Escaping Labor Scarcity: Innovation and Human Capital after WW1 in France*

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Abstract

We use quasi-random variation in the number of WW1 casualties to estimate the impact of this demographic shock on innovation in France. Our analysis shows that excess mortality led to higher patenting activity in counties with higher pre-war education, driven by labor-saving technologies. We estimate that an additional 6,000 patents were filed in the 15 years following the war, equivalent to the annual number of patents filed before the war. We also find a positive association between war-related mortality, wage, and the adoption of agricultural machinery, providing evidence that incentives to escape labor scarcity drove the innovation response to mortality.

Keywords: Patents, Demographics, WW1, human capital, directed technical change
JEL Codes: O33, J24, O15, J11, N34, N14

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1 Introduction

Episodes of severe labor scarcity have often left a lasting mark on technological progress. Economic theory on directed technical change (Hicks, 1932; Aghion and Howitt, 1996; Acemoglu, 2002; Hémous and Olsen, 2021) predicts that when key production factors become scarce, inventors are incentivized to economize on them. Labor shortages, in particular, have repeatedly spurred labor-saving technologies—from the mechanization that fueled Britain's Industrial Revolution (Allen, 2009) to productivity advances in 19th-century America (Habakkuk, 1962). These cases suggest that negative demographic shocks can accelerate structural transformation by redirecting the path of innovation. Yet we know less about how this response depends on local human capital, which may determine whether regions can turn scarcity into invention.

This paper asks whether labor scarcity alone is sufficient to spark innovation, or whether its effect depends critically on the presence of human capital. While theories of directed technical change posit that scarcity shifts the direction of innovation (Acemoglu, 2002), and a large literature highlights the role of human capital in enabling technological progress (e.g. Squicciarini and Voigtländer, 2015), we know little about how these forces interact. The aftermath of World War I in France provides an unusually sharp setting to study this question. The war created massive, uneven demographic losses—with more than 30% of young men killed or incapacitated—that generated profound local labor shortages.

Our empirical strategy builds on the fact that, although nearly every French city suffered wartime losses, these losses were highly uneven across regions. This spatial heterogeneity allows us to address three central questions. First, did the labor shortages caused by wartime mortality drive innovation out of necessity? Second, was human capital essential in enabling regions to translate scarcity into inventive activity? Third, how did these localized innovation responses shape the broader trajectory of French technological development in the interwar years, particularly by introducing labor-saving technologies.

France's mid-industrialized economy, together with substantial regional variation in wartime mortality, pre-war education, and patenting, offers an ideal setting to address these questions. We assemble a new dataset combining *département*-level mortality records, patent filings, and socio-economic characteristics. Exploiting regional differences in excess wartime mortality as a quasi-random shock, and using a difference-in-differences design, we identify the causal effect of labor scarcity on innovation and its interaction with human capital. This approach enables a transparent assessment

of whether areas with stronger educational foundations were better able to redirect inventive effort toward labor-saving technologies in response to demographic shocks.

France faced a paradox at the end of WW1. While emerging as the dominant power in continental Europe after defeating Germany, the nation was deeply scarred. The war left 30,000 square kilometers of French territory, more than 5% of the total surface, devastated by 4 years of fighting and the systematic destruction by German troops during their 1918 retreat. The economic impact was staggering: losses included 20% of agricultural output, respectively 70% and 90% of coal and iron extraction along with 65% of steel production. In 1921, French economist Alfred Sauvy estimated that the overall costs of physical destruction to be 34 billion Francs, seven times the government budget for 1913 (Deperchin 2004). This burden was intensified as the government had substantially increased public debt to finance the war, amounting to around 210 billion francs, nearly 40 times the 1913 budget. On top of that, the national output in 1918 had fallen by 30% compared with its pre-war level.

Perhaps more critical was the human cost of the conflict (Rohrbasser, 2014; Héran, 2014). The war claimed the lives of 1.3 million French soldiers, representing 30% of men aged 18 to 35, while another 1.2 million sustained serious injuries. This demographic crisis birthed the concept of the "hollow classes", which dominated political discourses for years. The war left 1 in every 12 children orphaned; no family, including those of high-ranking officers and politicians, was untouched by loss. Notably, Supreme Allied Commander Ferdinand Foch lost his only child, while future French President Paul Doumer lost all four sons (Araud 2023). Due to the war, the French birth rate declined by about 40%, fueling concerns about France's ability to counter future German aggression. These fears were not unfounded: as World War II began, the French army could only muster 4 million men aged 20 to 34, compared with Germany's 9 million.[1]

The literature broadly suggests that the losses sustained by France during World War I could affect innovation in two main ways. First, the mortality rate could lead to a direct loss in human capital, hereby reducing the stock of accumulated knowledge. Fewer people inherently translate into fewer new ideas, which may hinder long-term growth (Jones, 2022). More broadly, this human capital effect aligns with the learning by doing hypothesis proposed by Arrow (1962), which emphasizes the importance of experience in enhancing productivity. With an average age at death of approximately 29 years, the loss of 1.3 million men represents a significant erosion of experiential knowledge, potentially contributing to a decline in overall productivity. Another

[1]Figures from Germany are taken from Feldgrau.com (2025).

mechanism driving the human capital effect could work through the "Lost Einsteins" hypothesis documented by Bell et al. (2019) who show that many children would have found highly impactful inventions had they been exposed to innovation in childhood. In a similar spirit, WW1 might have killed young men that, in the absence of the war, would have become inventors; in the meantime, their death deprived their kids from exposure to invention and made the finding of potential radical ideas less likely.

On the other hand, labor scarcity induced by WW1 might have provided incentives to improve productivity either through innovation (Acemoglu, 2002)[2] or to substitute scarce and expensive labor with capital. This latter suggestion was explored by Ilzetzki (2023) who showed that, when facing large positive demand shocks and capacity constraints, firms are more likely to increase their Total Factor Productivity, implying that a tension on inputs might lead to a need for a higher innovation rate: this is the "learning by necessity" effect. It is also in line with Voth et al. (2022) who analyze the effect of military conscription in early 19^{th} century Great Britain during the Napoleonic wars and show that labor scarcity induced entrepreneurs to substitute machines for missing workers.

In order to assess the effect of mortality on innovation in France after WW1, we construct a new dataset at the *département* level, which we designate as county throughout. This new dataset combines information on the number and type of patents, population, education, GDP, wage, share of agricultural and industrial sectors and mortality from the Great War. To measure the impact of the war, we construct a mortality indicator which measures whether a county suffered abnormally low or abnormally high losses in light of its initial characteristics. We then leverage the heterogeneity of this indicator across French counties to estimate the effect of human losses on innovation measured by the patenting activity per inhabitant.

Our findings indicate that mortality alone had a small positive average effect on innovation. However, this effect was magnified in counties with higher levels of education. We further show that this was primarily driven by the development of labor-saving automation technologies, which underwent rapid advancement, particularly in counties reliant on "labor-intensive" economic activities, thereby having the greatest incentive to adopt these new technologies in response to the negative technological shock. We interpret this as evidence that the "innovating by necessity" channel was indeed active post-war. In response to the lack of young men, in particular in the agricultural sector, counties that have the capabilities to innovate redirected their effort toward

[2]Naturally this price effect might be somewhat offset by a labor scarcity-induced decline in the size of the overall market (Acemoglu and Linn, 2004).

the development of machines that could substitute for the missing workers. For these counties, this positive effect extended beyond a mere recovery from four years of war and the impact on innovation remained positive into the 1930s. All in all, back-of-the-envelope computations suggest that mortality improved patenting activity by about 6,200 patents in the fifteen years after the war, corresponding to the average yearly number of patents in France prior to the war.[3]

Our paper contributes to the literature exploiting major historical events and the changes they imply for input scarcity in order to test for the presence of directed technical change. Hanlon (2015) exploits the sudden scarcity of US-grown cotton during the Civil War and shows that British manufacturers switched to Indian cotton and developed technologies that augmented this type of cotton, resulting in a long-run increase in the relative price of Indian cotton. Franck (2024) uses the cholera pandemics of the 19th century in France as a natural experiment to study the relationship between labor scarcity and technological progress, finding that short-run increases in literacy offset the negative effects of population loss on industrial technology adoption. Voth et al. (2022) documents an increase in the adoption of agricultural machinery in British counties most affected by military recruitment for the Royal Navy during the Napoleonic wars. In comparison with these papers, we exploit a larger, more persistent demographic shock and use more detailed data on patents in order to measure and detect directed technical change in the context of a structural shift away from agriculture. We additionally document the role of education in driving the magnitude of the *innovation* response to labor scarcity—as opposed to the *adoption* response, the focus of Voth et al. (2022). Finally, the yearly frequency of the patent data allow us to implement a dynamic difference-in-difference model, enabling us to examine the absence of differential pre-trends.

Another stream of literature emphasizes the potential positive long-term effects of wars on innovation. Moretti et al. (2023) shows that public military R&D spending has positive spillovers on private innovation and ultimately boosts productivity (see also Mowery, 2010 for a survey). Kantor and Whalley (2023) show that public procurement during the space race boosted increased local manufacturing value-added in impacted US counties even after procurement was scaled back. In the context of wars, Gross and Sampat (2023) highlights the enduring impact of the American Office of Scientific Research and Development, established during WW2 to support military-related technological advancements. Ilzetzki (2023) attributes the rise in plant-level productivity in the U.S. during WW2 to a learning by necessity channel: aircraft man-

[3]More details regarding the method are exposed in Appendix C.1.

ufacturers, faced with a surge in demand and a scarcity of production factors, were compelled to increase productivity in the short term. More generally, Azoulay et al. (2019b) underline the significant influence of the DARPA agency, founded amid the military rivalry between the US and the USSR, which contributed substantially to the productivity dynamics observed in the US during the Cold War (Dyevre, 2023; Cozzi and Impullitti, 2010). We depart from the extant literature in two main ways. First, we focus on the demographic aspect of war as opposed to public procurement, and hence zoom in more explicitly on directed technical changes—as opposed to Hick-neutral improvement in productivity. We show, moreover, that our results hold even after controlling for the local importance of wartime contracts.[4] Second, we exploit textual data on patents to unveil the impact of large shocks not only on the quantity but also on the direction of innovation.

We contribute as well to the literature on the interaction between demography, education, and innovation (see Mokyr and Voth, 2010 for a comprehensive review). A broad set of studies shows that adverse shocks can have complex effects on long-run development: some highlight losses of human capital, while others emphasize how scarcity or adversity can foster innovation. For instance, Voigtländer and Voth (2013) demonstrate how the Black Death led to significant labor scarcity, resulting in higher wages and greater incentives to automate production and transition from less productive agriculture to more productive industry and services (Li and Van Zanden, 2012). In a related context, **?** show that U.S. counties more heavily exposed to the 1918 influenza pandemic became simultaneously more religious and more innovative, illustrating how negative shocks can trigger heterogeneous societal responses. Beyond these direct effects, an additional negative channel may emerge from the loss of the upper tail of the knowledge distribution, which is crucial for most development and innovation (see Valero and Van Reenen, 2019 for a discussion and Squicciarini and Voigtländer, 2015 for an application to the French Industrial Revolution). Even if the demographic shock does not affect the tail of the distribution, significant potential innovation losses could result from the disappearance of many potential "lost Einsteins" (Bell et al. 2019)—innovative talents distributed across the entire population but potentially overlooked due to inadequate policies (Van Reenen 2022). A population shock that reduces the size of the population makes the emergence of a new Einstein or Marie Curie even more improbable. Our paper considers these two channels and test them using a newly assembled dataset which includes a precise measure of the nature of innovation from patent data. In our context, these channels are indeed

[4]Moreover, we do find a positive relationship between the procurement and innovation.

potentially relevant regarding the development of future innovation: first, WW1 casualties also concerned officers which were predominantly highly educated young men; second, WW1 occurred at a time where many innovators were working in low-skilled occupations (Bergeaud and Verluise, 2024) and where (knowledge) barriers to innovation were arguably lower than today. We document that a number of known inventors, and likely many more potential ones, were among the hundreds of thousands killed. We further show that whereas overall local mortality is associated with an uptick in innovation, the direct loss of prewar innovators depresses post-war innovation.

Our paper further contributes to the nascent literature on the social and economic consequences of the major demographic changes brought about by World War 1 in France. Most papers have focused on the gender imbalances caused by the war casualties. Boehnke and Gay (2020) study the impact of labor scarcity induced by war-related mortality on female participation in the labor market; more specifically, they show that the scarcity of men due to the war generated an upward shift in female labor force participation that persisted throughout the interwar period. In those counties where female labor force participation did not increase consistently with the high fatality rate, it could nevertheless be that firms had no choice but to substitute machinery for missing workers. Abramitzky et al. (2011) find that after the war men had more favorable outcomes on the marriage market in regions that experienced higher mortality rates. Cagé et al. (2023) study the local political legacy of being exposed to fighting under the leadership of general, and future WW2 collaborationist, Pétain.

The remainder of this paper is organized as follows: Section 2 details the data sources and outlines the methodology employed to construct our mortality indicator. Section 3 presents our main findings and Section 4 examines potential mechanisms. Threats to identification and robustness are discussed in Section 5.

2 Data and Methodology

We have constructed a novel dataset at the county level, assembling information from a large variety of different sources for each of the 87 French counties that existed at the beginning of the 20^{th} century. This dataset includes both time-varying and time-invariant socio-economic characteristics from 1907 to 1939. We begin by briefly describing the dataset and then explain how we constructed our indicator of excess mortality, our main regressor.

2.1 Data

2.1.1 The "Morts pour la France" dataset

The data on soldier casualties during World War I are derived from the "Morts pour la France" dataset (Gay and Grosjean, 2023), which offers comprehensive details on each of the 1.3 million men who lost their lives in combat. Key information includes their birth county, birth date, death location, and names. By integrating this dataset with the French Census of 1911, we calculate a mortality rate for each of the 87 counties in our sample. This sample represents the 90 mainland counties as they were before the 1962 administrative reform minus Haut-Rhin, Bas-Rhin, and Moselle, then in Germany and returned to France following the Versailles Treaty in 1919.

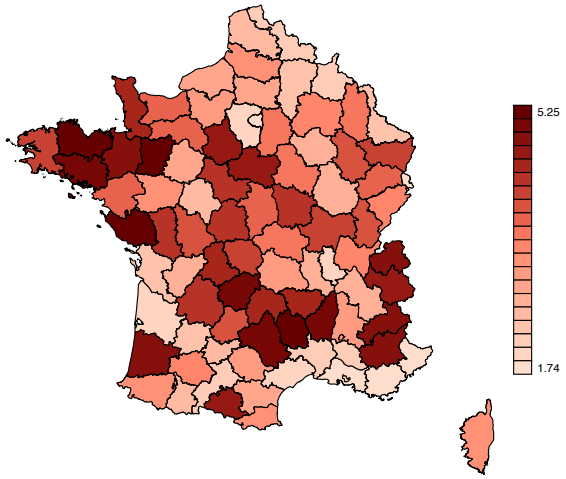
The average mortality rate in France was 3.38% of the population as of 1911, involving 1,246,785 casualties. However, this average masks significant variations among the French counties, as evidenced by a standard deviation of 0.6% and further illustrated in Figure 1a. In particular, more rural counties appeared to bear the heavier brunt of mortality. For instance, counties like Lozère (5.08%), Vendée (4.32%), Mayenne (4.49%), and Aveyron (4.10%) experienced higher casualty rates despite their relative distance from the front lines. One plausible explanation is that rural workers were more likely to be conscripted and less likely to be employed in essential wartime industries, which often granted exemption from military service (Férier, 1991). Additionally, rural workers, typically with less education than their urban counterparts, were less likely to hold officer ranks. However, the same dispersion is to be observed for the analysis of officers deaths: the average ratio of dead officers to the 1911 population hovers around 0.1% with a standard deviation of around 0.3%, implying significant heterogeneity at the national scale.

2.1.2 Measure of innovation

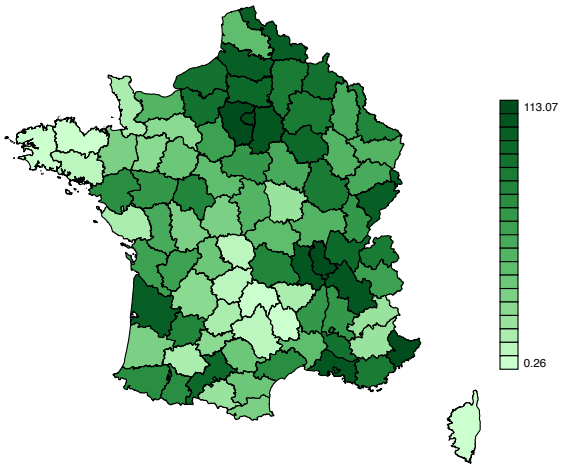
Our main dependent variable is a measure of local innovation that we construct by counting the number of newly issued patents filed by resident inventors per 100,000 inhabitants. We recover patent data from the *PatentCity* dataset (Bergeaud and Verluise, 2024), which provides information on the location and nature of every patent filed in France since 1907, including the county and name of the inventor and the technological class. More specifically, we restrict our attention to the set of patents filed by French inventors in the French patent office and allocate a patent to a county

FIGURE 1: Death rate during WW1 and patenting activity

(a) Death Rate



(b) Patents per capita



Notes: Left-hand side map shows the ratio between the number of people killed during WW1 in each county (*département*) divided by the population of the county in 1911. The right-hand side map shows the average number of patents filed every year between 1907 and 1936 by inventors residing in each county, divided by the population in 1911.

based on the location of its inventors.[5]

The geography of patenting activity in France over the 20^{th} century is fairly concentrated (see Bergeaud and Verluise, 2024) and this was notably true during the first half of the century. The county of Seine (roughly similar to the current city of Paris and its immediate suburb) counts on average 113 patents per 100,000 inhabitants, a number that is 15 times larger than the average county. Seine accounted for around 60% of total French patenting activity between 1907 and 1939. Figure 1b shows a map of the average number of patents per inhabitants during the period 1907-1936 in each county.

We a priori consider all patents regardless of their technological classes. However our analysis will sometimes require to restrict specifically to labor-saving technologies. We achieve this classification by looking at specific keywords in the title of the patents and then select technological classes where these keywords are overrepresented. More details are given in Section 4.3 and Appendix B.3

[5]In case of multiple inventors in a single patent, we split the patent across the different counties from which its inventors come, so that each county is assigned a fraction of the patent.

2.1.3 Additional data

A key determinant of a county's innovation response is its level of human capital. We measure this using the 1901 census, which provides detailed information on education in France. This is the same source used by Squicciarini (2020), who analyzed the impact of schooling on industrial development during the Industrial Revolution (*L'enseignement primaire et secondaire de 1865 à 1906*). Our primary indicator of education level is the share of young men who surpassed the basic primary curriculum, as recorded in the conscription lists. While several measures could be considered, this one is preferred because it reflects a relatively young population in 1901—many of whom would be in their 30s after the war—and is directly available as a share in the census, reducing the risk of measurement error from merging multiple sources. In addition and in order to capture different facets of human capital, we also consider alternative indicators: (i) the average enrollment rate of children aged 5 to 15 across censuses from 1851 to 1901; (ii) the proportion of young men in the French army holding a baccalauréat degree[6], derived from the *Annuaires Statistiques de la France*; (iii) the prevalence of Catholic schools, measured by their proportion among all schools. As noted by Squicciarini (2020), Catholic schools emphasized history and theology more than public schools, which focused on technical subjects which had implications for local human capital composition, particularly in relation to technology adoption. Appendix B.4 provides a detailed discussion of these measures and their correlation with economic characteristics prior to World War I.

Finally, to complete our dataset, we collected additional economic, social, and geographic characteristics for each county. Specifically, we hand-collected sectoral employment data from all available censuses (1906, 1911, 1921, 1926, 1931, and 1936) and estimated the level of local GDP per capita before and after the war. We also include measures of conscription rates, population size, and age structure. More details are provided in Appendix B.

2.2 An indicator of excess mortality

The goal of our empirical analysis is to identify the causal effect of local exposure to WW1-induced mortality on subsequent innovation activity. However, the assumption that mortality rates are exogenous—i.e., unrelated to pre-existing local innovation

[6]The baccalauréat is an exam taken at the end of high school (around age 18) and a prerequisite for university admission. In the early 20th century, it was highly selective: in 1910, only 19,000 candidates took the exam, and fewer than 50% passed.

trends—raises concerns. Various factors correlated with county-level WW1 mortality may also influence innovation capacity, such as geographic proximity to battlefronts or pre-war socio-economic conditions. For instance, Gilles et al. (2014) argue that the proportion of immigrant populations was negatively correlated with conscription rates during the war, while a large body of literature links immigration to innovation (e.g., Kerr and Lincoln, 2010). Similarly, Guillot and Parent (2018), in a comprehensive study on the determinants of soldier mortality during WW1, suggests that even for a given conscription rate, local social characteristics influenced mortality rates. In particular, they find that soldiers from wealthier counties had lower chance of survival at the front. Appendix B.2 examines these points by looking at the correlation between the raw WW1 mortality per capita and a number of pre-war economic and demographic characteristics measured at the county level before the conflict.

To address these concerns, our analysis explicitly controls for several pre-1914 local characteristics: the share of young men in the total population, foreign-born population share, population density, and agricultural sector share. Consequently, our estimation of the marginal effect of mortality on innovation activity is conditional on local time trends correlated with these initial characteristics. Furthermore, rather than using raw mortality rates directly, we construct a measure of *excess mortality*. We first regress the mortality rate on the conscription rate, as this measure likely captures unobserved factors influencing local exposure to the war. We further include GDP per capita and the distance to the frontline. We interpret the residual from this regression as deviations from an *expected* mortality level given a proxy that measures soldiers' exposure intensity, which we cannot observe directly.[7] This residual thus reflects unexpected mortality shocks unrelated to observable determinants. To enhance interpretability, we standardize the residual mortality rate (subtracting the mean and dividing by the standard deviation).

There is an inherent degree of arbitrariness in constructing such an index, and the inclusion of alternative variables could inevitably result in a different measure. To demonstrate the robustness of our findings against reasonable variations in the formulation of this residualized mortality rate, we conduct a series of checks detailed in Appendix A.2. Finally, we present the spatial distribution of our baseline excess mortality rate in Figure B2.

[7]The inclusion of GDP per capita indirectly captures the idea that poorer counties may have a higher share of entry-level soldiers that for a given level of conscription may be more exposed. The distance to the frontline captures the idea that more local soldiers may have a better knowledge of the field, be more motivated or more prepared to the environmental conditions. None of our results are affected by measuring excess mortality simply by residualizing on the conscription rate, see Appendix A.2.

2.3 A dynamic difference-in-differences

To evaluate the impact mortality from WW1 on future patenting activity, we adopt an event-study design on our yearly panel of 87 French counties between 1907 and 1936. Our dependent variable proxy for the intensity of innovation by dividing the number of new patents filed by inventors residing in each county normalized by its population taken in 1906. We use 1906 as the reference population first because this is the most recent pre-sample year for which we have direct information taken from the Census and second because we have used 1911 (the year of the next census) to measure excess mortality rate (see Section 2.2) which mitigates the risk of division bias. Formally, we estimate the following model:

$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1913}}^{1936} \mathbb{1}_t(k)\left(\lambda_k \tilde{m}_d + \phi_k \mathrm{C}_d\right) + \alpha_d + \beta_t + \eta_{d,t}, \tag{1}$$

where $\tilde{m}_d$ is the modeled excess mortality indicator in county d and C_d is a vector of additional control variables included more flexibly in the model. $\mathbb{1}_t(k)$ is a binary variable that takes the value 1 if the year k is equal to t and 0 otherwise. Finally, β_t and α_d are, respectively, year and county fixed effects. The estimated coefficients λ_t can be causally interpreted under the identifying condition that the treatment is orthogonal to the error term in equation (1) conditional on county and year fixed effects. Formally, this identifying assumption writes as:

$$\forall (d,t) \quad \mathbb{E}\left[\eta_{d,t} \,\middle|\, \alpha_d,\, \beta_t,\, C_d,\, \tilde{m}_d\right] = 0. \tag{2}$$

This identifying assumption states that, in the absence of the mortality suffered during WW1, the different counties would have followed similar innovation patterns conditional on all the observables included in equation (1) and summarized by the vector $X_{d,t}$. While this common trend assumption cannot be directly tested in the data, we report the values of λ_t for all t prior to the treatment. The fact that each of these values is not significantly different from 0 before the treatment, that is before 1914, constitutes a first hint in favor of the absence of differential pretrends and indirectly supports the parallel trend assumption. Naturally, pretrend tests are suggestive at best and we conduct a number of falsification exercises in Section 5 and discuss the causal validity of our results.[8]

[8]This equation is estimated using the standardized number of patents as the dependent variable. In Appendix A.4, we examine alternative functional form assumptions, including the logarithm of the

3 Main results

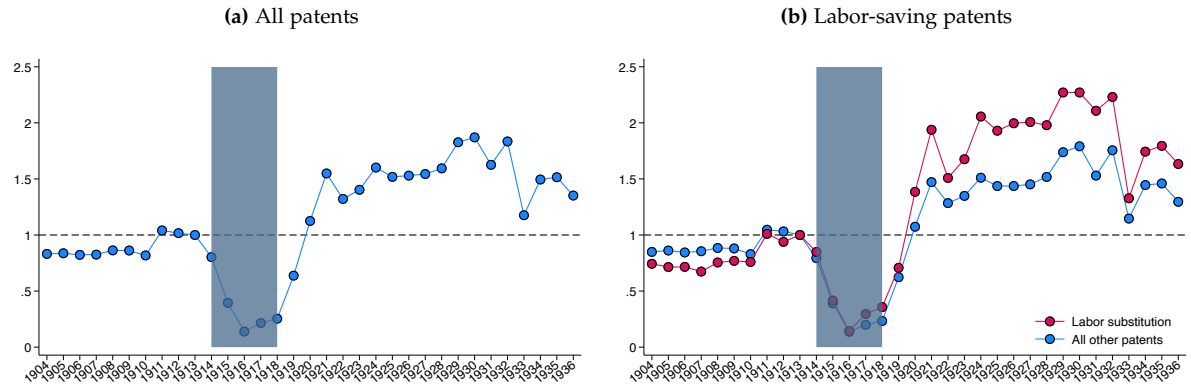
In this section, we present our main findings regarding how mortality affected patenting activity in France after World War I. We begin by presenting aggregate evidence on patenting around the war years (Section 3.1). We then turn to county-level regressions that exploit cross-county variation in excess mortality (Section 3.2). In Section 3.3, we investigate how human capital shaped the patenting response, finding that counties with stronger educational foundations exhibited the largest increase in innovation following high mortality. In Section 3.4, we focus on inventor mortality and show that, unlike general excess mortality, it is associated with a *decline* in patenting. Finally, Section 3.5 considers the role of the nature of education as a driver of adoption.

3.1 Graphical evidence

As shown in Figure 2a, France experienced a sharp decline in patenting activity during World War I, with the number of patent applications dropping by approximately 80% from its peak in 1911 to its lowest point in 1917. Nonetheless, innovation rebounded rapidly, and by 1921, France had not only regained its pre-war levels but also embarked on a decade of sustained growth. This pattern suggests that the post-war surge was not merely a mechanical rebound but rather an indication of the French innovation system's resilience in spite of the war's severe demographic toll. Figure 2b further distinguishes between patents related to labor substitution and all other patents, following the classification detailed in Section 4.3. In that category, the rebound is especially pronounced, suggesting that post-war labor scarcity redirected inventive efforts toward automation.

number of patents and a Poisson count model. The main results remain robust under these modifications.

FIGURE 2: Patents in France: 1907-1936



Notes: Figure 2a plots the yearly total number of new patents from 1904 to 1936. Figure 2b splits the sample between patents in labor-saving technologies and others. Each series is standardized to 1 in 1913. Data are from Bergeaud and Verluise (2024), including all patents filed in France by inventors residing in France (even if county information is missing). The definition of labor-saving patents is provided in Section 4.3.

3.2 The unconditional effect of mortality on patenting activity

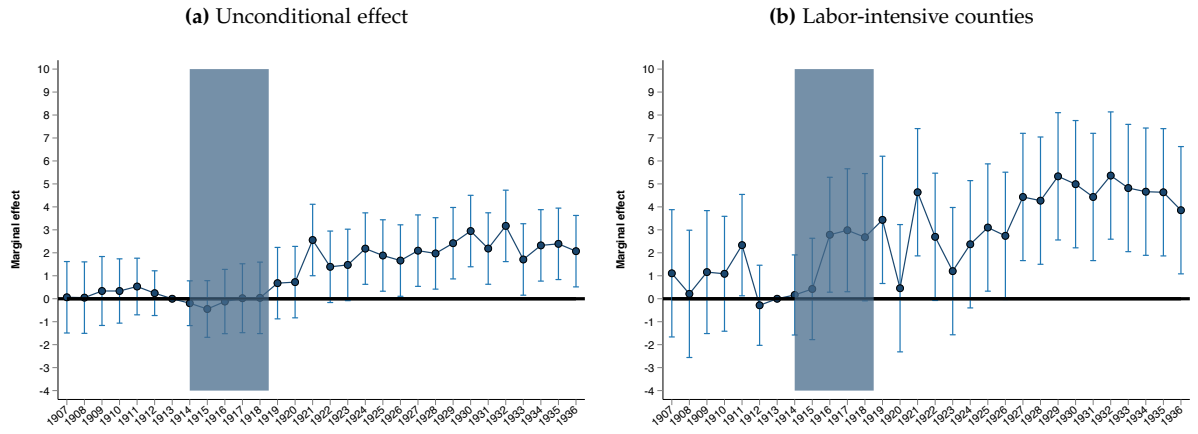
We begin our empirical investigation by estimating equation (1) via OLS. In this setup, we focus on the coefficients λ_t, which, under assumption (2), measure the causal effect of a one-standard-deviation increase in excess mortality on patenting per capita. We normalize $\lambda_{1913} = 0$, so all estimates can be interpreted relative to the last pre-war year. Figure 3a shows that pre-treatment coefficients are all close to zero, while a modest positive effect emerges in the early 1920s. This points to a weak but positive *unconditional* effect of WWI-related mortality on local patenting. The average post-war effect over the entire interwar period is about 1.991 (standard error of 0.609), meaning that a one-standard-deviation increase in excess mortality raises patents per 100,000 inhabitants by roughly 2—around one-tenth of the 1913 cross-county standard deviation of patenting. In all subsequent analyses, in order to quickly summarize the magnitude of the post-war effect, we systemically provide a static estimation of our dynamic model from equation:

$$\text{pat}_{d,t} = \mathbb{1}_t(P)\left(\lambda_S \tilde{m}_d + \phi_S \mathrm{C}_d\right) + \alpha_d + \beta_t + \eta^S_{d,t}, \tag{3}$$

where $\mathbb{1}_t(P)$ is an indicator equal to 1 if t belongs to the post-1919 period. The parameter λ_S thus represents the average deviation in patenting relative to 1913 for counties experiencing a one-standard-deviation increase in wartime mortality. The first row of Table 1 reports this coefficient.

To get a sense of the magnitude, our results imply that going from the bottom to the top quartile of the mortality distribution increase local patents per capita by about 3 per 100,000 people, which is about 50% of inter-quartile range in patenting activity in

FIGURE 3: Regression results: mortality and innovation



Notes: Figure 3a: estimation of equation (1) with OLS. The figure plots $\widehat{\lambda}_t$, the estimated marginal effect of an increase in the excess mortality rate during WW1. The control vector C_d includes the share of the agricultural sector, the share of young men in the total population, foreign-born population share, population density all taken in 1911. Figure 3b: estimation of equation (4) with OLS. The figure plots $\widehat{\delta}_t$, the additional marginal effect of excess mortality for counties that are in the top quartile of the distribution of labor intensity, defined as the number of workers in the agricultural sector per cultivated hectare. Standard errors are estimated using a Newey-West estimator with bandwidth of 5 years. Corresponding confidence intervals at the 95% levels are presented. The navy-blue-shaded areas denote the war period.

1913 or 25% of a standard deviation.

It is remarkable that heightened local mortality is not associated with a *decline* in post-war innovation, which might have been expected given the war's destructive toll on human capital. This suggests that certain counties rebounded quickly and may have been prompted to innovate by local labor shortages. In Section 4.4, we discuss the logic behind the fact that the response is essentially local and show support for it. If this necessity-driven channel was particularly strong where labor was more essential, we would expect a larger response in counties relying on labor-intensive activities. To test this hypothesis, we modify equation (1) by adding an interaction with a labor-intensive indicator L_d, which equals 1 if county d was in the top quartile of agricultural workers per cultivated hectare in 1911:

$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1914}}^{1936} \mathbb{1}_t(k)\Big(\lambda_k \tilde{m}_d + \delta_k \tilde{m}_d \times L_d + \gamma_k L_d + \phi_k \mathbf{C}_d\Big) + \alpha_d + \beta_t + \eta_{d,t}. \tag{4}$$

Figure 3b displays $\widehat{\delta}_k$; the estimated post-war coefficients are larger than the unconditional estimates, with an average around 2.525 (standard error 0.758). Thus, the positive effect of mortality on patenting is substantially amplified in highly labor-intensive counties. The corresponding static equation:

$$\text{pat}_{d,t} = \mathbb{1}_t(P)\left(\lambda_S \tilde{m}_d + \delta_S \tilde{m}_d \times L_d + \gamma_S L_d \phi_S \mathbf{C}_d\right) + \alpha_d + \beta_t + \eta^S_{d,t}, \tag{5}$$

is also estimated and coefficients λ_S and δ_S can be found in row 2 of Table 1.

3.3 The role of human capital

Figure 3a showed that, absent a severe shock to core inventive talent, local economic actors responded to labor shortages by innovating away from scarcity. This mechanism presumably operates more effectively if the local level of human capital is sufficiently high. A broad empirical literature demonstrates that human capital is pivotal for driving technological development (e.g., Lucas, 1988; Van Reenen, 2022; Aghion et al., 2009; Bell et al., 2019) as well as for fostering technology adoption and diffusion (Squicciarini, 2020; Mokyr and Voth, 2010). We therefore investigate whether areas with higher levels of human capital were primarily responsible for the observed post-war increase in patenting. Concretely, we extend model (1) by including an interaction between the excess-mortality measure, $\tilde{m}_d$, and an indicator e_d that captures local education levels. Consistent with model (4), this interaction allows wartime mortality to have a larger marginal impact on innovation precisely in counties that had a stronger human-capital base:

$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1913}}^{1936} \Big[\mathbb{1}_t(k) \left(\lambda_k \tilde{m}_d + \delta_k \tilde{m}_d \times e_d + \gamma_k e_d + \phi_k \mathrm{C}_d \right) \Big] + \alpha_d + \beta_t + \eta_{d,t}. \tag{6}$$

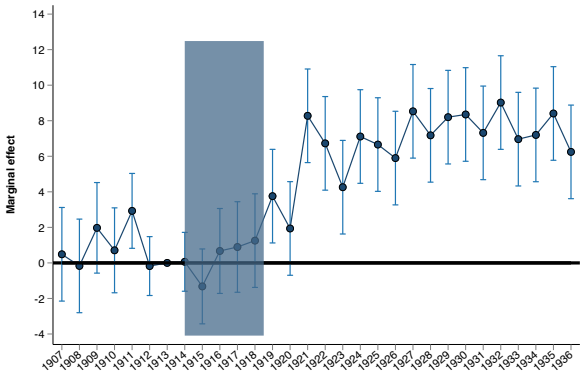
We set $e_d = 1$ for counties that rank in the top 25% of the education distribution. In our baseline specification, e_d is derived from the 1901 conscription lists, which record the fraction of young men who attained more than basic primary schooling (see Section 2). Figure 4a shows the corresponding coefficients δ_t over time, illustrating that the marginal effect of mortality on innovation is significantly larger in counties with stronger human capital. This finding suggests that high-education counties were better able to rebound and innovate in the face of pronounced demographic shocks. Figures 4b and 4c confirm the same qualitative pattern when we redefine e_d using two alternative measures of education. First, we use the average enrollment rate of children aged 5–15 in the 1861–1901 censuses. Although schooling became compulsory for ages 6–13 in 1881, examining earlier enrollment rates offers a broader perspective on each county's historical commitment to primary education. When $e_d = 1$ under this alternative measure, it indicates that a county had persistently high levels of educational investment (Figure 4b). Second, we use the share of young men in the 1901 conscription lists who held the *baccalauréat*, the highest secondary degree at the time. As fewer than 1% of any birth cohort completed this degree, this measure focuses on the upper tail of human capital, which is especially relevant for technology

adoption (Squicciarini and Voigtländer, 2015) (Figure 4c). While these three measures are positively correlated, they do not fully overlap: only six counties are consistently classified as high-education counties across all measures. Panel B of Table 1 presents the associated static coefficients for these two definitions of e_d. Figures A1a, A1b, and A1c report analogous results where the interaction with excess mortality employs a continuous measure of education, rather than a simple binary indicator.

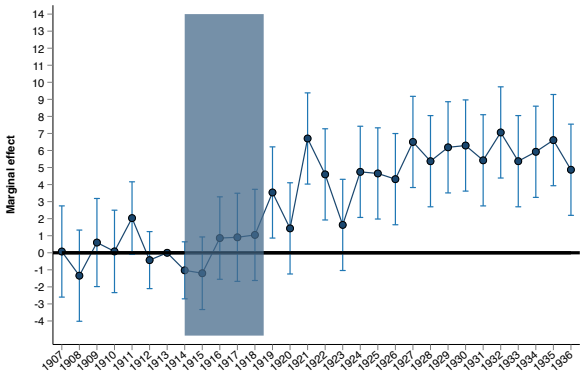
In the case of our baseline measure of education in Figure 5a, the average value of post-1919 coefficients is equal to 6.171 (standard error of 0.719) and suggests that in counties where the level of education is high, a one standard deviation of excess mortality during WW1 is associated with 6 additional patents per 100,000 inhabitants than in other counties.

FIGURE 4: Regression results: interaction between mortality and education

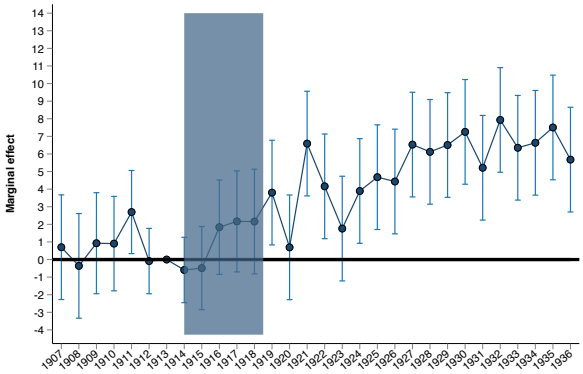
(a) Baseline measure of education



(b) Average enrollment rate



(c) *Baccalaureat rate*



Notes: Figure 4a estimates equation (6) with OLS and plots $\widehat{\delta}_t$, the additional marginal effect of excess mortality for counties in the top quartile of the education distribution, defined by the share of young men who surpassed the basic primary curriculum according to the 1901 conscription lists. Figure 4b reports estimates using the same model but measuring education via the average enrollment rate of children aged 5–15 in the 1861, 1866, 1871, 1876, 1881, 1891, and 1901 censuses. Figure 4c estimates the same model and uses the share of young men incorporated in the French army that hold the *baccalauréat* degree in 1901. In all panels, the control vector C_d includes the share of the agricultural sector in 1911 and a dummy for direct exposure to the front. Standard errors are calculated via a Newey-West estimator with a five-year bandwidth, and 95% confidence intervals are shown. The navy-blue-shaded areas indicate the war period.

TABLE 1: Summary of the effect of mortality for various specifications

	Static coefficient		Pre Trends		Observations
Panel A (Section 3.2)					
1. Figure 3a					
Excess Mortality	1.920***	(0.417)	0.223	(0.491)	2610
2. Figure 3b					
Excess Mortality	0.953**	(0.441)	0.047	(0.510)	2610
Interaction (labor intensive dummy)	2.525***	(0.758)	0.803	(0.876)	
Panel B (Section 3.3)					
3. Figure 4a					
Excess Mortality (baseline)	0.481	(0.428)	0.055	(0.497)	2610
Interaction (high education dummy)	6.171***	(0.719)	0.821	(0.834)	
4. Figure 4b					
Excess Mortality (enrollment rate)	0.646	(0.444)	0.188	(0.516)	2610
Interaction (high education dummy)	4.935***	(0.727)	0.145	(0.846)	
5. Figure 4c					
Excess Mortality (baccalaureat)	0.993**	(0.446)	0.045	(0.518)	2610
Interaction (high education dummy)	4.497***	(0.810)	0.683	(0.940)	
Panel C (Section 3.4)					
6. Figure 5a					
Inventors Mortality (county)	-0.163	(0.126)	-0.028	(0.149)	2610
7. Figure 5b					
Inventors Mortality (technology)	-0.099***	(0.010)	0.007	(0.008)	3630
Panel D (Section 3.5)					
8. Figure 6a					
Excess Mortality (baseline)	1.901***	(0.422)	0.234	(0.496)	2610
Interaction (high education - above median catholic dummy)	1.051	(1.533)	-0.389	(1.801)	
9. Figure 6b					
Excess Mortality (baseline)	0.598	(0.419)	0.037	(0.480)	2610
Interaction (high education - below median catholic dummy)	7.004***	(0.798)	1.127	(0.913)	

Notes: Column Static coefficient: each row corresponds to a static regression following the model (3) (rows 1, 6 and 7) or following model (5) (rows 2, 3, 4, 5, 8 and 9). "Excess Mortality" coefficient corresponds to the estimate of λ_S and "Interaction" corresponds to the estimate of δ_S. Column Pre Trends reports the average values of pre-treatment coefficients (1907 to 1913) of the corresponding dynamic models. Standard errors in parenthesis estimated similarly to the dynamic coefficient of the corresponding model. Stars indicate significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4 The direct effect of inventors' mortality

The above findings show that overall WWI-related excess mortality did not depress patenting in the post-war period and may even have stimulated it, especially where labor was more critical. However, not all types of workforce losses are alike. In particular, the deaths of inventors or scientists could undercut local innovation capacity, because inventors are scarce and less easily replaced by capital.[9] To examine this possibility, we construct a measure of *inventor-specific* mortality by matching pre-war patentees from the *PatentCity* data to the *Morts pour la France* database. We link in-

[9] Although the death of inventors or scientists may have an ambiguous effect on the development of their respective fields as shown in Azoulay et al. (2019a).

dividuals by comparing first and last names and drop any apparent matches who continued to file patents after the war, as these were obviously not deceased. While some noise is inevitable, the share of matched inventors is generally consistent with overall death rates for French men aged 15–45. In total, inventors correspond to 0.64% of total war-related deaths and 12.3% of the French inventors who filed a patent between 1900 and 1914, which is consistent with the fact that 15% of the male population aged from 15 to 45- a subpopulation in which inventors are overrepresented (Akcigit et al., 2017)- died during the war.

Two prominent examples highlight the breadth of inventor backgrounds: Jacques Alexandre Marie Danlos, who filed a railway signaling patent before joining the Marne battle and dying in early 1916; and Charles Henri Lindecker, an air-force commander who had filed ten vehicle-related patents. Although one might expect some scientists to be protected from conscription, many young engineers and scientists still served at the front. For example, more than 800 engineers from École polytechnique, the most prestigious engineering school died during the Great War, including 260 (20%) from the cohorts of 1911-1918 alone (Lévy-Lambert, 2014).

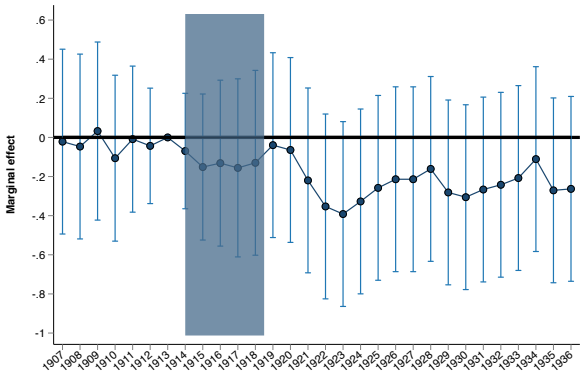
We evaluate the impact of these inventor losses using two approaches. First, we re-estimate equation (1), replacing the excess mortality index with i_d, the fraction of a county's pre-war inventors who died during the war. Second, we run a technology-level regression exploiting the fact that some technology classes were more severely affected, based on the fraction of pre-war inventors (in that class) who died. Specifically, we estimate a dynamic difference-in-differences model interacting this fraction i_c with a time fixed effect; we then regress the number of patents per year on that interaction using Poisson Pseudo Maximum Likelihood to estimate the coefficients. The key identifying assumption is that, conditional on being an inventor, the probability of dying in the war is orthogonal to the future trajectory of each technology class. Figure 5 shows that while the county-level coefficient is slightly negative it is not precisely estimated. At the technology level the effect is clearly detrimental: technology classes in which a larger share of inventors died experienced slower post-war growth. The corresponding static coefficients of all these estimations can be found in panel C of Table 1.

Going even further, we exploit simultaneously the geographical and technological heterogeneity of the effect. We construct the number of patents filed every year in county d and technology c as well as the share of inventors in this pair of county and technology that died during the war. We then estimate the same dynamic difference-in-difference model and add a rich set of fixed effects: technology-year, county-year and technology-county. This saturated model only leverages variations in patenting that

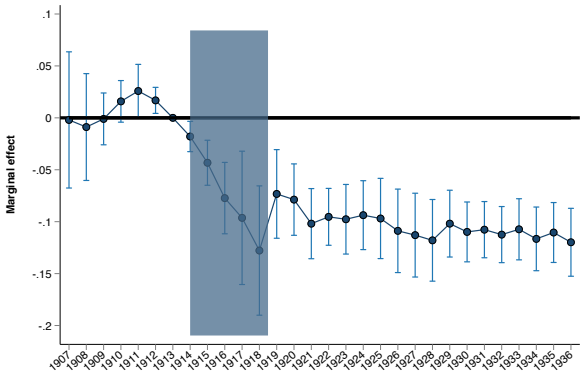
are specific to a given county-technology pair over time, after removing all common shocks at the county or technology level. In particular, the county-year fixed effect controls for any potential unobserved confounding factor correlated with excess mortality. The remaining identifying variation thus comes from differences in patenting behavior across technologies within the same county, relative to their pre-war trends, and differences across counties within the same technology, while controlling for nationwide technological trajectories. Results can be found in Figure 5 and confirm the negative effect presented in Figures 5a and 5b.

FIGURE 5: Regression results: inventors losses

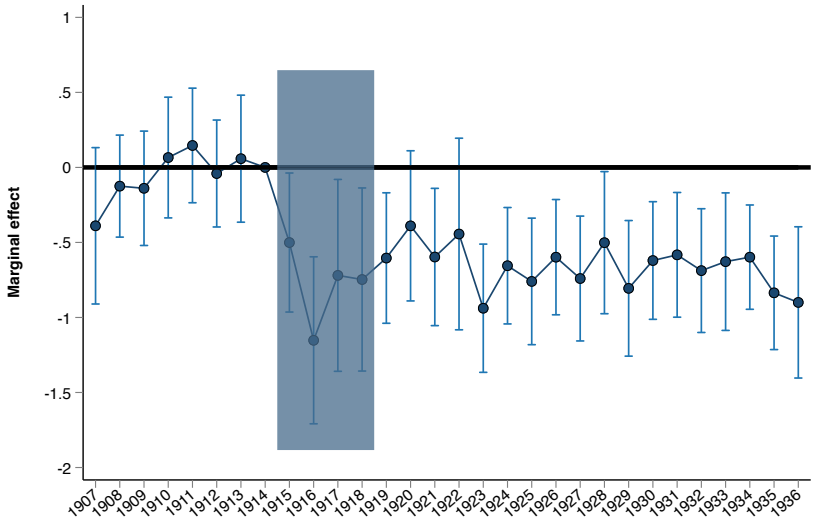
(a) At the county level



(b) At the technology-county level



(c) At the technology level



Notes: Figure 5a: estimation of equation (1) with OLS. The figure plots $\widehat{\lambda}_t$, the estimated marginal effect of an increase in the share of pre-war inventors killed during during WW1 in a given county. The control vector C_d includes the share of the agricultural sector in 1911 and a dummy variable indicating direct exposure to the front. Standard errors are estimated using a Newey-West estimator with bandwidth of 5 years. Figure 5b: reports the dynamic coefficient of a regression of the share of pre-war inventors killed during WW1 in a given technology on the logarithm of the number of patents filed in this technology. The model is estimated using Poisson Pseudo Maximum Likelihood (Gourieroux et al., 1984). Figure : reports the dynamic coefficient of a similar regression at the county $\times$ technology level, including technology-year, county-year and technology-county fixed effects. Standard errors are clustered at the county level. Corresponding confidence intervals at the 95% levels are presented. The navy-blue-shaded areas denote the war period.

3.5 The nature of education matters

We have shown so far that mortality-induced labor scarcity boosted innovation primarily in counties with sufficiently high initial education levels. Our measure of education however is purely quantitative and does not account for the nature of education.

During the 19^{th} century, the French education system was divided into secular (public) and Catholic (private religious) institutions, a division deeply rooted in France's history of secularization and the emergence of *laïcité* (state secularism). Throughout the 19^{th} century, significant tensions arose between secular republicans advocating for an education system free from religious influence and Catholic institutions committed to traditional curricula emphasizing religious instruction. This conflict culminated with the Jules Ferry laws (1879-1885), which established free, secular, and compulsory public education. However, Catholic schools, though receiving no state funding, remained influential in many regions, maintaining their traditional, less technically-oriented curriculum.

Building upon insights from Squicciarini (2020), who emphasized that secular schools adopted more modernized, technically oriented curricula aligned with industrial needs, we hypothesize that secular rather than Catholic schooling was instrumental in enabling counties to respond innovatively to labor scarcity. Thus, analyzing the share of Catholic school enrollment—averaged from successive censuses after 1850—helps us distinguish the effects of these two educational systems on innovation outcomes following demographic shocks.

More precisely, among the top educated counties according to our baseline measure, we distinguish those that are above the median in terms of Catholic enrollment. We then estimate the baseline dynamic specification twice, first measuring the interaction term between education and mortality only for above median counties in terms of catholic education and second for secular education. Formally we estimate:

$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1913}}^{1936} \Big[\mathbb{1}_t(k) \big(\lambda_k \tilde{m}_d + \delta_k^{(1)} \tilde{m}_d \times e_d \kappa_d + \gamma_k^{(1)} e_d \kappa_d + \phi_k C_d \big) \Big] + \alpha_d + \beta_t + \eta_{d,t} \tag{7a}$$

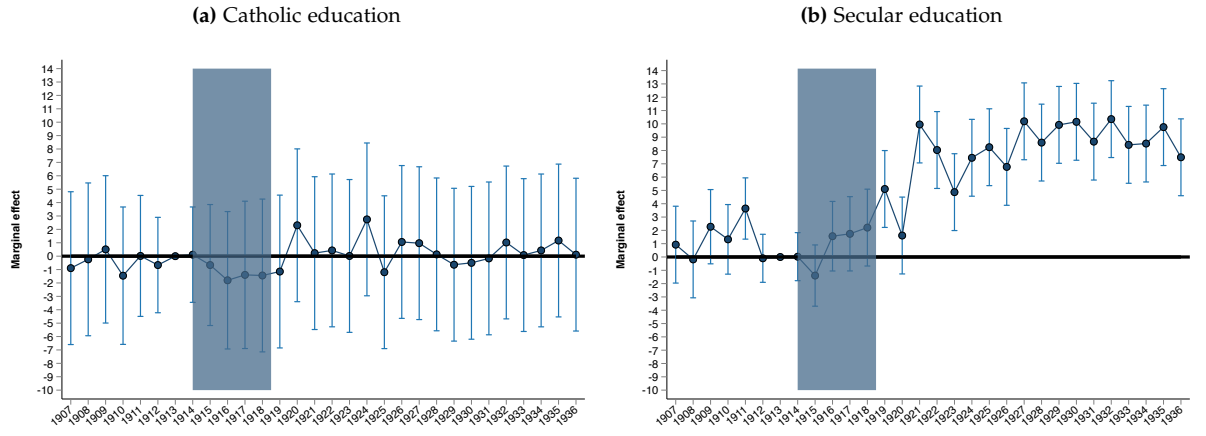
$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1913}}^{1936} \Big[\mathbb{1}_t(k) \big(\lambda_k \tilde{m}_d + \delta_k^{(2)} \tilde{m}_d \times e_d (1-\kappa_d) + \gamma_k^{(2)} e_d (1-\kappa_d) + \phi_k C_d \big) \Big] + \alpha_d + \beta_t + \eta_{d,t} \tag{7b}$$

where κ is equal to 1 if the county is above the median in terms of catholic education, measured by counting the share of catholic schools over various censuses of the 19^{th}

century. Results are presented in Figure 6. Figure 6b and Figure 6a show the interaction between education and excess mortality for secular and Catholic education respectively. The results show that mortality, when interacting with secular education, has a positive and significant effect on patenting activity—somewhat higher in magnitude than the general specification. Conversely, the interaction between mortality and Catholic education is associated with insignificant coefficients. The corresponding static coefficients are presented in Panel D of Table 1

These findings align with Squicciarini (2020)'s results on French industrialization in the late 19th century, where secular education accelerated industrial development, while Catholic schooling had no significant effect.

FIGURE 6: The nature of education



Notes: These Figures report coefficients $\delta_k^{(1)}$ (Figure 6a) and $\delta_k^{(2)}$ (Figure 6b) from model (7). The share of catholic schools (κ_d) is measured using school censuses recorded every five year between 1861 and 1901. Standard errors are clustered at the county level. Corresponding confidence intervals at the 95% levels are presented. The navy-blue-shaded areas denote the war period.

4 Mechanisms

In this section, we explore the potential mechanisms underpinning our main results. We start by examining several aspects of labor substitution. In particular, we show that wages in the agricultural sector increased in response to excess mortality, validating the idea that exposure to excess mortality drove the cost of labor up after the war (subsection 4.1). We further use data on the number of machines in the agricultural sector to assess whether technology adoption also responded to the mortality shock 4.2. We then use detailed information on the nature of patents in order to assess whether our results are driven by the response of patenting activity related to labor-saving technologies (subsection 4.3). Finally, we discuss the local nature of the response in section 4.4.

4.1 The impact of mortality on real wages

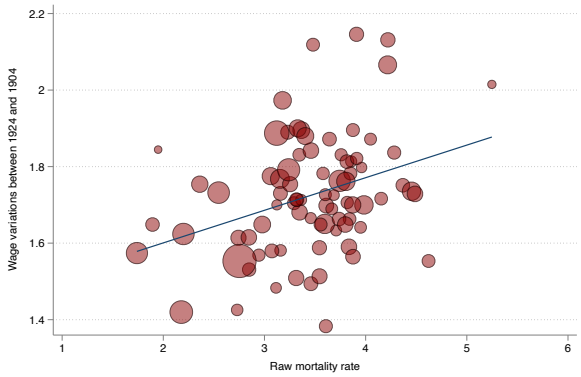
The findings in Section 3.3 suggest that WWI-related mortality created significant labor shortages, which, in turn, incentivized inventors and entrepreneurs in the most affected counties to develop labor-saving technologies. If labor scarcity is indeed the driving force behind this response, one would expect to see that higher mortality rates are associated with increases in relative wages—particularly in labor-intensive sectors such as agriculture.

Unfortunately, Census data do not systematically report wages by occupation or sector at the county level, and when available, coverage is incomplete. However, two editions of the *Annuaires statistiques de la France* (1904 and 1924) provide relevant data, offering county-level average wages for agricultural workers, except for six counties.[10]

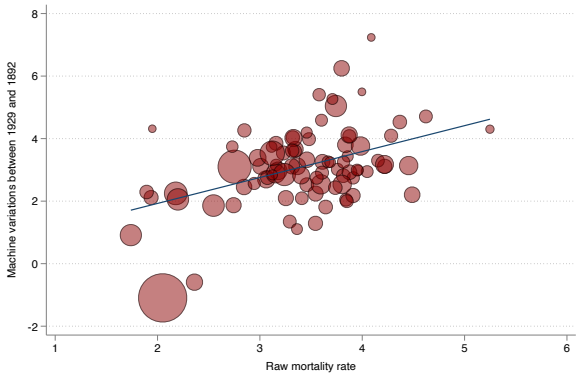
To assess the relationship between mortality and wages, we compute the log variation in agricultural wages over the 1904–1924 period and examine its correlation with mortality. Figure 7a first illustrates the relation between wage variation and raw mortality rates.

FIGURE 7: Correlation between wage and machine variation in agriculture and mortality rate

(a) Agricultural wages



(b) Agricultural machines



Notes: Each circle represents a county and the x-axis reports the actual mortality rate. The size of each bin is proportional to the 1911's population. Figure 7a: The y-axis is the first difference of the logarithm of the average wage in agriculture in 1924 and in 1904. All counties are included except 6 for which no information on the wage in agriculture is available either in 1904 or in 1924 (Alpes-Maritimes, Basses-Alpes, Charente-Inférieure, Corse, Hautes-Alpes, and Seine). Figure 7b: The y-axis is the first difference of the logarithm of the number of agricultural machines in 1929 and in 1892. All counties are included. The correlation is significant in both cases with coefficients respectively equal to 0.097 (robust standard error of 0.027) and 1.485 (robust standard error of 0.487). See Table 2.

The observed positive correlations suggest that the war-induced labor shortage was particularly impactful in agriculture, the largest employment sector and the one with the highest wartime mortality. Estimations of this relationship confirm that the correlation is statistically significant even when we use the excess mortality measure or

[10] Alpes-Maritimes, Basses-Alpes, Charente-Inférieure, Corse, Hautes-Alpes, and Seine.

conditional on the share of the agricultural sector before the war (see columns 1, 2 and 3 of Table 2). This result suggests that the positive response in terms of innovation, induced by the increase in the cost of labor, did not fully compensate for labor scarcity, in line with a weak induced-bias hypothesis (Acemoglu, 2002). That is, while the labor shock may have triggered technological adjustments favoring labor-saving innovations, these adjustments were not sufficient to counteract the overall effect of reduced labor supply on wages.

4.2 Evidence on technology adoption in the agricultural sector

Our results so far focus on innovation as captured by patenting activity. A related question regarding the mechanism is whether *actual technology adoption* responded to labor scarcity, as has been shown in different contexts (see e.g. Voth et al., 2022). To investigate this, we focus on agricultural mechanization, drawing on rich data from the *Enquêtes agricoles* surveys of 1892 and 1929. These county-level administrative studies provide detailed records of crop yields and machinery use, offering a valuable lens through which to measure technological adoption over time. Although the survey was discontinued after 1892 and resumed only in 1929—preventing us from looking at pre-war dynamics—, the available data allows us to compute the change in the degree of agricultural mechanization before and after WWI across counties with varying mortality rates.[11]

The raw correlation is presented in Figure 7b and the corresponding coefficients can be found in columns 4, 5 and 6 of Table 2. Column 6 shows a positive and significant coefficient of excess mortality on the adoption of agricultural machinery, with a coefficient of 0.894—implying that 1 sd increase in excess mortality is associated with a 44 percentage point increase in the growth rate of agricultural machinery. The results remain robust and significant when we control for the share of the agricultural sector in 1911 or use excess mortality.

While these estimates should be interpreted with caution—given the relatively small sample size and the long interval between the surveys—they offer suggestive evidence that the rise in machinery-related patenting activity in high-mortality counties coincided with a meaningful increase in technological adoption.

We can relate the magnitude of the adoption response to that of the wage response.

[11] We focus on key labor-saving machines—faucheuses (mowers), moissonneuses-lieuses (reapers-binders), and semoirs mécaniques (mechanical seeders)—and assess how mortality influenced their adoption.

Focusing on our baseline specification (col 2 and 5), we get a ratio of 10 : a 1% increase in wage is associated with a 10% increase in adoption of machines. This elasticity of 10 is very large. However, in the presence of directed technical change, this ratio does not only depend on the elasticity of substitution between machine and labor in the agricultural production function but also decline in the quality-adjusted cost of machines. In appendix section C.4, we develop a simple conceptual framework, to see how upward biased the elasticity of capital to wages is with respect to the elasticity of substitution. Once we account for this, our estimates are consistent with an elasticity of substitution of about 4, which is large but less than half the magnitude of the naive estimate.

TABLE 2: Effect of mortality on wages and agricultural machinery

	Wages			Agricultural machines		
	(1)	(2)	(3)	(4)	(5)	(6)
Mortality	0.097***	0.112***	0.035*	1.485***	1.087***	0.894**
	(0.027)	(0.037)	(0.018)	(0.487)	(0.354)	(0.395)
Share of agricultural sector (1911)		-0.001			0.016	
		(0.002)			(0.020)	
R Squared	0.158	0.162	0.041	0.442	0.458	0.265
Obs.	81	81	81	87	87	87

Notes: OLS estimation. Columns 1, 2 and 3, the dependent variable is the variation of the logarithm of the average wage in the agricultural sector in 1924 and in 1904. The sample includes all counties except 6 for which information is unavailable (Alpes-Maritimes, Basses-Alpes, Charente-Inférieure, Corse, Hautes-Alpes and Seine). Columns 4, 5 and 6 use the variation of the logarithm of the number of agricultural machines between 1929 and 1892. All counties are included. Mortality is defined using the total number of deaths in the "Morts Pour la France" register in columns 1, 2, 4 and 5 and our transformed measure of excess mortality defined in Section 2.2. Standard errors are robust to heteroskedasticity. Stars summarize the level of the p-value of the Student test on the nullity of the coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Empirical evidence on labor substituting patents

Another implication of the "escape scarcity by innovating" mechanism is that an increase in agricultural wages triggered by the wartime disappearance of many workers should translate into a relatively stronger innovation response in technologies that substitute for labor. In this section, we use detailed information on patents in order to assess whether our results are driven by the response of patenting activity related to labor-saving technologies. We first explain how we characterize patents as labor-saving (section 4.3.1) and then present the results of the empirical analysis (section 4.3.2).

4.3.1 Identifying labor saving technologies

We classify patents into labor-saving technologies and all others, following the same classification used in Figure 2b.

Over the past few years, multiple methods have been proposed to identify patent documents that capture mechanization, automation, or broader labor-substitution devices (see, e.g., Hémous et al., 2024; Mann and Püttmann, 2018; Webb, 2019; Kogan et al., 2023). Most of these approaches focus on modern technologies—for instance, Webb (2019) examine the impact of Artificial Intelligence, while Mann and Püttmann (2018) study post-1976 patents. Our objective by contrast is to retrieve patents that belongs to technology that would substitute for human labor in the early 20^{th} century and in particular in agriculture—a sector which accounted for about 40% of the population in 1914 and where workers experienced high casualties, representing 550,000 deaths and 500,000 incapacitated workers (Ministère de l'agriculture, 2023).For example, patent FR533229A filed in 1920 by Etienne-Joseph-Ernest Gau describes a new machine that accelerate and semi automate the plantation of potatoes.

In order to retrieve such patents, we first select each patent filed in France over the period we consider that belongs to one of the following CPC technological classes: "A01B" (Soil working in agriculture), "A01C" (Planting, sowing, and fertilizing), "A01D" (Harvesting and mowing), "A01F" (Processing of harvested crops), "A01G" (Horticulture and cultivation of plants) or "A01M" (Pest control and plant protection). These include about 4700 patents which is only about 2% of the total. In order to expand this set, we look at the titles of these 2% patents and measure the semantic distance between each patent's title and this reference set. Appendix B.3 provides more technical details.

Patents scoring within the top 10% of similarity scores are categorized as *labor-saving technologies*. Conversely, patents falling into the bottom 10%, showing minimal semantic overlap with the reference set, are classified as *non-labor-saving technologies*.

As a robustness, we also adapt the methodology of Hémous et al. (2024) to historical data, leveraging bibliographic information in patent documents to compute keyword frequencies for each technological class, thereby assigning each class a propensity for labor-saving technologies. To adapt this methodology to the context of the early 20^{th} century France, we select keywords that are specific to the mechanization of agriculture and industry in patent titles. We focus on four stems that are most plausibly connected to labor-saving innovation at that time: "machine," "automat," "mecan," and "elec." While the first three terms naturally evoke mechanization and automation, the labor-substitution relevance of electricity may appear less obvious. Yet Pavel

(2023) underscores that electricity began finding wide applications as early as the turn of the twentieth century in Europe, "*replacing both human and animal strength*" as a power source for agricultural and industrial machinery.

After calculating these keyword frequencies by CPC, we classify each CPC in the top 20% for the occurrence of these stems as related to machinery, automation, or electricity, respectively (see Figures B3). We form a corresponding control groups from classes in the bottom 20% of the distribution for these keyword.

4.3.2 Empirical results on labor-saving patents

With this classification, we can now look at the post-war dynamic focusing on labor saving patents. To test whether counties more affected by mortality were also more likely to accelerate their production of labor substituting inventions, we estimate the models specified in equations (1) and (6) but restrict the numerator of the dependent variable to only include these patents. Results of these regressions are summarized in Panel A of Table 3 which displays the corresponding static coefficients and in Figures 8a and 9a.

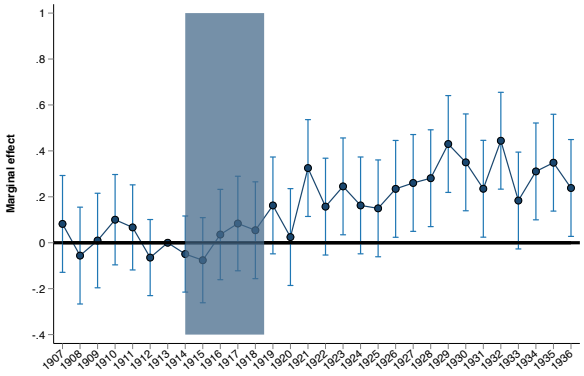
The results are consistent with what we found when we considered all patents in Figures 3a and 4a: there is an uptake of patents that are associated with automated technologies in the agricultural sector and this increase is larger in mode educated counties. But when we restrict to an equally large set of patents that are as far as possible from automation technologies, then we see little to no effect (Figures 8b and 9b and Panel B of Table 3). Quantitatively, the effect on labor-saving patents per capita is more than 3 time larger than for the control group. In Appendix A.3, we show that the results are similar when using an alternative, more flexible, classification based on the prevalence of keywords by CPC.

4.4 A local response

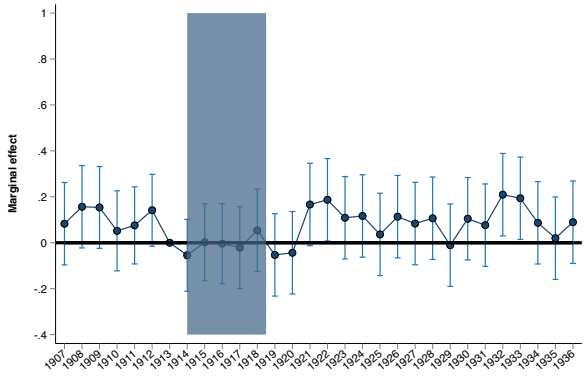
The link between the geography of production and of innovation. Our results so far rely on the fact that a local excess mortality shock would generate a local response in terms of innovation, provided the existence of local capabilities. This localized effect is strongly predicted by theories on the economics of innovation, which emphasize that the information required to solve a problem is often "sticky" and costly to transfer from its source. As argued by Von Hippel (1994), innovators require a deep and nuanced understanding of a user's specific needs, and this information is most easily and cheaply acquired by being physically close to the problem itself. By

FIGURE 8: Regression results: mortality and innovation in labor saving technologies

(a) Labor saving patents



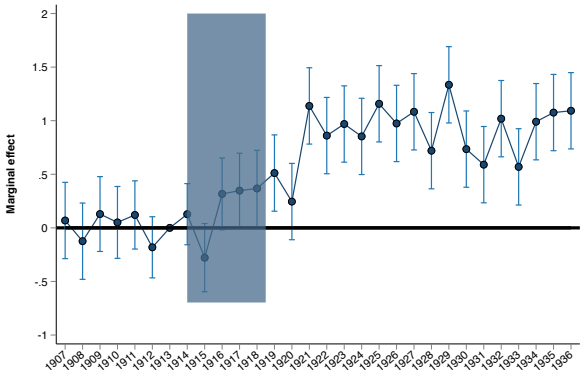
(b) Non labor saving patents



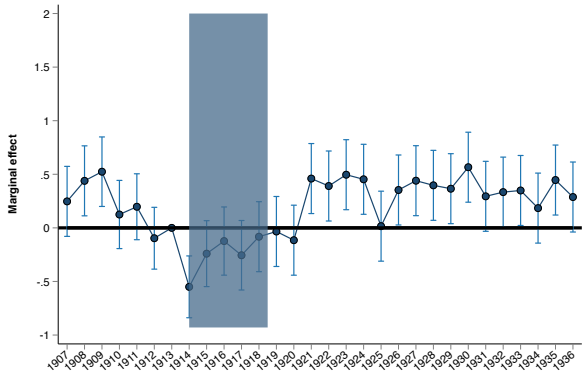
Notes: These two figures replicate Figure 3a but use a different dependent variable. Figure 8a uses the number of patents identified as "labor saving" based on their technological class following the methodology outlined in Section 4.3 per 1906's population (in 100,000 inhabitants). Figure 8b uses patents identified as "non labor saving" following the same methodology.

FIGURE 9: Regression results: mortality, education and innovation in labor saving technologies

(a) Labor saving patents



(b) Non labor saving patents



Notes: These two figures replicate Figure 4a but use a different dependent variable. Figure 9a uses the number of patents identified as "labor saving" based on their technological class following the methodology outlined in Section 4.3 per 1906's population (in 100,000 inhabitants). Figure 9b uses patents identified as "non labor saving" following the same methodology.

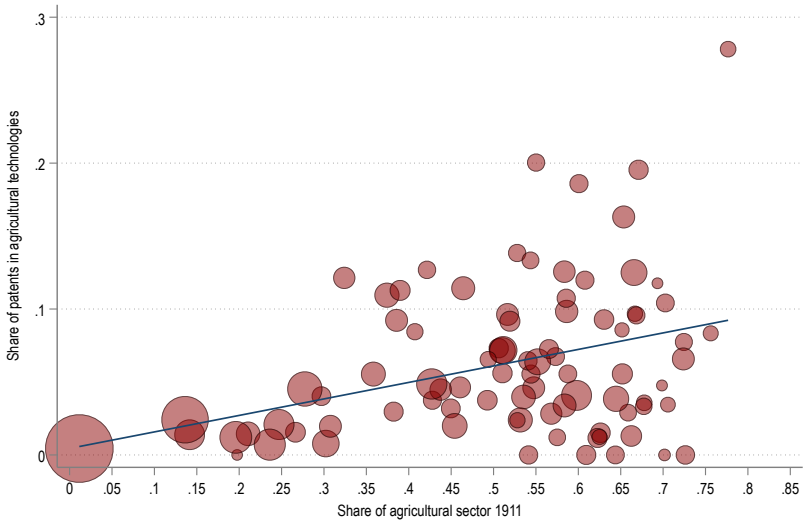
this logic, an inventor in Paris would face significant costs in trying to understand the precise labor challenges of a vineyard in Burgundy, whereas a local mechanic or entrepreneur would possess this "sticky" information implicitly. The most effective innovations are therefore more likely to emerge from actors who are directly embedded in the local context where the problem is most acute.

This localization is further reinforced by the nature of knowledge spillovers. The process of developing a new technology also benefits from proximity to related expertise and suppliers, and these spillovers are themselves geographically bounded (Jaffe et al., 1993). Thus, both the crucial problem information and the solution-oriented knowledge are concentrated locally, creating a powerful incentive for the innovation response to mirror the geographic distribution of the mortality shock.

These mechanisms are particularly potent in the context of early 20th-century France due to pronounced sectoral and agricultural specialization. The labor-saving needs were highly heterogeneous: a machine designed for the large, flat wheat fields of the Beauce would be of little use in the terraced, specialized farms of another region. This required tailored solutions that could only be effectively designed and implemented by local agents, leveraging their intimate knowledge of the region's unique economic landscape.

While the granularity of our data precludes a systematic test of the link between technological and economic specialization, we nevertheless provide suggestive evidence by examining the pre-war alignment between a county's innovative activity and its economic structure. Figure 10 plots the correlation between the share of agricultural employment in 1911 and the share of pre-war patents classified in agricultural technologies (CPC category A). First, and reassuringly, the county of Seine (Paris)—the nation's primary innovation hub—exhibits a near-zero share of agricultural patents, consistent with its negligible agricultural sector. Second, across the full sample, we find a positive and significant correlation, confirming that counties with a larger agricultural footprint tended to specialize in developing agricultural technologies.

FIGURE 10: Correlation between share of agricultural sector and share of patents in agricultural technologies



Notes: Each circle represents a county and its size is proportional to the 1911's population. The x-axis reports the share of the agricultural sector in employment in 1911. The y-axis measures the share of agricultural patents (with a CPC category A) in total patent filed before WW1. The correlation is significant in with a coefficient equal to 0.113 (robust standard error of 0.0167).

Accounting for spatial spillovers. Nonetheless, this pattern of local specialization does not rule out the possibility of spatial spillovers that would extend across a

county's borders. Technologically specialized regions might not be perfectly contained within administrative county boundaries but could instead span across them. In such cases, the significant labor shock experienced in one county could trigger an innovation response in a neighboring one. If such spillovers exist, our estimates of the local effect of mortality would be impacted by a contagion bias. Specifically, the measured effect of a county's own mortality might be confounded by the influence of its neighbors' shocks, leading to an incorrect assessment of the true, localized response.

To test the geographical spreading of our effect, we test the following transformed static model:

$$\text{pat}_{d,t} = \mathbb{1}_t(P) \left(\gamma_S^{(k)} \sum_{d'} \tilde{m}_{d'} w_{d,d'}^{(k)} + \phi_S \text{C}_d \right) + \alpha_d + \beta_t + \eta_{d,t}^S, \tag{8}$$

where the weight $w_{d,d'}^{(k)}$ are defined using an exponential decay function, which ensures that closer counties receive more weight than distant ones:

$$w_{d,d'}^{(k)} = A \cdot e^{-\delta(d,d')\frac{\ln(2)}{k}}. \tag{9}$$

Here, $\delta(d, d')$ is the geographical distance between the centroids of counties d and d', and A is a constant that normalizes the weights to sum to one for each county d. The crucial parameter is k, which represents the spatial half-life of the effect in kilometers. It defines the distance at which the influence of a neighboring county is reduced by half. For instance, if we set $k = 100$, the weight of a county 100 km away is 50% of an adjacent one, and the weight of a county 200 km away is 25%. A small k implies that spillovers decay rapidly and are confined to immediate neighbors, while a large k suggests that effects are geographically widespread. Note that the sum includes county d so we expect the coefficient $\gamma_S^{(k)}$ to be close to our baseline as when k is small and to diminish progressively as we include more and more county and reduce the weight on d. This would provide evidence that the innovation response is a truly localized phenomenon, not driven by contagion.

We report the value of $\gamma_S^{(k)}$ for values of k between 0 and 1000 km in Figure A11 in the Appendix. The top horizontal line represents the baseline static coefficients equal to 1.9 and as expected, increasing k makes the estimated coefficient $\gamma_S^{(k)}$ smaller and smaller. Ultimately this coefficient converge to a value that is insignificant but slightly positive, representing the residual effect of county d.

TABLE 3: Static coefficients on labor saving technologies

	Static coefficient		Pre Trends		Observations
Panel A Labor saving (baseline)					
1. Figure 8a					
Excess Mortality	0.237***	(0.048)	0.020	(0.068)	2610
2. Figure 9a					
Excess Mortality	0.055	(0.048)	0.020	(0.069)	2610
Interaction (high education dummy)	0.806***	(0.081)	0.009	(0.115)	
Panel B Non Labor saving (baseline)					
3. Figure 8b					
Excess Mortality	0.035	(0.036)	0.095	(0.059)	2610
4. Figure 9b					
Excess Mortality	-0.044	(0.040)	0.041	(0.063)	2610
Interaction (high education dummy)	0.301***	(0.067)	0.205	(0.107)	
Panel C Labor saving (alternative)					
5. Figure A7a					
Excess Mortality	0.700***	(0.125)	0.208	(0.152)	2610
6. Figure A8a					
Excess Mortality	0.117	(0.120)	0.076	(0.139)	2610
Interaction (high education dummy)	2.596***	(0.201)	0.625***	(0.233)	
Panel D Non Labor saving (alternative)					
7. Figure A7b					
Excess Mortality	0.147**	(0.073)	-0.053	(0.098)	2610
8. Figure 9b					
Excess Mortality	-0.024	(0.080)	-0.058	(0.105)	2610
Interaction (high education dummy)	0.635***	(0.135)	0.051	(0.177)	

Notes: Column Static coefficient: each row corresponds to a static regression following the model (3) (rows 1, 3, 5 and 7) or following model (5) (rows 2, 4, 6 and 8). "Excess Mortality" coefficient corresponds to the estimate of λ_S and "Interaction" corresponds to the estimate of δ_S. Column Pre Trends reports the average values of pre-treatment coefficients (1907 to 1913) of the corresponding dynamic models. Standard errors in parenthesis estimated similarly to the dynamic coefficient of the corresponding model. Stars indicate significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Threats to identification and robustness checks

Our diff-in-diffs analysis relies on the parallel trends identifying assumption, i.e. the assumption that trends in county-level patenting in the absence of the war (change in untreated potential outcome) are uncorrelated with the actual excess mortality experienced during the conflict. Our dynamic diff-in-diffs estimates consistently point to insignificant pre-trend coefficients, which, while reassuring and lending credibility to the parallel trends assumption, is only directly informative about the pre-war period.

It is possible that contemporaneous shocks that do not show up in the pre-trends correlate with mortality and drive local innovation potentials after the war. In this section, we explore the robustness of our results, mostly by isolating specific sources of the variation in mortality which we view as less likely to correlate with underlying trends in local innovation potential.

First, in sections 5.1 and 5.2, we exploit exposure to the Battle of Verdun and how it varies across counties to isolate a presumably more exogenous component of mortality (Cagé et al., 2023). Second, we build on Boehnke and Gay (2020) leverage differences in mortality related to the uneven experience of the mobilized cohorts, exploiting fine local variation in the age structure of the conscripts (section 5.3). We finally investigate the role of public procurement contracts both as a driver of local innovation and as potential confounding shocks for our results (section 5.4).

5.1 Exploiting the Verdun Battle

Our regressor of interest measures county-level mortality. It is a function of how many inhabitants were mobilized in any given time and the mortality among soldiers in the specific places and times where they were sent. One might suspect for instance that the mobilization and assignment of locals to specific battles might be endogenous. It could be for instance that soldiers from places with higher level of human capital were sent to less dangerous parts of the front.

However, the richness of the *Morts pour la France* dataset allows us to make an adequate robustness check, by leveraging the intuition of Cagé et al. (2023) who argue that the exposure of soldiers during the Battle of Verdun was as good as random with respect to their county of origin. The battle of Verdun, which occurred between February and December 1916, was one of the deadliest and most famous battles of WW1. It was a brutal, prolonged battle of attrition, deliberately initiated by the German command with the aim of "bleeding the French army white". More than 160,000 French soldiers were killed in less than 10 months. The intensity and duration of the

fighting created unprecedented conditions that demanded a unique tactical response from the French command.

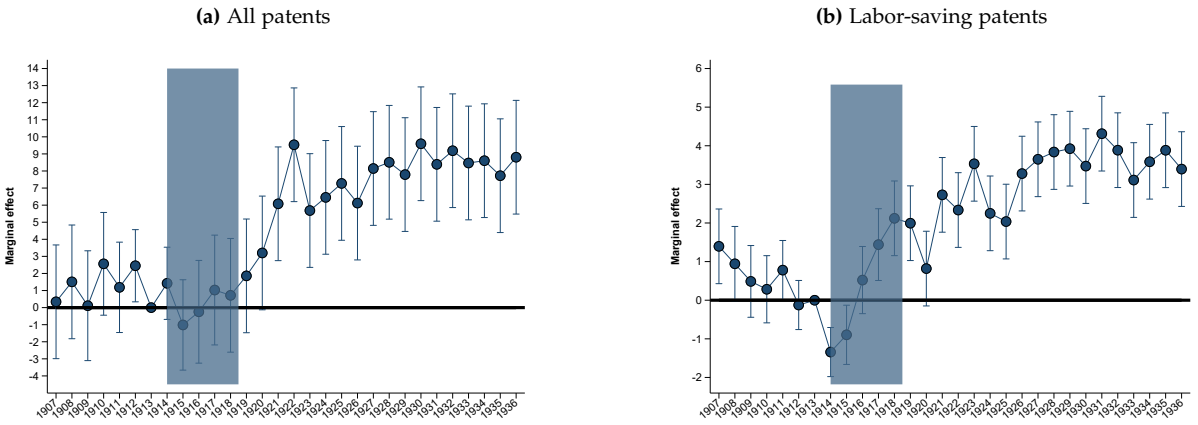
Indeed the commander in chief of the French army for this battle, Maréchal Pétain, implemented a system of troop replacements known as the *Noria*, which implied that line regiments were rotated only after a few days to limit the level of de-motivation, before their numbers were decimated and morale impaired. In turn, by May 1st, 53% of the entire French line infantry had been rotated through Verdun. As reported in Figure C2, the battle of Verdun was associated with a sustained higher number of casualties per day, 543 on average, but with a high degree of heterogeneity. Accordingly, Verdun represents an ideal experiment to assess whether our results exploiting all variation in excess mortality are biased by confounding factors. Additional details are given in Appendix C.2.

More specifically, we retrieve the number of victims during the Verdun battle by recovering the place and time of death of each soldier from the *Morts Pour la France* dataset. A soldier is said to have passed during the Battle of Verdun if he died between February, 16^{th} and December, 18^{th} in the Meuse county in which the city of Verdun is located. This leaves us with roughly 97,000 victims over a nine months period [12]. We then start from our baseline model for human capital (see equation (6)) and replace the residualized mortality indicator by the mortality rate suffered during the Battle of Verdun. We estimate this model using patents and for labor-saving patents only.

Results are displayed in Figure 11. For both specifications, almost all coefficients on the interaction terms are significant at the 5% or even at the 1% level after the war, supporting the idea that mortality boosted innovation in counties where the initial education level was large enough to ensure innovation abilities. Overall, the results summarized in this subsection are very similar to those derived under the general framework and bring further support to the idea that war-related mortality induced firms to innovate in order to escape labor scarcity.

[12] That this figure is lower than the 160,000 officially reported stems from the fact that we miss data for some soldiers regarding the timing of their death or their birth county.

FIGURE 11: Effect of mortality × education at Verdun on patenting activity



Notes: This graph pictures the effect of a marginal increase in the mortality suffered at the Verdun battle interacted with education. Panel (a) plots the overall effect for all kinds of patents while Panel (b) plots the effect for labor saving patents.

5.2 Dealing with non random exposure

While our residual mortality indicator aims at capturing excess mortality with respects to department specific features, it is still conceivable that unobserved characteristics which we fail to capture might influence this measure. For instance, Guillot and Parent (2018) suggest that political features such as voter abstention rates—perceived as indicative of weaker allegiance to Republican values—could have led to "punishments" of certain departments through increased conscription rates to counteract pacific sentiments during the war. To the extent that such political variables would be correlated with the innovation potential post-war in the absence of the war, this could bias our estimates. Hence, we implement a complementary robustness check by slightly adapting the framework developed by Borusyak and Hull (2023) in the context of the Verdun battle. Leveraging the battle of Verdun to build this complementary robustness check stems from two reasons: first, extensive details on the rotation of units during the battle were collected by Cagé et al. (2023) which allows us to perform simulation exercises based on a measure of exposure to the battle Verdun; second, the battle of Verdun accounted for a substantial share of total losses incurred during World War I, meaning that the battle is large enough to be thought as being representative of war casualties. More specifically, we build on the dataset collected by Cagé et al. (2023) who retrieved the exposure of soldiers from each city to the battle of Verdun based on whether the military units associated with their hometown was deployed and active at Verdun during a given month. We then aggregate this exposure at the county level and compute the relative exposure $e_{c,m}$ of county c during month m as the ratio between its exposure and the total exposure of all counties. We start by defining $v_{c,m}$ as the predicted number of victims of county c during month m

based on exposure and aggregate mortality. It wrties as:

$$v_{c,m} = e_{c,m} \times v_m, \tag{10}$$

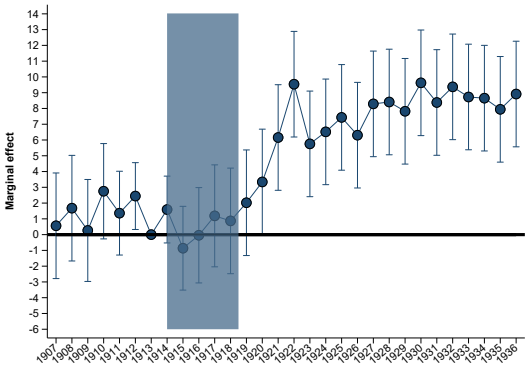
where v_m denotes the total actual number of dead soldiers during the month m. To check whether the results derived from the Verdun battle are not driven by the exposure to the battle, which may not be exogenous, we randomly reallocate the fatalities across the different months while keeping the exposure constant. Formally, we run 100 permutations of the monthly number of victims v_m and then compute a *placebo* fatality rate f_c for each county c defined as:

$$f_c = \sum_{m=1}^{11} e_{c,m} \times \tilde{v}_m, \tag{11}$$

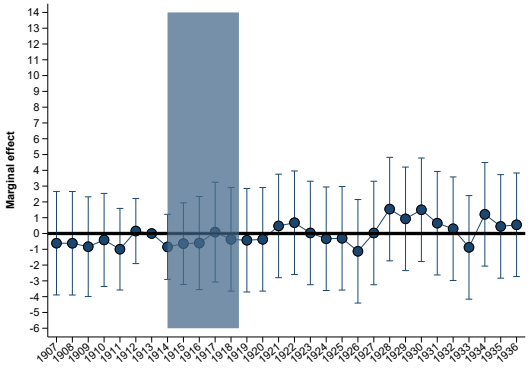
where $\tilde{v}_m$ indexes the average value of the 100 permutations in the total monthly number of victims. Once we have built these counterfactual fatality rates, we add them as controls in our main specification where all patents are taken as dependent variable. Figure 12a summarizes the results of this falsification test in a twofold manner. Panel (a) summarizes the coefficients obtained on the interaction between mortality at the Verdun battle and education when controlling for (i) the placebo mortality rates and (ii) their interaction with education. Meanwhile, Panel (b) plots the coefficients obtained on the interaction between placebo mortality rates and education. Clearly, both figures suggest that our results are not driven by potentially non-random exposure: indeed, the coefficients on the interaction term between mortality at the Verdun battle and education all remain positive and significant at the 5% or even at the 1% level for the post-war period, while the coefficients obtained on the interaction between placebo mortality rates and education are not significantly different from 0.

FIGURE 12: Regression results: actual and counterfactual mortality at Verdun, education and innovation

(a) Actual mortality rates



(b) Counterfactual mortality rates



Notes: This graph pictures the effect of a marginal increase in the mortality suffered at the Verdun battle interacted with education when counterfactual fatality rates are added as well as the effect of placebo mortality rates interacted with education. Panel (a) plots the effect of mortality at Verdun when controlling for placebo mortality rates as well as their interaction with education while Panel (b) shows the coefficients attached to the interaction between placebo mortality rates and education.

5.3 Exploiting variation in 1911 to 1914 cohorts: an instrument variable approach

To further validate our baseline results, we implement an instrumental variable strategy, adapting the methodology of Boehnke and Gay (2020) that leverages cohort-based discontinuities in military service duration at the onset of World War I. The French active army in 1914 was composed of several age cohorts—notably the classes of 1911 to 1914—that had received different amounts of military training. For instance, the class of 1911 had completed three years of training and was awaiting transfer to the reserves, whereas the class of 1914 had only just been conscripted.

This variation in preparedness creates a powerful instrument. Men from earlier cohorts, despite having more extensive training, were integrated into the same military units and sent to the same battlefields as their less-experienced counterparts. The validity of this instrument hinges on two conditions. First, for relevance, more military training should intuitively increase a soldier's effectiveness and survival chances. Therefore, our the share of soldiers from more-experienced earlier cohorts within a county's contingent is expected to be negatively correlated with the county's fatality rate. Second, for the exclusion restriction to hold, a county's pre-war cohort composition must be plausibly uncorrelated with any underlying trends in innovation that would have existed in the absence of the war, ensuring the instrument only affects innovation through its impact on war casualties.

Estimates of Table 4 further support the causal interpretation we provided so far, namely that mortality drove patenting activity up (column 1), and especially so in

counties where the initial education level was large enough (column 2). In terms of magnitude, the estimates are somewhat larger compared to the OLS estimates (see Table 1 panel A and B), but the differences are very small.

TABLE 4: Instrumental variables estimates

	(1)	(2)
Excess Mortality × Post war	2.818**	-0.472
	(1.219)	(1.004)
Excess Mortality × Post war × Educ		7.604***
		(1.371)
N	2610	2610
Counties	87	87
adj. R^2	0.578	0.615
Controls	Yes	Yes
KP Fstat	19.76	16.88

Notes: This table reports the two-stage least squares (2SLS) estimates designed to address potential endogeneity in the death rate, exploiting the discontinuities across conscription cohorts at the onset of World War I following the methodology of Boehnke and Gay (2020).

5.4 Accounting for spillovers from war effort

A recent literature (Gross and Sampat, 2023, 2021; Garin and Rothbaum, 2024) has laid the emphasis on the role played by the dramatic increase in public expenditures during crisis such as wars in shaping the direction, quality and quantity of innovation. As governments seek to gain a critical technological advantage over the enemy, they usually engage in a very state-oriented innovation policy which rely on the existing local technological landscape which is then subject to substantial additional founding. To the extent that such military projects generate spillovers in other sectors (see Moretti et al., 2023), such spillovers could be behind the forces explaining the increase in patenting after WW1. It is unlikely that these effects will be the only driver of our measured effects since there is no clear reasons spillovers are over-represented in counties that experienced an abnormally high mortality, but these increasing direct and indirect subsidies could have helped the more educated counties to develop the technologies they needed to compensate for the lack of workers and increasing cost of labor.

To test this more directly, we exploit newly digitized documents released by the French Ministry for Finance which comprises more than 10,000 public procurement contracts granted during World War I and worth at least 500,000 francs (about 2 millions current USD). Those contracts are classified according to both their location c

and the industry i they were attached to. In addition, we retrieve from this dataset a limited amount of textual data describing the aim and extent of the contracts. This dataset has already been leveraged by Alonso et al. (2023) who find that locations that received relatively more wartime industrial investments experienced a persistent post-war expansion of their manufacturing sector. We complete their findings by looking at the impact of these contracts on patenting.

To measure the influence of such contracts on innovation at the local level, we build a dataset at the county d times technology c level where the technology classes correspond to the subfields of the CPC. We then measure the exposure of technology class c to public procurement contracts in industry i by computing the Jaccard similarity between the 500 most frequently used words in patents belonging to technology class c and the 500 most frequently used words in industry i.[13] We then define the exposure $E_{d,c}$ of a cluster made of a technology class c and a county d to public expenditures as:

$$E_{d,c} = \sum_i \frac{s_{c,i}}{\max_i s_{c,i}} \times n_{i,d} \tag{12}$$

Where $s_{c,i}$ captures the similarity between technology class c and public procurement contracts assigned to industry i and $n_{d,c}$ captures the number of public procurement contracts assigned to industry i in county d. We finally estimate our model (1) using exposure E (in log) as a main regressor instead of excess mortality. Results are presented in Figure A10. This Figure suggests that indeed being more exposed to R&D procurement during the war led to a higher uptake of patents: the sum of post-war coefficients is equal to 0.883 (standard error of 0.395). Therefore, to ensure that our results are not driven by a correlation between excess mortality and exposure to these public contracts, we control directly for E in our main models (1) and (6). Results are presented in Panel A of Table 5 and in Appendix A.1 (Figures A2a and A2b) and confirm that our main findings hold.

5.5 Other robustness

In Appendix A.1 we present additional robustness checks of our main results. Figure A3 excludes military related patents from the sample, Figure A4 shows that our results hold when we exclude Paris and Figure A5 clusters standard errors at the county

[13] Formally, this similarity $s_{t,i}$ is computed by taking the ratio $\frac{n_{c\cap i}}{n_{c\cup i}}$ where $n_{c\cap i}$ is the number of words in both sets c and i and $n_{c\cup i}$ is the number of words in set c or in set i

level. These results are summarized in Panel A of Table 5. Appendix A.2 explores how our results hold with different measures of excess mortality and the static results are displayed in Panel B of Table 5. Appendix A.4 and Panel C of Table 5 explore different functional forms assumptions. Overall, our main results are robust to all these tests.

TABLE 5: Static coefficients on robustness

	Static coefficient		Pre Trends		Observations
Panel A Generic Robustness Test (Appendix A.1)					
1. Figure A2					
Excess Mortality	0.415	(0.428)	0.054	(0.495)	2610
Interaction (high education dummy)	6.077***	(0.717)	0.820	(0.830)	
2. Figure A3					
Excess Mortality	0.476	(0.429)	0.003	(0.494)	2610
Interaction (high education dummy)	6.085***	(0.720)	0.907	(0.830)	
3. Figure A4					
Excess Mortality	-0.133	(0.249)	0.132	(0.333)	2580
Interaction (high education dummy)	3.425***	(0.428)	1.166**	(0.574)	
4. Figure A5					
Excess Mortality	0.481	(0.801)	0.055	(0.238)	2610
Interaction (high education dummy)	6.171***	(1.661)	0.821*	(0.457)	
Panel B Alternative measure of excess mortality (Appendix A.2)					
5. Figure A6a					
Excess Mortality	-1.211	(0.815)	0.222	(0.948)	2610
Interaction (high education dummy)	11.419***	(1.419)	1.224	(1.651)	
6. Figure A6b					
Excess Mortality	-0.046	(0.456)	0.147	(0.603)	2610
Interaction (high education dummy)	2.555**	(1.160)	1.071	(1.534)	
7. Figure A6c					
Excess Mortality	0.128	(0.609)	0.026	(0.708)	2610
Interaction (high education dummy)	8.376***	(0.972)	1.145	(1.130)	
Panel C Alternative functional forms (Appendix A.4)					
8. Figure A9a					
Excess Mortality	0.024	(0.043)	0.029	(0.036)	2610
Interaction (high education dummy)	0.279***	(0.070)	0.041	(0.038)	
9. Figure A9b					
Excess Mortality	-0.003	(0.022)	0.010	(0.037)	2610
Interaction (high education dummy)	0.196***	(0.036)	0.104	(0.062)	
10. Figure A9c					
Excess Mortality	-0.002	(0.026)	0.010	(0.046)	2610
Interaction (high education dummy)	0.209***	(0.043)	0.125	(0.077)	

Notes: Column Static coefficient: each row corresponds to a static regression following the model (5). "Excess Mortality" coefficient corresponds to the estimate of λ_S and "Interaction" corresponds to the estimate of δ_S. Column Pre Trends reports the average values of pre-treatment coefficients (1907 to 1913) of the corresponding dynamic models. Standard errors in parenthesis estimated similarly to the dynamic coefficient of the corresponding model. Stars indicate significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Conclusion

Our analysis finds that mortality related to WW1 in France prompted a substantial boost to local innovative activity, particularly in counties that had a sufficiently strong human-capital base. We further show that the effect is stronger when considering labor-saving patents. These findings are robust to many robustness tests.

Our results suggest that war-related casualties increased the incentives to invent or improve labor-saving technologies in order to escape labor scarcity. This pattern is especially pronounced in areas where labor-intensive production made it crucial to escape labor scarcity with new machinery or techniques. Consistent with labor scarcity driving the incentive to innovate, we find a positive relationship between local mortality and wage growth, as well as with increases in machine adoption in the agricultural sector. In contrast to overall mortality, we find that the *mortality of inventors* had a negative effect on innovation.

Human capital emerges as a key mediator. Counties with higher educational levels, as measured by their prewar schooling achievements, exhibit a stronger positive innovation response to wartime mortality.

Overall, our paper shows that the interplay of "learning by necessity" (urgency in solving manpower shortages) and "learning by capacity" (preexisting educational advantages) drove the post-war jump in labor-saving innovation. Our results imply that the interaction between incentives and capabilities is central to our understanding of the pace and direction of technical change.

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ONLINE APPENDICES

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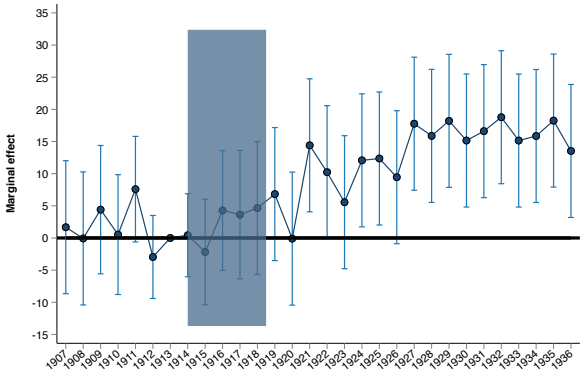
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A Results of Robustness Tests

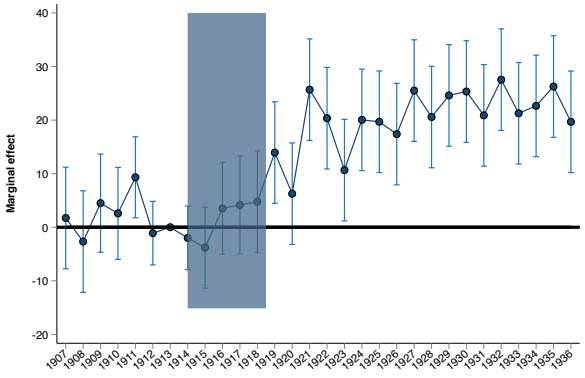
A.1 Generic Robustness Tests

FIGURE A1: Continuous measure of education

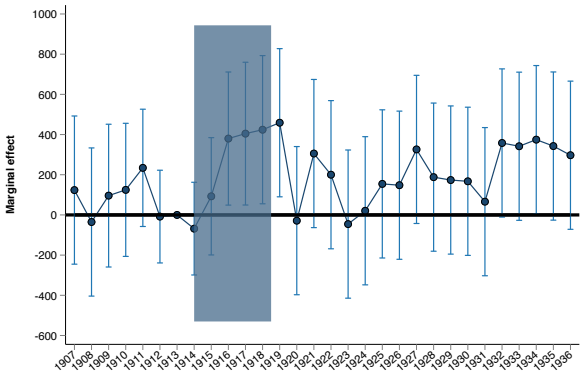
(a) Baseline measure of education



(b) Average enrollment rate



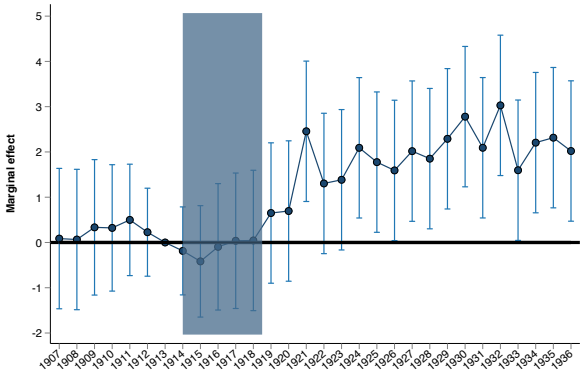
(c) *Baccalaureat* rate



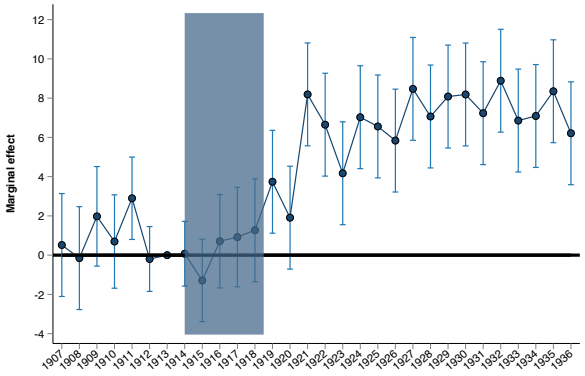
Notes: Replication of Figures 4a, 4b and 4c with a continuous measure of education to measure e_d instead of a dummy variable respectively using our baseline measure of education, the enrollment rate or the baccalaureat rate. See Figure 4 for more details.

FIGURE A2: Controlling for public procurement

(a) Unconditional effect



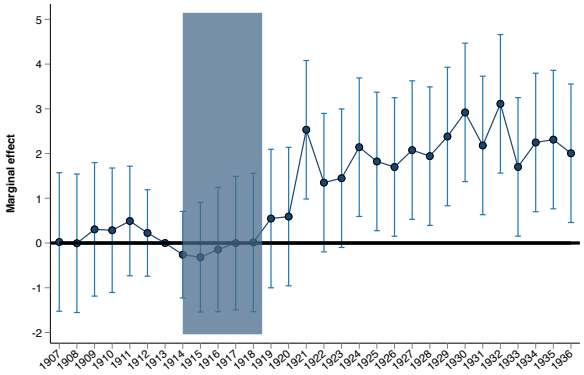
(b) Interaction with education



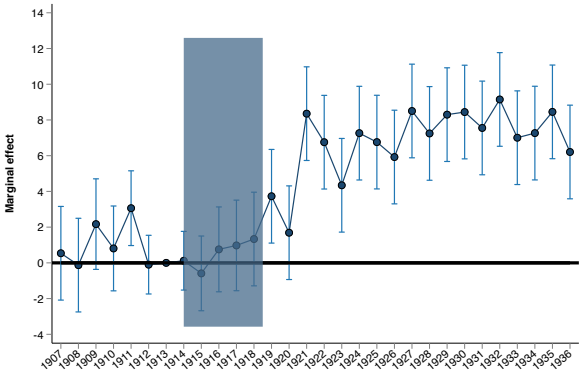
Notes: These Figures replicate Figures 3a and 4a but control for the logarithm of total R&D procurement received during the war (see Section 5.4.

FIGURE A3: Excluding military related patents

(a) Unconditional effect



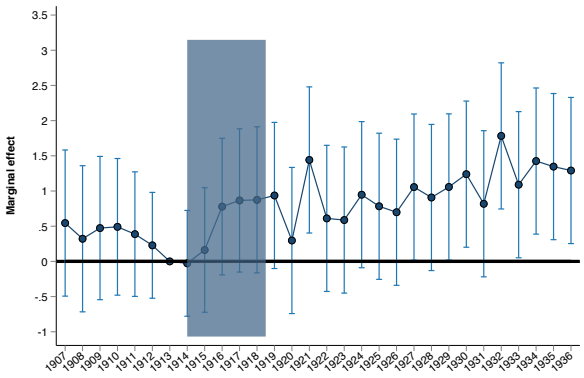
(b) Interaction with education



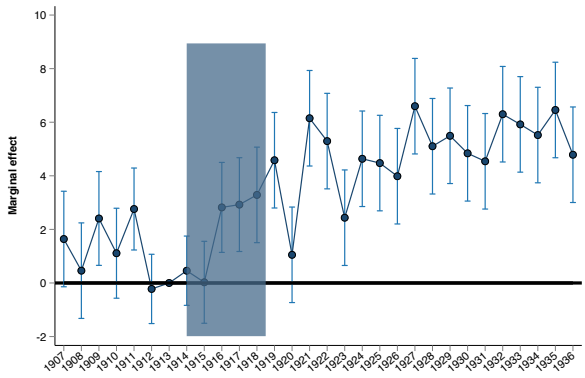
Notes: These Figures replicate Figures 3a and 4a but the dependent variable used here is the number of patents per inhabitant using 1906's population (in 100,000 inhabitants) when excluding the military patents from the sample. Military patents are identified by belonging to F41 and F42 CPC classes, which cover weapons and ammunition.

FIGURE A4: Excluding Paris

(a) Unconditional effect



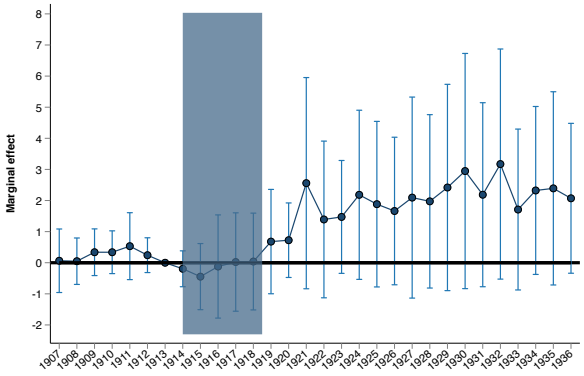
(b) Interaction with education



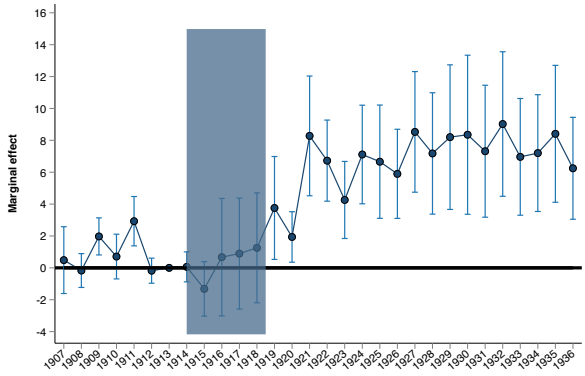
Notes: These Figures replicate Figures 3a and 4a but exclude Paris from the sample.

FIGURE A5: Clustered standard errors

(a) Unconditional effect



(b) Interaction with education

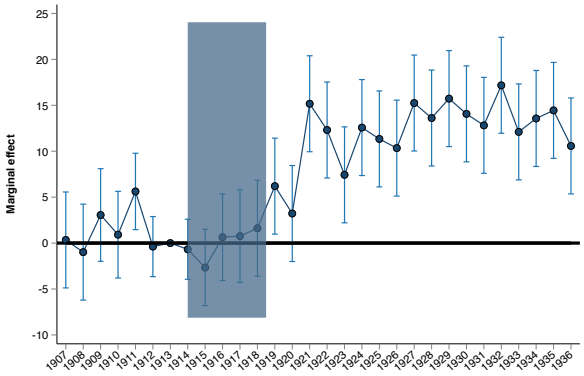


Notes: These Figures replicate Figures 3a and 4a but use a different estimation of standard errors (clustered by county).

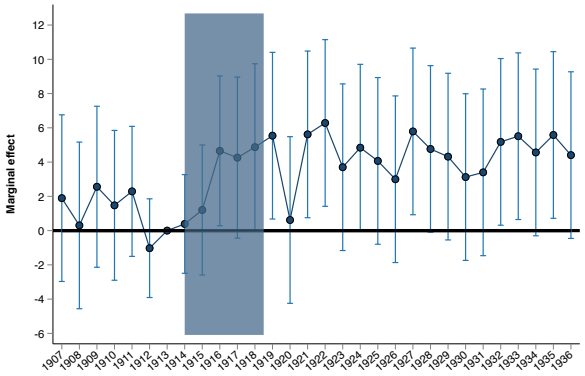
A.2 Alternative measures of excess mortality

FIGURE A6: Mortality, education and innovation: alternative measures of mortality

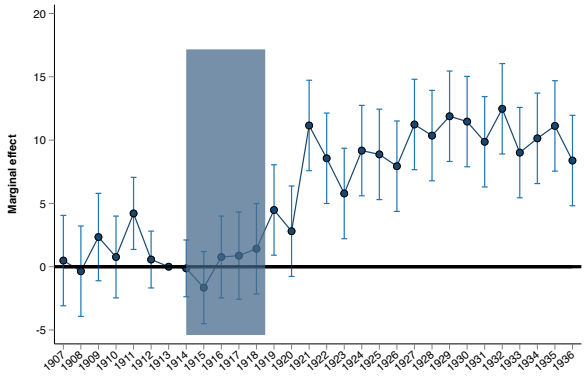
(a) Raw death rate



(b) Residual



(c) Death rate from Boehnke and Gay (2020)

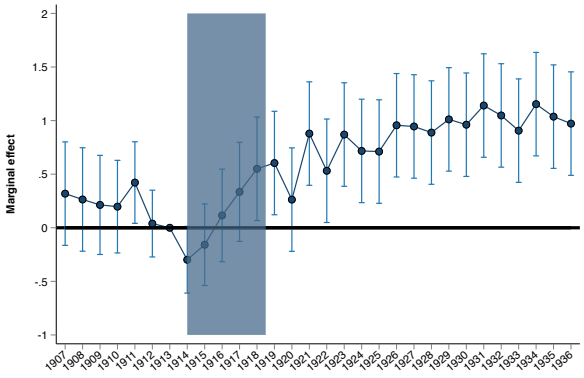


Notes: Replication of Figures 4a with different measures of mortality. Figure A6a uses the total number of deaths divided by the population in 1906 and includes the same set of controls as 4a. Figure A6b uses the residual of the raw death rate used in Figure A6a on the conscription rate, the share of young population, the share of young men, the share of the agricultural sector, the logarithm of GDP per capita, the distance to the frontline and the density, all measured in 1911. The regression does not include any additional control. Figure A6c uses the total number of deaths divided by the total number of soldiers mobilized (same measure as Boehnke and Gay, 2020) and includes the same set of controls as 4a.

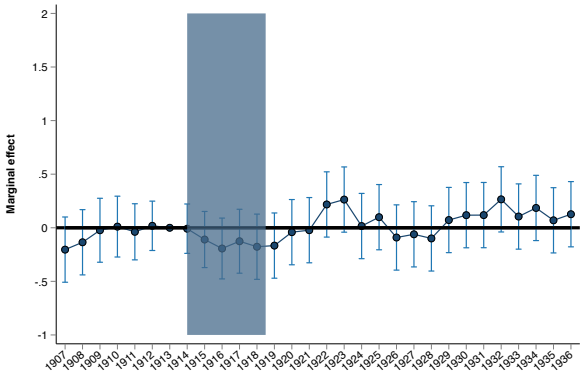
A.3 Alternative measures of labor saving patents

FIGURE A7: Alternative measure: mortality and innovation in labor saving technologies

(a) Labor saving patents



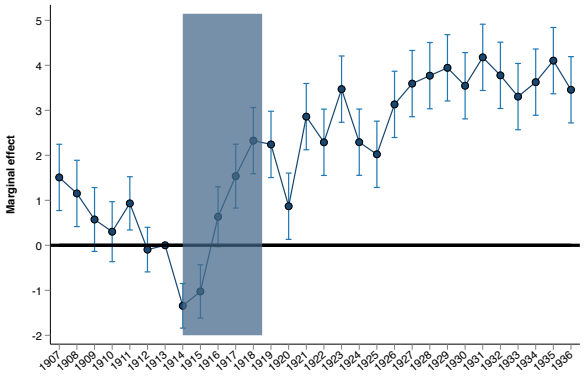
(b) Non labor saving patents



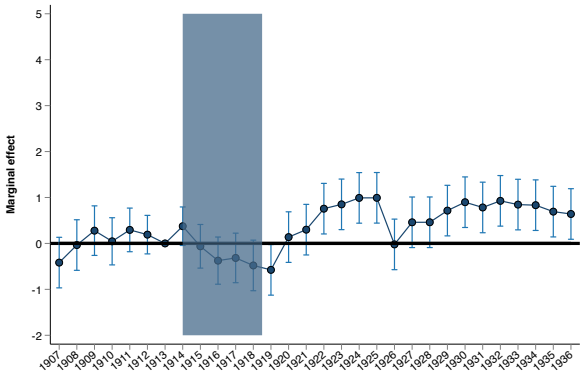
Notes: These two figures replicate Figures 8a and 8b but use a different way of classifying patents into "labor saving" and "non-labor saving" technologies described in A.3

FIGURE A8: Alternative measure: mortality, education and innovation in labor saving technologies

(a) Labor saving patents



(b) Non labor saving patents

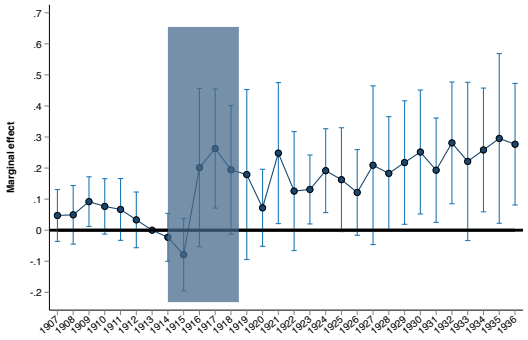


Notes: These two figures replicate Figures 9a and 9b but use a different way of classifying patents into "labor saving" and "non-labor saving" technologies described in A.3

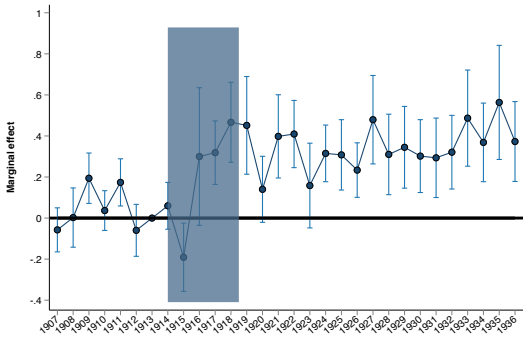
A.4 Alternative functional forms

FIGURE A9: Alternative functional forms

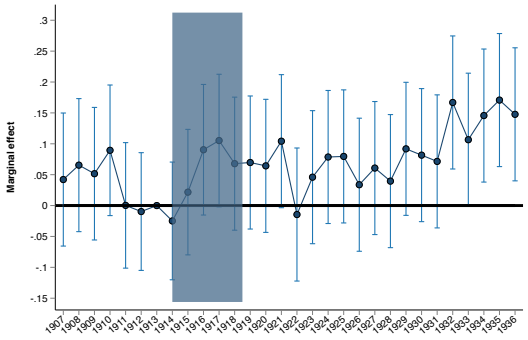
(a) Poisson Count model: unconditional



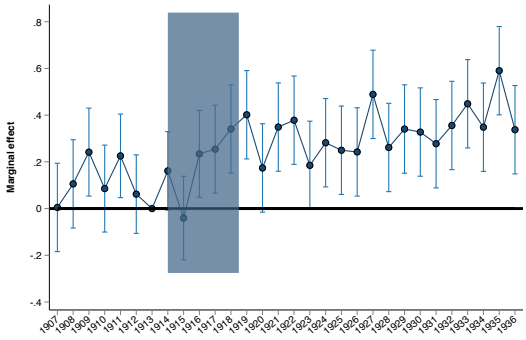
(b) Poisson Count model: interaction



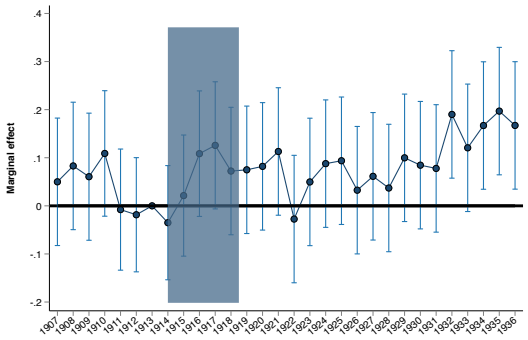
(c) $log(1+x)$: unconditional



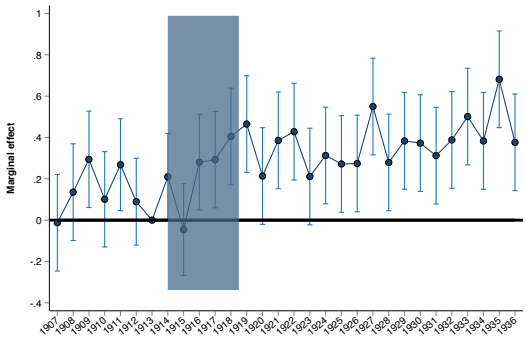
(d) $log(1+x)$: interaction



(e) $asinh(x)$: unconditional



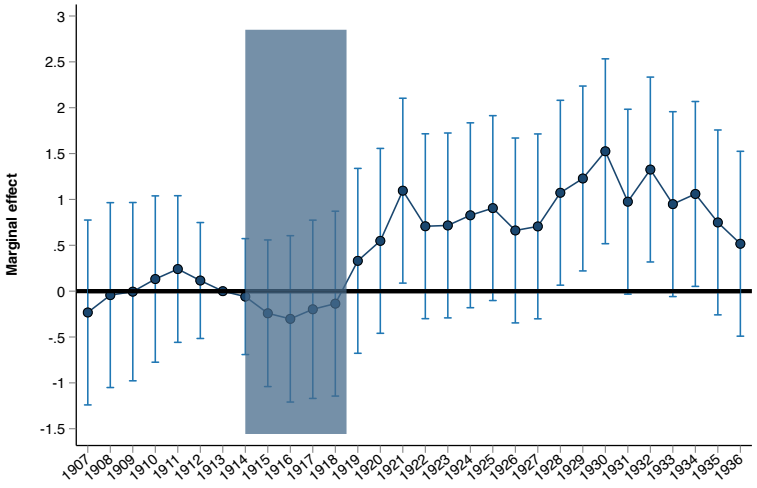
(f) $asinh(x)$: interaction



Notes: Each row replicates 3a and 4a but use a different functional form. First row uses a log model and estimates the coefficient using Poisson Pseudo Maximum Likelihood (Gourieroux et al., 1984). Second row uses the $log(1+x)$ where x is the number of patents divided by the 1906's population. Third row uses the *asinh* transformation.

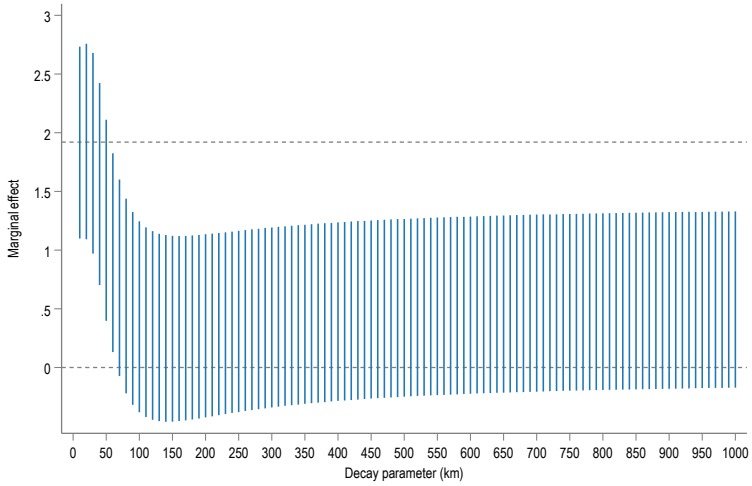
A.5 Additional results

FIGURE A10: Public contract during WW1 and patents



Notes: This Figure replicates Figure 3a but uses the logarithm of the exposure to public contract during WW1 as a regressor (instead of excess mortality). This exposure is defined in Section 5.4 and taken in logarithm.

FIGURE A11: Public contract during WW1 and patents



Notes: This Figure reports coefficients $\gamma_S^{(k)}$ from equation (8) for $k = 10, 20, \ldots 1000$. Top horizontal line represents the coefficient obtaines when $k = 0$ (same as the one from Table 1 panel A, row 1).

B Data Appendix

B.1 Patent data

Patent data comes from Bergeaud and Verluise (2024), a project that aims at geocoding early patents using Natural Language Processing. We used the version from 2024 which includes patents filed at the French Patent Office and geocoded at the county level since 1907. Patents are located according to their inventors. The vast majority of patents have either a single inventor or several inventors residing in the same county in which case there is no ambiguity. In the remaining few cases with multiple inventors in more than one county, we allocate a fractional count of the patent to each county. Finally, we used the publication number to merge this dataset to Google Patent Public data to retrieve the title and the CPC class of each patents.

Our dataset includes 172,072 patents matched to at least one county between 1907 and 1936.

B.2 Excess mortality

B.3 Labor-saving patents

B.3.1 Baseline measure

We systematically classify French patents filed between 1906 and 1936 to identify those related to labor-saving agricultural innovations. Our analysis leverages textual information contained in patent titles, utilizing the Term Frequency–Inverse Document Frequency (TF–IDF) vectorization method coupled with cosine similarity.

Starting from a dataset comprising approximately 208,000 French patent titles, we first identify a reference set of about 4,000 patents (roughly 2% of the total) belonging explicitly to six agricultural Cooperative Patent Classification (CPC) classes: `A01B` (Soil working in agriculture), `A01C` (Planting, sowing, fertilizing), `A01D` (Harvesting and mowing), `A01F` (Processing of harvested crops), `A01G` (Horticulture and plant cultivation), and `A01M` (Pest control and plant protection).

To ensure robust textual comparisons, we preprocess patent titles by decoding HTML entities, removing accent marks and special French-language characters (e.g., transforming "é" into "e"), and converting all text to lowercase to eliminate case sensitivity.

We then apply the TF–IDF algorithm to the cleaned titles. Specifically, TF–IDF assigns weights to each word in a patent title, increasing the importance of terms that frequently appear in an individual title yet remain relatively uncommon across the entire corpus of patent titles. Using the Scikit-learn implementation of TF–IDF vectorization, each patent title is transformed into a numeric vector reflecting its lexical composition.

Next, we construct a reference centroid by calculating the average TF–IDF vector of the approximately 4,000 patents within our agricultural reference set. This centroid captures the shared semantic features characteristic of known labor-saving agricultural patents.

We then measure the semantic similarity between each patent in the entire dataset and this reference centroid using cosine similarity, which quantifies the angle between their respective TF–IDF vectors. Cosine similarity scores range between 0 (no semantic overlap) and 1 (identical semantic content). Patents scoring in the top decile (highest 10%) of similarity to the centroid are classified as *labor-saving technologies*, indicating substantial semantic alignment with agricultural innovations. Conversely, patents

scoring in the lowest decile (bottom 10%) are classified as *non-labor-saving technologies*, reflecting minimal lexical resemblance to our agricultural reference set.

B.3.2 Alternative measure

Figures B3a, B3b and B3c respectively show the distribution of the token "machine", "automat" and "elec" in all the 3-digit CPC technologies based on every French patents filed between 1907 and 1936. The top 20% classes are used to define our measure of automation at the patent level, and then at the county level. Those classes are plotted in red while the other categories are plotted in grey.

B.3.3 Some examples of labor-saving patents

To further support our interpretation, namely that counties where the mortality rate was the highest had no choice, but to substitute labor saving devices for missing workers, we provide in this subsection some instances of patents that we classify as labor saving patent. Additionally, we shed light on the fact that most of them stemmed from individual inventors rather than from large companies. The typical patent labeled as machinery-patent by our algorithm was filed by some unknown inventor rather than by a company and allowed firms to replace human activity with machinery. Let us take the instance of patent FR-643896-A which brought to the market circular knitting machines specially adapted for producing goods of particular configuration stockings, or portions thereof; it was filed by Madeleine Maire as of 1927; two features clearly stand out from this document: first, it allowed for further mechanization of sewing knitting activities; second, it was filed by an unknown women who probably happened to suggest this improvement upon noticing or feeling the need for it. A similar case would be that of patent FR-583151-A which improved the mechanical working of cork which is widely used in the clothing industry, a very labor-intensive one, suggesting that this patent brought contribution to the mechanization of an industry that used to rely on a large labor supply. Again, this patent was filed by a man named Louis Canavera of whom we found no record on the internet. In a different spirit, patent FR-546819-A allowed for the automation of an agricultural task, namely the slaughtering of animals; its inventor, Jean Verlaak, filed it in the Cher county and only filed 3 patents in his life, suggesting that individual workers mattered for patenting activity at that time in France. A last example is provided by patent FR-600363-A filed by Alfred Spitz in Nantes to develop a machine designed to make croissants;

again, this machine aimed at replacing human force in a relatively labor intensive industry; the only record we found from Alfred Spitz made no mention of his activity as a regular inventor, but only mentioned his passing in Dachau as of 1945. All in all, those examples epitomize the main features of the machinery patents we found upon running our algorithm: patents that were rather filed by individual inventors and that effectively allowed for the generalization of labor substituting devices.

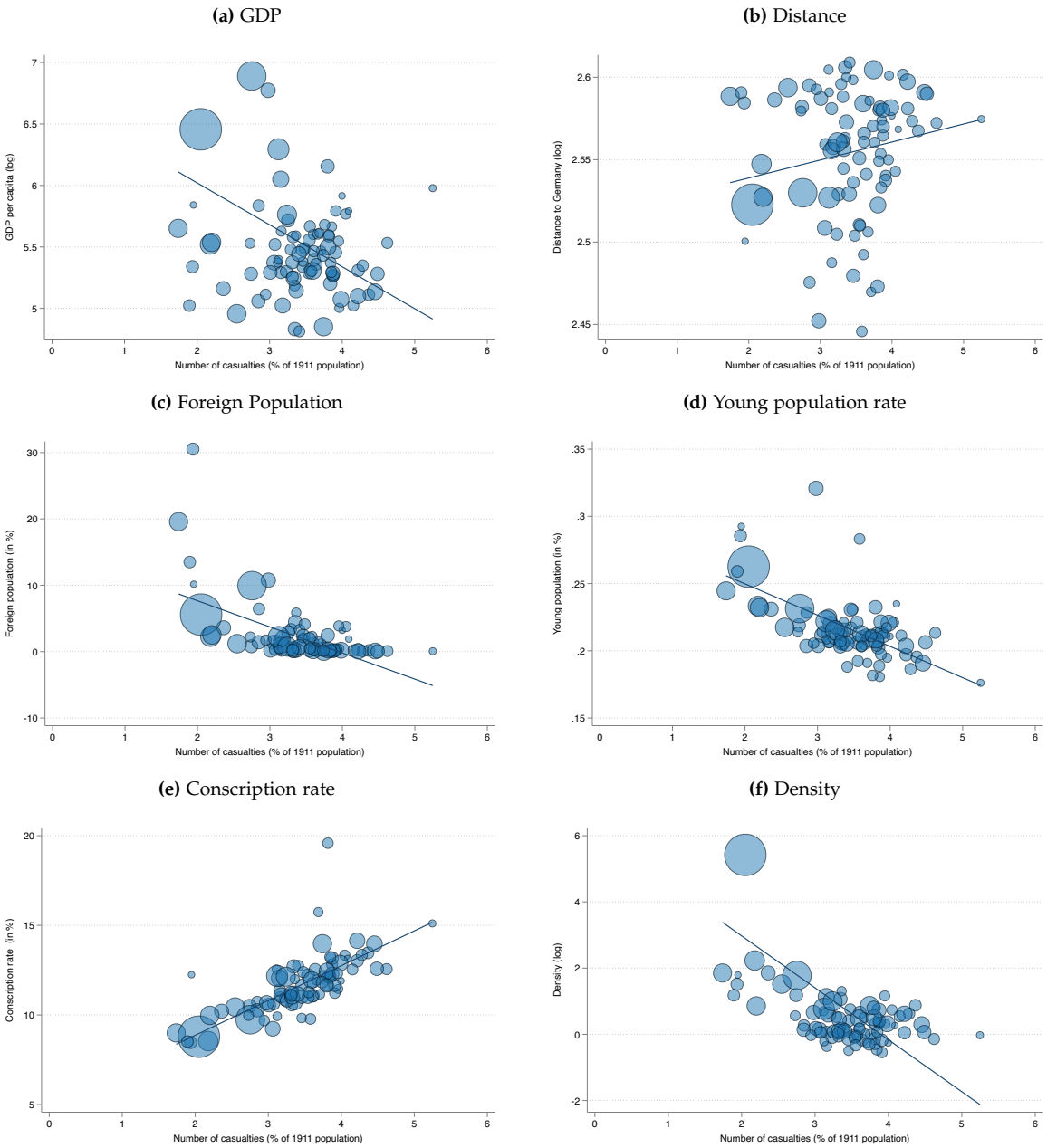
B.4 Education

In Section 4, we documented that the learning by necessity effect only occurred in counties where both mortality and the level of secular education were high enough. On the contrary, we found no effect of the interaction term between mortality and catholic schooling on patenting activity, suggesting that only valuable knowledge could act as a complementary force to transform the demographic shock into an incentive to increase productivity. In this section, we further support that interpretation by plotting the coefficients on mortality *per se* depending on whether mortality is interacted with catholic or with secular education. Clearly, mortality by itself exerts a positive and almost significant impact for counties ranging in the upper 33% of the distribution in terms of catholic education while it exerts close to no effect in the counties ranging in the upper 33% of the secular education measure. In other words, education had no value-added for counties rather attached to catholic than to secular schooling so that mortality by itself played an incentive which could not always be met in light of the poor quality of education. By contrast, mortality was complemented by a high quality education in counties ranging in the upper tail of the distribution in terms of secular schooling. Given that this kind of education was more prone to scientific knowledge, it helped more affected counties recover from the demographic shock and transform it into labor substituting inventions.

As shown by Figure B4, education varied widely across the French territory. On average, 75.8% of French children aged between 5 and 15 attended school on a regular basis between 1851 and 1901. This proportion spans from 50% in Côtes du Nord to 100% in Savoie. Also, this share grew over time for all counties as French ministry for education Jules Ferry made schooling from 6 to 13 mandatory in 1882. Beyond the disparity in the education levels, the geography of this dispersion is quite surprising. Education seems indeed higher in the Eastern part of the country when measured according to the average enrollment rate of children; this observation is quite robust to the introduction of a new measure, namely the share of young men incorporated

in the army who held a baccalaureate. While Western counties systematically exhibit below median education measures, most of Eastern counties show high levels of education. Importantly, education does not seem to correlate other major economic and social dimensions of counties which we later take as explanatory variables, which ensures that our measure of education is a proxy of the human capital level and does not mirror broader economic outcomes. While education slightly rises with the economic output as captured by the GDP, the education levels do not statistically different across bins of density, agriculture share or even industry share.

FIGURE B1: Death rate during WW1 and patenting activity

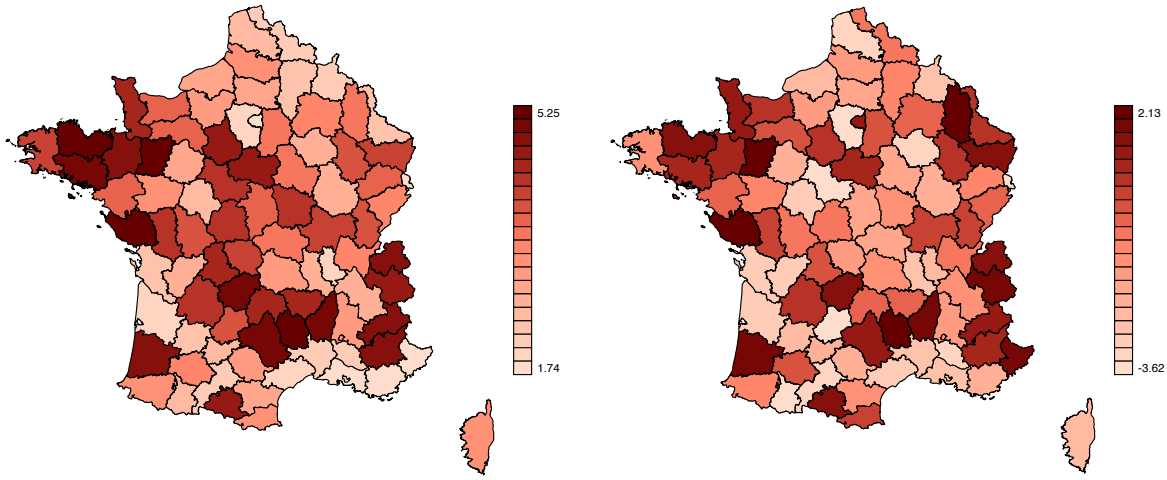


Notes: Raw correlation between the actual mortality rate (total number of death during WW1 divided by population in 1911) and various local characteristics measured in 1911. Each bin represents a county. The size of a bin is proportional to the population.

FIGURE B2: Death rate during WW1

(a) Actual Death Rate

(b) Excess mortlaity

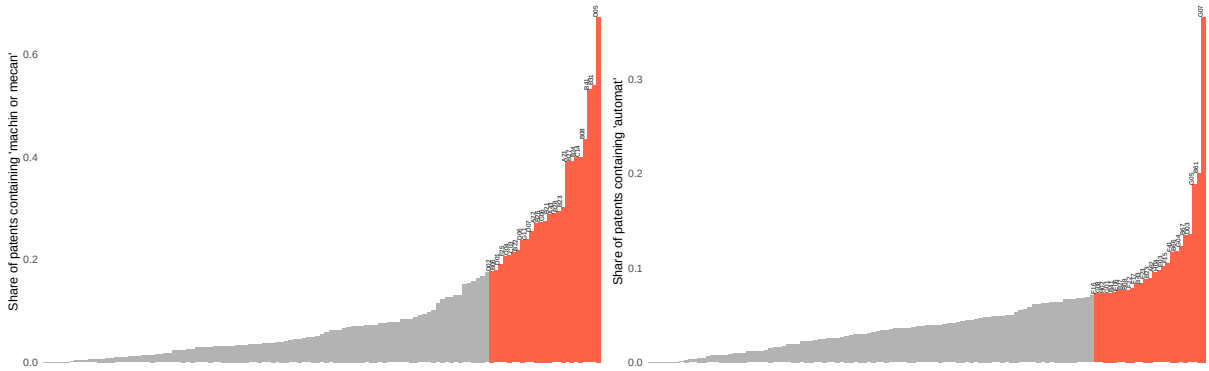


Notes: Left-hand side map shows the ratio between the number of people killed during WW1 in each county (*département*) divided by the population of the county in 1911. The right-hand side map shows excess mortality indicator constructed from residualizing the actual death rate on the conscription rate and other characteristics at the county level.

FIGURE B3: Frequency of different token by technological class

(a) Token *"machin"*

(b) Token *"automat"*

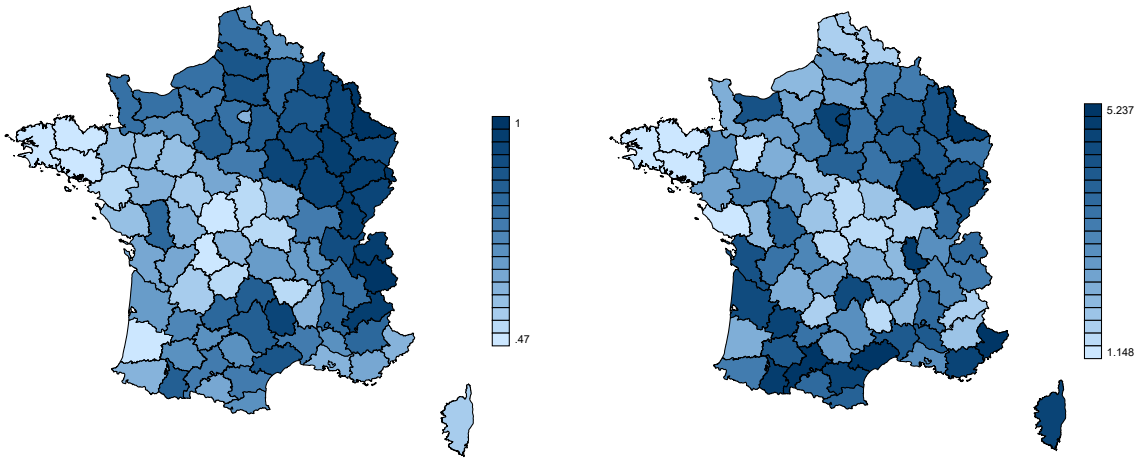


(c) Token *"elec"*



Notes: This figure plots the frequency of the token "machine", "automat" and "elec" for each 3-digit CPC code; bars plotted in red denote the 20% CPC with the highest frequency.

FIGURE B4: Education across French counties according to various measures



(a) Enrolment rate

(b) Baccalaureate rate across soldiers

Notes: Figure (a) plots the ratio between the number of kids aged between 5 and 15 enrolled at school and the total number of kids aged between 5 and 15 while (b) plots the ratio between the number of young men incorporated in the army holding the baccalaureate degree and the total number of young men incorporated in the army.

C Additional results

C.1 Counterfactual analysis: quantifying the impact of mortality

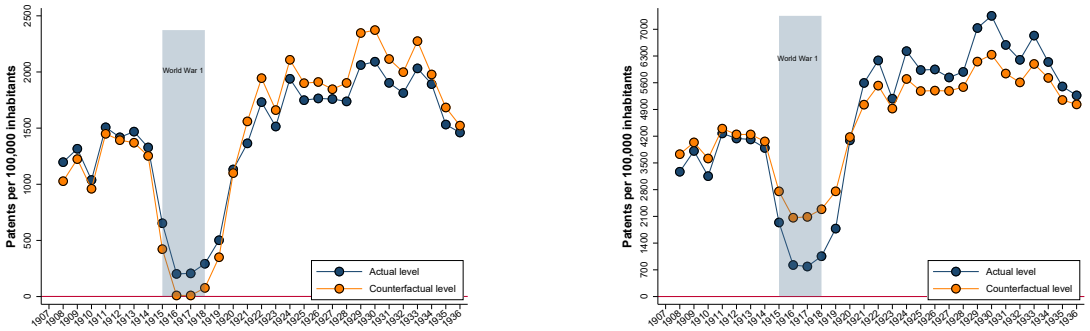
To get a more concrete sense of the magnitude of our results, we can wonder how patenting activity would have evolved in the absence of mortality. To answer this question, we do some back-of-the-envelope calculations to compute the predicted trends suggested by the results obtained on equation ((6)) after the subtraction of our estimated effects of mortality as well as of mortality interacted with education. We follow the procedure adopted in Malgouyres et al. (2021) and we compute the predicted outcome as the actual outcome minus the dynamic effects predicted by our dynamic specification. This exercise suggests that mortality started by inducing a net negative effect on patenting activity during the war, even when allowing for the interaction term: all in all, French counties allegedly lost 4,543 patents due to human losses during the conflict. However, the sharp recovery identified in 2, and which can be causally attributed to the role played by mortality and education as pointed in 3, more than compensated that decline: in the absence of mortality, the total number of French patents filed between 1920 and 1936 would have been lower by 6,267, corresponding to the average yearly patenting activity in France prior to the war.

Those estimates are summarized in Figure C1 which pictures respectively the actual level and the simulated level of patenting activity in a counterfactual scenario in which no mortality would have hit the country. Those results are plotted respectively for below median mortality counties and for above median mortality counties. While we are aware that this exercise does not constitute a full fledged aggregate analysis given that it precludes any spillover which might be relevant in our case, it still illustrates the magnitude of the increase in patenting activity triggered by mortality after the war. Also, it further confirms that above median mortality counties were more positively affected than above median mortality in terms of patenting activity.

C.2 Additional comments on the battle of Verdun

As suggested in Section 5.1, Verdun fits a quasi-random experiment allowing to test for the main findings summarized in this paper. In particular, Verdun showed both a high number of casualties since it was perceived by German commanders as an opportunity to exhaust French forces and win a decisive battle at a time when both

FIGURE C1: Actual and excess mortality rates



(a) Below median mortality

(b) Above median mortality

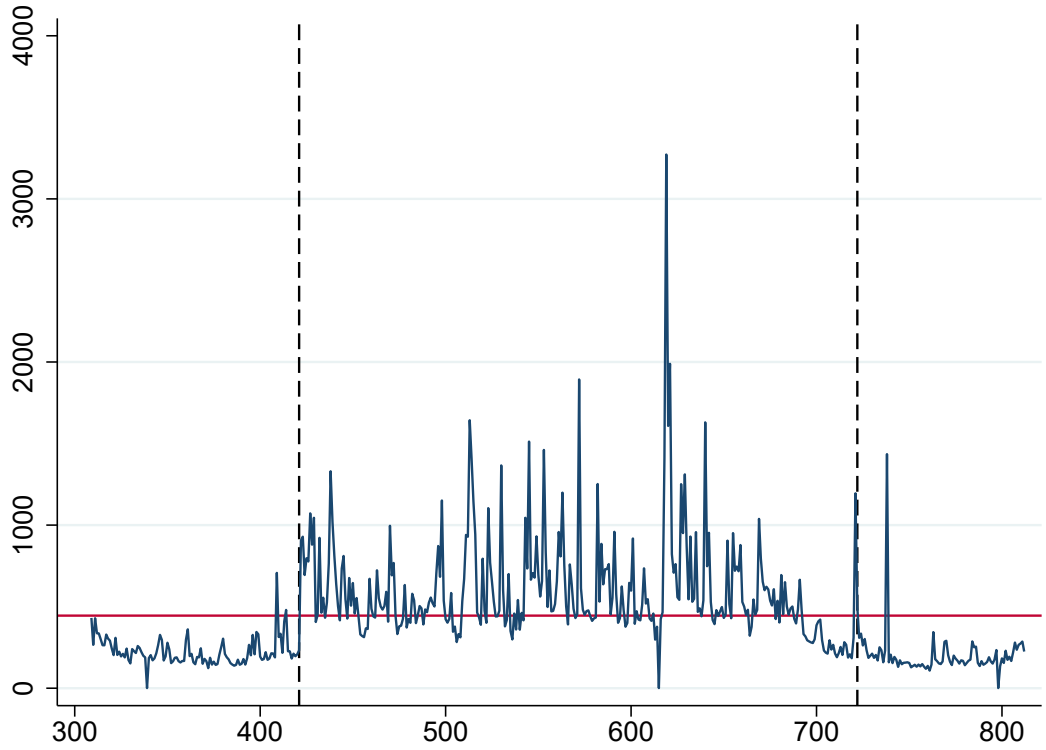
Notes: Counterfactual levels of patenting activity are plotted agains the actual level of patenting activity for counties ranging respectively in the lower and in the upper tail of the mortality distribution.

resources and morale were scarce. That Verdun was peculiarly lethal in the light of the rest of the war is suggested by Figure C2 which pictures the daily number of French victims during WW1 from the end of 1915 to the beginning of 1917; black dotted lines show respectively the beginning of the battle of Verdun in February 1916 and the end of it in December 1916. Clearly, the daily number of victims during the battle outweighs the average over the sample, indicating that, in a time when the war was coming to a sort of standstill, this conflict was peculiarly violent.

C.3 Instrument variable strategy

As explained in 5.3, we leverage an instrumental variable designed by Boehnke and Gay (2020) to further support the validity of our main specification estimates. This strategy exploits the heterogeneity in fighting skills at the county level resulting from the different weights of each cohort in the conscription. Intuitively, earlier classes (respectively classes of 1911 and 1912) had received more training at the onset of the war (respectively three and two years) than later classes (respectively classes of 1913 and 1914) which were barely trained (respectively two and one year). Therefore, counties where the share of earlier classes was larger should have experienced lower fatality rates while counties where the share of later classes was larger should have experienced higher fatality rates. In the meantime, there is little relation between the share of each cohort in the military recruitment and the innovation ability of each county. That the share of each cohort and the fatality rate are substantially correlated is asserted by C3. Indeed, we clearly see a negative and significant relationship between the share of earlier classes (1911 and 1912) and the fatality rate, further confirming

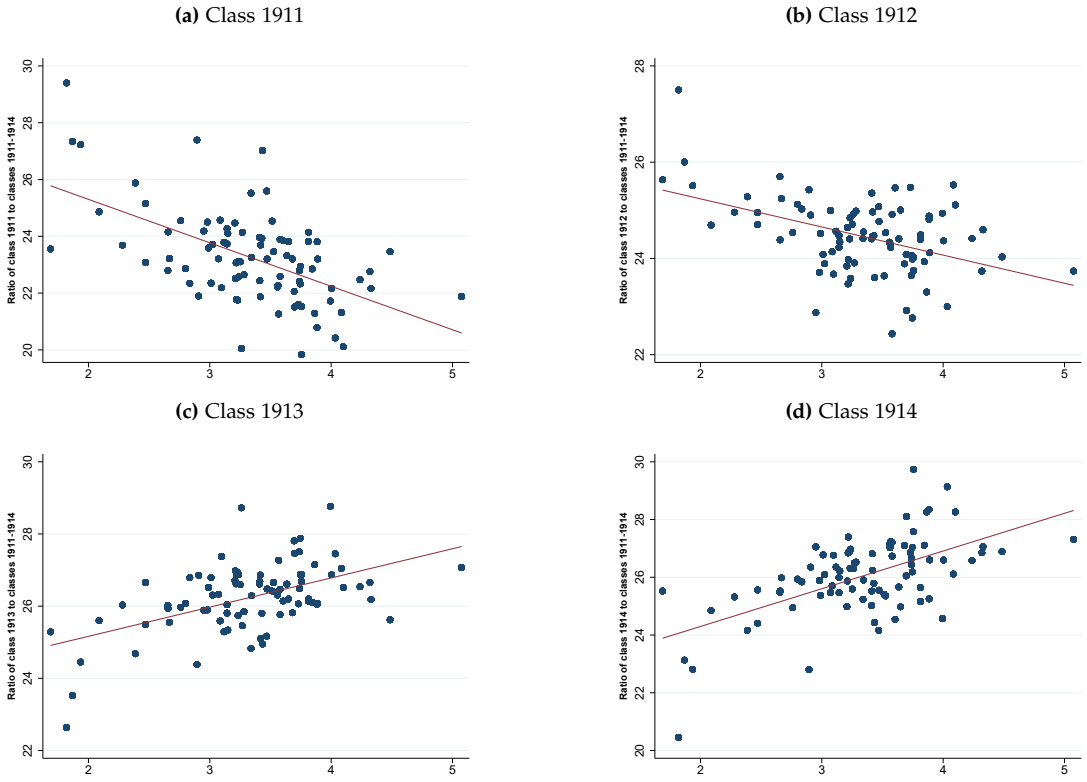
FIGURE C2: Daily number of casualties (November 1915 - March 1917)



Notes: Black dotted lines represent the beginning and the end of the battle of Verdun.

that counties where soldiers had received more training suffered fewer losses with respects to counties where soldiers had received a poorrer training.

FIGURE C3: First stage of IV strategy: relation between share of each of the 1911-1914 cohorts and fatality rate



Notes: Fatality rate is the deathrate as reported in the *Morts Pour la France* dataset.

C.4 Linking Demographic Shocks, Wages, and the CES Elasticity

In this appendix section, we interpret our results through the lens of a simple conceptual framework. We set up . Farms combine capital K and labor L in a CES technology:

$$Y = \left[(1-a)^{1/\sigma} L^{\frac{\sigma-1}{\sigma}} + a^{1/\sigma} K^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where a indexes the direction of technical change. Cost minimization gives the capital–labor ratio

$$\ln k = \ln\left(\frac{a}{1-a}\right) + \sigma\big(\ln w - \ln r\big),$$

with $k \equiv K/L$, wage w, and rental rate r.

Reduced-form effects of the demographic shock. Let m denote the WWI mortality shock. We estimate:

$$\ln x_{d,t} = \alpha_d + \lambda_d + \beta_{\ln x, m} m_d \times \text{Post}_t + u_{d,t},$$

for $x \in \{w, k, \texttt{patents}\}$, so that $\beta_{\ln w,m}$, $\beta_{\ln k,m}$, and $\beta_{\ln \texttt{patents},m}$ capture the elasticities of wages, capital intensity, and patents with respect to the mortality shock.

We make the assumption that directed technical change is related to changes in patents. In particular, we assume that they are related by a factor κ which we cannot estimate but about which we will make different assumptions. Building on Hémous et al. (2024), we consider the case where $\kappa = 1.5$ based on their estimate of the effect of the increase in the automation patent share on the labor share.

Recovering the elasticity of substitution. Differentiating the optimality condition yields

$$\frac{\partial \ln k}{\partial \ln w} = \sigma + \frac{1}{1-a}\frac{\partial \ln a}{\partial \ln w}.$$

Under the exclusion restriction that m affects a only through wages,

$$\frac{\partial \ln a}{\partial \ln w} = \kappa \frac{\beta_{\ln a,m}}{\beta_{\ln w,m}} = \kappa \frac{\beta_{\ln \text{patents},m}}{\beta_{\ln w,m}},$$

where the second equality stems from our assumption that a is related to patent through the factor κ. Hence the observed elasticity of capital intensity with respect to wages satisfies:

$$\frac{\beta_{\ln k,m}}{\beta_{\ln w,m}} = \sigma + \frac{1}{1-a}\kappa \frac{\beta_{\ln \text{patents},m}}{\beta_{\ln w,m}}.$$

Directed-technical-change–corrected estimate of σ. Rearranging gives an elasticity of substitution,

$$\hat{\sigma} = \frac{\beta_{\ln k,m}}{\beta_{\ln w,m}} - \frac{1}{1-\bar{a}}\frac{\beta_{\ln a,m}}{\beta_{\ln w,m}},$$

where $\bar{a}$ is the sample mean of a prior to the shock.

In standard setting holding technology fixed, a is unresponsive to wages ($\partial \ln a / \partial \ln w = 0$), the second term vanishes and the simple ratio $\beta_{\ln k,m}/\beta_{\ln w,m}$ identifies σ. A positive wage–innovation elasticity $\partial \ln a / \partial \ln w > 0$ makes this ratio larger than the true substitution elasticity, so subtracting the innovation component delivers an estimate of σ net of directed technical change.

Our estimates provide 3 key inputs into this formula:

$$\beta_{\ln k,m} = 1.087 \qquad \beta_{\ln w,m} = 0.112 \qquad \beta_{\ln a,m} = 0.30.$$

Based on $\kappa = 1.5$, we obtain that our elasticities are based 5.68 when assuming $\bar{a} = 0$

(no labor in farming prior to WW1) and 3.96 when assuming $\bar{a} = 0.3$ whereas the non-corrected elasticity is about twice as large as 9.70. Overall, this exercise shows that, in the presence of directed technical change, the ratio of the elasticity of capital to wage is likely to be strongly upward biased as an estimate of the elasticity of substitution. However, even accounting for this bias, our results remain consistent with a very strong elasticity of substitution between labor and capital in the farming sector.