The Missing Worker
Innovation, Demographics and Human Capital after WW1*

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Abstract

We use quasi-random local variations in the number of young men who died as a result of World War I in France to assess the relationship between demographics, education, and innovation. Our analysis explores two distinct mechanisms: firstly, mortality directly undermines human capital due to the loss of potential inventors. Secondly, the war led to a significant reduction in labor supply, which increased labor costs and incentivized the substitution of missing workers with machinery in particular in the agricultural sector. We provide evidence supporting these mechanisms. Specifically, we document that the latter effect predominates only when the initial level of human capital is sufficiently high.

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

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1 Introduction

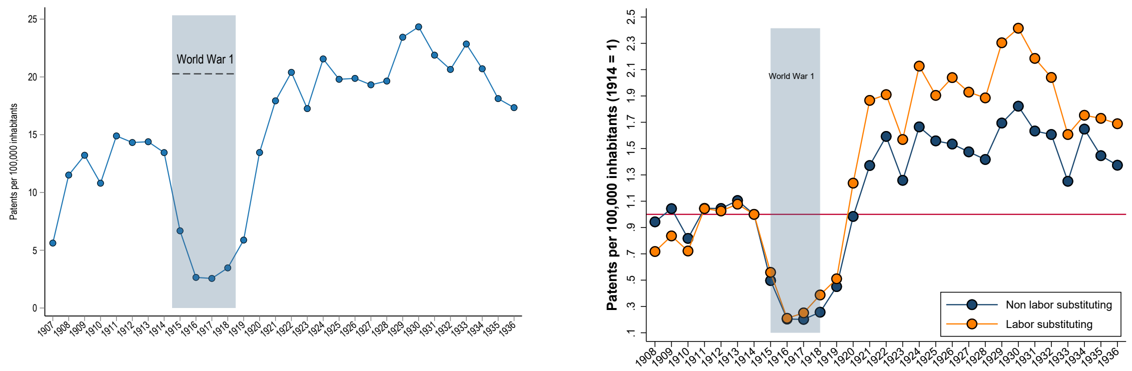
France faced a paradox at the end of World War I (WW1). While emerging as the dominant power in continental Europe after defeating Germany, the nation was deeply scarred. The war left 30,000 square kilometers of French territory, more than 5% of the total surface, devastated by 4 years of fighting and 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. French economist Jacques Rueff estimated that the cost of reconstruction would be seven times as large as the government budget for 1913 (Araud 2023). 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.

But perhaps more critical was the human cost. 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. 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.

In this article, we question whether this dramatic demographic shock had an impact on the quantity and direction of innovation. This question is motivated by a somewhat surprising fact. As depicted in Figure 1, France witnessed a significant surge in patenting activity post-World War I. Notably, after a steep decline in innovation activities, with the number of patent applications plummeting by roughly 80% from its peak in 1911 to the lowest point in 1917, there was a rapid and marked recovery. By 1921, France had not only reclaimed its pre-war innovation levels but also continued this ascending trend for the next decade. This resilience indicates that the revival extended beyond a mere mechanical rebound. Contrary to expectations, the swift recovery suggests that the French innovation system was surprisingly robust, showing little long-term detriment from the severe demographic impact. Perhaps even more strikingly, Figure 1 reveals that patents related to labor-saving technologies[1] experienced a quicker and sharper recovery after the war compared to patents unrelated to labor substituting techniques, suggesting that the increase in patenting activity after the war was mostly driven by labor substitution concerns.

FIGURE 1: Patents in France: 1907-1936

(a) Total patenting activity **(b)** Labor-saving patents



Notes: Figure (a) plots the yearly total number of new patents per 100,000 inhabitants in France from 1907 to 1933. Figure (b) plots the number of patents per 100,000 inhabitants, standardized to 1 in 1914, respectively for labor-saving patents and non labor-saving patents. Source: Bergeaud and Verluise (2024)

Intuitively, and following the related literature, the losses suffered by France throughout WW1 could indeed have exerted a twofold effect on innovation. On the one hand, mortality might be associated to a direct negative *human capital* effect corresponding to a decrease in the stock of accumulated knowledge. A simple effect could come from the fact that less people also mean less new ideas which can impact growth negatively in the long-run (Jones 2022). But more generally, this human capital effect is first related to the *learning by doing* assumption outlined by Arrow (1962) who stresses the role of experience in increasing productivity: as the average death age hovered around 29 years old, it cannot be precluded that the passing of 1.3 million men was associated with large experience losses and, in turn, in a decrease in total productivity. Another mechanism driving the human capital effect could then resemble the "Lost Einsteins" assumption made by Bell et al. (2019) who show that many children would have found highly impactful inventions should they have been exposed to innovation in childhood; in a similar spirit, it could be argued that WW1 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.

[1]The classification of patents into various technological categories defined more extensively in Section 4; broadly speaking, they refer to patents related either to electricity devices, machinery or automation.

On the other hand, labor scarcity induced by WW1 might have provided incentives to either improve the productivity of firms through innovation 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 (TFP), 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 analysed the effect of military conscription in industrialized Great Britain during the Napoleonic wars in the early 19^{th} century and show that a higher labor scarcity induced entrepreneurs to substitute machines for missing workers. In a similar though different spirit, Boehnke and Gay (2020) emphasize the impact of labor scarcity induced by war-related mortality on female participation in the labor market; more specifically, they exploit the *Morts pour la France* dataset and show that 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.

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 demographic, economic, social and geographic 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 aggregate effect on innovation. However, this effect was magnified in counties with higher levels of education. We further show that this effect 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 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 6,267 patents in the fifteen years after the war, corresponding to the average yearly number of patents in France prior to the war.[2] We also present evidence that this long-term effect was facilitated by the positive spillovers from the wartime economy, particularly through innovation and industrial policies enacted by the French government from 1914. These policies aimed to accelerate the development of new weapons and machinery to aid soldiers on the battlefield and expedite the production of materials behind the front lines.

Our paper thus contributes to the literature examining the impact of significant shocks on innovation, particularly within the context of productivity constraints imposed by wars. As highlighted, Voth et al. (2022) documents an increase in the adoption of agricultural machinery in British counties affected by military recruitment for the Royal Navy during the Industrial Revolution. Similarly, Ilzetzki (2023) attributes the rise in plant-level productivity in the U.S. during WW2 to a learning by necessity channel: aircraft manufacturers, faced with a surge in demand and a scarcity of production factors, were compelled to increase productivity in the short term. We demonstrate that a comparable mechanism influenced innovation following WW1 in France and additionally document the role of education and other local characteristics in conditioning this effect.

Another stream of literature emphasizes the potential positive long-term effects of wars on the quantity and direction of innovation. Moretti et al. (2023) shows that public military R&D spending have indeed positive spillovers on private innovation and ultimately boost productivity (see also Mowery, 2010 for a survey). In the context of wars, Gross and Sampat (2020) highlights the enduring impact of the American Office of Scientific Research and Development, established during WW2 to support military-related technological advancements and Kantor and Whalley (2023) show the effect of the space race during the Cold War increased local manufacturing value added. 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). Large shocks may also stem from pandemics: Gross and Sampat (2021) draws parallels between World War II and the Covid-19 pandemic to explore the economics of innovation, while

[2]More details regarding the method are exposed in Appendix D.11.

Berkes et al. (2023) observe that both religiosity and innovation can surge following a major health crisis, such as the influenza pandemic. Our contribution in that field is twofold: first, our paper is, to the best of our knowledge, the first to design an identification strategy such that we can distinguish between the human capital effect and the learning by necessity channels that related mortality and innovation during and after WW1 ; second, we exploit textual data on patents using the framework suggested by Dechezleprêtre et al. (2020) to unveil the impact of large shocks not only on the quantity but also on the direction of innovation.

Additionally, we contribute to the extensive literature that examines the interplay between demography and education in shaping human capital and its long-term impact on innovation over extended time horizons (see Mokyr and Voth 2010 for a comprehensive review). Berkes et al. (2023) investigates the differential impact of education on the outcomes of the Industrial Revolution in 20^{th}-century France. More broadly, our analysis of the effects stemming from human capital aligns with two main strands of literature. Firstly, studies examining the direct impact of population shocks on income and development; 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). Beyond this direct effect, 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 2021). 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 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 show that indeed, several innovators, and probably many more potential innovators, counted among the hundred of thousands of deaths.

Finally, one contribution of our paper is to provide a new dataset of economic characteristics at the county level for the period 1900-1939. In particular, we develop a new methodology to estimate GDP at the local level in France. This complement existing work such as Bazot (2014) who estimates local income in France from 1840 to 1911 using data on the " patente", a French tax levied at the business level and Bonnet et al. (2021) who document the evolution of income inequality across French counties over the 1922 - 2022 period.

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 the empirical framework and discusses the primary findings. Section 4 examines into potential underlying mechanisms, while Section 5 is dedicated to robustness checks and the presentation of additional results.

2 Background and Data

We have constructed a novel dataset at the county level, assembling information from various 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

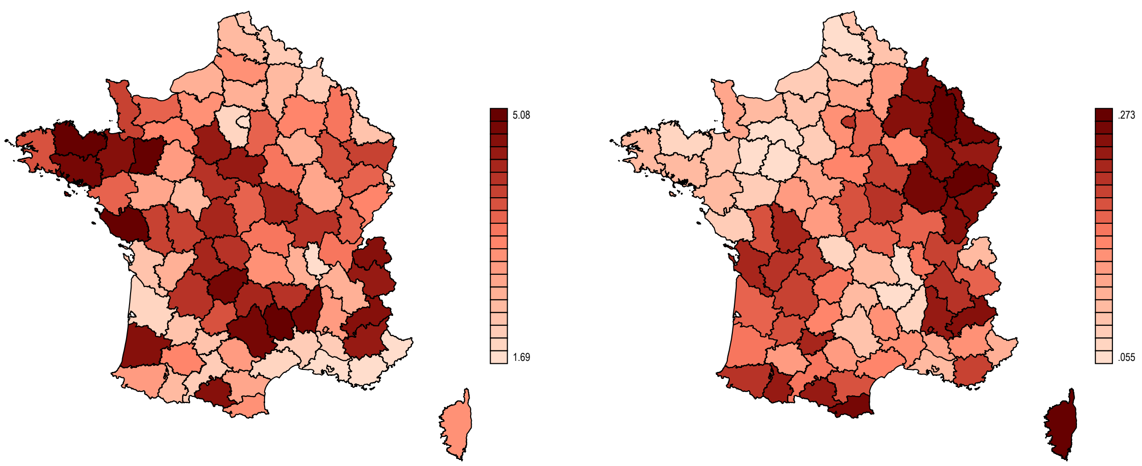
The "Morts pour la France" dataset The data on soldier casualties during World War I are derived from the "Morts pour la France" dataset, which offers comprehensive details on each of the 1.3 million men who lost their lives in combat. Key information includes their birth county, birth date, death location, and names.[3] 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, excluding Haut-Rhin, Bas-Rhin, and Moselle, which were returned to France following the Versailles Treaty in 1919.

[3] Technically, the dataset does not include all soldiers who died between 1914 and 1918. Approximately 95,000 dead soldiers (around 7%) are absent because they did not receive the "Mort pour la France" (literally: died for France) designation, a title requiring adherence to specific legal criteria.

The average mortality rate across France was 3.38% of the population as of 1911, amounting to 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 2. Notably, more rural counties appeared to bear a heavier brunt of the mortality. For instance, counties like Lozère (5.08%), Vendée (4.32%), Mayenne (4.49%), and Aveyron (4.10%) experienced high 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. 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. Heterogeneity in terms of officers mortality however goes along different lines: namely, Eastern counties which were both closer to the border and endowed with a higher initial education level exhibit substantially higher losses among the officers sub sample.

FIGURE 2: Death rate for soldiers and officers during WW1

(a) Soldiers mortality **(b)** Officers mortality

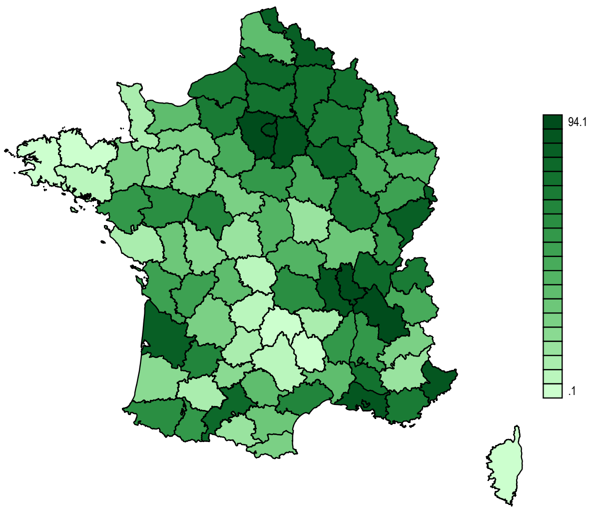


Notes: Figure (a) plots the ratio between the number of dead soldiers and the 1911 population while figure (b) plots the same ratio restricting the sample to soldiers labeled as "sous-lieutenant", "lieutenant", "capitaine", "commandant", "colonel" or "général".

Measure of innovation Our main dependent variable is a measure of local innovation that we construct from 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 based on the location of its inventors.[4]

We have implemented a minor adjustment to the patent dataset to align with the timeline of World War I, which began in August 1914. To accurately capture the impact of the war, we reclassified the allocation of patents and assigned a given patent to year t if it was filed between August of year $t-1$ and July of year t. This adjustment allows us to use 1914 as the baseline year in our empirical model, ensuring that our reference year is not influenced by the onset of the war. Consequently, the pre-WW1 period in our analysis spans from 1907 to 1914. The geography of patenting activity in France over the 20^{th} century is extremely 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 94 patents per 100,000 inhabitants, a number that is 15 times larger than the average county. In other words, Seine accounted for around 60% of total French patenting activity between 1907 and 1939. Figure 3 shows a map of the number of patents per inhabitants during the period 1907-1939 in France.

FIGURE 3: Geographical distribution of patents per capita



Notes: Total number of patents filed between 1907 and 1939 divided by the population in 1906 (in patents per 100,000 inhabitants).

[4]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.

Education Data To measure education at the county level, we utilize the dataset compiled by Squicciarini (2020), which examines the impact of schooling on industrial development in France during the Industrial Revolution. This dataset provides comprehensive details, including the number of young students and the types of schools they attended at the county level. Our primary measure of education is the enrollment rate, defined as the proportion of children aged 5 to 15 who are attending school compared to the total number of children in this age group. However, this measure captures only a facet of educational attainment. As an alternative, we also consider the proportion of young men in the French army holding a "baccalauréat" degree[5], data derived from the *Annuaires Statistiques de la France*. Moreover, for a robustness check, we evaluate the prevalence of Catholic schools, as determined by both the proportion of Catholic schools among all schools and the proportion of students enrolled in Catholic schools, based on data from Squicciarini (2020). As Squicciarini (2020) highlights, there exists a notable distinction between public and Catholic schools, with the former focusing on technical subjects and the latter on history and theology. This difference suggests that counties with a greater presence of Catholic schools were less likely to undergo industrialization compared to those with a predominance of public schools. We exploit this heterogeneity to test our mechanisms. Appendix C.1 provides a detailed discussion of these various educational measures and examines their correlation with economic characteristics prior to WW1.

Additional data To complete our working dataset, we gathered and constructed additional economic, social, and geographic characteristics for each county. Specifically, we hand-collected data on the number of workers per sector of activity for all years a census was available, namely: 1906, 1911, 1921, 1926, 1931, and 1936 which we interpolated. From the census data, we also extracted the number of foreign immigrants in each county at each census point and the share of young people (aged 15 to 35) in the total population. Additionally, we estimate a measure of GDP at the county-year level for the years 1906, 1911, 1921, 1926, 1931, and 1936 following a methodology described in Appendix A. For intervening years, we apportioned the nationwide GDP indicator, obtained from the series in *Annuaires Statistiques de la France*, according to the relative economic weight of each county in the preceding census year. We also measure the average wage from the *Annuaires Statistiques de la France* for almost every year of our sample, filling in gaps through linear interpolation. Finally, from the same

[5] The "Baccalauréat" is an exam that is taken by students at the end of high school (around 18 year old) and necessary to enter to university. In the beginning of the 20^{th} century, the "Baccalaureat" was a highly selective exam. In 1910, only 19,000 candidates took the exam, and fewer than 50% passed.

source, we measure the share of agriculture and industry in total county employment every year. More information is given in Appendix C.

2.2 Construction of the mortality indicator

Our empirical analysis relies on the ability to identify a causal effect of a negative demographic shock on subsequent innovation activity. However, the assumption of exogeneity for the mortality rate as a treatment variable is problematic. Specifically, there are concerns that the exposure of counties to soldier mortality during WW1 was not entirely random. This non-randomness could be due to factors such as geographic proximity to battlefronts or pre-war socio-economic conditions, which potentially correlate with both the likelihood of higher mortality and the capacity for innovation. Those concerns have already been highlighted in existing literature. Gilles et al. (2014) notably argue that factors such as proximity the proportion of immigrant populations influenced mortality rates during the war and there is a large literature that link immigration to innovation (e.g. Kerr and Lincoln, 2010). Similarly, in a comprehensive examination of the determinants of soldier mortality during WW1, Guillot and Parent (2018) suggests that various local social characteristics were predictive of mortality rates: typically, their results show that soldiers coming from wealthier counties exhibited, on average, lower survival rates throughout the war. Appendix C.4 indeed reports the significant correlation between the mortality rate during WW1 and some economic and demographic features of each county taken before the conflict (see in particular Figure C3).

In order to construct a mortality indicator that would more accurately reflect deviation from the predicted mortality rate based on observed pre-treatment local characteristics, we purge the actual mortality of most of the potential confounding factors we can measure. More specifically, we regress the mortality rate observed at the county level on the average conscription rate in the years before the war, as well as on the share of young men in population, the distance to the front line and the share of agriculture in employment. In particular, the average conscription rate is a crucial parameter given that it very likely encompasses most of the unobservables that might drive the mortality rate up. Using the estimates from this regression, we predict an *expected* mortality rate for each county. We then define our excess mortality indicator as the gap between the *actual* mortality rate and the *predicted* one. In other words, our mortality indicator captures the residual of the regression specified as:

$$\text{mortality}_d = \alpha + \beta_1 \text{conscriptionrate}_d + \beta_2 \text{shareofagriculture}_d + \beta_3 \text{distance}_d \qquad (1)$$
$$+ \beta_4 \text{shareofyoungmen}_d + \varepsilon_d,$$

where d denotes a county. The young population rate is computed as the share of young men aged between 15 and 45, the conscription rate is the average number of young men incorporated in the French army between 1900 and 1914 divided by the 1911 population, distance is the distance of the county's prefecture to the closest point of the front line,[6] and agriculture is the share of agriculture in total employment in 1911.

In line with the intuition discussed previously, we first regress the mortality rate on the conscription rate and find a very positive and significant effect on the mortality rate as documented in column 1 of Table 1; indeed, the larger the average percentage of young men incorporated in the French army, the higher the losses ratio. We then augment our equation by adding the share of agriculture as reported in the 1911 census and also find a positive and very strong relationship, in light with the estimates from the history literature, as suggested by column 2. We also test whether the distance to the border plays any role, and column 3 supports the idea that there exists a negative and significant correlation between the distance to the battle zones and the mortality rate; finally, we test for the share of young men in the population, which, as reported in column 4, plays a negative though not significant effect at the 5% level. Overall, we retain the model presented in column 4 as our preferred specification and calculate the residualized mortality rate, denoted $\tilde{m}_d$, from it. It is noteworthy that this model captures almost 72% of the variations in the mortality rates across French counties, implying a substantial explanatory power.

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 robustness checks detailed in Appendix D. Finally, we present the spatial distribution of our baseline excess mortality rate in Figure C4.

[6] In concrete terms, the distance of the county d to the front line is defined as the minimum distance between the centroid of the prefecture of this county and the closest place on the battle line

TABLE 1: Mortality rate and observed pre-WW1 characteristics

	(1)	(2)	(3)	(4)
Average conscription rate	0.268***	0.175***	0.165***	0.154***
	(0.068)	(0.057)	(0.055)	(0.054)
Share of agriculture		0.019***	0.025***	0.021***
		(0.004)	(0.004)	(0.003)
(Log) Distance to the frontline			-0.343***	-0.371***
			(0.073)	(0.081)
Share of young men				-4.549*
				(2.615)
Observations	87	87	87	87
R-squared	0.471	0.648	0.701	0.715

Notes: The dependent variable is the mortality rate defined as the ratio of the total number of deaths during WW1 over the population in 1911. Share of agriculture is taken by looking at employment share in the 1911 Census, young population rate depicts the share of men aged 15 to 45. Distance is the logarithm of the distance of the county's prefecture to the front line. Coefficients are estimated using OLS with robust standard errors clustered at the county level. Stars summarize the level of the p-value of the Student test on the nullity of the coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3 Main results

3.1 Simple empirical specification

To measure 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 inventor 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 mitigate the risk of division bias. Formally, we estimate the following model:

$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k \neq 1914}}^{1936} \mathbb{1}_t(k) \left(\lambda_k \tilde{m}_d + \phi_k \text{e}_d + \rho_k b_d + \eta c_d\right) + \alpha_d + \beta_t + \eta_{d,t} \tag{2}$$

Where $\tilde{m}_d$ is the modelled excess mortality indicator in county d, e_d measures education in county d prior to the war and b_d is a binary variable that takes the value 1 if the county was directly hit by battles during the war and 0 otherwise, and c_d controls for the (ln) number of public procurement contracts received by county d during the war. Also, $\mathbb{1}_t(k)$ 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 respectively capture year and county fixed effects.

At times, we allow for a vector of time varying covariates including the share of agriculture and industry in employment, the wages level or the GDP, to ensure that our effect is not driven by structural change patterns. The estimated coefficients λ_t can be causally interpreted under the identifying condition that the treatment is orthogonal to the error term in equation (2) conditional on county and year fixed effects. Formally, this identifying assumption writes as:

$$\forall (d,t), \mathbb{E}[\eta_{d,t}(\mathbb{1}_t(k) \times \tilde{m}_d)|\alpha_d, \beta_t, X_{d,t}] = 0 \tag{3}$$

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 (2) 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 any pre trends. Nevertheless, recent extensions of the literature devoted to two-way fixed effects with heterogeneous treatment intensities, in particular De Chaisemartin and d'Haultfoeuille (2024) and Borusyak and Hull (2023), suggest that this condition neither ensures that the model identifies a causal effect nor guarantees that the exposure of each unit treated to the shock was fully random. To mitigate this concern, it should first be noticed that we constructed our treatment variable in such a way that it limits the risk of non random exposure to the shock. Nevertheless, we conduct a number of falsification tests in Section 5 and discuss the causal validity of our results. Importantly, we implement this equation using the Stata *reghdfe* command from Correia (2016); however, we present at times results using the Pseudo-Poisson maximum likelihood estimator using the *ppmlhdfe* command from Correia et al. (2019) and show in Appendix D.12 that all our main results hold under flexible functional forms.

3.2 A first motivating result

We start our empirical analysis by estimating equation (2) using the OLS.[7] In particular, we are interested in the values of the coefficients λ_t which, according to assumption (3), captures the causal effect of a marginal variation in the treatment. The results are presented in Figure 4. We have standardized $\tilde{m}_d$, the mortality indicator,

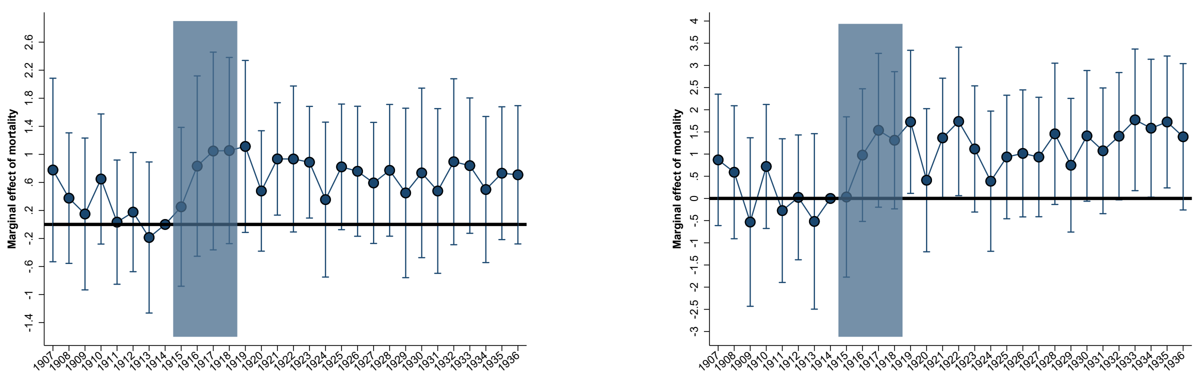
[7]In Appendix D we present our main results using different functional form assumptions for the dependent variable.

by its standard deviation so that the coefficients measures the increase in the number of patents (standardized by population in 1906) brought by a one standard deviation increase in the modelled excess mortality rate. The point estimates of the coefficients of interest λ_t (shown in Figure 4a for every year from 1907 to 1933) after the war are almost always superior to the reference year of 1914 and the yearly coefficient are significant at the 10% level for 1920 and 1923. To get a sense of the overall impact of the treatment, we will report the static coefficient λ_d obtained as the sum of all λ_t for t larger than 1919. λ_d therefore measures the total average marginal impact of mortality after WW1 from a one standard deviation increase in excess mortality and is estimated at 0.69 with a standard error of 0.35 (see Panel A of Table 2), meaning that mortality after the war exerted an overall positive effect but potentially relatively small in magnitude in particular given the level of precision.

FIGURE 4: Regression results: mortality and labor-intensiveness

(a) Average effect

(b) On labor-intensive counties



Notes: Estimation of equation (2) with OLS. Figure (a) plots λ_t and Figure (b) plots λ_t when we restrict the sample to counties labelled as labor-intensive ones, with confidence intervals at the 95% levels. The navy-blue-shaded areas denote the war period.

Despite the imprecision of the effect, it is noteworthy that mortality from WW1 is not associated with a relative decline in innovation activity, which could have been anticipated given the human capital channel. This suggests that, even in the short run, some counties were able to quickly rebound and foster increased innovation, indicating that the "innovating by necessity" channel was operational. To examine this more directly, we replicated the analysis shown in Figure 4a, but limited it to counties where female labor force participation was below its median level at the national scale during the war. In such counties indeed, the pressure to replace missing or expensive workers with labor-saving devices was much higher. The results presented in 4b confirm that these counties indeed responded by accelerating their rate of innovation as soon as the war started with the positive effects persisting into the 1930s. The corresponding coefficients are given in Panel A of 2.

3.3 Did mortality had no negative impact?

Strikingly, those first motivating results seem to preclude the eventuality that mortality exerted a negative effect on innovation following the war. This appears all the more surprising as a simple direct negative impact would come from the death of inventors during the battle.[8] To test this hypothesis, we use information on patentees from *PatentCity* combined with the granularity of the *Morts pour la France* dataset to match dead soldiers with inventors with a patent filed before WW1 in France. More specifically, we compare the first and last name of all dead soldiers with those of French inventors who filed a patent between 1900 and 1914: whenever we find a match on both items, we keep track of the dead soldiers as being a *possible* inventor prior to the war. [9]

Through this exercise, we retrieved around 7,000 potential matches. Among them counts Jacques Alexandre Marie Danlos, an engineer from the prestigious "Corps des Mines", died in the beginning of 1916 after having contributed, among others, to the Marne battle; before the war, he had filed a patent devoted to signalling in the railway industry.[10] Another example is Charles Henri Lindecker, commandant in the airplane force who had been filing 10 patents related to vehicles before the war. In total, inventors correspond to 0.64% of total war-related deaths. On average, those figures suggest that 12.3% of the French inventors who filed a patent between 1900 and 1914 died during the war, 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. This relatively large share may seem surprising, given that many scientists were mobilized by the Ministry of War, particularly to oversee the financing of research projects directly relevant to the war effort, as discussed in Section 4.2. Two reasons can explain this high number.

[8] Even though the death of inventors or scientists may have an ambiguous effect on the development of their respective fields, this is demonstrated by Azoulay et al. (2019a).

[9] Given that some surnames and even last names were very common in France at that time - typically, "Pierre", "Paul" or "Louis"- this procedure necessarily include some noise. Hence, we perform a wide range of robustness checks to ensure that the matches we retrieve are trustworthy: first, we remove from the matches all inventors who still filed a patent after the war, as, by nature, they cannot have passed; also, we check that the proportion of dead inventors is consistent with the overall death rate in the French male population; with rates spanning from 4.47% to 15.6%, we find a lower mortality across inventors compared to the c. 15% average across the French male working population of that time which stems from two facts: (i) the fact that inventors might have been protected from conscription to ensure a continuity in the invention process at a time when it was especially useful to win the battle; (ii) the fact that we necessarily miss some of the matches due to the carefulness with which we select dead inventors.

[10] More specifically, he had filed patent FR-429545-A applicable for devices initiating the release of detonators in a certain position of a signal

First, at the beginning of the 20^{th} century, patents were filed by workers across various skill levels, including farmers, production workers, and craftsmen, not exclusively by engineers or highly educated scientists (see Bergeaud and Verluise, 2024). Second, young French engineers often received military training during their education. This is notably true for the *École polytechnique*, which trained approximately 200 engineers annually who were supervised by the Ministry of War and integrated into military regiments in 1914.[11]

To look at the direct impact of these losses, we perform two separate analyses. First, we estimate equation (4):

$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k \neq 1914}}^{1936} \mathbb{1}_t(k) \left(\lambda_k i_d\right) + \alpha_d + \beta_t + \eta_{d,t}, \tag{4}$$

where i_d is the ratio of dead inventors in county d over the number of inventors in that county before the war. Second, we adopt a different approach and run a similar analysis at the technological level, exploiting the feature that some technologies are more impacted than other based on the fact that a larger share of inventors in these technologies were killed during the war. We measure technologies using the 3-digit IPC technological class and estimate the parameters in equation (5):

$$\text{pat}_{c,t} = \sum_{\substack{k=1907 \\ k \neq 1914}}^{1936} \mathbb{1}_t(k) \left(\lambda_k i_c\right) + \alpha_c + \beta_t + \eta_{c,t}, \tag{5}$$

where i_c is the ratio of dead inventors in technology class c over the number of inventors in that technology before the war. [12] In this case, the causal interpretation of the post treatment coefficients is supported by the assumption that conditional on being an inventor, the likelihood of being killed during the war is independent of the type of technology. We report the results from these two exercises in Figure 5 and corresponding coefficients in Panel B of Table 2. Figures 5a and 5b respectively summarize the effect of inventor losses at the county and technology class level. Both graphs clearly draw the same conclusions: inventors losses deprived both the counties and

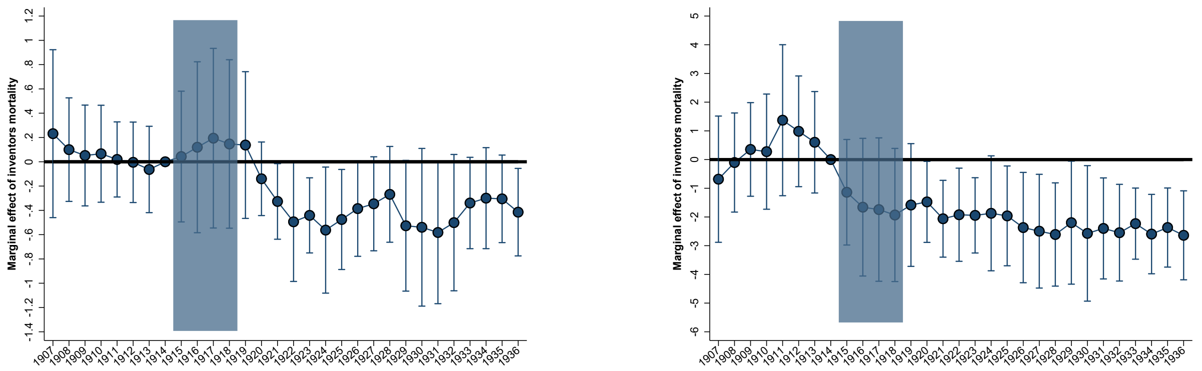
[11] More than 800 engineers from École polytechnique died during the Great War, including 260 from the cohorts of 1911-1918 alone (Lévy-Lambert, 2014).

[12] More specifically, a dead inventor is assigned to technological class c whenever the patents he filed prior to the war were all attached to this specific technological class; in case we find more than 1 patent, we "split" this dead inventor among the different technological classes in which he had filed a patent. The total number of inventors prior to the war is set to the total number of inventors with a patent in technology class c between 1900 and 1914

the technology classes they were associated to of the specific skills those inventors had displayed before the war. Hence the positive effect reported from the previous analysis hold even though the war-related losses dampened the existing human capital by depriving the society from existing inventors.

FIGURE 5: Regression results: inventors losses

(a) At the county level **(b)** At the technology level



Notes: Estimation of equation (2) with OLS. Figure a plots λ_t where county is the panel variable and Figure b plots λ_t where 3-digit CPC class is the panel variable, with confidence intervals at the 95% levels. The navy-blue-shaded areas denote the war period.

3.4 Exploring the impact of education

The results presented in Figure 4 and the negative local impact from the death of inventors might be indicative of a heterogeneous effect of mortality on innovation which depends on some underlying local characteristics. The level of education appears as a natural candidate give its emphasize in the theoretical and empirical literature on the determinant of innovation activities (see, in particular, Lucas, 1988, Van Reenen, 2022, Squicciarini, 2020, Aghion et al., 2009 and Bell et al., 2019). To test this, the regression equation has been modified to include an interaction term between education levels and the mortality indicator. This interaction term allows for a potential varying effects of mortality across different education levels. Formally, this means that our regression now writes:

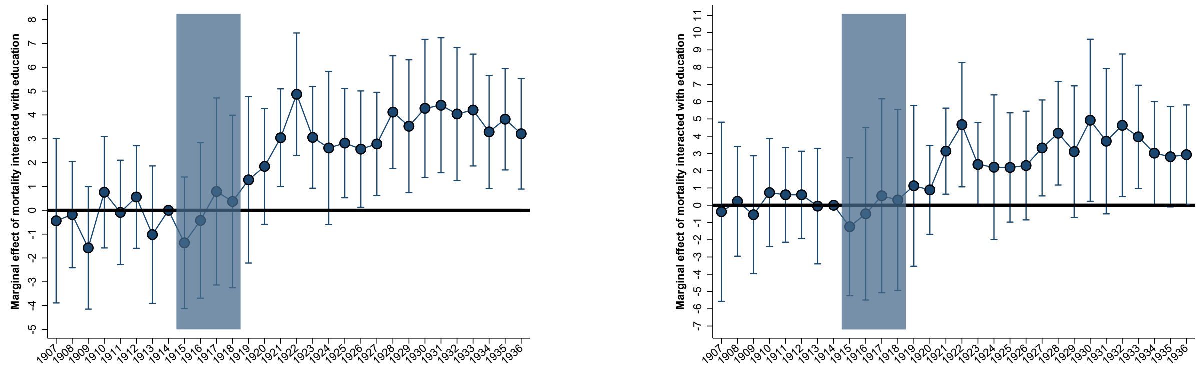
$$\text{pat}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1914}}^{1936} \mathbb{1}_t(k)\left(\lambda_k \tilde{m}_d + \phi_k \mathrm{e}_d + \rho_k b_d + \eta c_d + \theta_k e_d \times \tilde{m}_d\right) + \alpha_d + \beta_t + \nu_{d,t}, \tag{6}$$

where e_d takes the value 1 whenever county d belongs to the top 33% of the education distribution.[13].

[13]In Appendix D, and more specifically in subsection D.2, we also test this augmented equation by

FIGURE 6: Regression results: mortality and education interacted

(a) Enrolment rate **(b)** Baccalauréat



Notes: Estimation of equation (6) with the OLS. Figure a plots θ_t when enrolment rate is taken as the education variable and Figure b plots θ_t when baccalauréat is taken as the education measure, with confidence intervals at the 95% levels. The navy-blue-shaded areas denote the war period.

Figures 6a and 6b reports the values of θ_t with two alternative measures of education. In both case, the additional effect of excess mortality on innovation for counties that are in the top tercile in terms of education before WW1 is clearly positive. The direct effect, as measured by λ_t is either negative or insignificant and shown in Table 2 (Panel C) and in Figure D4 in Appendix D.3. Additionally, the magnitude of the effect of mortality in counties where initial education was large enough is sizeable: a one standard deviation increase in the mortality rate throughout the war raised innovation in counties in the top tercile of the enrolment rate distribution by around 2 patents per 100,000 inhabitants, meaning a 38% increase compared to their prewar level on average. Using an alternative measure of education, the *baccalauréat* rate, yields a 20.5% increase on average for the top tercile counties. In the end, these results suggest that mortality was a necessary, but not a sufficient condition, to ensure an increase in the patenting activity after the war. Only when initial education was large enough could counties transform the demographic shock into an increased patenting activity.

To wrap up, we report in Table 2 the estimates of our main regressions as defined by 2, 6 and 4. In particular, we derive the main results depending on whether we use the baseline model, in which we do not introduce any interaction term, or the augmented framework in which we allow for an interaction term between mortality and education. Also, we let education be either a continuous variable, capturing respectively the share of kids attending school between 5 and 15 (the *enrolment rate*)

using a continuous measure of the level of education rather that this discrete one, and show that the results are similar. Also, we derive the static coefficients resulting from a continuous measure of education in 2

TABLE 2: Summary of the effect of mortality for various specifications

	Static coefficient		Pre Trends		Observations
Panel A: Simple specification (Section 3.2):					
Excess Mortality (Full sample)	0.698**	(0.353)	0.247	(0.323)	2,610
Excess Mortality (labor-intensive counties)	1.308**	(0.656)	0.078	(0.591)	2,610
Panel B: Inventors mortality (Section 3.3):					
County level (model (4))	-0.409***	(0.127)	0.050	(0.121)	2,610
3-digit IPC class level (model (5))	-0.0937***	(0.0106)	-0.0028	(0.0095)	3,360
Panel C: Interaction with education (Section 3.4):					
Regression 1: binary measure, enrollment rate					
Excess Mortality	-0.746***	(0.249)	0.291	(0.236)	2,610
interacted with education	3.368***	(0.927)	-0.238	(0.850)	2,610
Regression 2: binary measure, baccalauréat rate					
Excess Mortality	-0.279	(0.203)	0.110	(0.196)	2,610
interacted with education	3.196***	(1.083)	0.149	(1.019)	2,610
Regression 3: continuous measure, enrolment rate					
Excess Mortality	-7.284**	(2.855)	-0.474	(2.586)	2,610
interacted with education	10.163***	(3.949)	0.865	(3.576)	2,610
Regression 4: continuous measure, baccalauréat rate					
Excess Mortality	-5.739***	(1.118)	0.604	(1.147)	2,610
interacted with education	5.329***	(1.120)	-0.422	(1.084)	2,610

Notes: The dependent variable is the total number of patents normalized for the 1906 population or the total number of patents divided by the year-on-year population when the panel variable is the 3-digit IPC class rather than the county. In Panel A, we estimate equation 2 for the full sample of counties and for the top 25% counties that are more labor-intensive. In Panel B, we estimate models 4 and 5. In Panel C, we augment the simple specification with an interaction term between various measures of education and estimate model 6. Static Coefficient corresponds to the sum of λ (excess mortality) and θ (interaction) from 1919 to 1936. Pre-trends coefficients correspond to the respective sum before 1914. Coefficients are estimated using OLS with standard errors clustered at the county level in parentheses. Stars indicate significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and the share of young men incorporated in the French army that hold the *baccalauréat* degree, or a discrete variable taking the value 1 whenever a given county ranges in the upper tail of the distribution either in terms of enrolment rate or in terms of the *baccalauréat* rate. Those results suggest that the positive effect of mortality captured in the baseline model is confirmed by a more parsimonious approach in which we allow the effect of mortality to be heterogeneous depending on the initial education level. Perhaps more strikingly, the augmented specification reveals that the effect of mortality for counties ranging in the upper tail of the education distribution was substantially larger than the effect identified in the baseline model: in other words, this finding is consistent with our conclusion that mortality acted as an incentive to increase patenting activity, but that such an incentive could only be met for counties with a large enough education level. Finally, let us mention that we obtain similar results under the augmented specification where education is a continuous measure rather than a discrete one: while mortality *per se* now exerts a negative and significant effect, mortality interacted with education generates a positive and significant effect, the magnitude of which is large enough to compensate for the negative effect induced by mortality, provided that the county shows a large enough initial education level. Overall, we retain as our preferred specification that involving a discrete measure of education, the interpretation of which is easier than the specification relying on a continuous measure of education [14].

To summarize, our main findings so far show that mortality during the war exerted a positive and significant effect on patenting activity in France after the war especially in counties ranging in the upper tail of the education distribution. By contrast, counties who suffered large inventors losses were dampened in their innovation process. In other words, mortality seems to have acted as an incentive to raise innovation, but this incentive was rather a necessary than a sufficient condition: indeed, only when mortality was combined with substantial knowledge did it raise the innovation effort. One way to interpret those results would be be that firms substituted labor-saving devices for missing workers, but that they could only do so provided that they relied on a large enough initial level of education.

4 Mechanisms

In this section, we explore the main mechanisms underpinning our global results. In particular, we show that our results are notably driven by the effect of mortality on patenting activity related to labor-saving technologies and in particular industrial and agricultural machinery.

4.1 The labor substitution mechanism

4.1.1 The impact of mortality on real wages

One way to interpret the findings summarized in 3.4 is that mortality generated labor scarcity, which, in turn, drove wages up, implying that counties where the mortality

[14] Indeed, the coefficient on mortality in the specification exploiting a continuous measure of education measures the marginal effect of a one standard deviation increase in mortality in a county where education would be set to 0; given that the minimum value of education lies around 0.5, interpreting such a coefficient might prove misleading

rates were the highest had no choice but to substitute labor-saving devices for missing workers. This, however, was possible only to the extent that such counties were relying on a large enough initial level of education. This interpretation, however, can only be causally validated to the extent that we first observe an effect of mortality on real wages. We recover nominal wages at the county level from the *Annuaires Statistiques de la France*; given that strong inflationary pressures appeared in the war context, and especially in those places where food provision was made peculiarly tough given war damages, using nominal wages as a proxy for the *real* labor cost might however be misleading. To get a sense of the level of prices, we thus divide the nominal wages by the inverse corn output per acre right after the end of the war, to reflect the heterogeneity in local prices [15].

We then estimate equation 7:

$$\mathrm{w}_{d,t} = \sum_{\substack{k=1907 \\ k\neq 1914}}^{1936} \mathbb{1}_t(k)\left(\lambda_k m_d + \xi_d\right) + \alpha_d + \beta_t + \eta_{d,t}, \tag{7}$$

Where $w_{d,t}$ is the real wage in county d at time t, m_d is the mortality in county d during the war and ξ_d is a vector of initial characteristics of county d prior to the war. Whatever the specification retained, 3 shows that we clearly obtain a positive and significant correlation between the after-war real wages level in French counties and the excess-mortality as defined in equation 1. This suggests that the labor scarcity induced by the war-related mortality strongly affected the labor costs supported by firms. It is noteworthy that this effect remains sizeable and significant at the 1% level even when controlling for various socio-economic outcomes such as the share of agriculture in employment or the (ln) number of public procurement contracts received by counties during the war. In line with expectations, the initial share of agriculture in employment exerted a negative and significant effect on real wages while public procurement contracts drove wages up as expected in case of a large demand shock. In the end, the coefficient on mortality always hovers around a 13.5 value implying that a one standard deviation increase in mortality was conducive of a c. 23% increase in the real wages compared to their 1914 level. This brings further support to our interpretation, namely that counties where the mortality rates were the highest had no choice but to replace either missing or expensive workers with labor saving devices in order to maintain sufficiently high profits.

[15]Should the productivity of land crops have been strongly affected by war damages, we would then expect prices to rise sharply which, in turn, would imply that the increase in wages would rather be related to agriculture conditions rather than to mortality.

TABLE 3: Summary of the effect of mortality on wages for various specifications

	Static coefficient		Pre Trends		Observations
Panel A: Model 1					
Excess Mortality	13.47**	(6.186)	-1.324	(5.650)	2,610
Panel B: Model 2					
Excess Mortality	13.470***	(4.471)	-1.324	(4.073)	2,610
Share of agriculture in 1911	-3.357***	(0.432)	0.073	(0.393)	2,610
Panel C: Model 3					
Excess Mortality	13.643***	(4.434)	-1.337	(4.041)	2,610
Share of agriculture in 1911	-2.957***	(0.449)	0.028	(0.413)	2,610
(Ln) public procurement contracts	9.145***	(2.975)	-0.687	(2.698)	2,610
Panel D: Model 4					
Excess Mortality	13.745***	(4.919)	-1.136	(4.481)	2,610
Share of agriculture in 1911	-2.946***	(0.496)	0.049	(0.453)	2,610
(Ln) public procurement contracts	9.210***	(3.082)	-0.559	(2.802)	2,610
Share of women in working population in 1911	-0.080	(0.846)	-0.158	(0.772)	2,610

Notes: The dependent variable is the real wages at the county $\times$ year cell, where the real wage is taken to be the wage divided by the inverse crop productivity of each county right after the war in 1919. In Panel A, we estimate equation 7 when only mortality is included in the explanatory variables; in Panel B, we add the share of agriculture in total employment before the war, while we respectively add the (ln) number of public procurement contract at the county level in Panel C and the share of women in the working population in 1911 in Panel D. Static Coefficient corresponds to the sum of the coefficients on the interaction between year dummies and the variables of interest from 1919 to 1936. Pre-trends coefficients correspond to the respective sum before 1914. Coefficients are estimated using OLS with standard errors robust to heteroskedasticity. Stars indicate significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.1.2 Identifying patents related to labor substitution

Identifying patents related to mechanization, automation or, more broadly, to labor substitution devices, has garnered growing interest in the literature over the past few years. Various methods have been specified to estimate the propensity of a patent to be indicative of labor-saving technology (see, e.g., Dechezleprêtre et al., 2020; Mann and Püttmann, 2018; Kogan et al., 2023; Webb, 2019). However, most of these approaches focus on recent technologies; for example, Webb (2019) examine the effect of Artificial Intelligence, and Mann and Püttmann (2018) consider the period post-1976. We rely on an approach that builds on Dechezleprêtre et al. (2020), which involves exploiting the bibliographical information of patents to compute the frequency of specific keywords in patent texts for each technological class and assigning each class a propensity to relate to labor-saving technologies.

Following this approach, we extracted the title text of all French patents relevant to our study period from the Google Patents database. For each 3-digit IPC class, we calculated the frequency of different stems that trace back to the notion of labor substitution. In particular, we focus separately on three of them which, in our view, and in light with macroeconomic evidence, are closely related to labor substitution; namely, we retain “machine” ”automat” and ”elec”, respectively to capture inventions related to machines, to automation or to electricity. While the relation between machine or automation and labor substitution seems quite straightforward, it might be doubted that electricity brings direct support in case of labor scarcity. And yet, Pavel (2023) recalls that electricity soon found a wide range of applications as soon as the beginning of the 20^{th} century in Europe: as he put its, electricity could "replace human arms but also animal strength" and give power to industry machines.

Subsequently, we classify a technology to be related respectively to machinery, automation and electricity whenever it belongs to the top 20% highest scoring IPC in terms of frequency of respectively the token ”machine”, ”automat” and ”elec”. In contrast, we formed a control group of respectively “non-machine”, ”non automation” and ”non electricity” patents by considering patents in IPC classes from the bottom 20% IPC based on the frequency of the tokens “machine”, ”automation” and ”electricity”. The distribution of the score per technology for each key-token is plotted in Figure B1. Ultimately, we identified 24 IPC categories for each token, namely ”machine”, ”automat” and ”elec”. Technology classes related to machinery comprise, on average, 13.98% of patents featuring the word “machine” in their title. The lower boundary of this upper 20% exhibits an average frequency of 6.46% for the same token, significantly higher than the overall sample average of 4% and the median value of approximately 1.4%. We discuss in more details the classification in Appendix B.

4.1.3 Empirical evidence on labor substituting patents

TABLE 4: Effect of mortality interacted with education on patents depending on labor substitutability

	Static coefficient		Pre Trends		Observations
Panel A: labor substituting patents					
Machinery-related patents	1.542**	(0.781)	0.486	(0.693)	2,610
Automation-related patents	2.151**	(0.920)	0.694	(0.815)	2,610
Electricity-related patents	2.583***	(1.004)	0.876	(0.889)	2,610
Panel B: non labor-substituting patents					
Patents unrelated to machinery	0.247*	(0.133)	-0.039	(0.127)	2,610
Patents unrelated to automation	0.161	(0.102)	-0.129	(0.093)	2,610
Patents unrelated to electricity	0.055	(0.106)	-0.204*	(0.105)	2,610

Notes: Estimation of model (6) with different dependent variables. In Panel A, the dependent variable is the total number of patents related to labor substitution normalized for the 1906 population. In Panel B it is the number of patents unrelated to labor substitution normalized for the 1906 population. The regressor considered here is the mortality indicator interacted with a binary variable taking the value 1 whenever the county is in the top 33% of the education distribution (θ_t). Static Coefficient corresponds to the sum of θ from 1919 to 1936. Pre-trends coefficients correspond to the same sum before 1914. Coefficients are estimated using OLS with standard errors clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Analyzing the local intensity of innovation in labor-saving technologies sheds light on the notable labor substitution effect arising from human labor shortages. This effect could explain the positive coefficients on the interaction term exhibited in Figure 6 and suggest that counties that experienced an excess mortality from WW1 developed technologies dedicated to replacing workers with machinery or automation related devices, but only to the extent that they relied on large enough human capital resources to facilitate such a transition. Before testing this formally, we show in Figure B9 that France saw a more pronounced take-up of machine-related patents compared to countries like the United States from 1914 to 1924, highlighting a strategic shift towards mechanization in response to labor constraints. Additionally, Figure 1b documents a faster increase in the patenting activity related to labor-saving inventions after the war compared to other patents. Patenting activity related respectively to automation, machines and electricity actually improved by respectively 150%, 90% and 80% at their peak around 10 years after the end of the war, suggesting that such patents were peculiarly affected by the war.

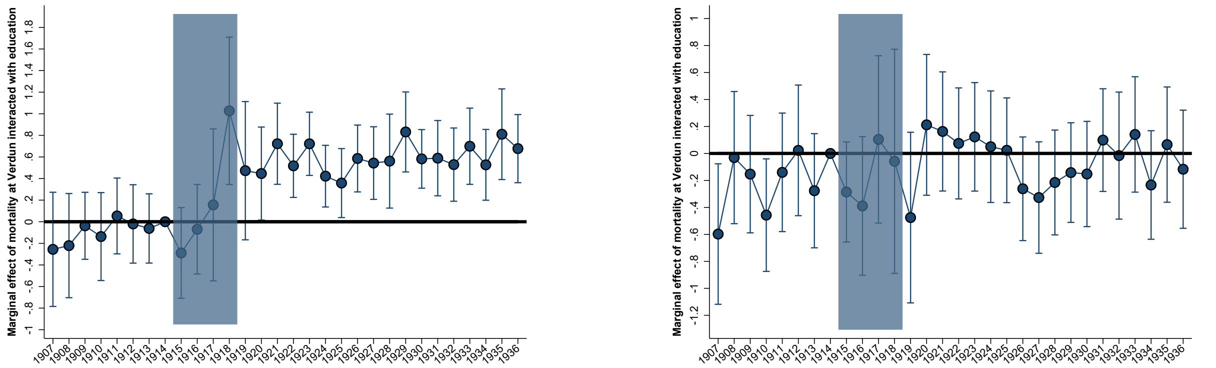
To test whether counties more affected by mortality were also more likely to adopt labor substituting inventions, we estimate the model specified in equation (6) but restrict the numerator of the dependent variable to count alternatively machines-related patents, automation-related patents and electricity-related patents. Again, for the sake of clarity, we use a binary measure of education that takes the value 1 whenever the county belongs to the top 33% of the distribution in terms of education level before the war to allow for an easier interpretation of our findings but the results are robust to using a continuous measure. Results of these regression are summarized in Table 4 which displays both the average pre-trend coefficients and the post-treatment coefficients on the interaction term between mortality and education obtained from a static regression. Results are respectively reported for machinery-related, automation-related, electricity-related patents and their control counterparts as defined above. The results related to the coefficients on mortality *per se* are summarized in Appendix B.3, but they all point to either a negative but small effect or an insignificant effect of mortality alone, suggesting, again, that only the combination of a high level of mortality and of a high enough initial level of human capital could trigger counties to improve their productivity.

All results are suggestive of a labor substitution mechanism induced by labor shortages in the aftermath of the war. In the meantime, the implied magnitudes are telling: a one standard deviation in mortality increased machinery-related patenting activity by c. 40% in counties belonging to the upper tail of the education distribution; similarly, it raised the innovation effort related to automation by 54.3% compared to its 1914 level while it improved electricity-related patenting activity by 85.6%. And yet,

FIGURE 7: Effect of mortality interacted with education on labor saving and non labor saving patents

(a) Labor saving patents

(b) Non labor saving patents



Notes: Estimation of equation (6) with the pseudo poisson specification. Figure a plots θ_t when labor-saving patents is the dependent variable and Figure b plots θ_t when non labor saving patents is taken as the dependent variable, with confidence intervals at the 95% levels. The navy-blue-shaded areas denote the war period.

such an increase in mortality had close to no effect on patenting activity unrelated to machinery, automation or electricity, as shown by the insignificant coefficients obtained on the interaction term after the treatment for electricity and automation-related patents. Only for machinery-related patents is the coefficient on the interaction term slightly positive after the war and significant at the 10% level, but its magnitude is less than a fifth of that for machinery-related patents. That labor-saving and non labor-saving patents were very differently affected by mortality can also be seen form Figure 7 which pictures the impact of the interaction between mortality and education on respectively labor saving and non labor saving patents [16] using a pseudo Poisson estimator. While the coefficients on the interaction term after the war are clearly positive and largely significant for labor saving patents, they hover around 0 for non labor saving patents which further supports our argument that counties which faced the highest mortality rates had no choice, but to adopt labor-saving technologies to replace missing workers. Further robustness checks, including allowing for flexible functional forms, are provided in D.12.

4.1.4 Does the effect come from military related patents?

Patents related to machinery could potentially encompass technologies underlying weaponry or military-related devices. One concern is that the effects we observe may be primarily explained by the adoption of technologies developed during the war to

[16] Labor saving patents are patents belonging to the top 20% IPC categories in terms of frequency of the stems "machine", "automat" and "elec", meaning that they are patents that are the likeliest to be related either to machine, electricity or automation.

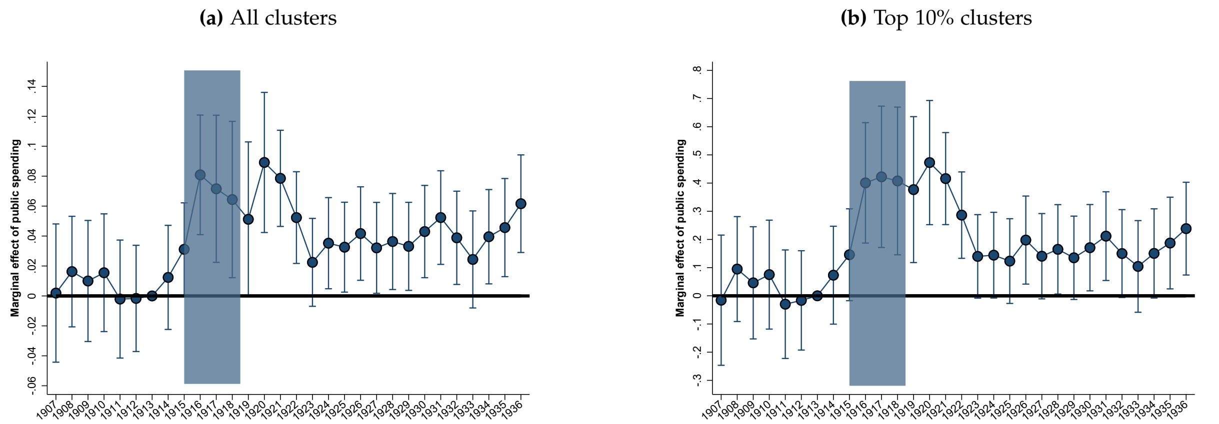
enhance military strength. The possibility that such projects had externalities on post-war innovation is plausible and discussed in more detail in Section 4.2. However, for this to pose a threat to our identification, the prevalence of such patents would need to correlate with excess mortality after the Great War. For instance, counties with higher conscription rates might also be more likely to host military-related firms. To address this concern, we exclude patents related to the military field from our main model—specifically, those in the F41 and F42 IPC classes, which cover weapons and ammunition. The results, presented in Figure D2, do not statistically differ from those shown in Figure 6.

4.2 Spillovers from war effort

A recent literature (Gross and Sampat, 2020, 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 channel 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 some 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 complement their analysis by studying the impact of such contracts on patenting activity at the cluster (technology x county) level. To measure the influence of such contracts on innovation at the local level, we

FIGURE 8: Effect of government spending on clusters innovation



Notes: This graph pictures the effect of a marginal increase in the (ln) public spending on innovation in clusters as defined above, as given by (9). Panel (a) plots the overall effect for all clusters while Panel (b) plots the effect for the top 10% clusters in terms of funding received.

build a dataset at the county d times technology c level where the technology classes correspond to the 1-digit International Patent Classification. 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.[17] 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:

$$e_{d,c} = \sum_i \frac{s_{c,i}}{\max_i s_{c,i}} \times n_{i,d} \tag{8}$$

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 equation (9):

$$\text{pat}_{d,c,t} = \sum_{\substack{k=1907 \\ k \neq 1914}}^{1936} \mathbb{1}_t(k)\left(\lambda_k \tilde{e}_{d,c}\right) + \alpha_d + \beta_c + \psi_t + \nu_{c,d} + \rho_{d,t} + \gamma_{c,t} + \eta_{d,c,t} \tag{9}$$

Where $\tilde{e}_{d,c}$ depicts the logarithm of the exposure $e_{d,c}$ of cluster (d,c) to government spending, and where a large set of counties, technology and time fixed effects are allowed. The identification assumption is that, in the absence of government support, the innovation patterns should have followed parallel trends in the different clusters.

[17]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

Results from this regression are shown in Figure 8 which captures the marginal effect of a 1 standard deviation increase in the exposure to public spending of cluster (c, t). On average, a one standard deviation increase in the exposure to public expenditures during the war generated an increase in patenting activity by 1.45 in each cluster, corresponding to a c.22% increase compared to the average pre-war level.

4.3 The nature of education matters

Throughout this paper, we have attempted to show that mortality during the war was a necessary but not a sufficient condition to ensure an increase in the patenting activity posterior to the war. More precisely, we showed that mortality acted as an incentive to labor-saving devices to replace missing workers but only to the extent that counties could rely on a large enough initial education level. Little has been said, however, on the role played by education. In particular, it could be argued that education merely proxies for some hidden variables, whether it be development, beliefs, or even wealth. To some extent, these concerns should be mitigated in the light of the numerous controls we include in our models. Nevertheless, we further assert that education indeed reflected the ability to meet the incentive posited by labor scarcity by showing that only technical and science-related education helped counties improve their innovation effort after the war.

To do so, we rely, again, on the analysis of Squicciarini (2020). As briefly mentioned in Section 2, we distinguish between two kinds of schools: catholic schools, which laid the emphasis on philosophy and theology, and non catholic schools who rather focused on technical and scientific material. In turn, non catholic schools were more prone to scientific and industrial development. Hence, measuring education by restricting to catholic or to non catholic schools will capture different aspect of human capital: namely, we expect that the learning by necessity effect that we have been identifying throughout this paper must have been driven by technical and thus secular schooling rather than catholic schooling.

Figures D1 directly shows the interaction between education and excess from replicating model (6) in which education is measured respectively by a binary variable taking the value 1 whenever county d ranges in the upper 33% of the distribution in terms of secular education (Figure D1a) and by a binary variable that takes the value 1 whenever county d ranges in the upper 33% of the catholic education (Figure D1b). We also show the static coefficients in Table 5 for different measures of innovation in line with previous sections. The results clearly show that while mortality interacted with secular education played a positive and significant role, the magnitude of which is close to that derived in the general specification, the interaction between mortality and catholic education played a negative effect on patenting activity after the war. Actually, once we allow for an interaction term between mortality and catholic education, mortality *per se* starts playing a positive and significant role while the interaction with catholic education plays either a negative and significant or a negative and poorly significant role. This finding is consistent with the results derived by Squicciarini (2020) regarding industrialization in France in the late 19^{th} century; while secular education essentially accelerated industrial development in French counties, catholic schooling allegedly played no effect. In a similar spirit, the results we recover suggest that education, when conducive of scientific knowledge, was an important factor in the ability of counties to cope with the high death toll of the war, and transform this demographic shock into an economic incentive. In other words, not only did the scale of education matter but also the nature of it had an influence to meet the challenge posited by labor scarcity.

TABLE 5: Effect of mortality interacted with education on labor substituting patents depending on education quality

	Static coefficient		Pre Trends		Observations
Panel A: secular education					
All patents	3.261***	(1.060)	-0.072	(0.969)	2,610
Machinery-related patents	1.512*	(0.793)	0.612	(0.706)	2,610
Automation-related patents	2.163**	(0.982)	0.942	(0.69)	2,610
Electricity-related patents	2.373**	(1.111)	0.848	(0.983)	2,610
Panel B: catholic education					
All patents	-2.263***	(0.830)	-0.229	(0.773)	2,610
Machinery-related patents	-1.07*	(0.632)	-0.409	(0.562)	2,610
Automation-related patents	-1.487*	(0.765)	-0.567	(0.679)	2,610
Electricity-related patents	-1.692**	(0.858)	-0.659	(0.760)	2,610

Notes: Estimation of model (6) with different dependent variables. The dependent variable is the total number of patents related to labor substitution normalized for the 1906 population. The main regressor is the mortality indicator interacted with a binary for being in the top tercile in terms of education (θ) where education is measured as secular schooling (Panel A) and catholic schooling (Panel B). Static Coefficient corresponds to the sum of θ from 1919 to 1936. Pre-trends coefficients correspond to the same sum before 1914. Coefficients are estimated using OLS with standard errors clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Threats to identification and robustness checks

While our dynamic quasi-experimental setting allows to report the marginal effect of mortality before the war (the pre-trend coefficients) which is indicative of the fact that before 1914, counties more or less exposed to an excess mortality had parallel patenting activities, our identification relies on the stronger assumption that without any variation in mortality, these counties would have also experienced similar innovation dynamics. In this section we explore various potential threats to this identification assumption.

As a first exercise, we build on the Synthetic Cohort literature (Abadie and Gardeazabal, 2003) and construct a counterfactual county for each of our units of observation based on pre-war similarity with US Commuting Zones. We then consider the issue of non-random exposure to exogenous shocks as presented by Borusyak and Hull (2023): even if mortality is random, every day of the war was not equally mortal, and German shells did not discriminate based on the origin of the soldier, the exposure to the battlefront may be non-random and driven by unobserved characteristics. If these characteristics are correlated with future innovation potential, then our estimates may be wrongly attributing the take-up of innovation following the war to the high death toll. To address this concern, we run two different tests. First, in line with Borusyak and Hull (2023), we perform a randomization of the shock while keeping the exposure constant to construct a counterfactual excess mortality and show that this counterfactual has no predictive power. Second, we build on **?** and exploit exposure to the Battle of Verdun. An additional threat to identification relates to the issue of negative weighting in two-ways fixed effect difference-in-difference models as highlighted by De Chaisemartin and d'Haultfoeuille (2024) which can introduce bias whenever the treatment dose is heterogeneous across treated units. We discuss this in more details in Appendix D.5.

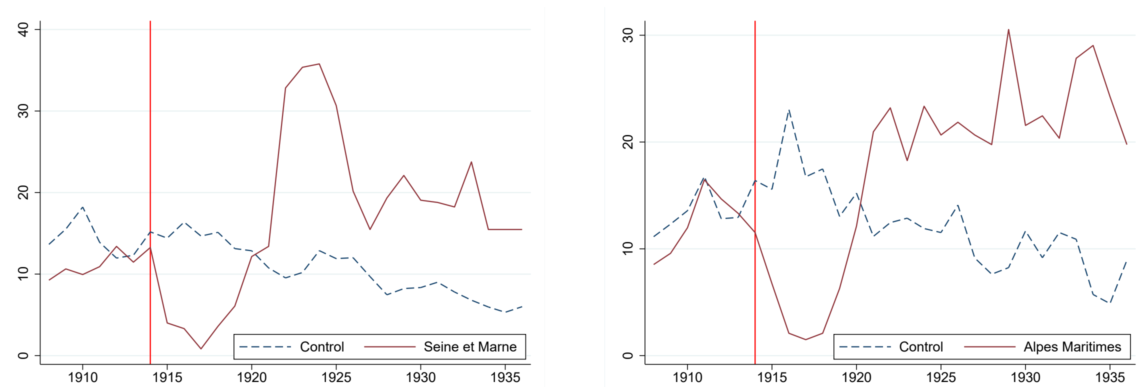
5.1 Building synthetic cohorts

The notion of Synthetic Control units was first introduced by Abadie and Gardeazabal (2003) who investigated the economic effects of the outbreak of terrorism in the Basque Country. The idea is to build a counterfactual for each unit of observation that is treated based on pre-treatment characteristics. To build this counterfactual, they construct a "synthetic" doppelganger by considering a combination of other regions. We implement their methodology by considering a set of 441 US Commuting Zones and build a synthetic unit for each French county based on population density and the share of patents in each 1-digit IPC technology taken from Bergeaud and Verluise (2024). This approach has two main advantages. First in the absence of clear control group in France as the whole country was impacted by the war, this allows to consider a counterfactual that is less affected by the war in terms of casualties. Second, because we match on the prevalence of different technologies before the war, this control group will capture any global boom in some specific technologies that was poised to happen after the war. If such a boom is concentrated on technologies that are more frequent in counties receiving a larger excess mortality, then our identification assumption would indeed be violated. However in such case, we should expect the synthetic control group to also experience a similar increase in the number of patents.

Empirically, we apply this method through the package described by Abadie et al. (2011). Our data set consists of our usual 87 French counties augmented with 441 commuting zones among the most populated ones in the US. The unbalance between the number of control regions and the number of tested counties allows for a large number of degree of freedom in the matching strategy; most of the time, counties are matched with a combination of around 10 commuting zones, ensuring goodness of the fit. More details can be found in Appendix D.4. To illustrate the result, we present in Figure 9 two cases of counties that suffered an abnormally high mortality: the *Alpes Maritimes* and the *Seine-et-Marne* which both rank in the top decile in terms of the distribution of $\tilde{m}$.

FIGURE 9: Evolution of patenting activity in two counties highly affected by war-related losses compared to their US synthetic counterparts

(a) Seine-et-Marne　　**(b)** Alpes Maritimes



Notes: Solid lines represent treated units while dashed lines represent their US synthetic counterparts. Treated unit of Figure a is Seine-et-Marne and treated unit of Figure b is Alpes Maritimes.

These two examples suggest that French counties and their US counterpart, which exhibited closely related trends prior to the war, had very different innovation trajectories from 1914 to 1936. An aggregation at the country level is shown in Figure D5 and report a similar pattern. While French innovation was divided by around 10 during the war, it remained on a slowly decreasing trend in the US during that period, in line with the variations observed before the war. However, starting in 1919, French counties show a substantial recovery, outperforming their pre war patenting activity as soon as 1920. In the meantime, the US synthetic cohort stabilized its patenting activity at a sustained lower level, around one half of that in France.

5.2 Dealing with non random exposure

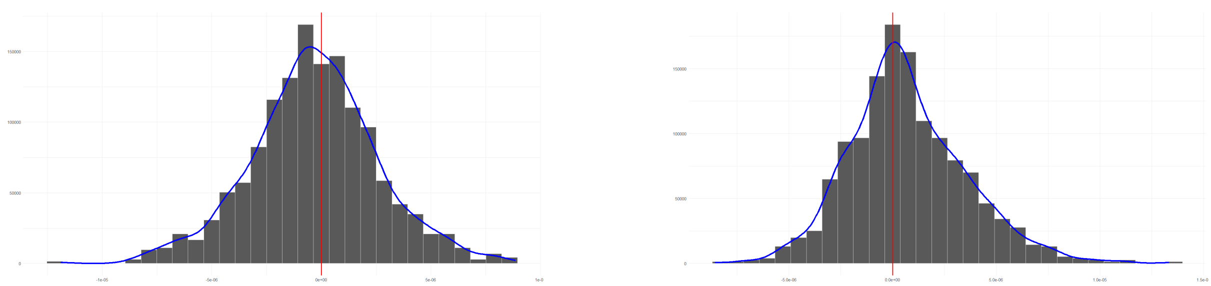
Total mortality in county d, m_d, is the sum over each month μ of the war period of the product of total monthly deaths, m_μ, and the war exposure of county d during that month, $c_{d,\mu}$. Although m_μ might appear randomly allocated with respect to future innovation activities, the distribution of $c_{d,\mu}$ could still be endogenous. This concern is particularly relevant to the measure of mortality at the county level m_d and led to the development of our excess mortality indicator, which adjusts for observed characteristics predicting m_d and future innovation potential. However, it is conceivable that other unobserved characteristics might also influence this measure. For example, Guillot and Parent (2018) suggests that political characteristics, such as voter abstention rates—perceived as indicative of weaker allegiance to Republican values—could have led to "punishments" of certain counties through increased conscription rates to counteract pacifist sentiments during the war.

To address this concern, we perform a robustness check in a spirit similar to that suggested by Borusyak and Hull (2023). We start from the fact that

$$m_d = \sum_{\mu} c_{d,\mu} \times m_\mu,$$

and assume that the distribution of the exposure $c_{\mu,d}$ is not necessarily random as the number of incorporated soldiers have been driven by characteristics endogenous to each county. We then build 1000 counterfactual values each made of a randomization of the total mortality mu_μ, keeping the exposure constant, and thus define 1,000 simulated mortality indicators $m_d^{(k)}$ for each county d which we residualized using the same procedure as the one described in Section 2.2.

FIGURE 10: Distribution of the coefficients on the counterfactual treatment effects



(a) Enrolment rate　　**(b)** General education measure

Notes: This graph pictures the distribution of the coefficients on the interaction term between the counterfactual mortality rate as defined before and the variable that codes for education. Panel (a) plots the distribution of such coefficients when education is a binary variable that takes the value 1 whenever the county belongs to the upper 33% of the enrolment rate distribution while Panel (b) plots the distribution when education is a binary variable that takes the value 1 if the county belongs either to the top 33% of the enrolment rate distribution or to the top 33% of the baccalauréat rate distribution.

Before implementing the test suggested by Borusyak and Hull (2023), we use these counterfactual to perform a randomization based inference. Formally, we run 1,000 static regressions corresponding to model (6) but use the corresponding simulated indicator of mortality $\tilde{m}_d^{(k)}$ instead of $\tilde{m}_d$. We then report the value of the sum of the interaction coefficients between $\tilde{m}_d^{(k)}$ and our measure of education after WW1, denoted $\hat{\theta}^{(k)}$. Figure 10 reports the result and show that the coefficients obtained running these placebo regressions are not statistically different from 0; on the contrary, they seem to be evenly distributed around the 0 cutoff represented by the red vertical line. This pattern holds whatever the measure of education is used, as suggested by the distribution centered around 0 for both measures of education.

We then more directly implement the test of Borusyak and Hull (2023) and construct a single counterfactual by averaging the different values of $\tilde{m}_d^{(k)}$ which we then use as a control in our main model. Table 6 shows the results. Whatever the classes of patents considered, the interaction between excess mortality and education continues to be significant while the counterfactual has no effect on patenting after WW1. It is noteworthy that, due to an increase in the precision of the estimates of mortality, the coefficient on the latter now appears significant and negative. In the meantime, its value lies significantly below that on the interaction between mortality and education, suggesting that in the counties with a large initial education endowment, the interaction term dominates. All in all, if an endogenous exposure of different counties were in fact driving our baseline results, then we would expect this control to be significantly correlated with the dependent variable. The fact that our baseline estimates are almost unchanged is therefore reassuring with respect to this potential threat to identification.

5.3 Exploiting the Verdun Battle

The counterfactual exposure constructed in the previous Section is based on the underlying idea that the exposure of a given county in a given month is proportional to the number of deaths reported. This is therefore only a proxy for the actual exposure, which would be more accurately measured by the number of soldiers from each county that were actively fighting each month. Unfortunately, such information is not readily available for the entirety of the war. 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. 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

TABLE 6: Effect of mortality interacted with education when counterfactuals are added as control

	Static coefficient		Pre Trends		Observations
Panel A: All patents					
Mortality interacted with education	3.395***	(0.898)	-0.155	(0.821)	2,610
Mortality	-0.654**	(0.255)	0.267	(0.241)	2,610
Panel B: All labor-saving patents					
Mortality interacted with education	2.480***	(0.902)	0.922	(0.797)	2,610
Mortality	-0.267**	(0.129)	0.028	(0.117)	2,610
Panel C: Machine-related patents					
Mortality interacted with education	1.616**	(0.753)	0.539	(0.669)	2,610
Mortality	-0.154**	(0.103)	0.040	(0.091)	2,610
Panel D: Electricity-related patents					
Mortality interacted with education	2.663***	(0.968)	0.955	(0.856)	2,610
Mortality	-0.404**	(0.123)	0.062	(0.113)	2,610
Panel E: Automation-related patents					
Mortality interacted with education	2.239***	(0.868)	0.783	(0.769)	2,610
Mortality	-0.122	(0.108)	0.118	(0.099)	2,610

Notes: The dependent variable is the total number of patents normalized for the 1906 population respectively for all classes of patents (Panel A), for all labor-saving patents (Panel B), for machinery-related patents (Panel C), for electricity-related patents (Panel D) and finally for automation-related patents (Panel E). Coefficients reported here are the results of equation 6 which includes the counterfactual mortality rates as defined in subsection 5.2 as a control variable. Static Coefficient corresponds to the sum of θ from 1919 to 1936. Pre-trends coefficients correspond to the same sum before 1914. Coefficients are estimated using OLS with standard errors clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

line regiments were rotated only after a few days to limit the level of demotivation, 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 D8, the battle of Verdun was associated with a sustained higher number of casualties per day (163,000 in total, 543 per day on average) but with a high degree of heterogeneity. To that extent, Verdun represents an ideal experiment to test the significance of our results. Additional details are given in Appendix D.6.

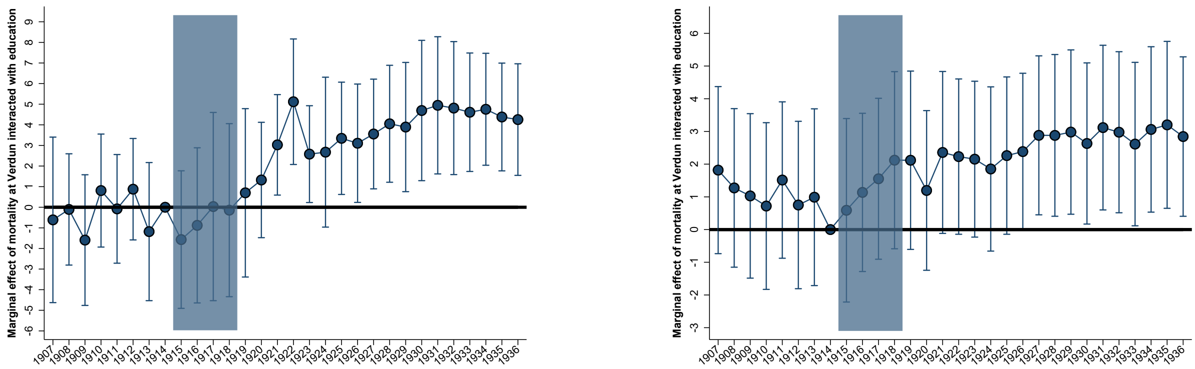
More specifically, we retrieve the number of victims during the Verdun battle by exploiting the richness of the *Morts Pour la France* dataset from which we recover the place and time of death of each soldier. A soldier is said to have passed during the Battle of Verdun if he died between February, 16th and December, 18th in a county adjacent to the Meuse county in which the city of Verdun is located. This leaves us with roughly 97,000 victims over a nine months period [18]. We then test 6 by substituting the mortality rate suffered during the Battle of Verdun for the residualized mortality indicator defined in 2.2, and run this specification respectively for all classes of patents

[18] 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.

and for labor-saving patents only. Table 11 further supports the results suggested by this paper, namely that mortality generated a large incentive to substitute labor saving devices for either missing or expensive workers, but only in those counties where the initial education level was large enough to ensure innovation abilities. For both specifications, almost all coefficients on the interaction terms are significant at the 5% level after the war, suggesting that the magnitude was large and robust.

FIGURE 11: Effect of mortality at Verdun on patenting activity

(a) All patents **(b)** Labor-saving patents



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.

5.4 Other robustness

In Appendix D we present additional robustness checks of our main result (from estimating equation (6)). Appendix D.7 shows that our results hold when we exclude Paris from the sample. Appendix D.8 considers alternative correction of standard errors. Appendix D.9 and Appendix D.10 consider respectively alternative measures of excess mortality and alternative ways of measuring labor saving technology using patents.

6 Extensions and discussions

All in all, our estimates show a sizeable effect of mortality on patenting activity in France after World War I. In particular, patenting activity related to machinery substantially improved in the counties that exhibited both a high level of mortality and a high enough initial level of education, suggesting that survivors had no choice but to substitute machines for missing workers or, at least, to improve the functioning of these machines to ensure adequate productivity in a time of labor scarcity. We explore various extensions to further assert the plausibility of this mechanism: we start by checking whether the labor substitution mechanism identified in Section 4 holds in particular for counties that lacked either of women labor force or of foreign labor force in the aftermath of the war; second, we provide evidence that the take-up of agricultural machines after the war was substantially higher in counties which were more severely hurt by mortality during the war; finally, we document a decrease in the share of agriculture as well as an increase in the urbanization process in places which were more affected by the war, further confirming the interpretation that mortality induced a shift from agriculture-related activities to industry-related activities. Finally, we briefly examine the impact of mortality on local GDP and show that inventors mortality rather than overall mortality exerted a negative and significant effect.

6.1 Further evidence on the learning by necessity effect

In Section 4, we provided extensive evidence that the learning by necessity effect was largely triggered by labor scarcity in counties which suffered higher losses during the war. In particular, we proved that this learning by necessity effect was peculiarly clear for labor-saviing patents while exerting close to no impact on patents unrelated to labor-saving devices, suggesting that not all patents were fostered by mortality in the aftermath of the war. To further confirm this interpretation, we check whether the effect of mortality on patents and on machinery-related patents was peculiarly stronger for counties where labor scarcities were especially binding. In particular, we use female participation in the labor market, ratio between the number of workers and the number of steam machines, and the number of agriculture workers per acre of cultivable area as proxies for the severity of labor scarcities in French counties after the war. Typically, counties where female labor force was low after the war were more subject to labor scarcity, given that the low participation rate of women suggests that they did not offer substantial enough labor force to substitute for missing workers. This channel was emphasized by Boehnke and Gay (2020) who provide evidence that counties where the fatality rate was large enough had an incentive to replace missing men with female labor force participation. Similarly, counties where the ratio of workers to the number of steam machines in 1911 was high were counties used to relying on labor rather than on capital to generate output. In a similar spirit, counties where the ratio between the number of agriculture workers and the cultivable area was the highest were likely to be used to relying on labor rather than on capital; in turn, as the war generated substantial losses, wage increases were more critical in those counties, which provided them more incentives to substitute machines for missing workers.

TABLE 7: Effect of mortality interacted with education depending on labor scarcity after the war

	Static coefficient		Pre Trends		Observations
Panel A: all patents					
Below median share of women	3.301***	(1.204)	-0.789	(1.102)	1,290
Above median share of labor to capital ratio	5.106***	(1.173)	-1.298	(1.156)	1,290
Above median labor intensiveness	6.562***	(1.107)	0.615	(1.073)	1,290
Panel B: machinery-related patents					
Below median share of women	0.524*	(0.283)	0.064	(0.254)	1,290
Above median share of labor to capital ratio	0.733***	(0.253)	-0.347	(0.237)	1,290
Above median labor intensiveness	3.799***	(1.289)	1.331	(1.142)	1,290
Panel C: automation-related patents					
Below median share of women	1.123***	(0.338)	0.142	(0.307)	1,290
Above median share of labor to capital ratio	1.668***	(0.355)	-0.482	(0.361)	1,290
Above median labor intensiveness	4.907***	(1.317)	2.020*	(1.173)	1,290
Panel D: electricity-related patents					
Below median share of women	1.168***	(0.313)	-0.021	(0.285)	1,290
Above median share of labor to capital ratio	2.252***	(0.553)	-0.190	(0.526)	1,290
Above median labor intensiveness	5.687***	(1.415)	2.414*	(1.258)	1,290

Notes: This Table replicates regression 1 of Panel C of Table 2 but consider alternative restrictions of the set of counties based on specific characteristics (Panel A). Panels B, C and D replicates Table 4 with the same sample restrictions.

The intuition that counties where labor scarcity was the highest were most positively affected by mortality in terms of patenting activity is further asserted by Table 7 which report the coefficients θ_d, the sum of the interaction coefficients between excess mortality and education, as well as the corresponding sum of pre-trends coefficients. While the effect of mortality interacted with education is insignificant before the war, it becomes positive and statistically significant most of the time at the 1% level and sometimes at the 5% level after the war. More strikingly, most of the point estimates of coefficients are substantially larger than those derived in the general framework: typically, the coefficients on the interaction term are respectively 1.5 and twice as large for respectively above median counties in terms of labor to capital ratio and above median counties in terms of labor intensiveness [19] compared to the full sample. Similar patterns emerge for the various measures of labor-saving patents, with coefficients most of the time significant at the 1% level with large values, either close or superior to that obtained in the full sample analysis. All in all, those findings further support the idea that counties facing a stringent labor scarcity issue after the war and relying on a large enough initial human capital level had no choice, but to adopt labor saving

[19] As a reminder, labor intensiveness is defined as the ratio between the number of agriculture workers and the cultivable area

devices for missing workers.

6.2 Further evidence on the take up of machines

TABLE 8: Effect of mortality on the take-up of agriculture machines

	(1)	(2)	(3)	(4)
Excess mortality	22.517*	23.191*	30.867*	31.253**
	(12.795)	(12.867)	(17.163)	(15.695)
Share of agriculture in 1911		3.441***	3.892***	4.119***
		(0.877)	(1.111)	(1.488)
Share of industry in 1911		3.288*	3.698**	1.883
			(0.073)	(0.081)
Cultivable area (sqm)			-0.0003	-0.0003
			(0.0002)	(0.0002)
Alphabetization rate				4.674
				(3.498)
Steam machines per capita in 1911				-0.006
				(0.0185)
Observations	87	87	87	87
R-squared	0.0199	0.0458	0.1062	0.1737

Notes: The dependent variable is the evolution in the number of agriculture machines per sqm of cultivable area between 1892 and 1929. Steam machines is the number of steam machines per inhabitant of the 1911 population while alphabetization captures the share of the county population that can read. Coefficients are estimated using OLS with robust standard errors. Stars summarize the level of the p-value of the Student test on the nullity of the coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

So far, our results show a substantial increase in machinery-related patenting activity in counties where mortality was large enough to trigger such an incentive. However, it could be that patents related to machinery were filed in counties where they were of little use; in that case, the interpretation we provided, namely that counties where labor scarcity was the most stringent had no choice but to substitute labor saving devices for either missing or expensive workers, would be challenged. To mitigate this concern, we leverage data on the mechanization of French agriculture in the 20^{th} century; more specifically, we exploit two rich data sources, namely the *Enquête agricole* from 1892 and 1929. *Enquête agricole* is an administrative study that used to be carried out at the county level in France throughout the XIX^{th} century, and providing extensive details on the harvest as well as on the material in each county. Unfortunately, that statistical inquiry interrupted in 1892 before being conduced again in 1929. To that extent, we can only assess the effect of mortality on the take-up of agriculture machines[20] by comparing the evolution in such a take-up between 1892 and 1929

[20]We define as "agricultural machines" the number of "faucheuses", "moissonneuses-lieuses" and

depending on the mortality rate, and controlling for a wide range of covariates.

The results derived from this analysis suggest, again, that there was a large and sizeable learning by necessity effect in the aftermath of WW1. Indeed, in all the specifications retained, Table 8 suggests that mortality exerted a positive and significant effect on the take-up of agriculture machines either at the 5% or at the 10% level. This finding is robust to the introduction of numerous control variables such as the share of industry, the share of agriculture, the number of steam machines per capita, alphabetization of the county or even the size of the cultivable area per county. Overall, the most detailed specification suggests that a one standard deviation increase in the mortality rate is associated to a c. 31 percentage point increase in the number of agriculture machines at the county level. While these estimates must be interpreted carefully for they only rely on a rather small number of observations and retain values that were computed with a roughly 40 years interval, they bring sizeable contribution to the idea that the increase in machinery-related patenting activity in counties where mortality was large was followed by an actual increase in the take-up of such machines.

6.3 A Farewell to Farms

The mechanism identified in the previous subsection, namely that counties which were more severely hurt by war-related mortality also showed higher take-up of agriculture machines after the war, is suggestive of a structural change pattern. Indeed, it should be noted that the share of agriculture substantially declined at the nation scale following the war, decreasing from an all-time high point of c. 53% of total employment to a low threshold of 48% as of 1936. Given that the number of agriculture machines increased quicker in more affected counties conditional on the share of agriculture in employment, we expect that the latter decreased quicker in counties that were more affected by the war. More specifically, we expect that counties with both a high level of war-related mortality and an ability to invent and adopt labor-saving techniques prior to the war must have exhibited a shift from agriculture to industry or service related activities.

Formally, we investigate the impact of mortality on structural change in France after the war by testing the following equation:

$$\mathrm{s}^{i}_{d,t} = \mathbb{1}_t(w)\,(m_d + m_d \times me_d + me_d + e_d + s_d + b_d) + \alpha_d + \beta_t \tag{10}$$

"semoirs mécaniques" as reported in the *Enquêtes agricoles*

Where $s^i_{d,t}$ captures the share of industry i at time t in county d in total employment, $\mathbb{1}_t(w)$ takes the value 1 if year t is after the war and 0 otherwise, m_d is the mortality indicator, me_d is the proxy for agriculture mechanization, e_d is the usual education control, s_d is the (ln) cultivable area and b_d is a control for the exposure to the battle zone. Interestingly enough, mortality negatively impacted the share of agriculture, suggesting that mortality reduced the share of workers employed in the agriculture sector. This effect was all the stronger as the initial development of the agriculture sector as proxy by the number of agriculture machines per capita in 1892 was the larger. Intuitively, such counties were already used to replacing workers with agriculture machines which, in turn, made them more able to transform the demographic shock into a structural change movement. Symmetrically, mortality affected positively and very significantly the share of services at the county level; again, this effect was all the larger as the initial development of agriculture was large, implying, again, that mortality transformed all the more the society as it was initially ready to turn to tertiary activities. In other words, mortality probably accelerated a pattern which, in any case, would have occurred but certainly at a slower pace and maybe not in the same counties as it did after the war.

TABLE 9: Effect of mortality and other covariates on structural change

	Static coefficient		Observations
Panel A: share of agriculture			
Excess mortality	-4.073*	(2.109)	522
Excess mortality x initial agriculture mechanization	-0.701**	(0.341)	522
Initial agriculture mechanization	0.420	(0.502)	522
Education	-12.166***	(3.90)	522
(Ln) cultivable area	-0.982	(0.848)	522
Exposure to battle zones	-0.647	(1.466)	522
Panel B: share of services			
Excess mortality	3.525***	(1.258)	522
Excess mortality x initial agriculture mechanization	0.642***	(0.214)	522
Initial agriculture mechanization	0.047	(0.231)	522
Education	-1.418	(1.838)	522
(Ln) cultivable area	-1.113**	(0.460)	522
Exposure to battle zones	2.903***	(0.684)	522

Notes: Estimation of model (10) with different dependent variables. The dependent variable is the share of agriculture and of services in employment. The main regressor is the mortality indicator interacted with a proxy for agriculture mechanization prior to the war. Static Coefficient corresponds to the sum of θ from 1919 to 1936. Pre-trends coefficients correspond to the same sum before 1914. Coefficients are estimated using OLS with standard errors clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.4 What about GDP?

So far, this paper said little on the impact of mortality on the yearly revenues generated by counties. While it has been shown that mortality increased patenting activity per capita in counties where the initial education level was large enough, the aggregate effect on output remains unclear. It could be indeed that counties more affected by mortality managed to increase productivity of individual workers to cope with labor scarcity but that this improvement in individual performance was not enough to offset the negative human capital effect. More specifically, the extensive endogenous growth literature (see, among others, Aghion et al. (2009), Arrow (1962)) has stressed the role of human capital in economic growth so that it would rather predict a negative effect of the human losses incurred during the war. To further assess our understanding of the impact of mortality on economic activity, we exploit the data collected by Piketty and Julia (2023) which, for every year of our dataset, provides the ratio between the revenue of each county and the average revenue at the national level. We then aim at evaluating equation 11:

$$\mathrm{r}_{d,t} = \mathbb{1}_t(w)\,(m_d + i_d + e_d + p_d + b_d) + \alpha_d + \beta_t \tag{11}$$

Where $r_{d,t}$ captures the ratio between the revenue of county d at time t and the average French revenue at year t, $\mathbb{1}_t(w)$ is a binary variable taking the value 1 if t is greater or equal than 1919, m_d is the mortality ratio of county d during the war, i_d depicts inventors losses during the war, e_d is the education level, p_d the (ln) number of public procurement contracts and b_d the binary indicator taking the value 1 if county d was in a battle zone during the war. Results of this regression are reported in 10 which shows that mortality generated no effect on wealth at the local level; this finding might seem surprising in the light of the human capital literature that insists on the decisive role of human capital in the wealth generation process. And yet, the very strong and negative impact of inventors mortality might account for this somehow puzzling result: while overall mortality had no impact, mortality of inventors was very detrimental to the local economy as was the exposure to the battle zones which was inductive of significant physical losses.

TABLE 10: Effect of mortality and other covariates on revenues per county

	Static coefficient		Pre-trends		Observations
Excess mortality	-0.000	(0.004)	-0.000	(0.003)	2,610
Inventors mortality	-0.004***	(0.001)	0.001	(0.001)	2,610
Education	0.062**	(0.030)	-0.034	(0.029)	2,610
Exposure to the battle zone	-0.092***	(0.014)	0.011	(0.013)	2,610
(Ln) public procurement contracts	-0.004	(0.002)	0.001	(0.002)	2,610

Notes: Estimation of model (11) with different dependent variables. The dependent variable is the ratio between the county revenue and the average national revenue. The main regressors are the mortality indicator, the inventor mortality ratio and the exposure to battle. Static Coefficient corresponds to the sum of θ from 1919 to 1936. Pre-trends coefficients correspond to the same sum before 1914. Coefficients are estimated using OLS with robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Conclusion

Exploiting quasi random local variations in the number of soldiers at the county level in France throughout WW1, we show that the mortality rate is associated with a twofold effect on patenting activity. On the one hand, mortality of inventors exerted a negative and significant *human capital effect* on innovation for roughy 15 years, while mortality interacted with education exerted a positive and significant *labor substitution* effect on innovation. Overall, whether counties were positively and significantly impacted by mortality in terms of innovation activity depends on their initial education endowment. Based on our preferred estimates, we show that at least 33% of French counties increased their innovation due to a higher mortality rate. This result is mostly driven by the labor scarcity effect induced by mortality, which, upon driving wages up, spurred firms into substituting machines for labor. This substitution effect translated in a higher patenting activity related to labor-saving devices in the counties where both mortality and the initial education endowment were large enough. These findings are robust to many falsification tests, including exploiting the battle of Verdun as a random shock, studying alternative measures of education or even running placebo simulations in the spirit of Borusyak and Hull (2023). Additionally, we shed light on the structural change pattern induced by this random shock, by showing that counties which exhibit both a high level of mortality and a high enough initial level of agriculture development converged towards a lower share of agriculture in employment as well as a higher share of services after the war.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller, "SYNTH: Stata module to implement Synthetic Control Methods for Comparative Case Studies," Statistical Software Components, Boston College Department of Economics October 2011.

_ **and Javier Gardeazabal**, "The Economic Costs of Conflict: A Case Study of the Basque Country," *American Economic Review*, March 2003, *93* (1), 113–132.

Aghion, Philippe, Leah Boustan, Caroline Hoxby, and Jerome Vandenbussche, "The causal impact of education on economic growth: evidence from US," *Brookings papers on economic activity*, 2009, *1* (1), 1–73.

Akcigit, Ufuk, John Grigsby, and Tom Nicholas, "The rise of american ingenuity: Innovation and inventors of the golden age," Working Paper w23047, National Bureau of Economic Research 2017.

Alonso, Anne, Victor Gay, and Ronan Tallec, "Weapons of Mass Production. World War I and the Modernization of the French Economy," *Working Paper*, 2023.

Araud, Gérard, *Nous étions seuls*, Tallandier, 2023.

Arrow, Kenneth J, "The Economic Implications of Learning by Doing," *Review of Economic Studies*, 1962, *29* (3), 155–173.

Azoulay, Pierre, Christian Fons-Rosen, and Joshua S Graff Zivin, "Does science advance one funeral at a time?," *American Economic Review*, 2019, *109* (8), 2889–2920.

_ **, Erica Fuchs, Anna Goldstein, and Michael Kearney**, "Funding Breakthrough Research: Promises and Challenges of the "ARPA Model"," *Innovation Policy and the Economy*, January 2019, *19*, 69–96.

Bazot, Guillaume, "Interregional Inequalities, Convergence, and Growth in France from 1840 to 1911," *Annals of Economics and Statistics*, 2014, (113-114), 309–345.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen, "Who becomes an inventor in America? The importance of exposure to innovation," *The Quarterly Journal of Economics*, 2019, *134* (2), 647–713.

Bergeaud, Antonin and Cyril Verluise, "A new dataset to study a century of innovation in Europe and in the US," *Research Policy*, 2024, *53* (1), 104903.

Berkes, Enrico, Davide M. Coluccia, Gaia Greta Dossi, and Mara P. Squicciarini, "Dealing with adversity: religiosity or science? Evidence from the great influenza pandemic," LSE Research Online Documents on Economics 121318, London School of Economics and Political Science, LSE Library Jun 2023.

Boehnke, Jörn and Victor Gay, "The Missing Men," *Journal of Human Resources*, 2020.

Bonnet, Florian, Hippolyte d'Albis, and Aurélie Sotura, "Income Inequality across French Departments over the Last 100 Years [Les inégalités de revenu entre les départements français depuis cent ans]," PSE-Ecole d'économie de Paris (Postprint) hal-03374099, HAL October 2021.

Borusyak, Kirill and Peter Hull, "Nonrandom exposure to exogenous shocks," *Econometrica*, 2023, *91* (6), 2155–2185.

Cagé, Julia, Anna Dagorret, Pauline Grosjean, and Saumitra Jha, "Heroes and villains: The effects of heroism on autocratic values and Nazi collaboration in France," *American Economic Review*, 2023, *113* (7), 1888–1932.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Difference-in-differences estimators of intertemporal treatment effects," *Review of Economics and Statistics*, 2024, pp. 1–45.

Correia, Sergio, "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator," Technical Report 2016. Working Paper.

_ , Paulo Guimar aes, and Thomas Zylkin, "ppmlhdfe: Fast Poisson Estimation with High-Dimensional Fixed Effects," Papers 1903.01690, arXiv.org March 2019.

Cozzi, Guido and Giammario Impullitti, "Government spending composition, technical change, and wage inequality," *Journal of the European Economic Association*, 2010, *8* (6), 1325–1358.

Dechezleprêtre, Antoine, David Hemous, Morten Olsen, and Carlo Zanella, "Automating labor: evidence from firm-level patent data," CEP Discussion Papers dp1679.pdf, Centre for Economic Performance, LSE February 2020.

Desmarest, Jacques, *La Grande Guerre*, Hachette, 1978.

Dyevre, Arnaud, "Public R&D Spillovers and Productivity Growth," 2023. Mimeo LSE.

Garin, Andrew and Jonathan L Rothbaum, "The Long-Run Impacts of Public Industrial Investment on Local Development and Economic Mobility: Evidence from World War II," Working Paper 32265, National Bureau of Economic Research March 2024.

Gilles, Henri, Jean-Pascal Guironnet, and Antoine Parent, "Géographie économique des morts de 14-18 en France," November 2014.

Gross, Daniel P. and Bhaven N. Sampat, "America, Jump-started: World War II R&D and the Takeoff of the U.S. Innovation System," NBER Working Papers 27375, National Bureau of Economic Research June 2020.

_ and _ , "The Economics of Crisis Innovation Policy: A Historical Perspective," *AEA Papers and Proceedings*, May 2021, *111*, 346–350.

Guillot, Olivier and Antoine Parent, "Adieu la vie, adieu l'amour : Analyse des inégalités de temps de survie chez les soldats Morts pour la France durant la Grande Guerre," November 2018.

Ilzetzki, Ethan, "Learning by Necessity: Government Demand, Capacity Constraints, and Productivity Growth," CEPR Discussion Papers 17803, C.E.P.R. Discussion Papers January 2023.

Jones, Charles I, "The past and future of economic growth: A semi-endogenous perspective," *Annual Review of Economics*, 2022, *14*, 125–152.

Kantor, Shawn and Alexander T Whalley, "Moonshot: Public R&D and growth," Working Paper w31471, National Bureau of Economic Research 2023.

Kerr, William R and William F Lincoln, "The supply side of innovation: H-1B visa reforms and US ethnic invention," *Journal of Labor Economics*, 2010, *28* (3), 473–508.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence D.W. Schmidt, and Bryan Seegmiller, "Technology and Labor Displacement: Evidence from Linking Patents with Worker-Level Data," Working Paper 31846, National Bureau of Economic Research November 2023.

Li, Bozhong and Jan Luiten Van Zanden, "Before the great divergence? Comparing the Yangzi Delta and the Netherlands at the beginning of the nineteenth century," *The Journal of Economic History*, 2012, *72* (4), 956–989.

Lucas, Robert E. Jr., "On the mechanics of economic development," *Journal of Monetary Economics*, July 1988, *22* (1), 3–42.

Lévy-Lambert, Hubert, *Pour la Patrie - Les polytechniciens morts dans les guerres*, X monument, 2014.

Malgouyres, Clément, Thierry Mayer, and Clément Mazet-Sonilhac, "Technology induced trade shocks? Evidence from broadband expansion in France," *Journal of International Economics*, 2021, *133.*

Mann, Katja and Lukas Püttmann, "Benign effects of automation: New evidence from patent texts," 2018. Available at SSRN 2959584.

Mokyr, Joel and Hans-Joachim Voth, "Understanding growth in Europe, 1700–1870: theory and evidence," *The Cambridge economic history of modern Europe*, 2010, *1*, 7–42.

Moretti, Enrico, Claudia Steinwender, and John Van Reenen, "The intellectual spoils of war? Defense R&D, productivity, and international spillovers," *Review of Economics and Statistics*, 2023, pp. 1–46.

Mowery, David C, "Military R&D and innovation," in "Handbook of the Economics of Innovation," Vol. 2, Elsevier, 2010, pp. 1219–1256.

Pavel, Ilarion, "L'histoire du moteur électrique," *Annales des Mines*, 2023, *109.*

Piketty, Thomas and Cagé Julia, *Une histoire du conflit politique: 1789 - 2022*, Seuil, 2023.

Reenen, John Van, "Innovation and human capital policy," Technical Report, National Bureau of Economic Research 2021.

_ , "Innovation and Human Capital Policy," in "Innovation and Public Policy," National Bureau of Economic Research, 2022, pp. 61–83.

Squicciarini, Mara P., "Devotion and Development: Religiosity, Education, and Economic Progress in Nineteenth-Century France," *American Economic Review*, November 2020, *110* (11), 3454–3491.

Squicciarini, Mara P and Nico Voigtländer, "Human capital and industrialization: Evidence from the age of enlightenment," *The Quarterly Journal of Economics*, 2015, *130* (4), 1825–1883.

Valero, Anna and John Van Reenen, "The economic impact of universities: Evidence from across the globe," *Economics of Education Review*, 2019, *68*, 53–67.

Voigtländer, Nico and Hans-Joachim Voth, "The three horsemen of riches: Plague, war, and urbanization in early modern Europe," *Review of Economic Studies*, 2013, *80* (2), 774–811.

Voth, Hans-Joachim, Bruno Caprettini, and Alex Trew, "Fighting for Growth: Labor scarcity and technological progress during the British industrial revolution," Working Papers 2022_15, Business School - Economics, University of Glasgow December 2022.

Webb, Michael, "The impact of artificial intelligence on the labor market," 2019. Available at SSRN 3482150.

ONLINE APPENDICES

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A Method to estimate local GDP

Quantifying the size of the economic output at the county level seemed necessary to analyse the causal effect of mortality throughout the war on innovation in the aftermath of WW1. Indeed, innovation and wealth are closely intertwined, in that a higher level of income per capita is often associated with higher investments in both human and physical capital. One concern however was the absence of a consistent economic indicator at the county level for our period of analysis. Bonnet et al. (2021) studied economic convergence across French counties, but their data set only starts as of 1922. In a similar spirit, Bazot (2014) exploits data on the "patente", a former French tax levied at the corporation level, to build an indicator of wealth per capita at the county level in France from 1840 to 1911. All in all, those sources appeared insufficient for at least two reasons: first, none of them covered the full period we wanted to study; second, they mostly were income data rather than real size economic activity. In fact, what we are looking at is an indicator that closely tracks the ability of each county to generate output; indeed, it could be that a county is receiving significant money flows without having the *actual* ability to generate on its own this economic activity. As patenting activity is likely to be higher in counties where economic activity, and not only income movements, is at its highest, we better build an indicator that closely matches the variations in the GDP.

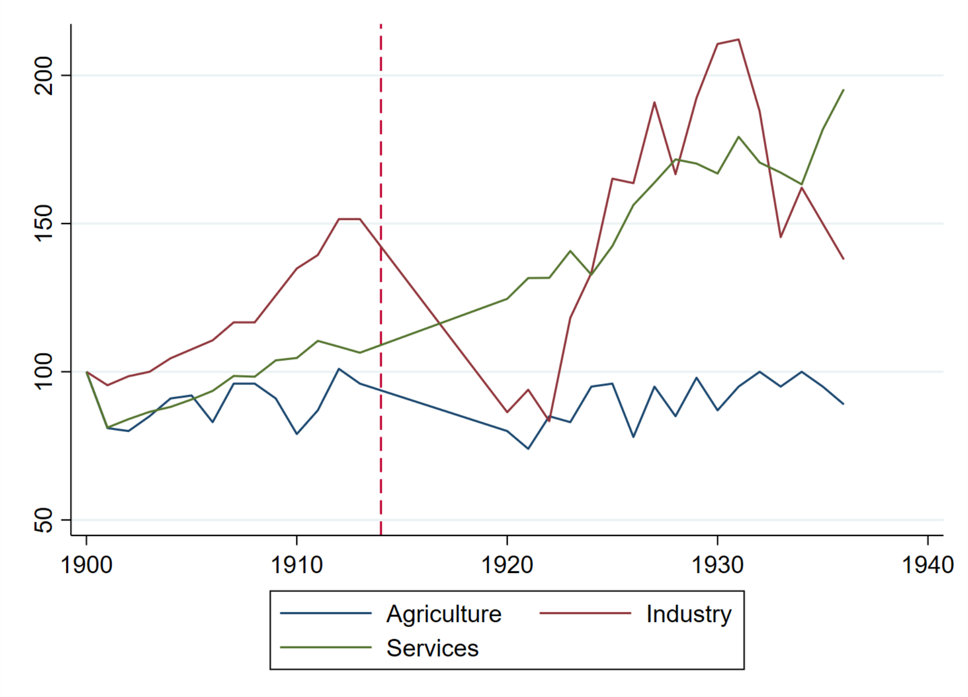
The construction of our indicator consists in a twofold process. First, we assess the dimension of economic activity at the French level, by computing the weighted sum of the indicators of dimension of each of the three sectors (respectively agriculture, industry and services) at the national level. Second, we establish a rule to split this macroeconomic indicators across all counties, depending on the real data we collect for each county. Formally, the first step involves computing GDP_t such that:

$$GDP_t = \sum_{j=1}^{3} s_{j,t} \times I_t^j \tag{A1}$$

Where $s_{j,t}$ captures the share of sector j in total employment at time t and I_t^j pictures the indicator of dimension of the output in sector s at time t recovered from the long time series delivered in the *Annuaires Statistiques de la France*. As plotted by A1, it is noteworthy that the war period impacted each sector very differently. Typically, services were almost unaffected; on the contrary, it even looks like they benefited from the war period in line with the point made by Desmarest (1978) on that topic.

Conversely, industrial output experienced a sharp decline starting 1914 until the beginning of the 20s, before progressively coming back to the pre-war period as of 1925; it then hit a record high level in 1930 before plummeting back to its pre war level in the aftermath of the 1929 crisis. Finally, the agricultural sector has been much more stable throughout the period, hovering around its 1914 level.

FIGURE A1: Evolution of indices for each sector, 1900-1936



From these values, we are able to construct the GDP estimation at the national level for every point in time, as explained in equation (A1): to do that, it suffices to collect the working population at the sector level from the French Census and compute the weights $w_{s,t}$ attached to each sector s at time t. The results obtained entail a few comments: first of all, the evolution of output at the national scale has been through 4 consecutive periods throughout the period under study. Between 1907 and 1914, output is progressively increasing with an annual average growth rate around 1% per year; this increase is mostly driven by the role of industry which grows by 22% before the war; then, comes the war period during which the economic activity is severely depressed: in line with the estimates suggested by Desmarest (1978), national GDP is down by more than 20% between 1914 and 1920 mostly on the part of the difficulties experienced both by the agriculture and by the industry sector. While average industry output declines by 40% between 1914 and 1920, the agriculture output goes down by 21%; in turn, the contribution of services rises sharply in the aftermath of WW1, reaching almost 30% in comparison with an average of around 20% prior to the war.

Economic activity is then rekindled in the after war period and reaches an all-time high in excess of 70% the level of 1920. Finally, economic activity is significantly hit by the consequences of the 1929 financial crisis, as suggested by the c. 15% decline in total GDP indicated by our computations.

To sum up, three main features are suggested by our computations: first of all, economic activity has been volatile throughout the first half of the 20^{th} century, on the part of WW1 on the one hand and of the financial crisis of 1929 on the other hand; second, the contribution of services has been rising all over the period, while that of agriculture has been systematically decreasing; finally, the role played by industry has been evolving cyclically: while it is was rising prior to the war, it suffered a hard time until 1922 when it started recovering to reach an all time high level which was finally questioned in the verge of the financial crisis. Those patterns should be kept in mind when we will turn to the county level analysis.

Once we have computed the national indicator of output, we aim at splitting it across the different counties according to a specific rule. Basically, we start by computing an indicator of dimension of the output for each pair (d, s) of county and sector. This involves gathering a rich data set to capture the size of the economic activity in each sector and county. Let us start with the agricultural activity: from the *Annuaires Statistiques de la France*, we are able to recover the corn harvest per year, as well as the corn output per square meter; from the Census, we also get the share of agriculture in employment at the county level. We then solve for α_t, the share of labor, by using (A2):

$$C_{d,t} = A_t \times L_t^{a\alpha_t} \tag{A2}$$

Where $C_{d,t}$ is the corn harvest in county d at time t, $L_{a,t}$ is the number of workers in the agriculture sector a at time t, A_t is the productivity of workers in the agriculture sector at time t and α_t is the share of labor. The unknown here is α_t given that we already collected corn output, output per square meter and the working population in agriculture. At that point, one may ask why we do not basically retain the corn output as indicator for the agriculture output at the county level: this stems from the fact that not all counties are massive corn producers; hence, using this variable as indicator of the dimension of agriculture activity might bias the estimates in favor of those counties which have a soil more adapted to corn. However, using corn output as a way to estimate α_t, i.e. the share of labor at each point t in time will enable us to estimate a more general function that will only used the production of corn per square meter as a proxy for productivity. In the end, we estimate the agriculture output function which is of the form:

$$F^a_{d,t}(A_{d,t}, L^a_{d,t}) = A_{d,t} \times L^a_{d,t}{}^{\alpha_t} \tag{A3}$$

Where the same notations as in A2 are used. Finally, we define the splitting rule of this total product, so as to compute the weight in the agriculture sector a of each county d at time t as:

$$w^a_{d,t} = \frac{F^a_{d,t}(A_{t,d}, L^a_{d,t})}{\sum_{j=1}^{87} F^a_{j,t}(A_{j,t}, L^a_{j,t})} \tag{A4}$$

At last, we recover the output $o^a_{d,t}$ of agriculture in county d at time t as follows:

$$o^a_{d,t} = w^a_{d,t} \times I^a_t \tag{A5}$$

We use the same kind of techniques to estimate the industrial output at the county level. Regarding industry variables, we collected the number of steam machines per county per year as well as the industry share in employment. Also, we recover the estimates from the agriculture sector to fix α_t, the share of labor in production. Formally, this means that the first step consists in computing the industrial output function for each county, which writes:

$$F^i_{d,t}(A_{d,t}, L^i_{d,t}) = A_{t,d} \times L^i_{t,d} \tag{A6}$$

Where $A_{d,t}$ is a proxy for industrial productivity and is given by the number of steam machines per capita in each county d at time t and $L^i_{d,t}$ is the number of workers in the industrial sector in county d at time t. From these estimates, we find the weight $w^i_{d,t}$ of each county d at time t in the total industrial output, which yields:

$$w^i_{d,t} = \frac{F^i_{d,t}(A_{d,t}, L^i_{d,t})}{\sum_{j=1}^{87} F^i_{j,t}(A_{t,j}, L^i_{j,t})} \tag{A7}$$

Finally, we get the output $o^i_{d,t}$ of industry in county d at time t as follows:

$$o^i_{d,t} = w^i_{d,t} \times I^i_t \tag{A8}$$

Hopefully, the computation of the services indicator is less involving, mostly on the part of a lack of data. Given that we found no proxy for the productivity of counties in the services sector throughout the first half of the 20^{th} century, we make the assumption that productivity is homogeneous across all counties. Hence, the split of national services output only derives from the share of each county in the national working population affected to the services sector. Formally, this means that the output $o^s_{d,t}$ of county d at time t in the services sector is given by:

$$o^s_{d,t} = \frac{p_{d,t}}{\sum_{j=1}^{87} p_{j,t}} \times I^s_t \tag{A9}$$

Where $p_{d,t}$ captures the population working in services in county d at time t and $I_{d,t}$ is the national indicator for the output in the services sector. In the end, we aggregate the output in the three sectors by weighting each of the three indicators depending on the share of each of the sectors in employment at the local level. Then, total output $o_{d,t}$ in county d at time t is given by:

$$o_{d,t} = \sum_{j=1}^{3} s^j_{d,t} \times o^j_{d,t} \tag{A10}$$

Where $s^j_{d,t}$ captures the share of sector j in employment in county d at time t. Nevertheless, though convincing this formula may seem, it still suffer from one important flaw: the $o_{d,t}$ might not sum to GDP_t, which might be seen upon rewriting the sum itself by combining equations (A8) and (A10):

$$\sum_{d=1}^{87} gdp_{d,t} = \sum_{d=1}^{87} \sum_{j=1}^{3} s^j_{d,t} w^j_{d,t} I^j_t \tag{A11}$$

By contrast indeed, (A1) implies that total GDP writes:

$$GDP_t = \sum_{j=1}^{3} s^j_t \times I^j_t \tag{A12}$$

It might then be proved that a necessary and sufficient condition for (A11) and (A12) to coincide is given by:

$$s^j_t = \sum_{d=1}^{87} s^j_{d,t} w^j_{d,t} \tag{A13}$$

In words, this condition would imply that the share of sector j in total employment in France at time t would be a weighted sum of the weights of each county d in the national output of sector j at time t , where the weights would be given by the share of sector j in employment in county d at time t. Trivially, this condition can hold if and only if either (i) the shares $s^j_{d,t}$ are homogeneous across all counties at each point in time or (ii) the weights $w^j_{d,t}$ are homogeneous across all counties at each point in time. Only under one of those conditions can we factor out one of the two terms included in the sum in (A10) to finally recover the equality between (A11) and (A12). To circumvent these issues, we scale each local output to compute our final value of interest, namely $gdp_{d,t}$:

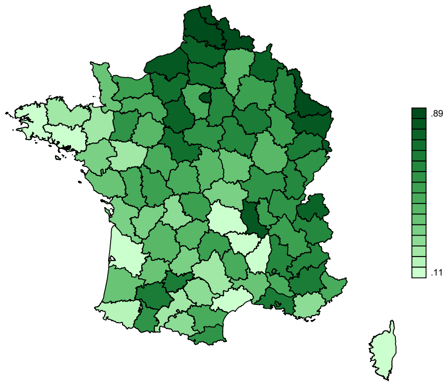
$$gdp_{d,t} = \frac{o_{d,t}}{\sum_{i=1}^{87} o_{i,t}} \times GDP_t \tag{A14}$$

The main drawback of this method is that we can only hinge on 7 points in time throughout the period under study; indeed, we were able to collect relevant data for 1901, 1906, 1911, 1921, 1926, 1931 and 1936. For the remaining years, we choose to linearly interpolate the weights attached to each counties and compute the corresponding values of GDP at the county level. While this method might be questionable, the fact that we were able to collect data every 5 years, except for the war period, sounds as a mitigating factor given that neither the shares of each sector in employment at the local level nor the other parameters such as the capital per county or the agriculture productivity varied substantially in a 5-year span.

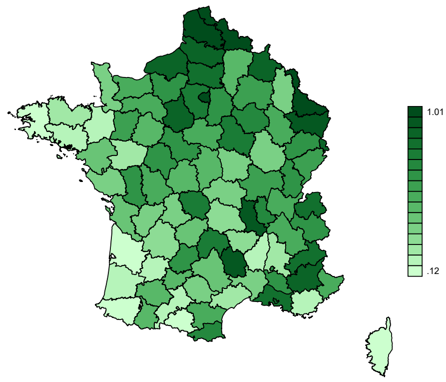
Figure A2 presents the evolution of the relative weights of each county in total absolute French GDP from 1906 to 1936 while A3 maps GDP per capita at the county level in France from 1906 to 1936. While the patterns revealed by those maps are quite similar, it seems interesting to compare the absolute and the relative dynamics. In a nutshell, those maps help perceive the massive shock that WW1 induced on the economic activity at the local level. While the emphasis has often been laid in public debate on the effect of WW1 on total economic activity, little has been said on the splitting of this shock throughout the different counties; our figures try to answer this shortcoming by shedding a light on the peculiarly strong impact WW1 had on the North Eastern quarter part of the country. Typically, our estimates suggest that the GDP in the "Nord" county fell by around 56% between 1911 and 1921; in the meantime, economic output had fallen by c. 45% in Somme and by almost 20% in Pas de Calais. These substantial losses might be explained both by the proximity to the conflicting zones as well as by the role played by industry in those counties.

On the contrary, Western counties were less affected by WW1 from an economic standpoint. Indeed, Basses Pyrenees saw an increase of their wealth per capita around 15%, similar to that experienced in Loir et Cher (+53%) or, to a less extent, in Indre et Loire (+6%). These conclusions do not change significantly whether one considers absolute GDP or GDP per capita. An interesting feature, however, is that the economic shock induced by WW1 does not seem to have been persistent across time. At least, one has to acknowledge the substantial recovery experienced by Northern counties as soon as 7 years after the war. In spite of having faced a 56% economic decline between 1911 and 1921, Nord quickly caught up with its pre war level as it almost doubled its GDP between 1921 and 1926 reaching an economic activity 16% higher compared with 1911. Similarly, Pas de Calais exhibited a GDP 1.XX times as large as that of 1911 as soon as 1926 in spite of having suffered a c. 20% decline in the aftermath of the war.

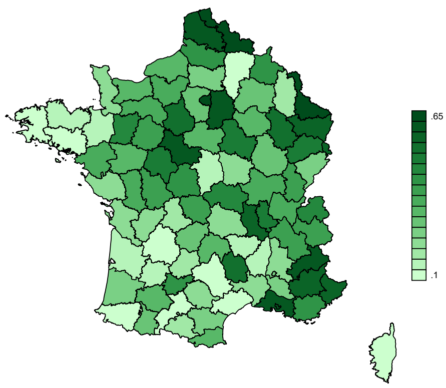
FIGURE A2: Evolution of GDP per capita in France, 1906 - 1936



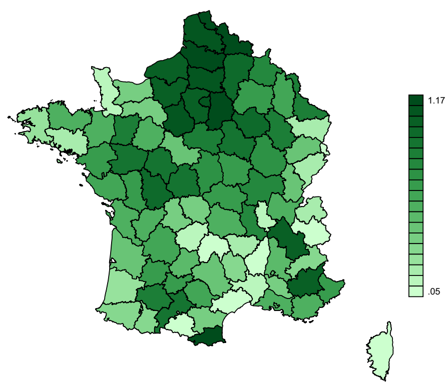
(a) 1906



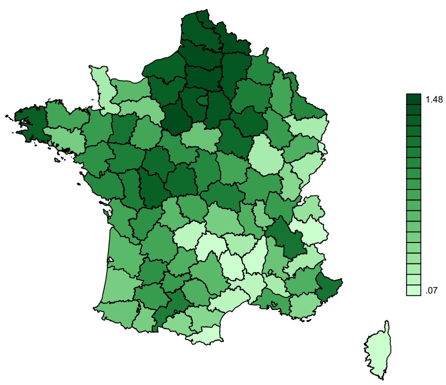
(b) 1911



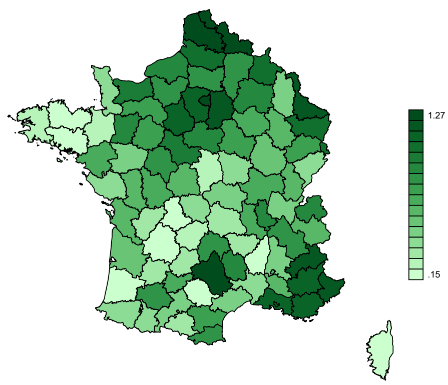
(c) 1921



(d) 1926

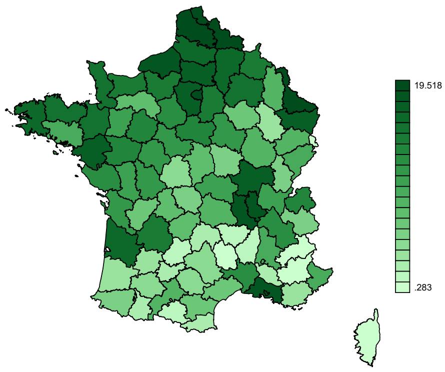


(e) 1931

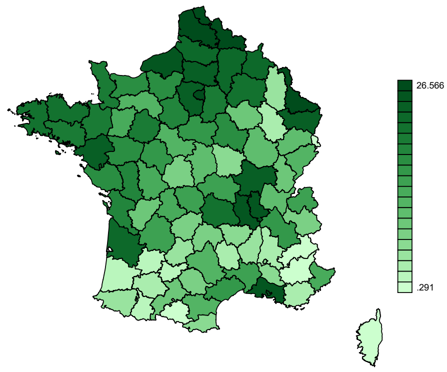


(f) 1936

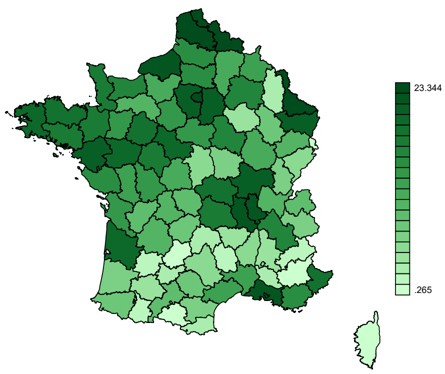
FIGURE A3: Evolution of GDP per capita in France, 1906 - 1936



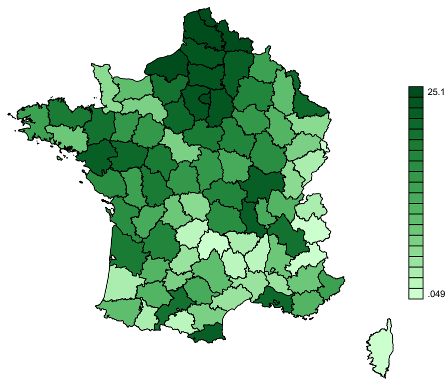
(a) 1906



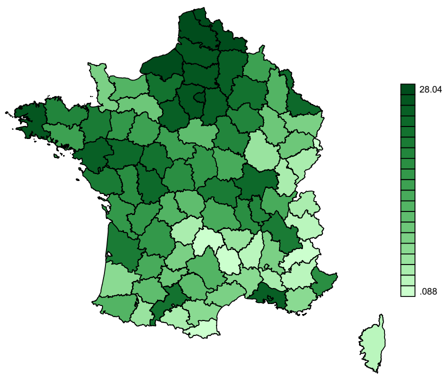
(b) 1911



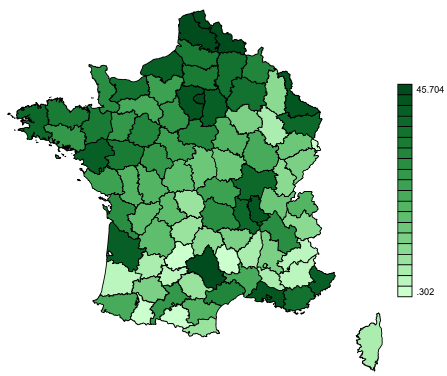
(c) 1921



(d) 1926



(e) 1931



(f) 1936

B Additional details on patents related to machines

This Appendix looks at our measure of patents related to machinery or more generally labor-saving technologies. Figures B1, B2 and B3 respectively show the distribution of the token “machine”, “automat” and “elec” in all the 3-digit IPC technologies based on French patents filed between 1907 and 1939. 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.

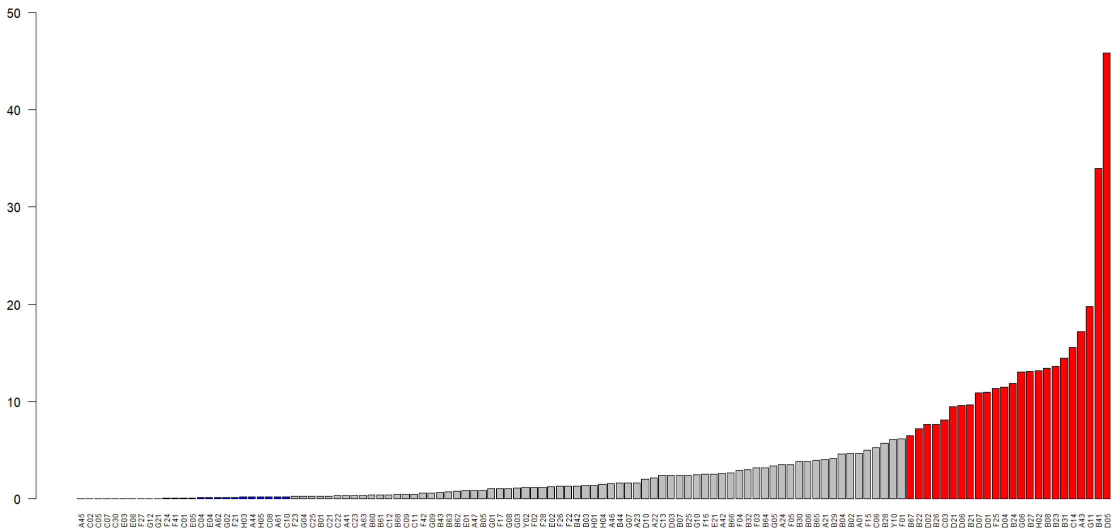
B.1 Identification of machines patents

To ensure whether the patents which we label as "machine", "automation" or "electricity" patents actually bear some relation to the notion of mechanization and, more broadly, labor substitution, we plot the network of most frequent words used in patents which we label as either machinery-related, automation-related or electricity-related. Some features deserve a quick comment. First, the tokens "machine", "automation" and "electricity" are prevalent in the graphs pictured below which ensures that our algorithm identifies technology classes related to those notions; additionally, it is noteworthy that the words most frequently related to these tokens are depicting actions such as "coudre", "fabriquer", "écrire", "laver" or "travailler: these associations suggest that the machinery-related, automation-related or electricity-related patents aimed, to some extent, at complementing or replacing a human activity. Finally, it is noteworthy that those different kinds of patents, namely machinery-related, automation-related and electricity-related exhibit similar keywords, which is consistent with the intuition that they all point to the same direction, namely labor substitution.

B.1.1 A link

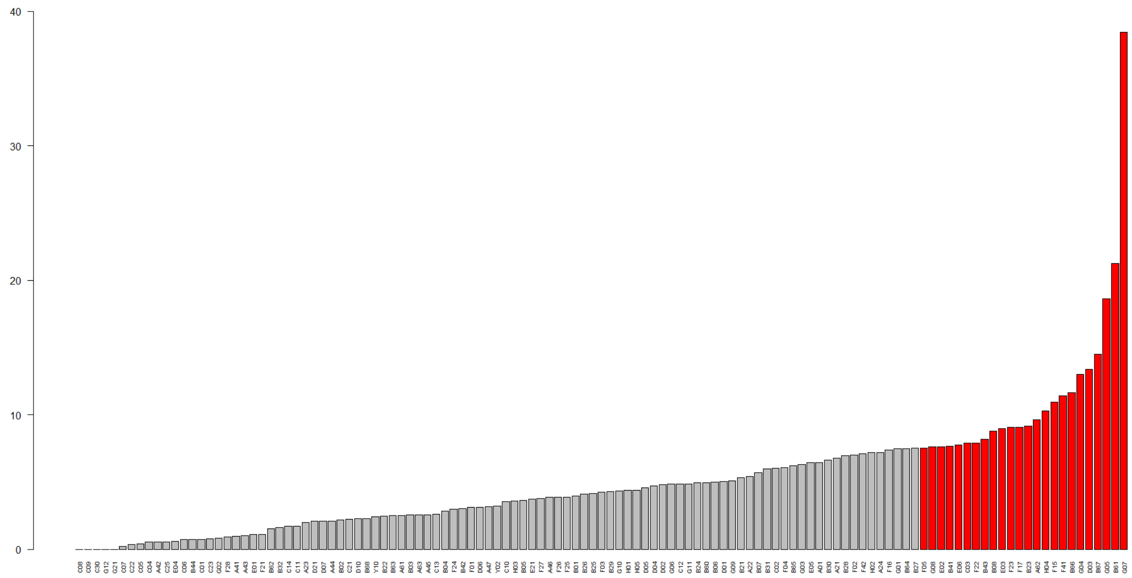
At the national level, convincing evidence can be brought in favor of the fact that counties with higher mortality rates also show a higher growth rate in the share of machines patents among total patents. This intuition is pictured in Figure B7 which plots respectively the evolution of the machines patenting activity per inhabitant and the evolution of the share of machines patents for counties respectively below and above the median mortality rate. Clearly, the two kinds of counties were exhibiting closely related trends before the war, though the above median mortality group al-

FIGURE B1: Frequency of the token "machine" by IPC code



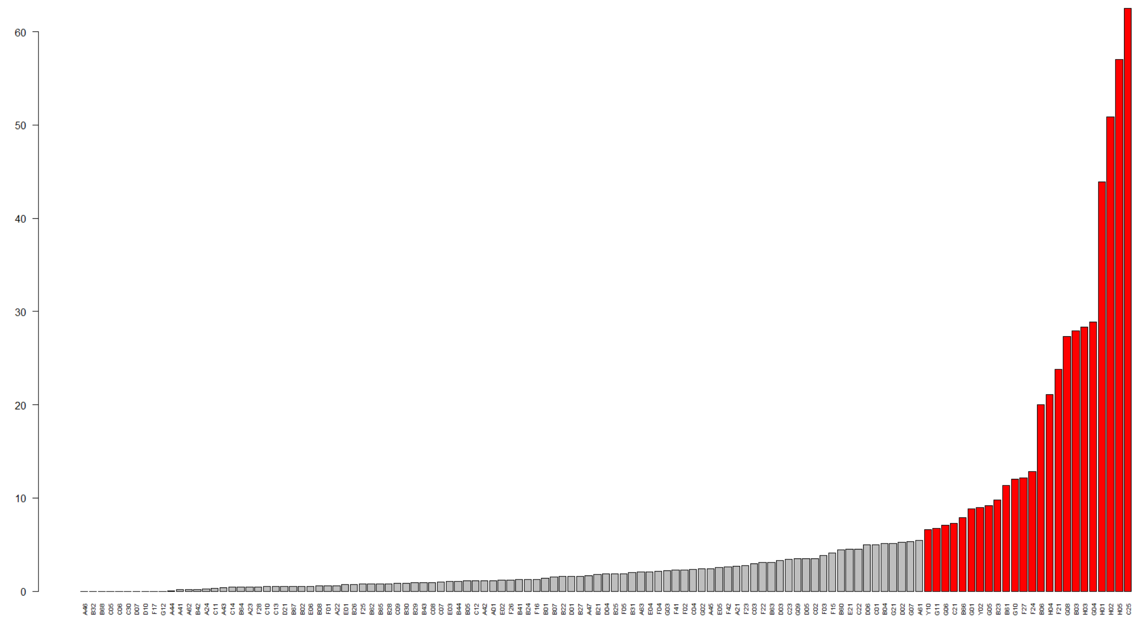
Notes: This figure plots the frequency of the token "machine" for each 3-digit IPC code; bars plotted in red denote the 20 highest percentiles, bars plotted in blue denote the 20 lowest percentiles while the grey bars denote the 60 intermediary percentiles of the distribution.

FIGURE B2: Frequency of the token "machine" by IPC code



Notes: This figure plots the frequency of the token "automat" for each 3-digit IPC code; bars plotted in red denote the 20 highest percentiles, bars plotted in blue denote the 20 lowest percentiles while the grey bars denote the 60 intermediary percentiles of the distribution.

FIGURE B3: Frequency of the token "machine" by IPC code



Notes: This figure plots the frequency of the token "elec" for each 3-digit IPC code; bars plotted in red denote the 20 highest percentiles, bars plotted in blue denote the 20 lowest percentiles while the grey bars denote the 60 intermediary percentiles of the distribution.

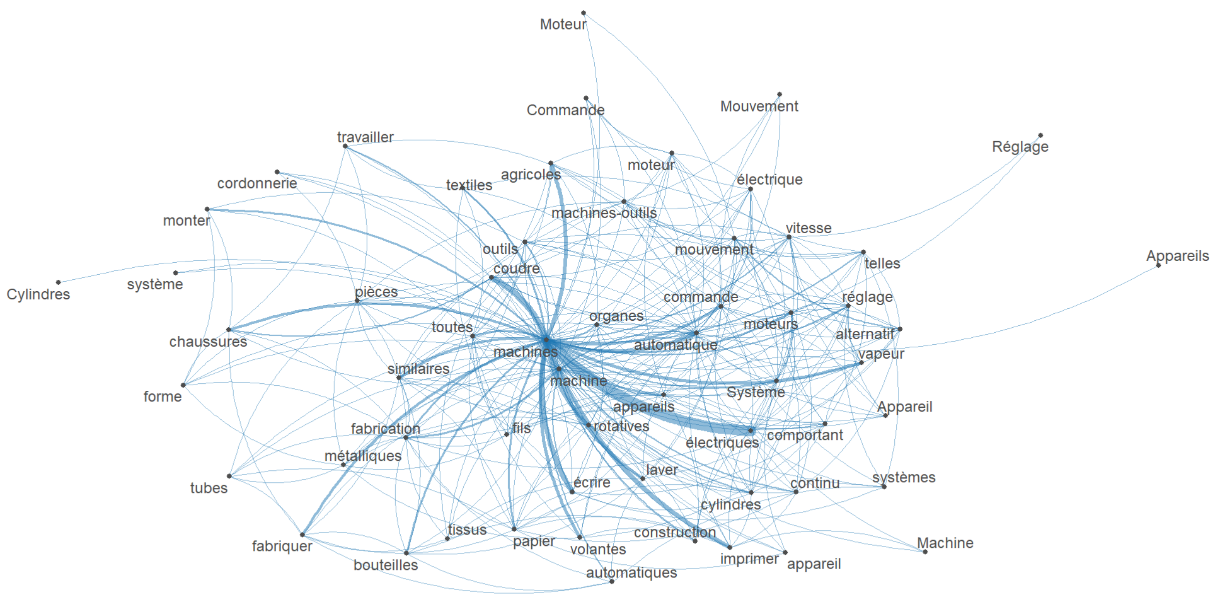


FIGURE B4: This figure plots the most frequently used words in the patents labelled as "machines" as well as the connection between those words. The thicker the line between two points, the more frequent their simultaneous apparition in the text of patents.

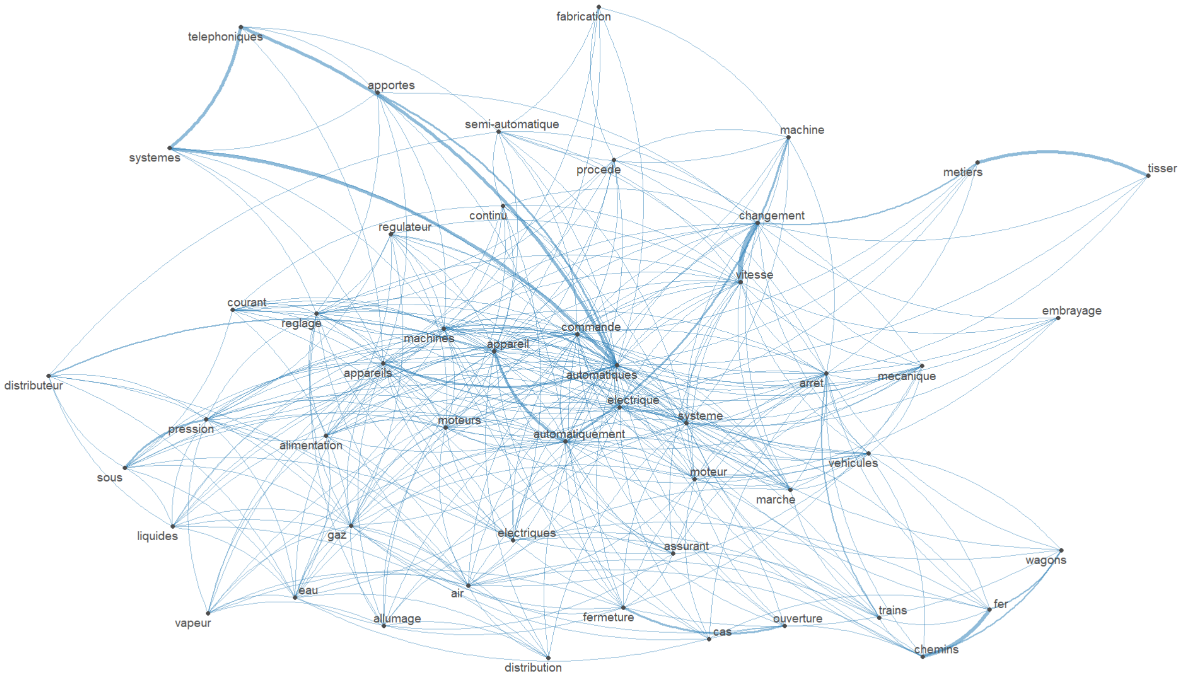


FIGURE B5: This figure plots the most frequently used words in the patents labelled as "automation" as well as the connection between those words. The thicker the line between two points, the more frequent their simultaneous apparition in the text of patents.

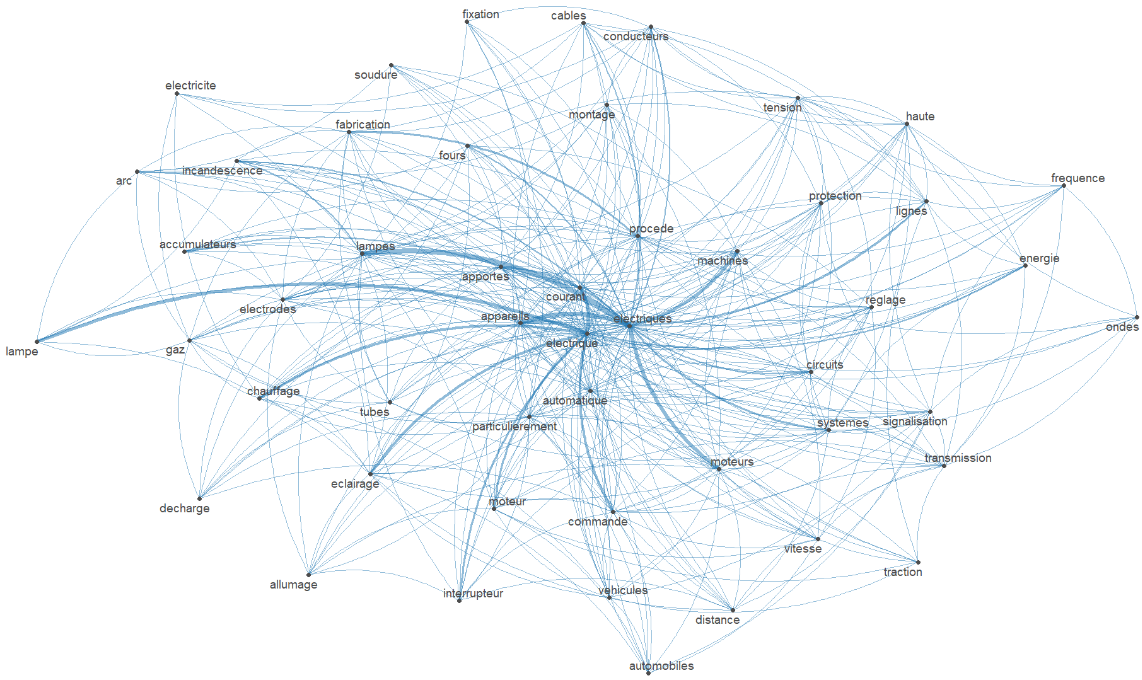
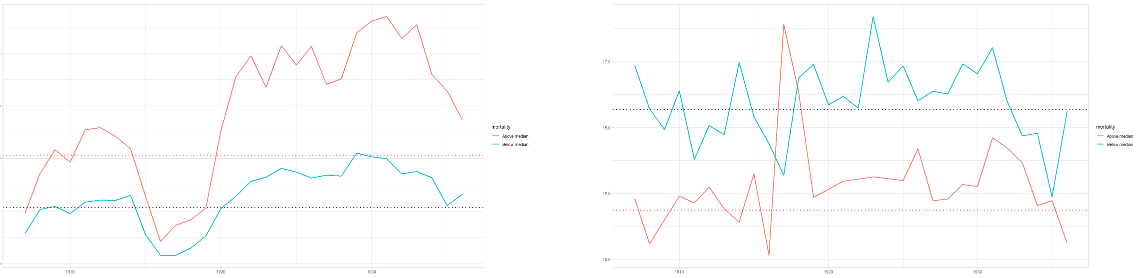


FIGURE B6: This figure plots the most frequently used words in the patents labelled as "electricity" as well as the connection between those words. The thicker the line between two points, the more frequent their simultaneous apparition in the text of patents.

FIGURE B7: Share of machine patents

(a) Total per capita **(b)** Share of total

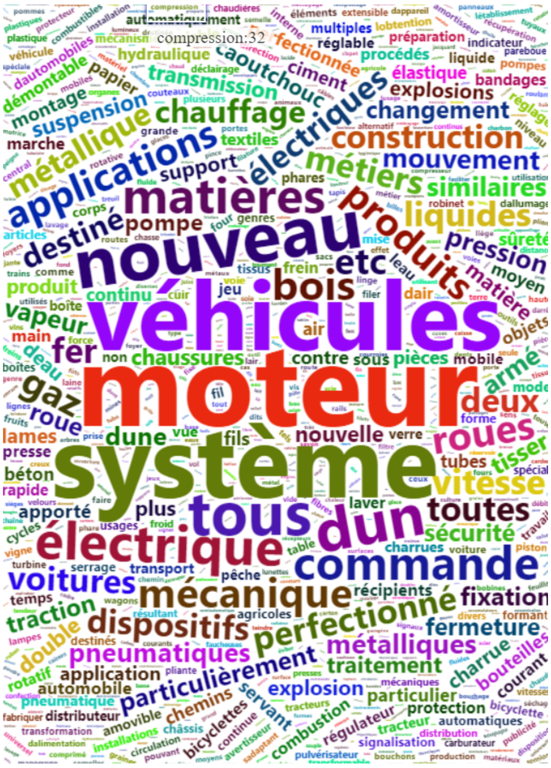


Notes: Panel (a) plots the evolution of the number of machines patents per inhabitant for below median mortality counties and above median mortality counties while panel (b) plots the evolution of the share of machines patents in total patents for the same two groups. Dotted lines represent the average of the outcome variable for each of the two groups.

ready showed significantly higher levels of machines patents per inhabitant. As the war came, the levels got closer before it spiked in the group of above median mortality counties while increasing at a much lower pace for the other counties. Numerically speaking, above median mortality counties had more than doubled their 1914 machine patents level by 1922 while it took until 1929 for counties below the median mortality level to near such an increase. That machines patents played a growing role in more affected counties after the war is also evidenced by the sudden increase in the share of machines patents in those counties after the war which was sustained, though at a lower level, for the 10 years in the aftermath of the war.

Last, the heterogeneity in the surge of machines patents during and after the war might be illustrated by Figures B8a and B8b which report the most frequent keywords used in patent titles filed in counties respectively in the first and in the tenth decile in terms of soldiers mortality during WW1. Strikingly, the word "machine" only appears for counties that were most affected by mortality while it is missing in the lowest mortality county sample. Of interest is also the fact that the stem "automobile" seems more prevalent in panel (b) compared with panel (a) though this comment might be mitigated by the fact that “vehicules” is one of the most frequently used words in patent titles of panel (a). All in all, there is substantial evidence that patents linked to machines seem to have been more frequent in counties more exposed to substantial mortality rates during the war: this intuition needs further support which we bring through the empirical analysis developed in the next subsection.

(a) First mortality decile



(b) Tenth mortality decile

FIGURE B8: Panel (a) plots the most frequent keywords in patents title for counties in the lowest decile of the mortality rate while panel (b) plots the most frequent keywords in patents title for counties in the highest decile of the mortality rate.

B.2 Aggregate perspective on patents related to machines

Figure B9 suggests that machines patents gained in importance in the aftermath of the war in France as well as in other countries, though with a different timing. While machines patents were hovering around 13% of the total amount of patents in France before the war, they suddenly jumped to reach around 18% of total patents during the war before coming back to a lower share though significantly higher than their long term pre war trend. Interestingly enough, the US also show a significant increase in the share of machines patents, though this increase happens with a delay with respects to France and, to a lesser extent, to the UK where the increase was less substantial. This might be indicative of the fact that France paved the way for the increase in the machines patents in the US, suggesting that labor scarcity might have driven machines inventions in France before those inventions were further adopted and improved in the US.

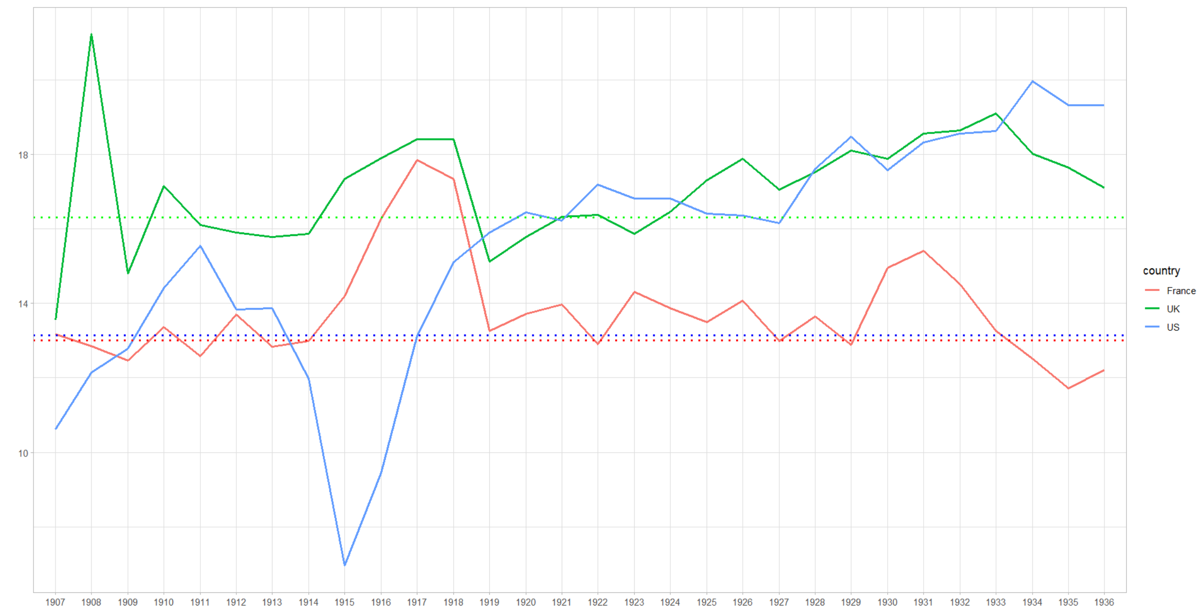


FIGURE B9: This figure plots the evolution of the share of machines patents in total patents for France, the United States and the United Kingdom throughout the 1907-1936 period. Patents are labelled as "machines patents" provided they satisfy the conditions imposed in subsection 4.1. Dotted lines represent the pre-war trend in the share of machines patents for each country.

B.3 Effect of mortality *per se* on patenting activity

For the sake of concision, we only reported the coefficients obtained on the interaction term between mortality and education in Section 4. To further confirm that mortality alone was not sufficient to induce a labor substitution process through related inventions, but that a sufficiently large initial level of education was also necessary, Table B1 reports the estimates of the coefficients λ obtained on mortality *per se* upon running equation (6). Clearly, none of the coefficients obtained, either prior to the war or after the treatment are statistically significant except for coefficient related to the effect of mortality on patenting activity unrelated to electricity. While the coefficient is statistically significant at the 5% level, it suggests that mortality per se increased patenting activity unrelated to electricity by c. 15% which is a modest contribution in the light of the substantial magnitudes documented in Section 4. To that extent, those estimates clearly suggest that, what ultimately mattered, not only was mortality, but rather the combination of a large mortality and of a high enough level of human capital.

TABLE B1: Effect of mortality on patents depending on labor substitutability

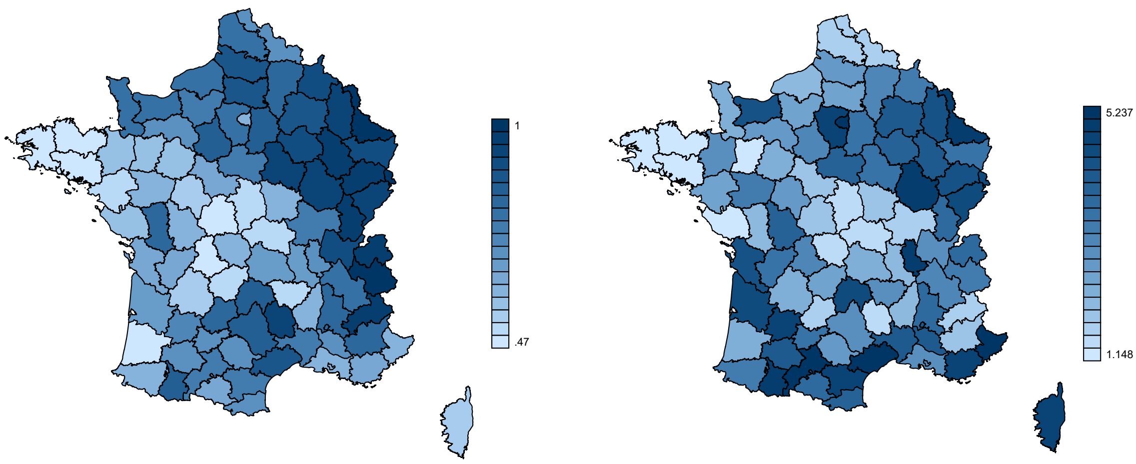
	Static coefficient		Pre Trends		Observations
Panel A: labor substituting patents					
Machinery-related patents	-0.0646	(0.106)	0.100	(0.0711)	2,600
Automation-related patents	-0.0797	(0.0876)	-0.0121	(0.0624)	2,600
Electricity-related patents	-0.0673	(0.192)	-0.0180	(0.0576)	2,600
Panel B: non labor-substituting patents					
Patents unrelated to machinery	0.0510	(0.0686)	0.0574	(0.0496)	2,600
Patents unrelated to automation	0.0305	(0.0786)	0.0795	(0.0485)	2,600
Patents unrelated to electricity	0.135**	(0.0662)	0.0485	(0.0487)	2,600

Notes: This table report the sum of the coefficient of excess mortality (λ_t) between 1919 and 1936 (Static coefficient) and before 1914 (Pre Trends) corresponding to the model shown in Table 4.

C Data Appendix

C.1 Education

FIGURE C1: Education across French counties according to various measures



(a) Enrolment rate

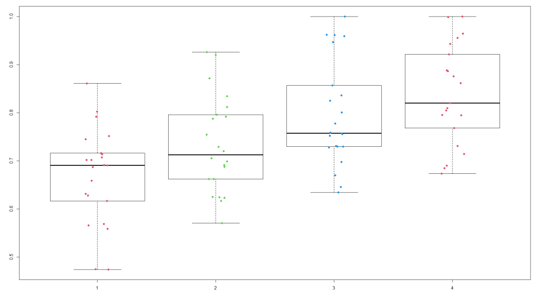
(b) Baccalaureate rate across soldiers

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.

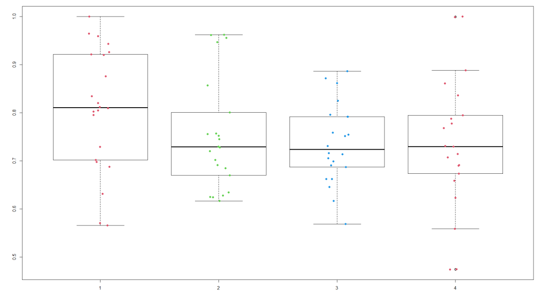
As shown by Figure C1, education varied widely across the French territory. On average, 75.8% of French children aged between 5 and 15 attended school on a regular basis between 1851 and 1901. This proportion spans from 50% in Côtes du Nord to 100% in Savoie. Also, this share grew over time for all counties 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 enrolment 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, Figure C2 suggests that 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.

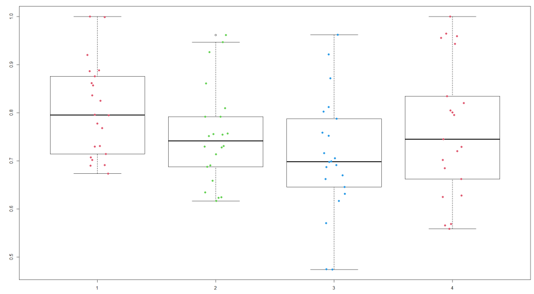
FIGURE C2: Education levels by groups



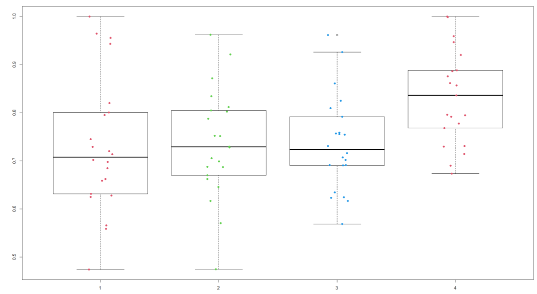
(a) GDP



(b) Density



(c) Share of agriculture in employment



(d) Share of industry in employment

Notes: Figure (a), (b), (c) and (d) respectively picture the dispersion of education, as measured by the enrolment rate, when dividing the sample in 4 bins depending on their percentile in the distribution of respectively GDP, density, the share of agriculture in employment and the share of industry in employment.

C.2 Patents

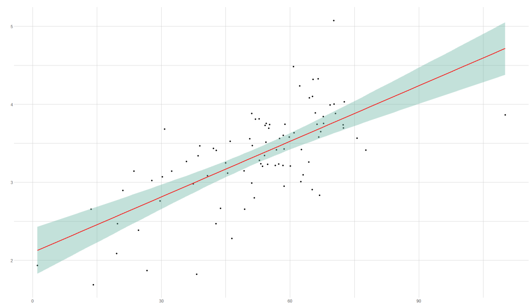
C.3 Other variables

C.4 Excess mortality

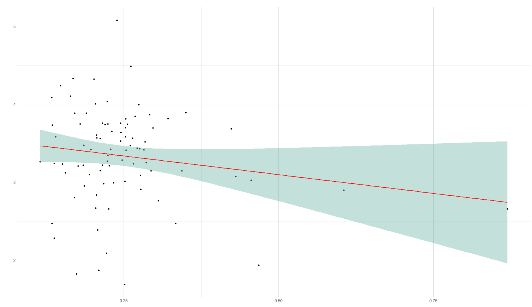
To consider the potential issue with using the raw death rate as an independent variable, we show in Figure C3 that there is a clear positive relation between the share of agriculture in the last census prior to the war (1911) and the mortality rate suffered during the conflict. By contrast, the mortality rate seems to be negatively correlated with the the GDP, which might be attributed to the fact that wealthier counties were more likely to retain some of their workers in order to ensure the war effort. While we do not report the results here, it should be noted that mortality correlates negatively with the share of foreigners in the population: this stems from the fact that a higher share of immigrants translated in a lower fraction of the population that could be incorporated in the French army. Also, mortality is negatively correlated with the distance to the German border, which might be explained by the fact that it took more time for men living in remote areas to reach the fighting zone; given that the first days of war were peculiarly lethal, counties further away from the German border might have enjoyed a slight advantage in terms of number of casualties.

FIGURE C3: Correlation between mortality rate and economic indicators

(a) Agriculture



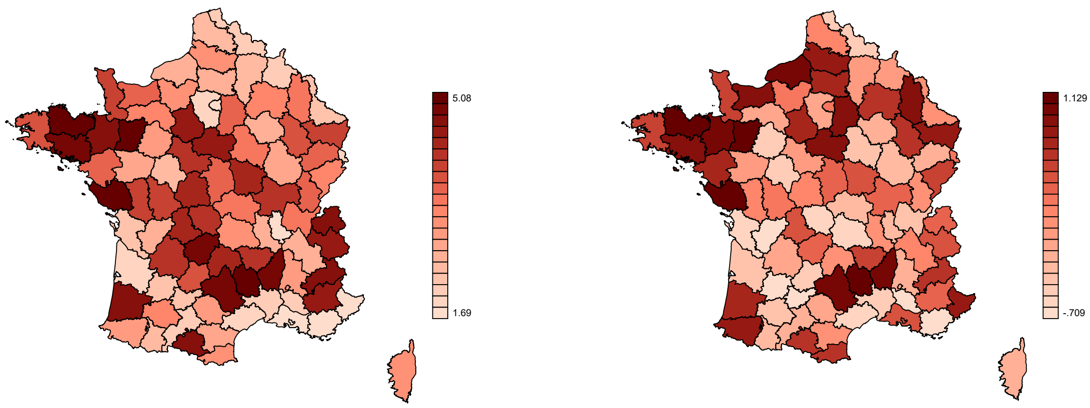
(b) GDP



Notes: Correlation between the actual mortality rate and the share of agriculture in total employment (Figure a) and the estimated GDP (Figure b).

As explained in Section 2.2, we "purge" the raw mortality rate by a series of pre-conflict observables and define the "excess mortality" as the residuals. Figure C4 maps the distribution of the raw mortality rate and our indicator.

FIGURE C4: Actual and excess mortality rates



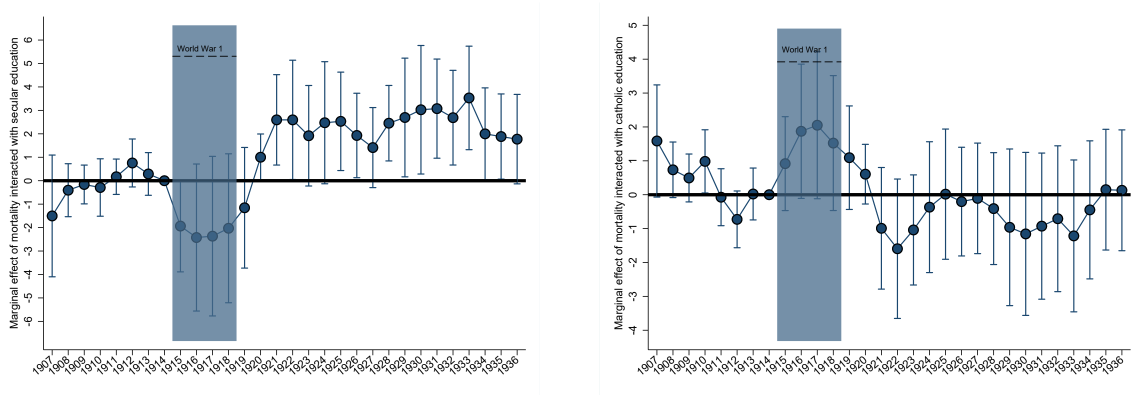
(a) Actual mortality rate **(b)** Excess mortality rate

Notes: Actual mortality rate is the total number of casualties in the county divided by population in 1911. Excess mortality rate is defined from estimating the residual of equation (1).

D Additional robustness checks

D.1 Additional Figures

FIGURE D1: Effect of mortality interacted with education on patents, depending on the type of education



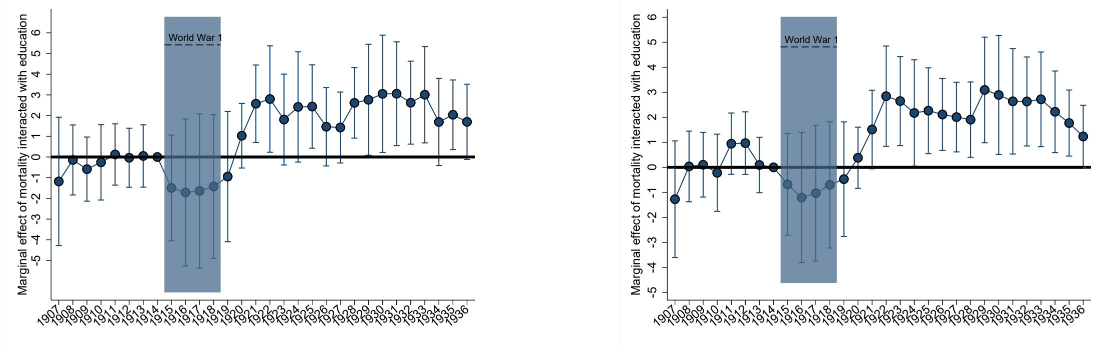
(a) Secular schooling **(b)** Catholic schooling

Notes: Figure (a) plots the effect of mortality interacted with secular schooling while figure (b) plots the effect of the mortality interacted with catholic schooling.

D.2 Results when the measure of education is continuous

As said before, we also test 6 by substituting a continuous measure of education for the binary variables we have been using more extensively throughout this paper.

FIGURE D2: Main estimates when removing military patents from the sample



(a) Enrolment rate

(b) Baccalauréat

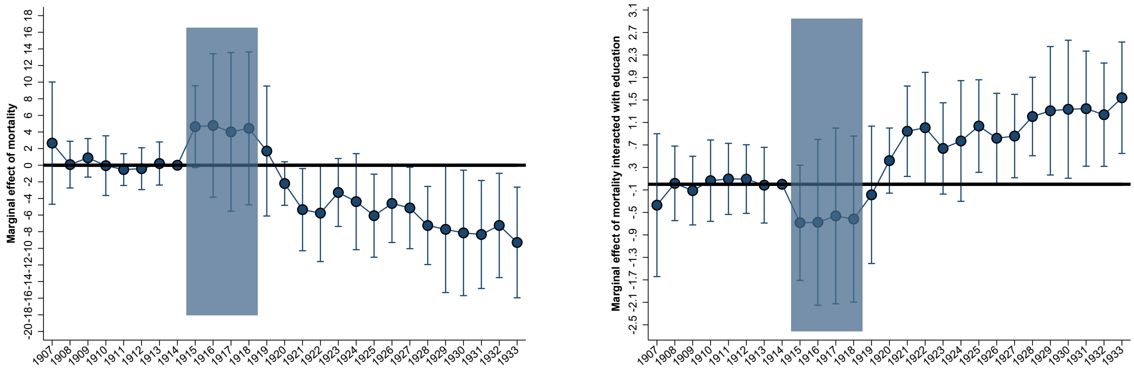
Notes: The dependent variable used here is the number of patents per 1906 100,000 inhabitants when excluding the military patents from the sample. See Section 4.1.4 for more details.

This specification disentangles between two effects: a negative human capital effect on the one hand, and a positive learning by necessity on the other hand, as shown by D3. Indeed, upon running 6 on a continuous measure of the enrolment rate, we find respectively a negative and significant effect of mortality and a positive and significant effect of mortality interacted with the enrolment rate. However, results should be carefully interpreted: in that framework, the marginal coefficient obtained on mortality captures the effect of a one standard deviation increase in mortality on the patenting activity of a county where education would be set to 0; given that no county displays a 0 enrolment rate, this specification is of little interest in terms of interpretation. Yet, the results suggested by this framework are similar to that derived in Section 3: provided that the initial education level is high enough, the learning by necessity effect dominates the negative human capital effect, implying that the impact of mortality on patenting activity is positive in the end.

D.3 Effect of non interacted mortality per se in the augmented framework

We report below the coefficients obtained on mortality *per se* in the augmented framework corresponding to equation (6). As discussed in Section 3, mortality no longer plays any role upon introducing the interaction variable between mortality and the education level. This finding is suggestive of the intuition that mortality was a necessary but not a sufficient condition to ensure a higher patenting activity in the aftermath of the war. Indeed, as was extensively documented in Section 4, mortality created a substantial incentive to substitute machines for missing workers; however, this incen-

FIGURE D3: Effect of mortality and mortality interacted with education, where education is a continuous



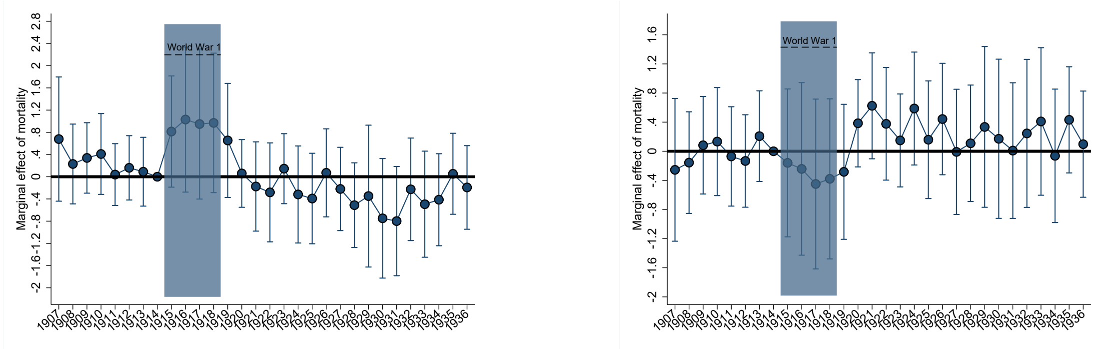
(a) Secular schooling

(b) Catholic schooling

Notes: Figure (a) plots the effect of mortality while figure (b) plots the effect of the mortality interacted with a continuous measure of enrolment rate.

tive could only be met provided that the initial level of education was high enough and, thus, that workers and managers were educated enough to implement and adapt their process to this need.

FIGURE D4: Effect of mortality per se when the interaction term is introduced, using two measures of education



(a) Enrolment rate

(b) Baccalauréat

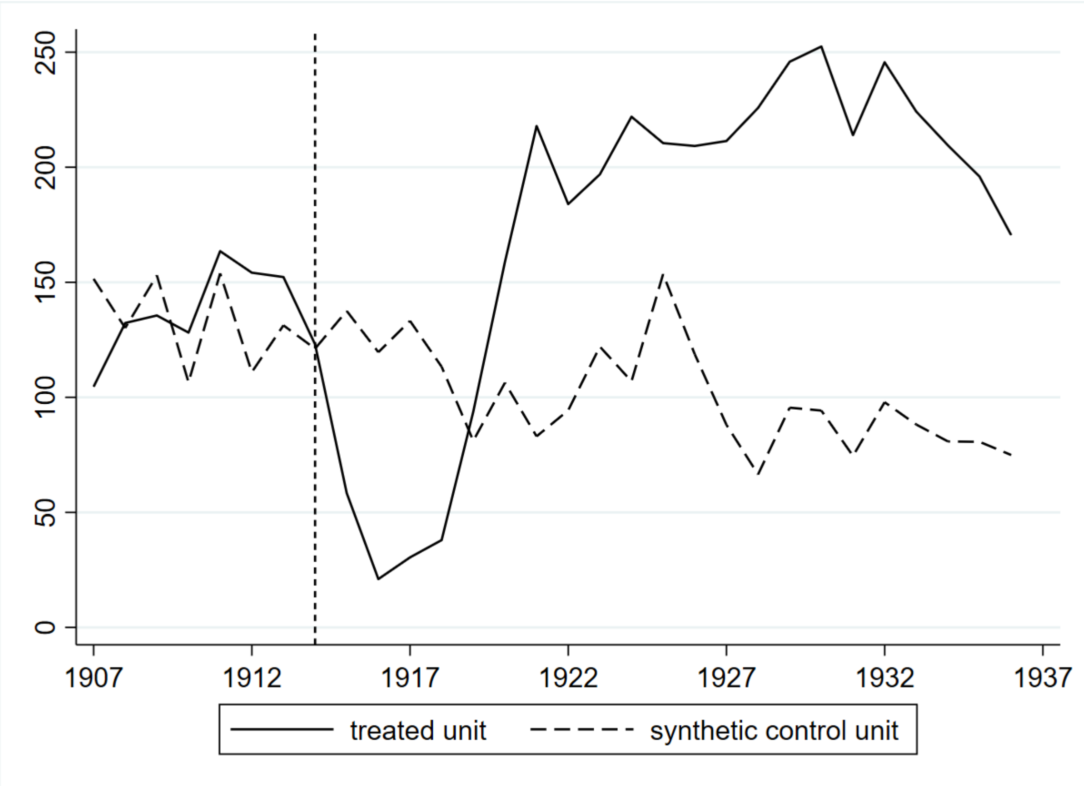
Notes: Baccalaureate rate is defined as the ratio between the number of young men incorporated in the French army and the total number of French young men incorporated in the army at the county level.

D.4 Further comments on the Synthetic Cohort Method

Formally, the framework introduced by Abadie and Gardeazabal (2003) involves three steps: first, one selects the sample of the control regions, indexed by j; second, the predictors of the outcome variables are chosen: depending on the frameworks, each of the predictor might be assigned the same weight, or the relative weights may vary; finally, the weights ω_j attached to each region in the synthetic control group are computed. More precisely, let us denote by x_1 the $K \times 1$ vector of pre event predictors, X_0 the $K \times J$ matrix containing the values of the same variables for the J possible control regions; finally, we denote by V a diagonal matrix with non-negative components reflecting the relative importance of the different predictors, and, again, ω_j captures the weights attached to each region j; then, the third step consists in minimizing:

$$D(\omega) = (x_1 - X_0\omega)'V(x_1 - X_0\omega) \tag{A15}$$

FIGURE D5: Patenting activity in France and in its US counterpart, 1907-1936



Notes: The solid line pictures the evolution of patenting activity per 1,000,000 inhabitants in France while the dashed line represents its synthetic US counterpart, as defined by the framework described by Abadie and Gardeazabal (2003).

D.5 Addressing the issue of negative weight

Another concern associated with our main specification could be the issue mentioned by De Chaisemartin and d'Haultfoeuille (2024), namely that two way fixed effects regressions in which a treatment is interacted with time fixed effects can produce biased estimates. In particular, De Chaisemartin and d'Haultfoeuille (2024) fear that the estimator might be biased for the effect of mortality in counties that were "more" treated than others. Typically, it could be that our estimator assigns higher weights for counties that exhibit either abnormally low or abnormally high mortality throughout the war.

Formally, we build on De Chaisemartin and d'Haultfoeuille (2024) to reformulate the problem. They decompose the coefficients in two way fixed effects regressions with treatment intensity I of a treatment D interacted with period FEs, and show that the coefficient associated with the interaction between treatment effect and period l, noted $E(\hat{\beta}_{fe,l}|D)$, is given by:

$$E(\hat{\beta}_{fe,l}|D) = \sum_{g:I_g \neq 0} w_g^{fe} \frac{\delta g, l}{I_g} \tag{A16}$$

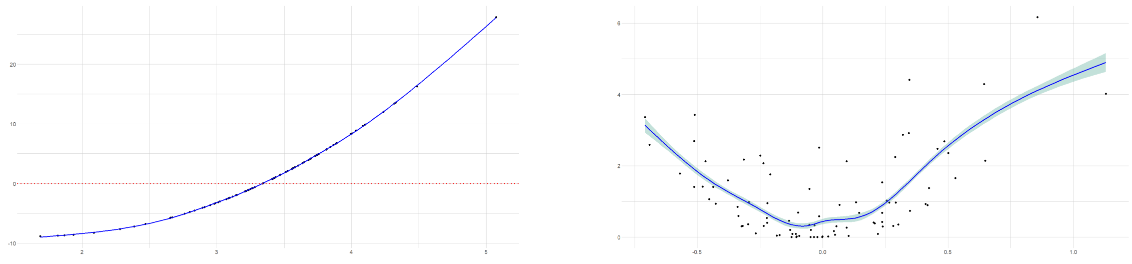
Where $w_g fe$ pictures the weight assigned to unit g in the sample, I_g captures the intensity of treatment received by group g and $\delta_{g,l}$ is the effect of having received I_g unit of treatment rather than 0 unit of treatment for l periods. What they fear is that the weights might be biased for the intensity of the treatment; indeed, the weights formally write:

$$w_g^{fe} = \frac{I_g(I_g - \bar{I})}{\sum_{g':I_{g'} \neq 0} I_{g'}(I_{g'} - \bar{I})} \tag{A17}$$

Where $\bar{I}$ captures the average treatment intensity across all groups. From this equation, it arises that whenever the treatment intensity I_g received by unit g is inferior to the average treatment intensity, then the weights might be negative. In that case, the estimator would assign negative weights to the average treatment effect for the groups with the lowest treatment intensity, while assigning, in turn, excessively high weights to counties that were most affected by the war. Then, the weights would still sum to 1, but the negativity associated with the coefficients estimated on least treated units would bias the estimates. How important that concern may seem, it turns out that it does not directly reach out to our analysis, given that our treatment is constructed in such a way that no unit can be assigned a negative weight.

As explained in Section 2.2, we indeed built a mortality indicator that describes the discrepancy between the *actual* mortality rate in a county and the mortality rate it should have experienced based on a predictive model. Said differently, our mortality indicator is, for each county, the residual of the regression of the *actual* mortality rate on a set of covariates listed in Table 1. To that extent, our treatment naturally averages to 0, implying that the product $I_g \times (I_g - \bar{I})$ of the intensity of treatment of unit g by the gap to the average treatment is necessarily positive: indeed, a positive treatment

FIGURE D6: Weights of each department depending on the mortality indicator



(a) Rough mortality rate **(b)** Modelled mortality rate

Note: These figures plot the weights attached to each county in the estimation of the coefficients of interest depending on the intensity of the treatment received. Panel (a) pictures the weights attached to each county if we consider the rough death rate, while panel (b) pictures the weights attached to each county if we use the modelled mortality indicator, as computed under the process detailed in Section 2.2.

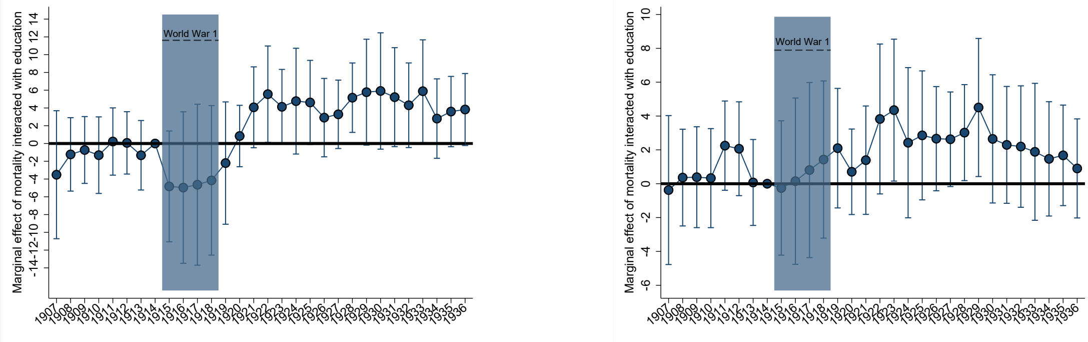
intensity is necessarily above the mean implying that the product is always positive for a county with excess mortality; conversely, a county with abnormally low mortality lies below the mean treatment, but its treatment is itself negative suggesting that the product will be positive, and that the weight will also be. In the end, our treatment variable is such that it precludes any negative weight. This is clearly suggested by Figure D6 which plots respectively the weights attached to each intensity of treatment for the "rough" mortality indicator - for which the issue of negative weights might arise - and for our modified treatment for which the issue of negative weight is absent.

Obviously, negative weighting is precluded in our set up where mortality is instrumented by the indicator described in Section 2.2; conversely, negative weighting arises in the case where rough death rate is used as the treatment. To that extent, our design slightly alleviates the concern pointed by De Chaisemartin and d'Haultfoeuille (2024). However, we remain aware that our method only partially answers to that problem, to the extent that our results are still derived under heterogeneity of the weights attached to each unit. We therefore test a simpler specification in which we consider a binary variable $\mathbb{1}_{\mathrm{d}}$ that takes the value 1 if the county ranges in the upper 33% of the distribution in terms of mortality. Clearly, this set up rules out both the negative and the heterogeneous weighting issues as the untreated units receive, by assumption, a weighting equal to 0 - which comes from the fact that they stand as the reference group - while the "treated" units, meaning those above the median mortality rate, all receive an equal weighting in the regression.

Results displayed in Figure D7 show that the results are robust to the introduction of this new measure of mortality. While pre trends cannot be ruled out, the magnitude and persistence of the coefficients are closely related, suggesting that our causal effect

FIGURE D7: Main estimates when using a binary measure of mortality

(a) Enrolment rate **(b)** Baccalauréat



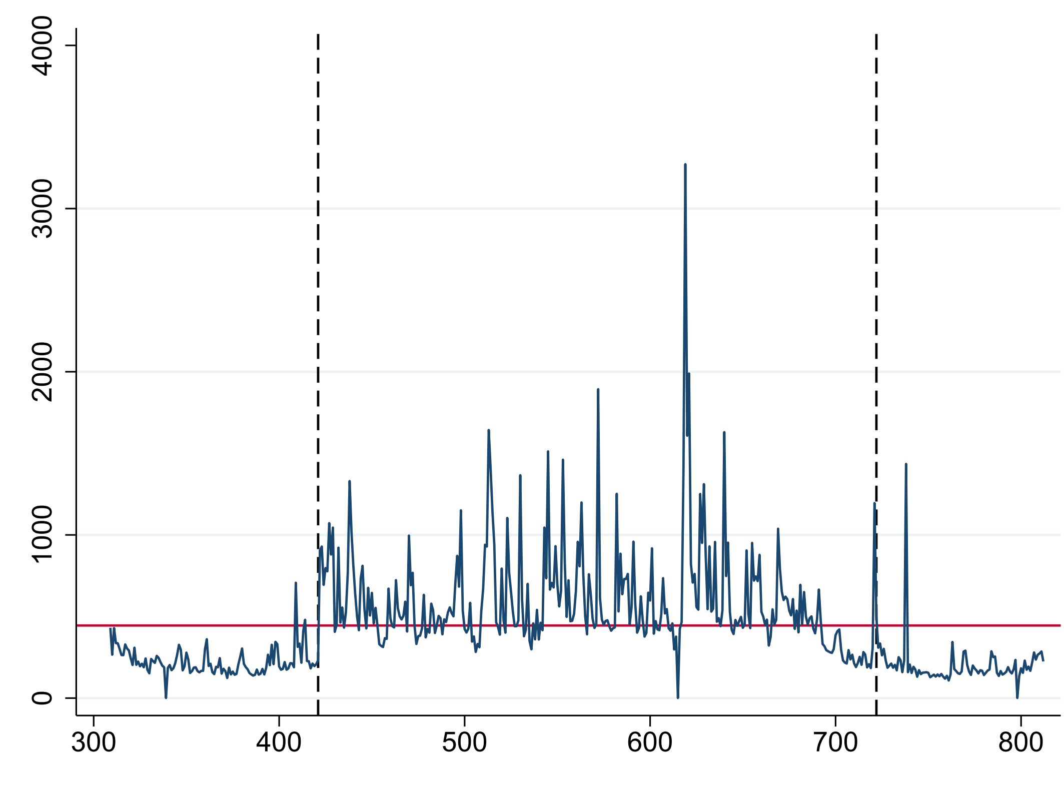
Notes: Mortality is captured by a binary variable that takes the value 1 if the department belongs to the upper 33% of the mortality distribution.

is not only driven by an heterogeneous weighting of the units in the sample. Indeed, almost all coefficients of the regression run on the indicator variable deliver coefficients significant at the 5% or even at the 1% level. It should be noted that results obtained upon using *baccalauréat* as the main education measure seem noisier than those derived upon using the enrolment rate as our main measure; this, however, should not be of much concern for two reasons. First of all, we have been extensively using enrolment rate as our main education measure throughout this paper, for two reasons: first, this education measure is more comprehensive in the sense that we can compute it for the whole second half of the 19^{th} century and for the total population while the baccalauréat measure only refers to young men incorporated in the army between 1881 and 1901 so that we cannot rule out endogeneity issue; second, and as suggested before, inventors did not necessarily belong to the top percentiles of the education distribution. Actually, and as suggested by the data assembled in Bergeaud and Verluise (2024), inventors did not necessarily need to rely on a as large education level as baccalauréat - which only represented around 2 to 3% of the population at that time - to be able to file patents. All in all, those results however ensure that our main conclusions do not stem from a sheer weighting issue that could bias the estimates.

D.6 Additional comments on the battle of Verdun

As suggested in Section 5.3, 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 resources and morale were scarce. That Verdun was peculiarly lethal in the light of the rest of the war is suggested by Figure D8 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.

FIGURE D8: Daily number of casualties (November 1915 - March 1917)



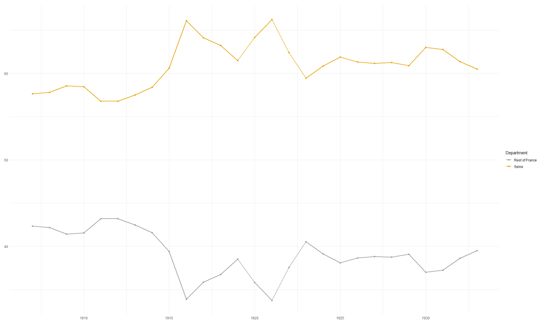
Notes: Black dotted lines represent the beginning and the end of the battle of Verdun.

D.7 Are all the results driven by Paris?

Another concern that may arise regarding the significance of our results is to find out whether all the results are driven by the Seine county or not. As was suggested above, Seine accounts for a substantial share of total patenting activity in France throughout the 20th century. Should Seine have suffered an excessively high or low mortality rate, it could be that the estimates are only brought about by the effect of such a mortality on Seine. First of all, that Seine could have exhibited either abnormally high or abnormally low mortality throughout the war can be ruled out: rough death rate reached 1.93%, implying that Seine ranks among the lowest 20 percentiles of the distribution; however, the correction induced by the modelled mortality indicator leads the county to show an instrumented mortality of -0.01%, suggesting that Seine neither suffered excess nor abnormally low mortality throughout the war given its initial characteristics.

FIGURE D9: Patenting activity in Seine and in the rest of France

(a) Share in total patenting activity



(b) Regression result

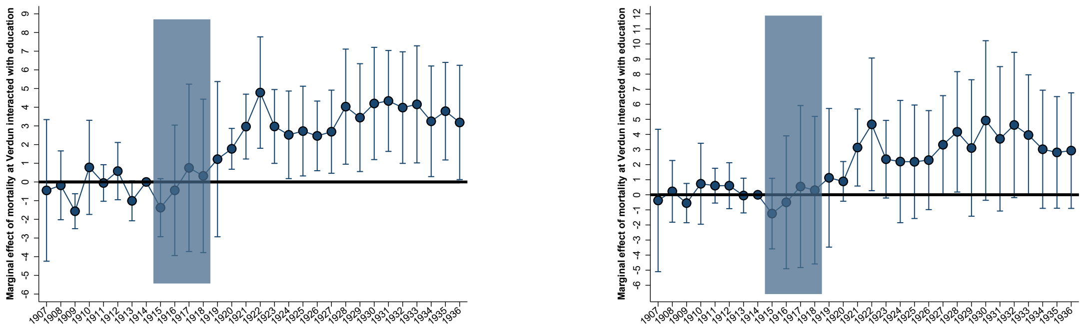
./img/app/figwithoutparis.pdf

Notes: Figure a plots the share of patents allocated to Paris area (Seine). Figure b reproduces Figure 6a where Paris is excluded from the sample.

While mortality does not seem to have been either peculiarly high or low in the Seine county, the overwhelming role played by Paris in the innovation network in France indicates that a test of the significance of the results in the absence of Paris might be adequate. Figure D9a indeed shows the role played by the Seine county in the patenting activity in France in the first half of the 20^{th} century: on average, around 60% of total patenting activity in France at that period was due to Seine, a share that increased over the sample period. Also, the gap in the number of patents per inhabitant is striking: while the Seine area hovers around an average of 75 to 100 patents per 100,000 inhabitants, the other counties are stuck at c. 7 to 8 patents per inhabitant. This heterogeneity might suggest, in turn, heterogeneous reactions to the demographic shock induced by WW1. Also, it could be that be that Paris, as the capital city in France, was given a major role during the war and attracted more inventors which, in turn, would have strengthened the role of the city irrespective of the number of casualties it suffered. This interpretation, however, is clearly ruled out by Figure D9b which replicates Figure 6a but excludes Paris (Seine county) from the sample. While we lose some significance upon removing the Seine county from the sample, we cannot exclude that the magnitude of the coefficients are equal under the two models. That the volatility of the estimates significantly increases upon excluding Seine from the sample is not that surprising owing to the substantial contribution brought by this county to total patenting activity in France throughout the first half of the century.

D.8 Alternative estimations of standard errors

FIGURE D10: Main estimates when clustering at the county level



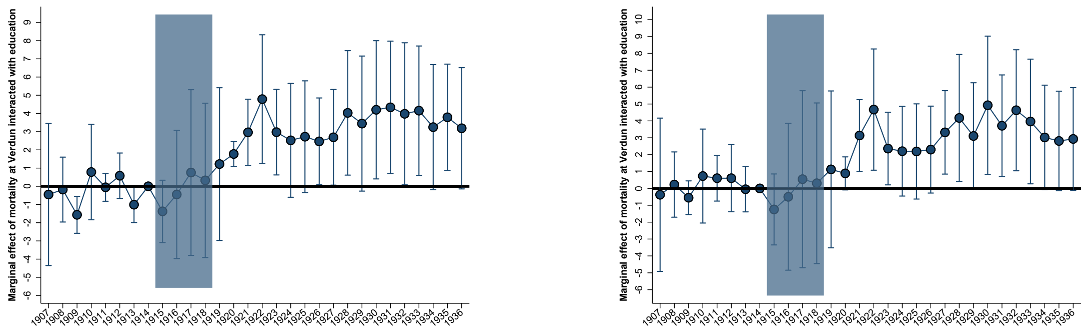
(a) Enrolment rate **(b)** Baccalauréat

Notes: Instead of using robust standard errors, we rather cluster them at the county level, allowing for spillovers within counties.

In this extension, we check the robustness of our results from alternative choice regarding the estimation of the variance-covariance matrix of the error term. Actually, most of the preferred specifications presented so far were estimated using robust standard errors; we however check in this subsection whether results remain unchanged when we cluster standard errors either at the county or at the *region* level, a higher administrative unit in France. To do so, We retain the French regions that were in place before the 2015 reform, corresponding to 22 geographical units. Roughly speaking, each region is approximately as large as 4 French counties, allowing for a robust clustering strategy. In the end, the estimates are not impacted by those alternative approaches, whether we retain county or region as the clustering unit. Figure D10 show that we still keep the same significance of the results whatever the measure of education is retained. Figure D11 acknowledges that we lose some significance in the results, though the gap between the estimates is very modest. Almost all coefficients remain significant at the 5% level, even when introducing region fixed effects on top of the county fixed effects. All in all, the increased noisiness in the sample estimates do not significantly reduce the causal effect which we identify in this paper.

We also explore alternative corrections: Newey-West, Conley, randomization based inference (TBD)

FIGURE D11: Main estimates when clustering at the region level



(a) Enrolment rate

(b) Baccalauréat

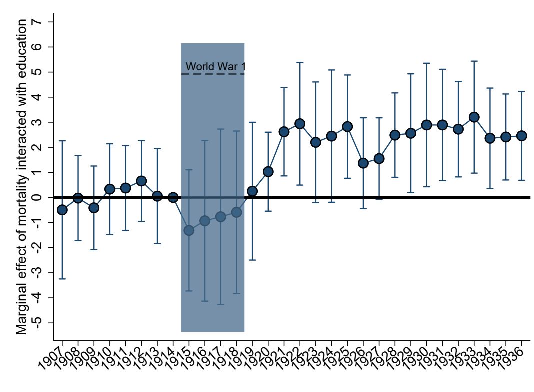
Notes: Instead of clustering standard errors at the county level as was done above, we rather cluster at the region level, allowing for spillovers not only within departments but even within regions.

D.9 Testing alternative measures of excess mortality

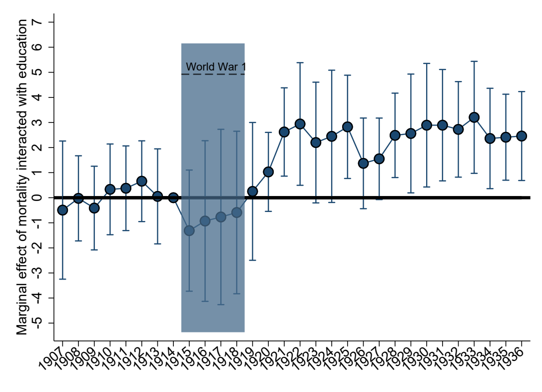
One concern raised in section 2 is that our results might be driven by the adjustment we impose on the mortality rate through the construction of our mortality indicator. To alleviate this concern, we test our main regression on various mortality indicators: first, we remove from the regression specified in equation (1) the share of foreigners as well as the share of young people as explanatory variables of mortality. We then remove education from the covariates, as the coefficient associated to this variable is not statistically significant. These two alternative tests leave us with almost unchanged results as suggested in Figure D12.

As a last robustness check, we decide to run a LASSO regression to be sure that our model retains the best predictors as covariates. Applying this method to our dataset suggests that we retain as predictors of the mortality rate the (logarithm) of the distance to the German border, the density of the 1906 population, the GDP per inhabitant, the share of industry, the share of agriculture, the share of foreigners and the exposure to the battle. This leaves us with a 67% R-squared, indicating a high goodness of fit in light of the relative randomness of deaths during a conflict. We then residualize the mortality rate stemming from this prediction and obtain the results summarized in Figure D13 which respectively plots the interaction between the mortality rate obtained upon running the LASSO and the enrolment rate and the interaction term between the mortality rate resulting from the LASSO and the *bac-*

FIGURE D12: Main results when excluding both the share of foreigners and the young population rate in the construction of the instrument



(a) The effect of the interaction term on innovation on innovation, where mortality is defined as the indicator resulting from the regression specified in equation (1) without the share of foreigners and the share of the young population.

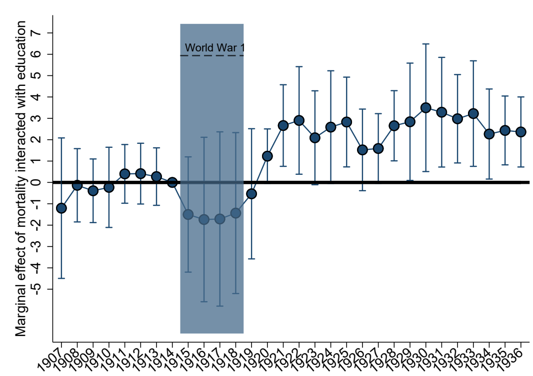


(b) The effect of the interaction term on innovation, where mortality is defined as the indicator resulting from the regression specified in equation 1 without the share of foreigners, the share of young population and education.

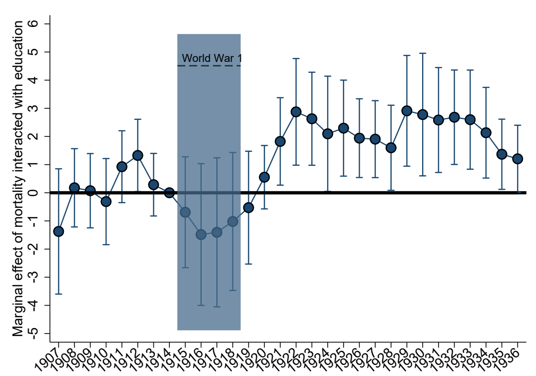
Notes: Left-hand-side figure plots the effect of mortality interacted with education on innovation obtained from the regression specified in equation (6). Right-hand side figure plots the effect of mortality interacted with education on innovation obtained from the same model but where education is removed as a covariate from the instrument construction. Confidence intervals are shown at the 5% level, while the navy-blue-shaded area pictures the war period. Mortality indicator derives from 1 where the share of foreigners and the share of young population are removed from the explanatory variables.

calauréat rate. Clearly, the estimates point again to the same effect identified before: mortality interacted with education exerted a positive and significant effect throughout the fifteen years following the war but only to the extent that the initial level of education was large enough.

FIGURE D13: Main results when removing the share of foreigners, the young population rate and the education measure from the construction of the instrument



(a) The effect of mortality interacted with education on innovation, where mortality is defined as the indicator resulting from a LASSO regression.



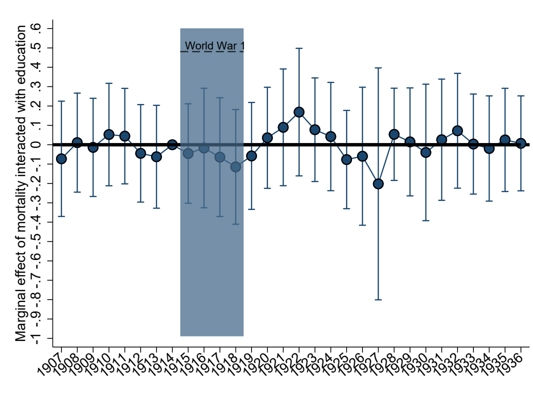
(b) The effect of the interaction term between mortality and the rate of *baccalauréat*, where mortality is defined as the indicator resulting from a LASSO regression.

Notes: Left-hand-side figure plots the effect of mortality interacted with education where mortality is computed as the result of a LASSO regression on our usual predictors while education is measured as the enrolment rate. Left-hand-side figure plots the effect of mortality interacted with education where mortality is computed as the result of a LASSO regression on our usual predictors while education is measured as the *baccalauréat* rate. Confidence intervals are shown at the 5% level, while the navy-blue-shaded area pictures the war period. Mortality indicator derives from 1 where the share of foreigners, the share of young population and education are removed from the explanatory variables.

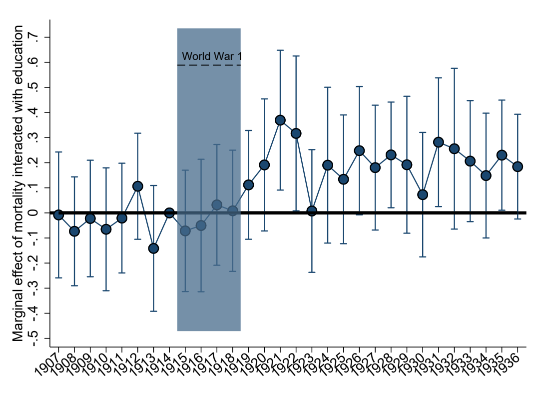
D.10 Testing alternative measures of labor substitution techniques

We argued in Section 4 that one of the mechanisms underpinning our results was that firms operating in counties where mortality had been especially high had but only the choice to substitute machines, automation, electricity, or any kind of labor-substituting device for labor provided that they had a sufficiently high endowment of skills. To identify this channel, we checked that running equation 2 on labor substituting patents yielded significant estimates. More specifically, we compared the estimates of equation 2 for respectively patents identified as either machine, automation, or electricity patents counterfactual groups consisting of patents related to neither machine, automation nor electricity. An issue could, however, be that our definition of such patents would not be accurate enough. As a proxy for labor substituting patents, we retained the top 20% IPC classes in terms of frequency of the tokens "machin", "automat" and "elec"; it could nevertheless be that those categories are too large and thus that they might encompass patents that bear little to no relation towards labor substitution techniques. We address primarily those concerns by testing whether our main results still hold upon restricting the set of labor substituting patents to the top 10% of IPC classes in terms of frequency of the stems "machin", "automat", or "elec"; similarly, we restrict the counterfactuals to belong to the bottom 10% IPC class in terms of frequency of these tokens.

FIGURE D14: Effect of mortality interacted with education on non-machinery-related patents and on machinery-related patents



(a) Bottom 10%

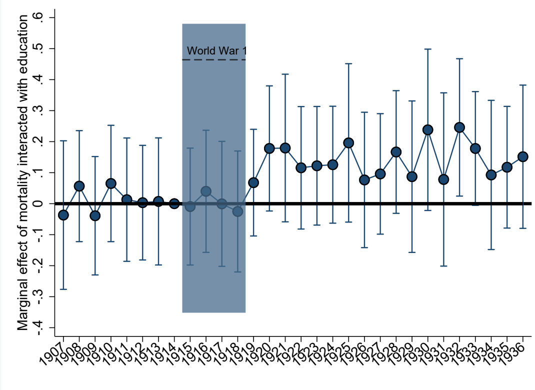


(b) Top 10%

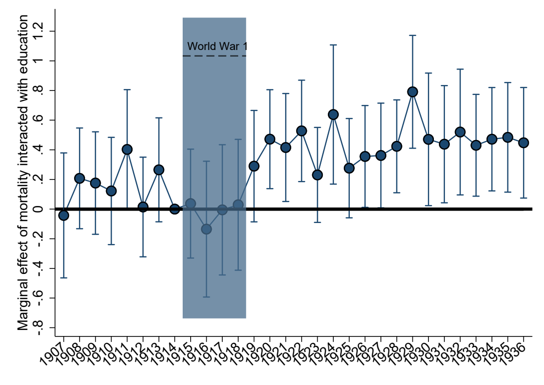
Notes: Left-hand-side figure plots the effect of mortality interacted with education on IPC classes belonging to the lower 10% of the distribution in terms of frequency of the token "machin" while right hand side figure plots the same effect for IPC classes belonging to the upper 10% of the distribution.

First, we check whether running 2 on patents belonging respectively to the top 10% and the bottom 10% of three-digit IPC categories in terms of prevalence of the token "machine". As suggested by Figure D14, the effect of mortality interacted with education is never significant, neither at the 5% nor at the 10% level throughout the period after the war. By contrast, the same coefficients look frequently significant and of a sizeable magnitude after the war for machinery-related patents, suggesting that our estimates in section 4 were not only driven by a very specific IPC category. Similarly, Figure D15 suggests that that patents belonging tot the bottom 10% of the IPC classes in terms of frequency of the token "automat" were somehow positively, but not significantly affected by mortality interacted with education, while the top 10% of the distribution was positively, strongly and significantly affected by that same interaction.

FIGURE D15: Effect of mortality interacted with education on non automation-related patents and on automation-related patents



(a) Bottom 10%



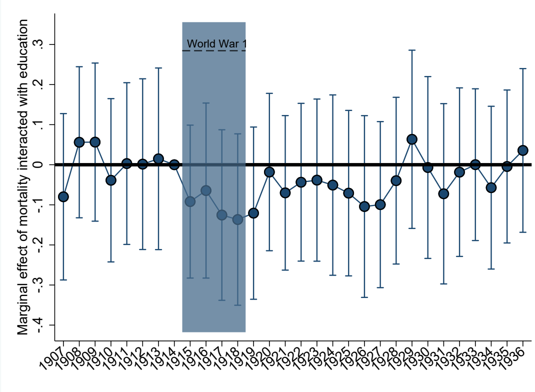
(b) Top 10%

Notes: Left-hand-side figure plots the effect of mortality interacted with education on IPC classes belonging to the lower 10% of the distribution in terms of frequency of the token "automat" while right hand side figure plots the same effect for IPC classes belonging to the upper 10% of the distribution.

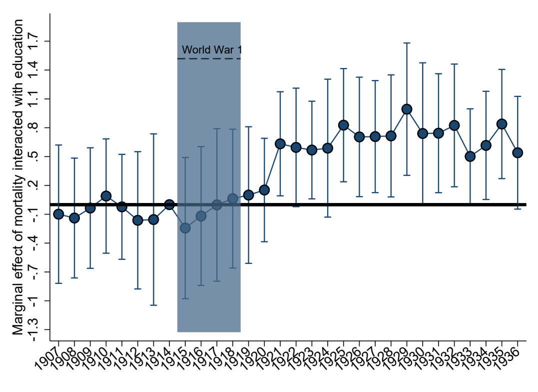
This, again, supports our interpretation that counties suffering substantial labor scarcity in the aftermath of the war had no choice but to substitute labor-saving device for missing workers, but only to the extent that they relied on a large enough initial level of education to file such patents. Finally, Figure D16 clearly proves that patents belonging to the bottom 10% of the distribution in terms of frequency of the token "elec" were unaffected by the interaction between mortality and education while the upper 10% of the distribution was positively and significantly affected by the same interaction term. Combined, these findings point to the same robust and sizeable effect: patents related to labor substituting devices increased significantly and in a sizeable way after the war, but only in counties exhibiting both a high number of casualties and a large enough pool of skills.

Additionally, we rely on an alternative strategy to unveil the labor substitution channel. Instead of selecting only patents belonging to either the top 20%, top 10%, bottom

FIGURE D16: Effect of mortality interacted with education on non electricity-related patents and on electricity-related patents



(a) Mortality



(b) Mortality interacted with education

Notes: Left-hand-side figure plots the effect of mortality interacted with education on IPC classes belonging to the lower 10% of the distribution in terms of frequency of the token "elec" while right hand side figure plots the same effect for IPC classes belonging to the upper 10% of the distribution.

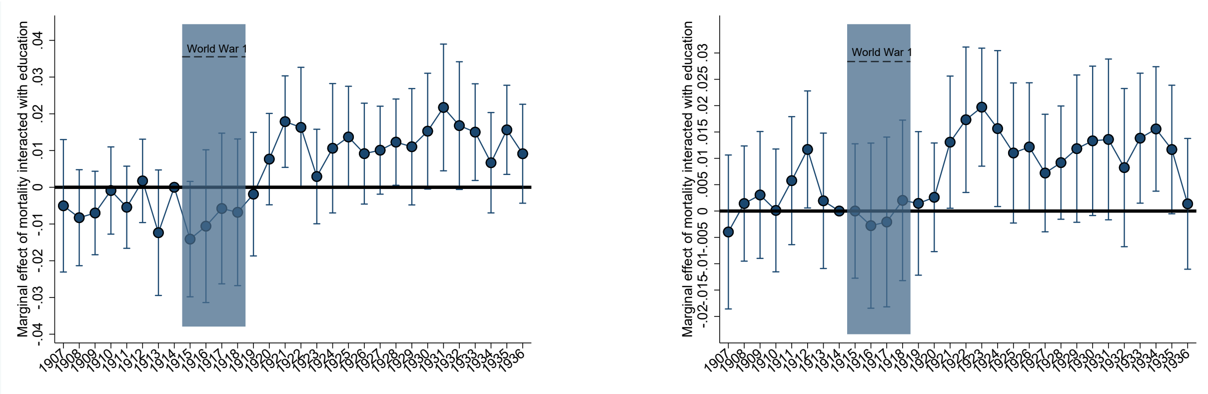
20% or bottom 10% of the distribution in terms of prevalence of the token "machine" or "automat", we weight each patent by the relative frequency of the token "machine" of its IPC category compared with all categories. Formally, this implies that we apply to each patent the weight $\omega_{c,t}$, where:

$$\omega_{c,t} = \frac{f_c}{\sum_{c \in C} f_c} \tag{A18}$$

Where C indexes the set of all IPC classes. In words, this method allows for patents that do not belong to the IPC classes that are closest to the notion of machines, but penalizes them by assigning them with a lower weight compared to patents which belong to IPC classes that range closer to the notion of machine. Again, estimates derived from equation 2 applied to those patents do not significantly differ from those obtained in the general framework. This is pictured in Figure D17 which shows respectively the effect of mortality and that of the interaction term on patents weighted by their relative proximity to the notion of machines. As in the general framework, coefficients are almost always significant at the 10% and even at the 5% levels while pertaining to the same signs and magnitudes.

Finally, we perform a last robustness check by exploiting the Term Frequency - Inverse Document Frequency (TF-IDF) method, a widely used statistical method in natural language processing. Basically, this method measures how important a term is WW1thin a document relative to a collection of document. Formally, for each patent p, we denote by $n_t(p)$ the number of times the token t appears in the title of p and

FIGURE D17: Effect of mortality interacted with education on patenting activity weighted by proximity to machine



(a) Enrolment rate

(b) Baccalauréat rate

Notes: Left-hand-side figure plots the effect of mortality interacted with enrolment rate on patents obtained from the regression specified in equation (6) where patents are weighted depending on the proximity of their IPC class to the notion of machines, while right-hand-side figure plots the same effect but when the rate of baccalauréat is substituted for the enrolment rate.

index by Ω_p the set of words that appear in the title of patent p; then, we compute the frequency $f_t(p)$ of the token f in the title of patent p:

$$f_t(p) = \frac{n_t(p)}{\sum_{\omega \in \Omega_p} n_\omega(p)} \tag{A19}$$

Also, we denote by $F_t(P)$ the frequency of the token t in the set of titles of all patents belonging to the sample. Hence, we compute the relative frequency $f_t^r(p)$ of token t in the patent p as:

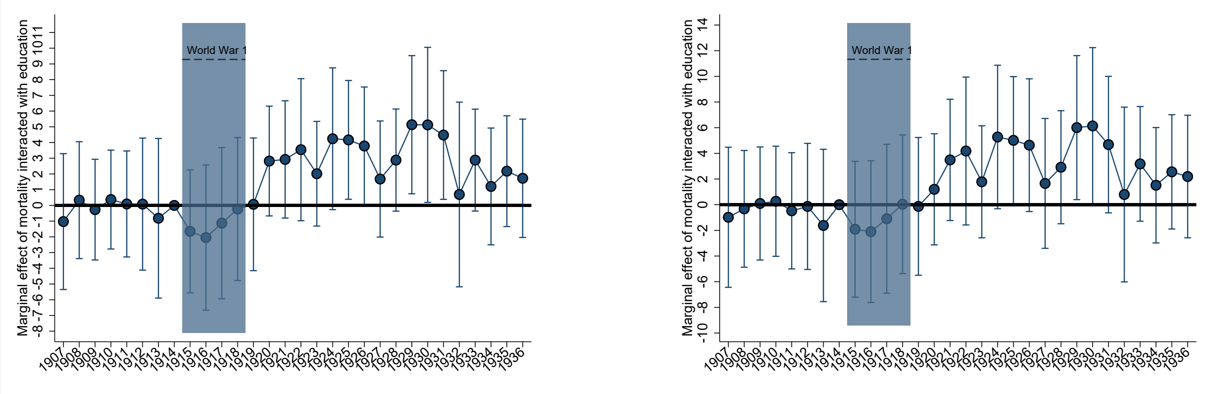
$$f_t^r(p) = \frac{f_t(p)}{F_t(p)} \tag{A20}$$

We then aggregate this statistic at the department $\times$ year cell, to get a measure of the significance $f_d^k(t)$ of token t in department d at period k:

$$f_d^k(t) = \sum_{p \in P_d^k} f_t^r(p) = \sum_{p \in P_d^k} f_t(p) \tag{A21}$$

Finally, we run the regression specified in equation (2) to test whether the importance of tokens related to terms related with labor substituting techniques was affected by mortality during the war or not. More specifically, we let t be a set of tokens which, we believe, are related to labor substituting techniques: in particular, we let t include the tokens "machin", "mecan", "automat", "elec" or "moteur", which all refer to words that are, to some extent, related to the notion of labor saving technologies. We end up with the results plotted in D18 which, again, suggest that our results related to machines are robust to the introduction of many flexible specifications.

FIGURE D18: Results when applying the TF-IDF method



(a) Machine

(b) All labor substituting devices

Notes: Left-hand-side figure plots the effect of mortality interacted with education on the relative frequency of the token "machine" while right hand-side plots the effect of the interaction of mortality and education on the relative frequency of the tokens "machin", "automat" and "elec" combined.

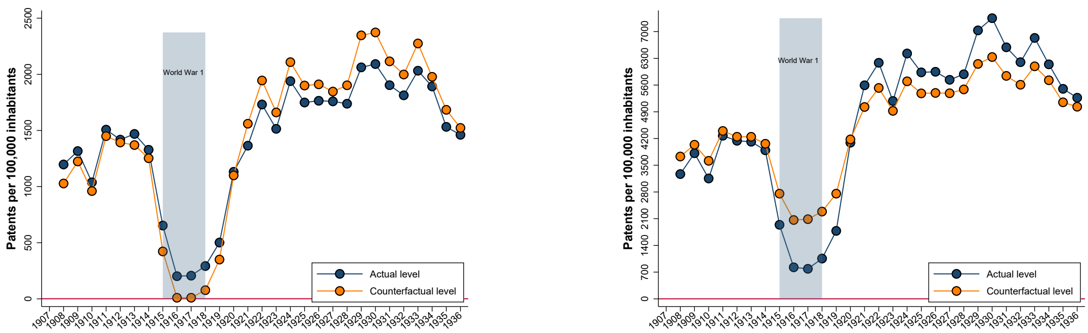
While the estimates lose some significance compared to the findings summarized in Section 4, we still get a positive and almost significant effect of the interaction between education and mortality on patenting activity related to machines after the war while no pre-trends are to be seen before the war. It is noteworthy that the relative loss of significance might also be attributed to the scarcity of the textual data we are using, in that we only have access to the titles of patents and not to their full text. To that extent, computing relative frequency of some tokens proves tricky and does not adequately reflect the proximity of a given patent to a given notion or subfield. Yet, that these estimates are in line with the general results derived in section 4 is reassuring regarding the causal validity of our interpretation.

D.11 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 D19 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 causal 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.

FIGURE D19: Actual and excess mortality rates



(a) Below median mortality

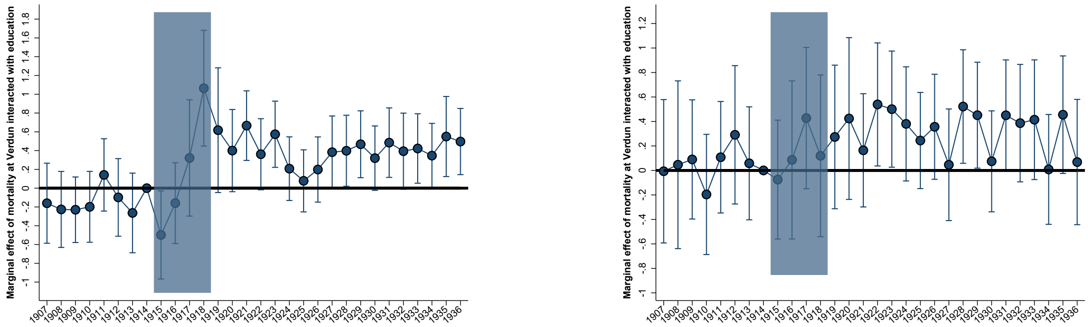
(b) Above median mortality

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.

D.12 Testing flexible functional forms

A concern could arise that our estimates are driven by the specific functional form we are leveraging in this paper, namely that introduced in equation 6. To ensure that this is not the case, we show in this subsection that our results are robust to using Pseudo-Poisson specifications, which prove peculiarly adapted whenever we are considering very specific classes of patents. Indeed, upon estimating the causal

FIGURE D20: Pseudo-Poisson estimates for the interaction term for machinery and non machinery-related patents



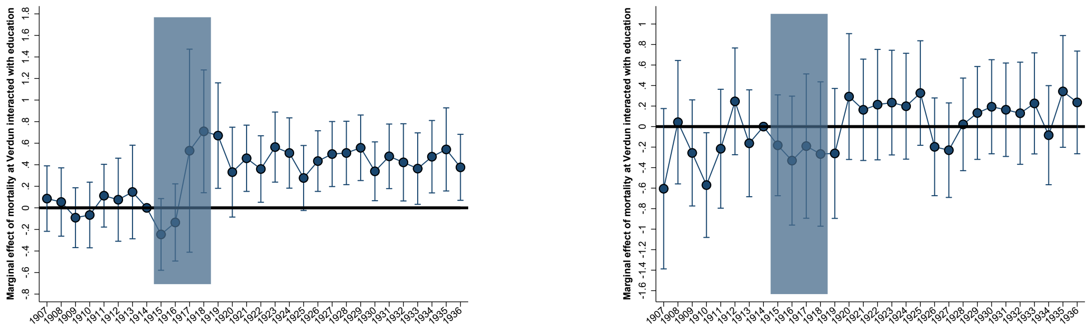
(a) Machinery-related patents

(b) Non machinery-related patents

Notes: Panel (a) plots the coefficients on the interaction term when the dependent variable is the number of machinery-relatd patents and a pseudo poisson specification is used; panel (b) plots the coefficients on the interactin term when the dependent variable is the number of non machinery-related patents and a pseudo poisson specification is used.

impact of mortality on labor-saving patents, we face a significant amount of cells with 0 value, given that labor-saving patents and non labor-saving patents only amount to c. 20% of the yearly number of patents; in that respect, a Pseudo-Poisson specification might prove more suitable. Actually, the estimates recovered through this analysis show even more robust results than those derived in the main text of this paper.

FIGURE D21: Pseudo-Poisson estimates for the interaction term for automation and non automation-related patents



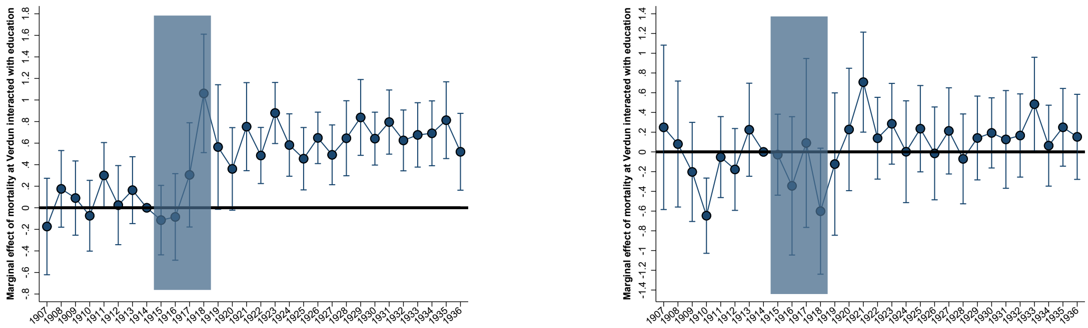
(a) Automation-related patents

(b) Non automation-related patents

Notes: Panel (a) plots the coefficients on the interaction term when the dependent variable is the number of automation-relatd patents and a pseudo poisson specification is used; panel (b) plots the coefficients on the interaction term when the dependent variable is the number of non automation-related patents and a pseudo poisson specification is used.

Figure D20 indeed shows the contrast between the impact of the interaction term on machinery-related patents and non machinery-related patents; while almost all coefficients are positive and significant at the 5% level for machinery-related patents, only a few of them are positive and significant for non-machinery related patents and are estimated with a much larger imprecision, suggesting that the few significant coefficients are not telling. Similarly, and even more clearly, figure D21 illustrates a sharp difference between the impact of mortality interacted with education on automation-related patents and non automation-related patents; while all but one coefficients are statistically significant at the 5% level and significant in the aftermath of the war for automation-related patents, none of them are statistically significant for patents unrelated to automation.

FIGURE D22: Pseudo-Poisson estimates for the interaction term for electricity and non electricity-related patents



(a) Electricity-related patents

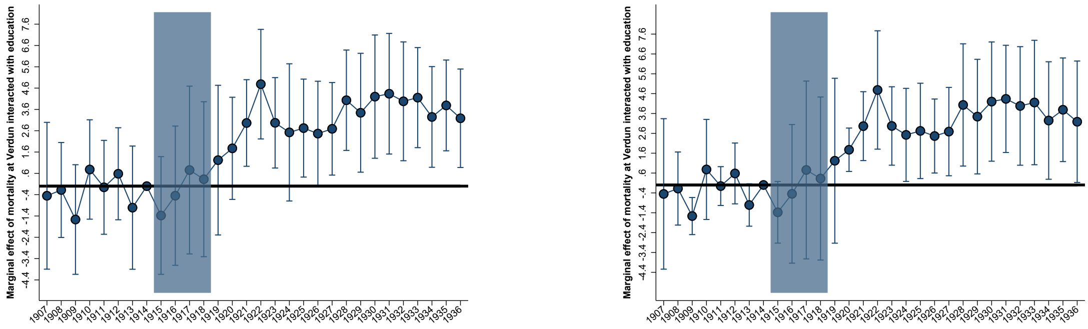
(b) Non electricity-related patents

Notes: Panel (a) plots the coefficients on the interaction term when the dependent variable is the number of electricity-relatd patents and a pseudo poisson specification is used; panel (b) plots the coefficients on the interaction term when the dependent variable is the number of non electricity-related patents and a pseudo poisson specification is used.

Similarly and perhaps even more clearly, patents related to electricity have been largely and positively affected by mortality in those counties where the education level was the highest. All coefficients on the interaction term derived from the pseudo Poisson specification are indeed positive and significant at the 5% level and all of them but one are positive and significant at the 1% level, further supporting the intuition that there existed a clear divide between labor saving and non labor saving patents after World War I in France. Indeed, non-electricity related patents exhibit no clear trend in the decade following the war; while most coefficients are positive, only one of them is statistically significant at the 5% level, the remainder being centered around 0.

Last, we test whether our results still hold when we use the hyperbolic sine of the number of patents per capita as the dependent variable as is sometimes done in the recent literature. We perform this test not only for all classes of patents but also for respectively labor-saving and non-labor saving patents as they encompass the core of our analysis. Clearly, results are unchanged and correspond to those we derived in other specifications such as the Pseudo-Poisson maximum likelihood estimator used right above or the main specification using the *reghdfe* command. More specifically, the coefficients on the interaction term are positive and significant when the dependent

FIGURE D23: Estimates for the interaction term with hyperbolic sine of patents as the dependent variable



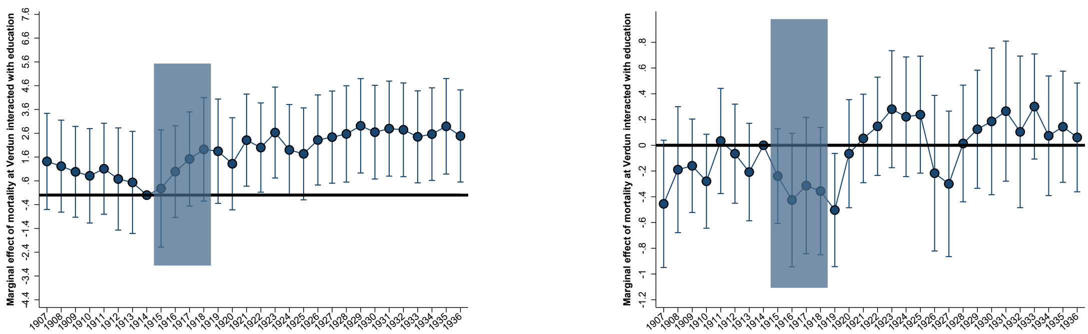
(a) Robust standard errors

(b) Standard errors clustered at the county level

Notes: Panel (a) plots the coefficients on the interaction term when the dependent variable is the hyperbolic sine of patents and standard errors are robust; panel (b) plots the coefficients on the interaction term when the dependent variable is the hyperbolic sine of all patents and standard errors are clusterd at the county level.

variable is the hyperbolic sine of the total number of patents, irrespectively of whether standard errors are robust or clustered at the county level. Also, the coefficients are positive and significant when the dependent variable is taken to be the hyperbolic sine of the number of labor saving patents per capita while the coefficients are either positive and non significant or even negative and non significant when the dependent variable is the hyperbolic sine of the number of non labor saving patents per capita. Hence, our results do not critically hinge upon one specification but reflect the causal effect of mortality for highly educated counties.

FIGURE D24: Estimates for the interaction term with hyperbolic sine of labor-saving and non labor-saving patents as the dependent variable



(a) Labor saving

(b) Non labor saving

Notes: Panel (a) plots the coefficients on the interaction term when the dependent variable is the hyperbolic sine of labor-saving patents; panel (b) plots the coefficients on the interaction term when the dependent variable is the hyperbolic sine of non-labor saving patents.