
Energy Intensity \times Proximity	363302.105***	22.900	0.714***
	(44874.338)	(19.908)	(0.117)
Crop, Cnty, Yr FE	Yes	Yes	Yes
N	86713	75168	86713
Panel C: Value of output per worker			
County Energy Intensity 1900 \times Proximity	16779.589***	7.229***	3.678***
	(4076.621)	(1.765)	(0.791)
Crop, Cnty, Yr FE	Yes	Yes	Yes
N	7840	7840	7840

Farms in geographical locations that got access to electricity expanded their production of crops that could benefit more from its application. Is this because farms got into new types of crops or simply because they became more intensive in crops where they were already producing? We check this by interacting our double-interaction with a dummy for whether the county was specialized in that crop in 1900, implying that at least 10 percent of its output was from that crop. Results are presented in Appendix Table A.4. It shows that in Panel A, it is less clear whether the expansion of production is concentrated in crops where the county was previously specialized. This may be because the unit of measures of some crops are very different than others. In Panel B, once we correct for this measurement variance, we find that the expansion is concentrated in sectors where the county had experience. This suggests that it is not random which energy-intensive crops are pushed forward once electricity arrives but that it depends on the suitability of the climate and soil and the experience that the county has in its cultivation. Our results thus indicate that proposition 1 is fulfilled.

If farms in counties that got access to electricity started focusing on crops that could benefit more from electricity, and those crops become more productive because of the arrival of electricity, we should expect an increase in output per worker. Panel C of Table 5 tests this formally. In order to

not include the endogenous shift in crop choice we documented before, we construct the measure of crop energy intensity in 1900 which is our base year. We are thus asking whether counties that became connected to the grid gained more in productivity when their crop mix was originally more favorable to the use of energy. The results in Panel C demonstrate that this is clearly the case, irrespective of the way we measure the increase in productivity. Thus, the higher productivity brought about by electricity to American farms that was already documented by [Lewis and Severnini \(2017\)](#) was not uniform. It particularly benefited counties that were better suited for energy-intensive crops in 1900.

5 Directed Technological Change

Having shown that farms responded to the arrival of electricity by focusing on crops that could benefit more heavily from them, we now asked whether this motivated inventors to also focus their invention towards those crops, as predicted by proposition 2. We then test whether these innovations are factor-biased, as suggested by proposition 3.

5.1 Evidence of product-biased innovation

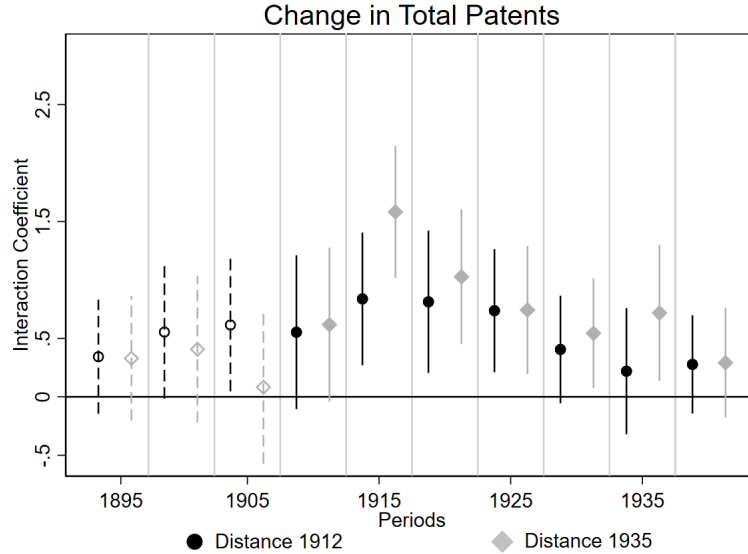
This section presents the results from the main specification in (1) on a balanced panel of county-crops where there is at least one patent in that cell over the full period.⁶ For each of the 5-years periods between 1910 and 1950 we estimate the coefficient of interest using the dummy that indicates if a county is less than 70km away from the nearest power plant - for both measures in 1912 and 1935.

We first estimate the impact of access to electricity on total patenting by crop and county. We report the coefficient and its 90% confidence interval for each year in [Figure 7](#). Each estimate corresponds to the effect in each of the 5-years period between 1895 and 1950. The estimates in black are obtained using the distance in 1912, whilst the ones in gray use the distance in 1935. We find that for a crop that is one percent more energy-intensive before the arrival of electricity observes 0.5 to 1.5 more patents than in 1890 when it is in a location that is within 70km of a power plant than when it is not. This interaction is statistically significant between 1915 and 1925 for the power plants established by 1912 and between 1915 and 1935 for those established by 1935. While one more patent may appear to be a limited impact, for the average change in the number of patents in a crop-county cell is only about 0.133. It is thus a very significant impact on patenting in each period. While it is not clear that any period is “pre-treatment” as many power plants in 1912 may have existed by 1895 or 1900 and similarly for 1935, we find less evidence of a difference across counties and crops in years before 1905, in particular for the 1935 power plants. This suggests that patenting activity responded to incentives generated by the increased intensity of some crops in counties that

⁶We were unable to get convergence for models where we added all cells with zeros. Results presented in [Appendix Table A.5](#) suggest that our interaction does not predict that a county-crop cell would have at least one patent before 1890 but yes for the period afterwards. This would thus suggest that our results are, in anything, an underestimate of what we would find if we added all cells where no patents were ever generated.

received electricity.

Figure 6: Effect of electricity local availability on agricultural 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 electrical patents compared to the total number of electrical 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.

In Appendix Figure A.1, we show the same figure but this time using the logarithm of the inverse distance. We see a similar pattern with crops being 1 percentage point more energy-intensive seeing 0.005 more patents when they are in a location that is 1 percent closer to a power plant.

We repeat the same exercise this time using electricity capacity from Vidart (2021). We observe a very similar pattern, as shown in Appendix Figure A.2.

Because the regressions presented in the previous figures allow for crop and county-specific fixed effects to differ every year, this specification is relatively costly in terms of statistical power. We thus next 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 restrict the sample to 1920 onwards as the effects appear to begin strongly after that date. It is also consistent 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.

By pooling all years, we also exploit more directly the change in access to electricity between 1912 and 1935. While most counties expand their access during this period, there are a few counties where 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.

Table 6 shows that, on average, being close to a power plant has a positive and significant effect

on total agricultural innovation in the 1900s in the U.S. differentially by a crop’s energy intensity. A one percentage point increase on the crop energy-intensity increases the total number of electrical patents by 0.004 patents more if the crop is harvested in a county that is closer to a power plant than if it is further away (column 1). This change corresponds to almost 3% increase compared to the 0.133 average total patents per county-crop in counties that are further than 70km from a power plant. For further context, comparing animal husbandry (one of the highest) with hay (the least energy-intensive that never mentioned the words related to energy use) would imply a difference of almost 0.03 patents or about 20 percent of the baseline mean.

Table 6: Change in number of patents by 5-year periods relative to 1890-1895

	Change in total patents			Change in electric patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Within 70km of a plant × Energy Intensity _{1850–1905}	0.393** (0.186)			0.178*** (0.045)		
Log Inv. Dist. to nearest plant × Energy Intensity _{1850–1905}		0.298*** (0.102)			0.064** (0.026)	
Electrical capacity × Energy Intensity _{1850–1905}			0.212** (0.087)			0.113*** (0.030)
Mean number of patents in counties far away		0.133			0.006	
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	60528	60528	60846	60528	60528	60846

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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.

Column (2) repeats the same exercise but using a continuous measure of distance to the nearest power plant - measured as the log of the inverse of the distance. We see that for crops that have the same energy-intensity, being patented in a county that is 1 log point closer to a power plant increases the number of total patents in around 0.298 per unit increase in energy intensity.

Column (3) estimates the impact of local availability of electricity by utilizing the county’s electrical capacity data [Vidart \(2024\)](#) 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 electrical patents.

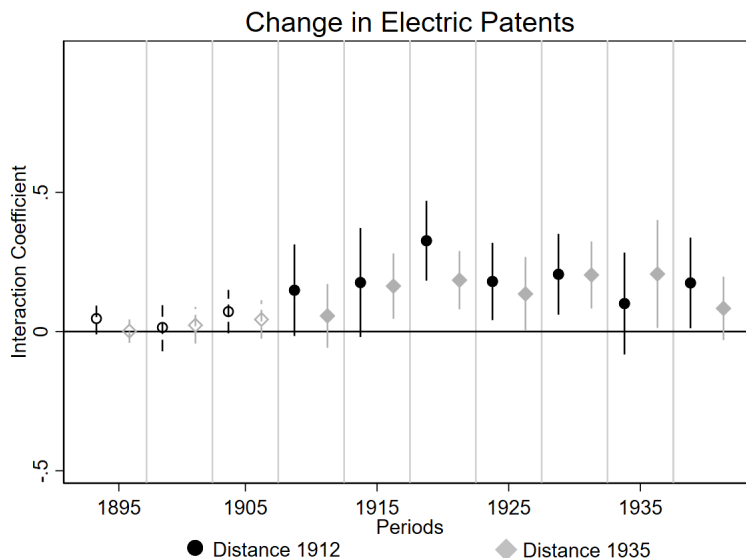
These results are consistent with the second proposition of our model. An increased availability of electricity generates more effort towards innovation in crops that are more suitable for its use.

5.2 Evidence of factor-biased innovation

We thus have so far demonstrated that incentives for innovation for crop that were more intensive in energy before the arrival of electricity increased when electricity became available. Proposition 3 states that this innovation may be biased towards energy when electricity is relatively cheap compared to labor.

We thus explore whether the new innovations are particularly focused on electricity or not. We first present the estimates on the change in the number of electrical patents in Figure 7. When we look at the change in the number of electrical patents, we see that a 1% increase in the crop energy intensity increases the number of electrical patents by around 0.003 patents if the patenting of these crops happens in counties that are close to a power plant. The estimates are precise 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 0.02 more electrical patents related to animal husbandry (7.4% energy intensive) compared to those related to hay (0.04% energy intensive) compared to a county without a power plant close by. While this number is small, we must consider that very few patents are electric and that the average change for a county more than 70km away was only 0.006, making our effect size very big compared to the average. The estimates that are dashed show that there are no pre-trends as there is no significant effect for electrical patents before 1910 since very few rural countries had access to electricity before this year. This suggests that the increased patenting in crops that were more energy intensive compared to those that were less energy intensive once electricity became available was in part visible in patents that exploited electricity.

Figure 7: 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 electrical patents compared to the total number of electrical 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 A.3 show the same specification with the continuous measure of distance, using the logarithm of the inverse of the distance for both years. 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.

Appendix Figure A.4 shows the change in total number of electrical patents obtained from utilizing the county’s electrical capacity data from Vidart (2024). 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.

We next turn to the last three columns of Table 6 where we repeat the pooled OLS analysis but this time restricting ourselves to patents that use the word “electr”. We see that about half of the increase in total patents observed in column (1) comes from patents that are electric. This corresponds to a 30-time increase compared to the mean change in electric patent for a county further

than 70 km away.

When using the inverse distance, we observe that the increase in electric patents correspond to about a quarter of the increase in total patents. It is still 10 times the average change for a county that is far away from a power plant. Finally, when using Vidart’s measure of energy intensity, we observe again that about half of the new patents are electric. This suggests that the overall increase in patenting observed in crops that were more energy intensive when close to a power point was disproportionately concentrated into patents that mentioned the word electricity.

However, mentioning the exact word for electricity may be a very restrictive way of focusing on patents that could use electricity. We thus explore two alternatives.

First, we search for a large number of action words that were the most often mentioned in patents.

In Panel A of Table 7, we divide these action words as “pre-harvest”, “post-harvest” and without any action words. We consider that post-harvest activities are the most likely to be suitable for electrification as many of these activities are conducted in the barn or close to the farm house where electricity is available. Results presented in Panel A suggest that all of the increase in total patents documented previously are due to patents related to post-harvest activities. This appears to suggest that the new patents were biased towards energy-related tasks even when not including the word electric. This highlights the potential complementarities between electric and non-electric patents within energy-potentiating activities. When restricting our attention to electricity-related patents in columns (3) and (4), we observe that the majority of new electric patents were also in post-harvest activities, emphasizing that our measure of post-harvest activities is where electricity was most useful.

Table 7: Change in the number of patents by agricultural steps

	Δ Total patents		Δ Electricity-related patents	
	(1)	(2)	(3)	(4)
Panel A: By pre- or post-harvest				
	Post-Harvest	Pre-Harvest	Post-Harvest	Pre-Harvest
Proximity \times Energy Intensity	0.326** (0.129)	0.001 (0.088)	0.109*** (0.030)	0.040** (0.019)
Mean number of patents for counties more than 70km away	0.079	0.034	0.004	0.001
Panel B: By use in electricity ads				
	Advertised Uses	Other uses	Advertised Uses	Other uses
Proximity \times Energy Intensity	0.474*** (0.136)	-0.055 (0.117)	0.134*** (0.040)	0.041*** (0.013)
Mean number of patents for counties more than 70km away	0.057	0.046	0.004	0.002
N	60528	60528	60528	60528
Crop FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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. Advertised uses are those that mention the words heat, cool, separate, thresh, clean, pump, extract, grind, provide, hoist, cut and mow. Post-harvest includes harvest, store, thresh, winnow, cool, grind, heat, cut, hoist, clip, load, separate, trim, hitch, cultivate, hive, extract, pack, wrap, pull, brooder, lift and elevate. Pre-harvest includes plow, harrow, irrigate, fertilize, sow, mow, pump, feed, protect, dig, scrape, spread, prune, drill and water.

To explore this in more detail, we used contemporaneous publicity made by the local electric companies or the rural electrification administration that detailed the use that electricity could provide on a farm. We then classified steps into a group that was mentioned by the publicity and those that were not. We include these pictures in Appendix Figures B.5, B.6 and B.7. Specifically, these indicate that electricity was particularly relevant in helping to heat, cool, separate, thresh,

clean, pump, extract, grind, provide, hoist, cut and mow. We thus separate patents by whether they mention any of these words or they do not. Results are presented in Panel B of Table 7. What it shows is almost the same pattern as in Panel A. The increase in total patents was entirely due to patents that mentioned the advertised uses of electricity, even if they did not mention electricity. We also see that the increase in electric patenting was stronger when those patents mentioned the steps included in electricity publicity. This strengthens our argument that patenting responded to local availability of cheap electricity in crops where it could be more productive, particularly developing electric or energy-related patents.

5.3 Robustness Checks

In this section, we explore whether the results are driven by certain type of counties or crops, whether it may be altered by confounding factors and whether the new patents are only marginal innovations.

We focus on electric patents because it corresponds to a sizable share of new innovation and is very different from that of counties without access to electricity. We also show the same robustness exercise for total patents in Appendix Table A.6, that for post-harvest patents in Appendix Table A.8 and those for advertised use patents in Appendix Table A.7. We will refer to the differences in those tables below.

Table 8 presents the estimated effect of local availability of electricity on electric rural agricultural innovation under specification (1), and for different robustness checks.

Different specifications. Panel A explores the robustness of our results to changes in specification of our model. First, we include the number of electric patents in the base period as a control. We find that the coefficient does not change at all. We next change the base period to 1850-1855 instead of 1890-1895. Since there are almost no electric patents in either period, results are almost identical. We next change the clustering by county and instead use county*crop clusters and find no difference. Finally, we also include county*year fixed effects to capture any county-specific elements that could influence the patenting intensity for all crops. We find that the coefficient increases a bit and remains very statistically significant and large compared to the average number of patents. For total patents, we observe a bit more sensitivity in terms of coefficients than for electric patents but the significance is not altered by any of these changes. Results for our other proxies of electric patents (post-harvest or advertised uses) are extremely similar to those mentioning electricity directly.

Table 8: Robustness Checks

Δ Electrical patents				
<i>Panel A: Alternative specifications</i>				
	Base year control	Diff. base period	County-crop clusters	County-year FE
Within 70km of a plant \times	0.184***	0.184***	0.178***	0.188***
Crop Energy Intensity	(0.044)	(0.044)	(0.042)	(0.046)
<i>N</i>	60528	60528	60528	58521
<i>Panel B: Geographical issues</i>				
	Excl. outliers	Excl. close	Excl. far	Excl. dustbowl
Within 70km of a plant \times	0.152***	0.209***	0.168***	0.209***
Crop Energy Intensity	(0.038)	(0.047)	(0.045)	(0.067)
<i>N</i>	59989	49050	57909	32241
<i>Panel C: Crop issues I</i>				
	Excl. outliers	Share E2 1850-70	Share E1 1850-90	Excl. animal
Within 70km of a plant \times	0.178***	0.509**	0.053**	0.135***
Crop Energy Intensity	(0.045)	(0.209)	(0.024)	(0.042)
<i>N</i>	60528	60528	60528	53184
<i>Panel D: Crop issues II</i>				
	Excl. No-crop	Only large groups	Grouping marg.	Group by ICC
Within 70km of a plant \times	0.205***	0.181***	0.199***	0.200***
Crop Energy Intensity	(0.041)	(0.037)	(0.037)	(0.037)
<i>N</i>	53,316	51,648	61,626	62,736
<i>Panel E: Different outcome</i>				
	Water patents			
Within 70km of a plant \times	0.110			
Crop Energy Intensity	(0.069)			
<i>N</i>	60,528			

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 electrical patents relative to 1890-1895 - except for the second column of Panel A that changes the base period to 1850-1855 and in Panel E where it is the patents that mention the word “water”. 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.

Geographical variations. In Panel B, we explore issues related to geography. In the first column, we eliminate counties that have at least 10 patents over the period. 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 in these counties it could be the case that these are also more likely to adopt new technologies. We see that the effect is slightly lower when eliminating these counties, but it is still significant and economically important. We next exclude counties that are within 20km of a power plant, basically excluding counties that have a power plant inside their boundaries. Despite the sizable reduction in sample size, we continue to see a very statistically significant and similar in magnitude effect. The next column excludes counties that were never within 300km of a power plant over the period. The coefficient shrinks a bit continues to be very

statistically significant. Finally, we exclude states that were classified by [Hornbeck \(2012\)](#) as having lost more than 50 percent of their topsoil during the Dust Bowl to make sure that our results are not driven by those counties. Results are almost identical in terms of coefficient size and significance, despite the large decrease in sample size. Results when using other proxies of electric patents are very similar and very robust to the exclusion of some specific types of counties. For total patents, we see that while the coefficients are not affected, the standard errors increase with these exclusions, decreasing the significance of the results in many cases.

Crop issues. The next two panels look at whether differences in terms of crops can explain our results. We start by excluding the four crops that have the most patents in each 5-years period. We find that this does little to alter our results. In the next column of Panel C, we use our second measure of energy-intensity for the same time period. We continue to find that an increase in the energy intensity leads to more electric patenting when one is closer to a power plant. A similar message is obtained when using energy-intensity but employing only patents between 1850 and 1890. We next exclude animal husbandry patents from the analysis. Although the coefficient shrinks a bit, the significance is unaltered. Something similar happens when we exclude patents to which we cannot assign a crop. The last 3 columns of Panel D group crops instead of using each crop independently as we have done so far. In the first case, we only keep crops that have more than XXX patents. We find a very similar result. We next group all of those small crops into one big mixed category and see almost no difference in terms of size and precision, indicating that those patents do not play a role in our analysis. Finally, we group patents by ICC category instead and repeat the analysis. We find almost identical results. The same type of robustness is shown for other ways of classifying patents as related to electricity. We do find that total patents are less robust to the exclusion of some crops or a change in our definition of energy-intensity.

Because of milk is such an outlier in our measure of energy intensity, we show, in [Appendix A.9](#), that results for electric patents are robust to the exclusion of milk patents. Without milk, the coefficient in column (1) becomes 0.195, which is very similar to our baseline results. Dropping milk, however, does weaken the impact of electricity on total patenting. For the dummy of closeness to a power plant, the impact of electricity is now null. For the other two measures of access to electricity, we find that the coefficients are not so much altered but the significance falls.

Water-related patents. Finally, Panel E estimates the same specification 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.

Overall, we argue that impact of electricity on the generation of electric patents in crops that could benefit from electricity is very robust to a number of elements. The increase in total patents is a bit more dependent on the inclusion of all geographical areas and crops.

Finally, one could be worried that the increase in patents we document is driven by marginal patents with little impact. As a measure of importance of these patents, we use the future number of citations of the specific patent to proxy how this invention influenced future innovations. Table 9 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, of the 0.4 total additional patents reported in Table 6, we observe that about 0.2 of them had more than 5 cites and 0.1 of them, more than 10 cites. This suggests that the increase in total patents was in part driven by patents that were cited often in future periods. Electrical patents that were widely cited in the future increased in 0.05 patents per county-crop, representing a 25% of the average total increase in electrical patents due to having access to cheaper electricity. This result is robust to using the log inverse distance to power plant. Therefore, cheaper electricity induced a generation of new electrical patents that were important and influenced future innovations. Whilst the overall number of non-electrical patents was unchanged, there is an increase in the importance of the non-electric innovations that were still taking place. This is suggestive that for patents that do not include mentions of electricity, there may have been a decrease in marginal patents, leading to a significant increase in patents that are more widely cited.

Table 9: Change in the number of patents with more than 10 and 5 cites

	More than 10 cites		More than 5 cites	
	Total (1)	Electric (2)	Total (3)	Electric (4)
Energy Intensity \times Within 70km	0.118*** (0.029)	0.032*** (0.010)	0.228*** (0.058)	0.072*** (0.017)
Mean number of patents for counties more than 70km away	0.009	0.001	0.027	0.002
Crop, Cnty, Yr FE	Yes	Yes	Yes	Yes
<i>N</i>	60528	60528	60528	60528

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.4 Heterogeneity by cost

We have thus found evidence that in response to the arrival of electricity, crops that could benefit more from its arrival expanded. In response to this, innovation also increased in those crops, particularly in tasks and activities where electricity could be useful.

Proposition 4 then suggests that this should be larger whenever the marginal cost of innovation is lower. We study this by looking at different proxies of costs. Given that we have so far found a higher proportional impact on electric innovation, we continue to focus on those in that section. This would thus require us to find sources of heterogeneity in marginal cost of producing electric innovations.

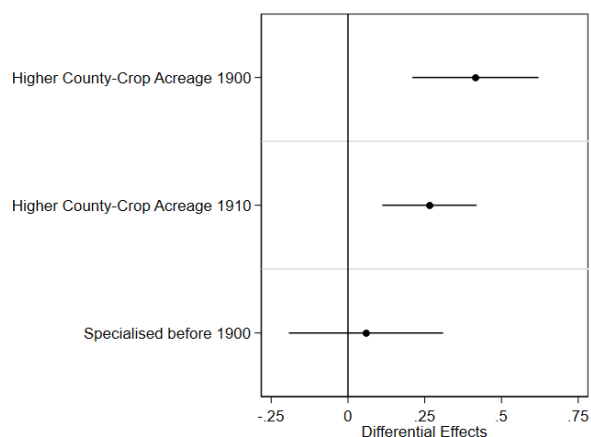
5.4.1 By previous specialization

The cost of innovation is likely to be lower in crops that were previously known to the local agricultural community. Electric patents about tomatoes would be more costly to emerge in a region famous for cotton.

We use data from the 1900 and 1910 U.S. Agricultural Census to understand county-crop specialization and the county's market value. First, we compare counties that are specialized in a specific type of crop, with those that are not. To determine specialized counties, we compare county-crops that have more than 40% of total county's farm acreage to those that do not. Finally, we define some counties as specialized innovation-wise as well by looking at counties-crop where the share of all patents before 1900 that were from a given crop were more than half of the patenting activity.

Figure 8 presents the estimates on the change in electrical patents for all the comparisons mentioned above. We find that being specialized in a crop in terms of acreage in either 1900 or 1910 significantly increases the number of electric patents generated with the arrival of electricity. The effect is not small since we observe 0.3 to 0.4 additional patents, which is much larger than the main effect estimated in Table 6. This suggests that the increase in electric patenting did occur in locations that already had significant knowledge of a given crop. However, we do not observe that counties that were specialized in terms of patenting responded more to the arrival of electricity. This may indicate that the main source of variation from this is not existing knowledge of patenting but rather that the crop could expand in response to the arrival of electricity. While not reported here, we find no evidence of heterogeneity when looking at total patenting.

Figure 8: Change in electrical innovation depending on local knowledge of specific crops



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 electrical 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.

5.4.2 By characteristics of the inventors

Next, we may think that some inventors face a lower cost of innovation than others. We thus examine the changes in the composition of inventors once counties have access to cheaper electricity. Older inventors may have more knowledge of a given crop but may face substantial costs of adapting to a new technology. Overall, 66% of the new electrical patents were developed by new inventors. Similarly, assigned patents may benefit from the sponsor's input which reduces the cost of innovation but may not be embracing the technological change as quickly as individual researchers. In 1915, only about 10% of electrical patents were assigned by businesses. However, over the following decades, there was a substantial increase in the utilization of this method of patenting.

We run the same specification in (1), but using the change in the number of patents by different types of inventors. Table 10 shows the results for total patents in Panel A and electric patents in Panel B. Columns (1) and (2) correspond 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. Columns (3) and (4) differentiate the change in total patents depending on whether the patent was assigned to a third entity or not. Results indicate that the increase in total innovation in response to the arrival of electricity mostly occurred through old inventors and assigned patents. The coefficient for new inventors is much smaller, while that of non-assigned patents is somewhat similar in size but much less precisely estimated.

A very different conclusion arises when looking at electric inventions. Both new and old inventors contributed similarly to the generation of these new patents in response to the arrival of electricity. Non-assigned patents were a bit more responsive than assigned patents. This suggests that non-electric inventions in crops that benefited from electricity were mostly generated by old and business-backed inventors. But for electric inventions where the marginal cost of innovating may have been higher for these more traditional inventors, we see that new agents of innovation entered into the market.

Finally, we can exploit the matched Census data and ask whether inventors that responded to the arrival of electricity are different than those in crops that are less intensive in energy and counties that do not get connected to power plants. We use the characteristic of the inventors as our dependent variable and run equation (1) on that dependent variable. We find, in Appendix Table A.10, only one difference in all of the measured characteristics between those innovating in crops that are more energy-intensive and less in locations close or far to power plants. Inventors for these additional patents generated by the arrival of electricity were less likely to be living in rural areas of the rural counties in our sample. All the other coefficients are relatively noisy.

Overall, we see this as indicative that the arrival of electricity did not change the identity of the inventors for general patents but that of electric inventors may have been modified towards newer and individually-motivated inventors.

Table 10: Innovations by type of inventors

	(1)	(2)	(3)	(4)
	Old inventors	New inventors	Assigned	Non-Assigned
Panel A: Total inventions				
Proximity \times	0.291***	0.072	0.213***	0.180
Energy Intensity	(0.105)	(0.138)	(0.077)	(0.168)
Mean number of patents for counties more than 70km away	0.034	0.099	0.024	0.109
Panel B: Electric inventions				
Proximity \times	0.087***	0.091***	0.063**	0.115***
Energy Intensity	(0.027)	(0.030)	(0.026)	(0.033)
Mean number of patents for counties more than 70km away	0.001	0.005	0.001	0.005
Crop, Cnty, Yr FE	Yes	Yes	Yes	Yes
<i>N</i>	60528	60528	60528	60528

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.4.3 By existing infrastructure

Was electric innovation potentiated by the presence of some characteristics at the local level?

It could be that electric innovation particularly required access to capital and credit. We thus 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.

We also look at human capital. It could be that electric inventions required specialized knowledge that made human capital particularly valuable. We explore this by using data on a variety of measures: experiment stations (obtained from [Kantor and Whalley, 2019](#)), number of engineers (as in [Maloney and Caicedo, 2022](#)), and fraction of the population with college education. The last measure is problematic because we can only measure it in 1940, once electricity has already been spreading through our counties, but we have no alternative source of data.

The results, presented in [Table 11](#), indicate that controlling for either of these factors does not affect our main impact: counties with access to cheaper electricity generated more electrical patents in crops that were initially more energy intensive, even when controlling for human capital measures. Furthermore, we find no added benefit of experiment stations, engineering tradition or college-educated population. Similar results are presented for the change in patents that mention actions that were included in electricity ads and those related to post-harvest activities in [Appendix Table A.11](#).

Overall these results suggest that agricultural patenting generated by the arrival of electricity was not enabled by existing human capital structures, maybe because, as we detailed before, most

inventors were not highly skilled themselves.

Table 11: Interaction effects with human capital

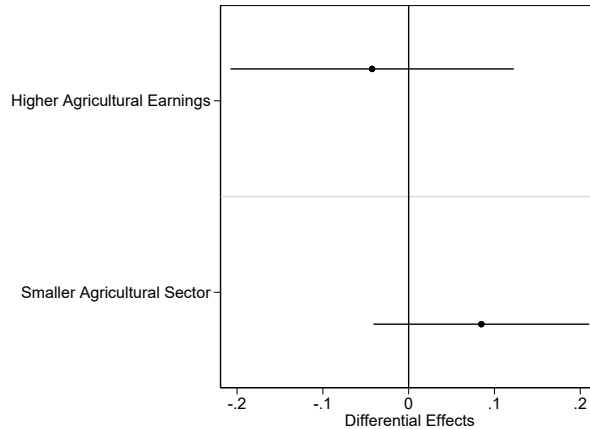
	(1)	(2)	(3)
	Dependent Variable: Electrical Patents		
<i>Variable capturing human capital:</i>	Experimental Stations	Engineers	College Share (Rural)
Proximity × Energy Intensity	0.176*** (0.045)	0.154*** (0.053)	0.371** (0.146)
Energy Intensity × <i>Variable</i>	0.032 (0.384)	0.000 (0.001)	0.036 (0.062)
Proximity × Energy Intensity × <i>Variable</i>	0.739 (0.761)	0.000 (0.001)	0.129 (0.091)
Crop, Cnty, Yr FE	Yes	Yes	Yes
<i>N</i>	60,528	53,199	60,480

5.4.4 By factor costs

Finally, we may think that facing higher costs of energy or labor could be relevant. However, our model assumes that we are in the cone of diversification and thus that there is factor price equalization across geographical unit. Nevertheless, in Proposition 3, we show that innovation could be more energy-biased when wages were initially higher. We use the 1930 U.S. Agricultural Census to understand each county’s agricultural labor market, in order to understand differences in agricultural labor 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. Furthermore, we compare the effect in counties that have an agricultural sector that employs more than 40% of the county’s labor force relative to those that have a smaller agricultural labor market. The latter could indicate a lower supply of agricultural labor force, hence the agricultural wages are probably higher.

Figure 9 presents estimates of the change in electrical patents for counties with greater relative wages, as proxied directly by earnings or by the size of the agricultural sector. We find no evidence that higher wages led to more or less electric patents. The coefficient is negative for counties with higher agricultural earnings and positive for those with smaller agricultural sector but neither are statistically significant.

Figure 9: Change in electrical patents by wage levels



Notes: 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 electrical 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.

6 Conclusion

Traditional studies of directed technological change have emphasized that a change in endowment of a factor can bias innovation towards that factor but this is assuming that sectors and factors are identical. We study the impact of the arrival of electricity on agricultural innovation relaxing that assumption and show that we should anticipate sector-biased more than factor-biased innovations. We show empirically that this is true by contrasting innovation in energy-intensive crops versus less energy-intensive ones, in counties that obtain access to electricity compared to those who do not. We also show that within the innovation targeting energy-intensive products, a substantial fraction were electric or connected to tasks where electricity could be used. These patents were widely cited in the future suggesting more than simply marginal innovations. Finally, we also show that new electric patents arose in places that already had agricultural (but not necessarily patenting) experiences in those crops; that they were more likely to be led by new and individually-motivated inventors; and that there seems to be limited role for experimental stations, high-skill workers or wage levels.

Innovation thus responded to local incentives in this context because sectors that could benefit from electricity also expanded. This suggests that studies that have so far focused on the county-level impact of the arrival of electricity in rural counties (Vidart, 2024; Kitchens and Fishback, 2015; Lewis and Severnini, 2017) may abstract from substantial differences across the type of products within each geographical zone.

While our context is historical, it suggests that local shocks can influence innovation when either innovators are local or when they perceive benefits from selling to local producers. This is relevant, for example, in the current context of exploration of new sources of energies that have geographical

components (green hydrogen, solar-powered electricity, etc). We leave to further research exploring these types of shocks in contexts where innovation may be less local like in the manufacturing sector.

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A Additional tables and figures

Table A.1: Descriptive statistics of inventors from Census

	Sample 1		Sample 2	
	Mean	SD	Mean	SD
Age	43.752	14.448	44.119	14.134
Foreign-born	0.127	0.333	0.121	0.326
Foreign-born or second-generation	0.313	0.464	0.307	0.461
Does not live in their birth state	0.510	0.500	0.489	0.500
Rural	0.696	0.460	0.679	0.467
Can read and write	0.885	0.319	0.886	0.318
Average years of education (only 1940)	10.199	3.479	10.181	3.472
Farm owners	0.316	0.465	0.314	0.464
All farmers	0.388	0.487	0.374	0.484
Craftsmen	0.148	0.355	0.151	0.358
Engineers	0.013	0.114	0.015	0.121
Electrical engineers	0.000	0.022	0.001	0.024
Occscore	21.357	14.246	21.751	14.335
N	12823		14078	

Table A.2: Ranking of crops the highest energy needs in 1850-1905

Crop	Main Energy Need Measure	Alternative Measures for Energy Needs				Proportion of Patents in 1910-1940
	<i>Share Energy 2</i>	<i>Share Energy 2</i>	<i>Share Energy 2</i>	<i>Share Energy</i>		
	<i>1850-1905</i>	<i>1850-1890</i>	<i>1850-1870</i>	<i>1850-1890</i>		
Milk	0.286	0.150	0.023	0.218	1.34%	
Animal husbandry	0.074	0.047	0.006	0.113	16.06%	
Nuts	0.059	0.059	0	0.294	0.20%	
No-Crop	0.051	0.038	0.017	0.199	29.80%	
Strawberry	0.047	0.028	0	0.066	0.40%	
Wheat	0.030	0.030	0.010	0.120	0.50%	
Tobacco	0.023	0.008	0	0.038	0.43%	
Onion	0.022	0.022	0	0.043	0.56%	
Rice	0.018	0.018	0.018	0.018	0.27%	
Grass	0.017	0.010	0.004	0.101	7.92%	
Grape	0.012	0.006	0	0.069	2.78%	
Cotton	0.008	0.006	0.003	0.041	7.19%	
Grain	0.007	0.005	0.002	0.107	9.37%	
Potato	0.006	0.002	0.001	0.061	2.80%	
Corn	0.004	0.003	0.001	0.059	11.51%	
Hay	0.004	0.002	0.001	0.107	5.82%	
Apple	0	0	0	0.045	0.37%	
Asparagus	0	0	0	0	0.14%	
Bean	0	0	0	0.083	1.28%	
Celery	0	0	0	0	0.13%	
Citrus	0	0	0	0	0.19%	
Cucumber	0	0	0	0.200	0.03%	
Lettuce	0	0	0	0	0.08%	
Melon	0	0	0	0	0.05%	
Oats	0	0	0	0.037	0.15%	
Rye	0	0	0	0	0.04%	
Sugarbeet	0	0	0	0	0.21%	
Sugarcane	0	0	0	0.103	0.20%	
Tomato	0	0	0	0	0.19%	

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.

Table A.3: Quality of the prediction of electricity intensity over time

	1910-1920 (1)	1915-1920 (2)	1920-1925 (3)	1925-1930 (4)	1930-1935 (5)	1935-1940 (6)	1940-1945 (7)	1945-1950 (8)
<i>Panel A: By energy intensity of crop</i>								
Energy Intensity	0.278*** (0.105)	0.386*** (0.124)	0.676** (0.274)	0.534*** (0.192)	1.463*** (0.343)	1.675*** (0.523)	2.288*** (0.613)	1.883*** (0.600)
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	1244	1133	839	834	674	365	408	246
<i>Panel B: By whether the county had a power plant within 70km in 1912</i>								
Plant within 70km in 1912	0.002 (0.006)	0.006 (0.007)	0.010 (0.009)	0.026** (0.012)	0.022 (0.015)	0.030 (0.019)	-0.003 (0.019)	0.008 (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	1950	1794	1447	1385	1176	755	823	568
<i>Panel C: By whether the county had a power plant within 70km in 1935</i>								
Plant within 70km in 1935	0.009* (0.005)	-0.014* (0.007)	0.016** (0.008)	0.020* (0.010)	0.034** (0.015)	0.037** (0.017)	0.046*** (0.018)	-0.020 (0.026)
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	1925	1768	1428	1372	1162	745	811	556
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1								

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 electrical patents for those county-crops in each period. County clustered standard errors in parentheses.

Table A.4: Impact of electricity availability on crop intensity and productivity, with specialization interaction

	(1)	(2)	(3)
	Δ level	$\Delta\%$	$\Delta \log(1+x)$
<i>Panel A: Product Acreage / Trees / Animals</i>			
Dummy Close \times Specialized \times Energy	11897.714*** (4507.375)	-96.361 (88.456)	-0.518** (0.209)
Crop, Cnty, Yr FE	Yes	Yes	Yes
<i>N</i>	63,064	52,158	63,064
<i>Panel B: Estimated Output Value</i>			
Dummy Close \times Specialized \times Energy	383,820** (175,907)	7.587 (20.525)	1.503*** (0.259)
Crop, Cnty, Yr FE	Yes	Yes	Yes
<i>N</i>	86,713	75,168	86,713

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Testing for sample selection

	At least one patent			
	Pre-1890 (1)	(2)	Post-1890 (3)	(4)
Within 70km of a plant in 1912*Energy intensity	0.018 (0.023)		0.229*** (0.041)	
Within 70km of a plant in 1930*Energy intensity		0.004 (0.017)		0.205*** (0.031)
<i>N</i>	69,542	69,542	69,542	69,542

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Robustness checks, total patents

<i>Panel A: Alternative specifications</i>				
	Base year control	Diff. base period	County-crop clusters	County-year FE
Within 70km of a plant ×	0.401**	0.680***	0.393**	0.478**
Crop Energy Intensity	(0.186)	(0.133)	(0.195)	(0.201)
<i>N</i>	60528	60528	60528	58521
<i>Panel B: Geographical issues</i>				
	Excl. outliers	Excl. close	Excl. far	Excl. dustbowl
Within 70km of a plant ×	0.261	0.299	0.306	0.569**
Crop Energy Intensity	(0.178)	(0.212)	(0.188)	(0.249)
<i>N</i>	59989	49050	57909	32241
<i>Panel C: Crop issues I</i>				
	Excl. outliers	Share E2 1850-70	Share E1 1850-90	Excl. animal
Within 70km of a plant ×	0.393**	1.173	-0.026	0.474**
Crop Energy Intensity	(0.186)	(1.766)	(0.215)	(0.217)
<i>N</i>	60528	60528	60528	53184

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 total patents relative to 1890- 1895 - except for the second column of Panel A 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.

Table A.7: Robustness checks, patents mentioning advertised uses

	<i>Panel A: Alternative specifications</i>			
	Base year control	Diff. base period	County-crop clusters	County-year FE
Within 70km of a plant ×	0.334***	0.335***	0.335***	0.372***
Crop Energy Intensity	(0.092)	(0.092)	(0.085)	(0.098)
<i>N</i>	60,528	60,528	60,528	58,521
	<i>Panel B: Geographical issues</i>			
	Excl. outliers	Excl. close	Excl. far	Excl. dustbowl
Within 70km of a plant ×	0.240***	0.262***	0.296***	0.467***
Crop Energy Intensity	(0.077)	(0.090)	(0.093)	(0.135)
<i>N</i>	59,989	49,050	57,909	32,241
	<i>Panel C: Crop issues I</i>			
	Excl. outliers	Share E2 1850-70	Share E1 1850-90	Excl. animal
Within 70km of a plant ×	0.335***	2.923***	0.368***	0.383***
Crop Energy Intensity	(0.092)	(0.692)	(0.092)	(0.102)
<i>N</i>	60,528	60,528	60,528	53,184

Note: 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 total patents mentioning advertised uses action words relative to 1890- 1895 - except for the second column of Panel A 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.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Robustness checks, patents mentioning post-harvest words

<i>Panel A: Alternative specifications</i>				
	Base year control	Diff. base period	County-crop clusters	County-year FE
Within 70km of a plant ×	0.374***	0.375***	0.375***	0.444***
Crop Energy Intensity	(0.078)	(0.078)	(0.080)	(0.089)
<i>N</i>	60,258	60,528	60,528	58,521
<i>Panel B: Geographical issues</i>				
	Excl. outliers	Excl. close	Excl. far	Excl. dustbowl
Within 70km of a plant ×	0.303***	0.380***	0.332***	0.470***
Crop Energy Intensity	(0.068)	(0.095)	(0.078)	(0.120)
<i>N</i>	59,989	49,050	57,909	32,241
<i>Panel C: Crop issues I</i>				
	Excl. outliers	Share E2 1850-70	Share E1 1850-90	Excl. animal
Within 70km of a plant ×	0.375***	3.844***	0.486***	0.420***
Crop Energy Intensity	(0.078)	(0.856)	(0.111)	(0.093)
<i>N</i>	60,528	60,528	60,528	53,184

Note: 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 total patents mentioning post-harvest actions relative to 1890- 1895 - except for the second column of Panel A 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.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Change in number of patents by 5-year periods relative to 1890-1895, excluding milk-related patents

	Change in total patents			Change in electric patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Within 70km of a plant × Energy Intensity _{1850–1905}	-0.037 (0.372)			0.195*** (0.071)		
Log Inv. Dist. to nearest plant × Energy Intensity _{1850–1905}		0.175 (0.203)			0.087** (0.040)	
Electrical capacity × Energy Intensity _{1850–1905}			0.278 (0.192)			0.194*** (0.052)
Mean number of patents in counties far away		0.134			0.006	
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	60528	60528	60846	60528	60528	60846

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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.

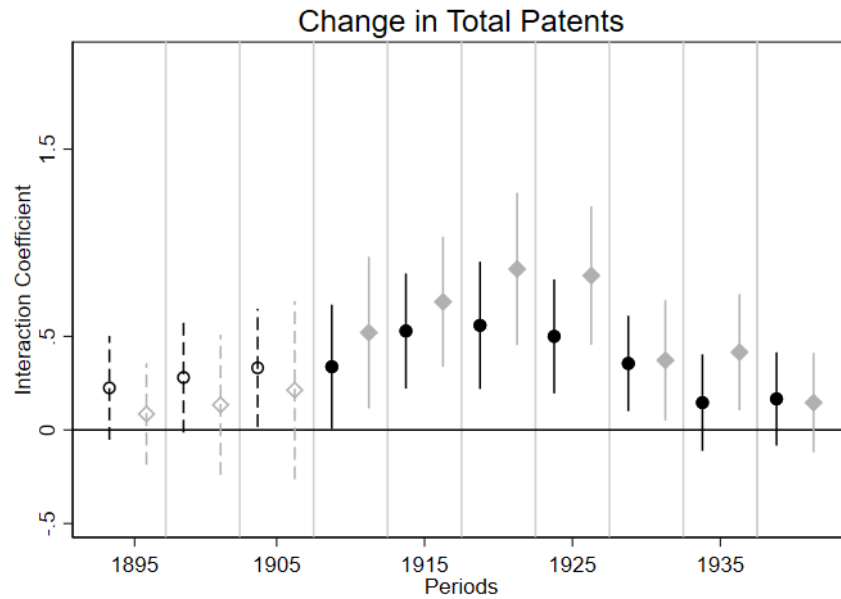
Table A.10: Impact of arrival of electricity on characteristics of inventors

	Sample 1			Sample 2		
	Coefficient	Observations	Adjusted R^2	Coefficient	Observations	Adjusted R^2
Age	7.514 (17.429)	1828	0.120	-10.233 (15.956)	2592	0.087
Foreign-born	0.660 (0.680)	1276	0.240	0.274 (0.603)	1774	0.221
Foreign-born or second gen.	-0.391 (0.652)	1293	0.317	-0.437 (0.621)	1793	0.299
Lives in a diff. state	0.023 (0.603)	1828	0.306	-0.019 (0.591)	2592	0.299
Rural	-1.125** (0.489)	1828	0.304	-1.020** (0.454)	2592	0.282
Can read and write	0.021 (0.167)	1828	0.907	-0.047 (0.156)	2592	0.915
Years of education	-0.463 (19.889)	353	0.426	7.797 (15.229)	559	0.300
Farm owners	-0.849 (0.776)	1828	0.209	-0.667 (0.592)	2592	0.193
All farmers	-0.681 (0.807)	1828	0.224	-0.399 (0.614)	2592	0.225
Craftsmen	-0.088 (0.444)	1828	0.065	-0.057 (0.370)	2592	0.057
Engineers	0.103 (0.296)	1828	0.187	-0.045 (0.233)	2592	0.181
Electrical Engineers	-0.035 (0.078)	1828	-0.034	-0.015 (0.049)	2592	0.066
Occscore	9.793 (17.850)	1828	0.170	1.128 (14.865)	2592	0.138

Table A.11: Interaction effects with human capital, patents with advertised uses

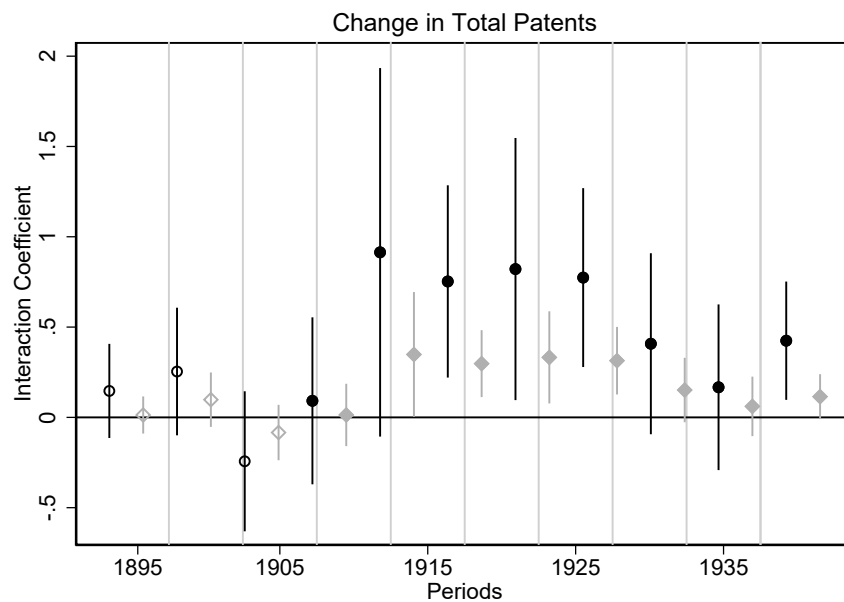
	(1)	(2)	(3)
<i>Variable capturing human capital:</i>	Experimental Stations	Engineers	College Share (Rural)
Panel A: Change in patents with advertised uses			
Proximity × Energy Intensity	0.480*** (0.045)	0.264** (0.053)	0.074 (0.146)
Energy Intensity × Variable	3.084* (1.576)	0.001 (0.001)	0.369** (0.147)
Proximity × Energy Intensity × Variable	-0.836 (1.516)	0.001 (0.001)	-0.169 (0.188)
Panel B: Change in post-harvest patents			
Proximity × Energy Intensity	0.334*** (0.129)	0.341*** (0.088)	0.412 (0.278)
Energy Intensity × Variable	4.744** (1.991)	0.003* (0.001)	0.163 (0.155)
Proximity × Energy Intensity × Variable	-1.422 (2.383)	-0.000 (0.001)	0.027 (0.170)
Crop, Cnty, Yr FE	Yes	Yes	Yes
<i>N</i>	60,528	53,199	60,480

Figure A.1: Change in Total patents - using the inverse of the logarithm of the distance in 1912 and 1935



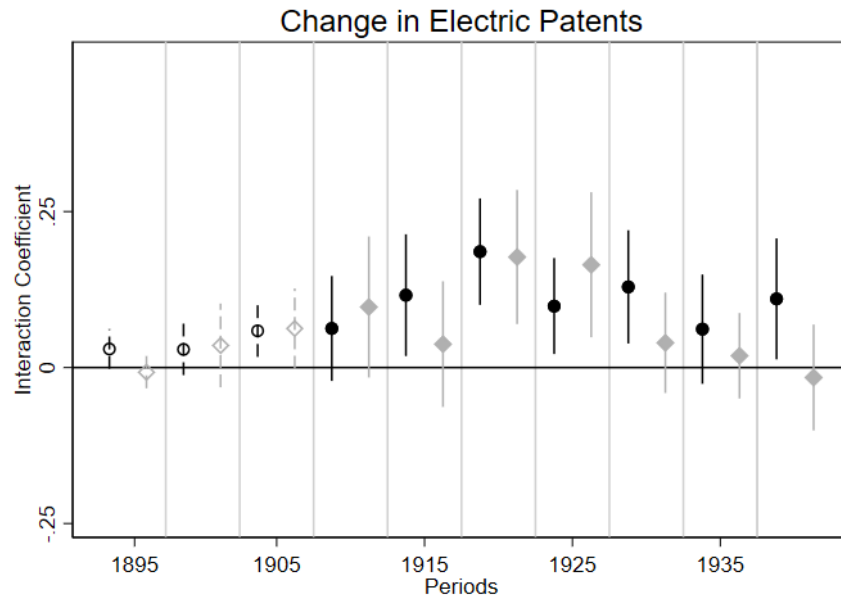
These figures present the coefficient of the interaction term in specification (2) using the change in the total number of patents compared to the total number of patents in 1890-1895 for each county-crop-electric for each of the cross-sections of 5-years periods between 1910-1950. The data is collected 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.

Figure A.2: Change in Total patents - using the Vidart's electric capacity



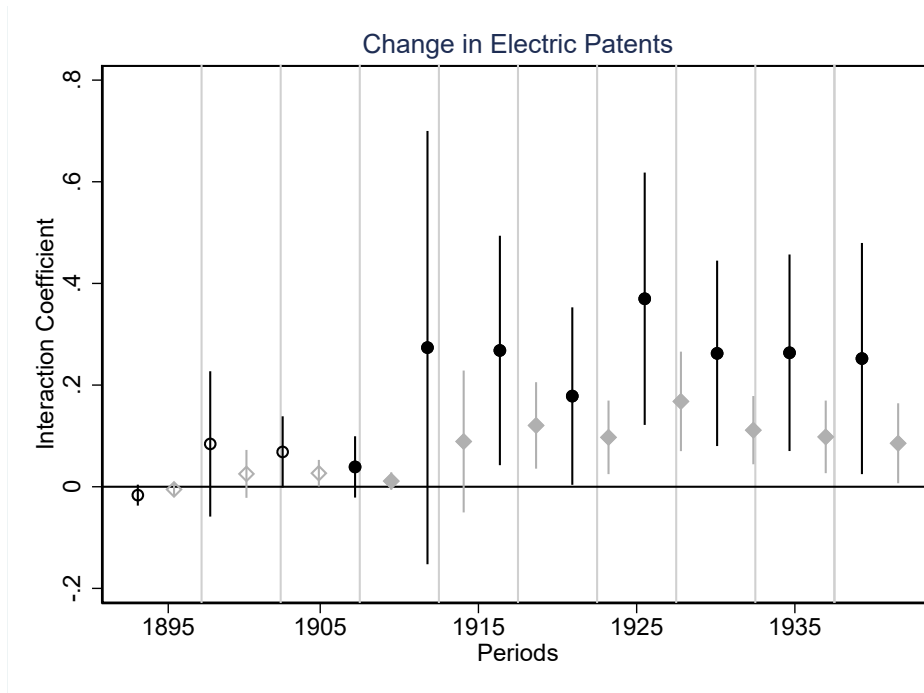
These figures present the coefficient of the interaction term in specification (2) using the change in the total number of compared to the total number of patents in 1890-1895 for each county-crop-electric for each of the cross-sections of 5-years periods between 1910-1950. The data is collected at the 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.

Figure A.3: Change in electrical patents - using the inverse of the logarithm of the distance in 1912 and 1935




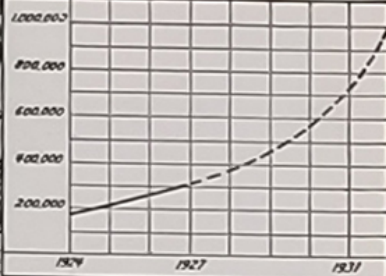
These figures present the coefficient of the interaction term in specification (2) using the change in the total number of electrical patents compared to the total number of electrical patents in 1890-1895 for each county-crop-electric for each of the cross-sections of 5-years periods between 1910-1950. 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.

Figure A.4: 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 \(2024\)](#)'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.

Figure B.6: Example 2

This chart shows the growth of electrical service in rural districts of the United States in the last three years and projected to 1931.

It is reasonable to believe that this rate of growth will be bettered—but even if it remains the same, there will be approximately one million electrified farms in this country by the end of 1931.

American farmers may safely depend upon the electric power companies to carry forward the electrical progress which the principle of individual initiative has made possible in the past.

Electricity is more than lighting— it is a power helper on the Farm!

Many people still think of electricity only in terms of lighting. Yet this is but one of the many things electricity can do.

Electricity as heat operates the electric range or cooker; heats the electric iron, toaster and percolator; and provides warm water throughout the year.

Electricity as power, pumps water, runs the washer, milks the cows, separates the milk, churns the butter, turns the grindstone, grinds the feed, cools the refrigerator, mixes concrete and performs a proved total of one hundred farm tasks.

There is a wider variety of uses for electricity in agriculture than in any other industry. Experimental work is constantly increasing these uses.

To obtain electrical service for yourself and your neighbors, consult your power company. You will find ready cooperation. Many companies have established rural service departments to provide the latest information on the application of electricity to agriculture.

The Committee on Relation of Electricity to Agriculture is composed of economists and engineers representing the U. S. Department of Agriculture, Commerce and the Laborer, American Farm Bureau Federation, National Grange, American Society of Agricultural Engineers, Individual Plant Manufacturers, General Federation of Women's Clubs, American Home Economics Association, National Association of Farm Equipment Manufacturers, and the National Electric Light Association.

NATIONAL ELECTRIC LIGHT ASSOCIATION

420 Lexington Avenue, New York, N. Y.

Figure B.7: Example 3

