Cultivating Productivity through Regulation: The Case of Pesticide Bans in France*

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Preliminary and Incomplete.

Abstract

This paper examines the long-standing debate on regulation's impact on productivity, technology adoption, and innovation using novel French agricultural data combining balance-sheet records, crop protection usage, and regulatory changes. The findings show that to minimize adverse productivity effects, regulation should only target inputs with available substitutes while encouraging preventive mitigation practices. When regulation bans inputs without substitutes, it causes short-term productivity losses that mitigation policies cannot offset but stimulates innovation in substitute products over the medium term. These results highlight the need for policies that balance short-term economic costs with long-term technological progress for optimal welfare outcomes.

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1 Introduction

The relationship between regulation, productivity, technology adoption, and innovation is at the heart of a long-standing debate in economics. While regulation is often justified as a means of mitigating negative externalities – such as environmental damages – it can also impose constraints on firms and producers, potentially hindering productivity growth and discouraging innovation (Aghion et al., 2023). However, if regulation provides economic incentives for innovation by creating new market opportunities, either by banning existing products or by precisely defining new markets, it can act as a catalyst for technological progress by increasing the expected returns on innovation, a central mechanism in endogenous growth models (Aghion and Howitt, 1992; Romer, 1990), or facilitate the adoption of new technologies.

This debate has gained renewed urgency with the rapid advancement of artificial intelligence (AI). As evidence of Europe's historical productivity slowdown continues to accumulate, particularly due to its declining position in the global race for innovation (Fuest et al., 2024; Draghi, 2024), the continent faces a paradoxical situation. Despite lacking a dominant player in the global AI ecosystem, Europe was the first to regulate the technology with the adoption of the AI Act in December 2023. While many view this regulatory move as a barrier to innovation, potentially exacerbating Europe's competitive disadvantage, others argue that it provides an opportunity by establishing a clear regulatory framework, which could guide investment choices in R&D and foster innovation. Similar tensions have arisen during past technological revolutions, from calls to regulate industrial machinery due to fears of technological unemployment (Keynes, 1930; Leontief, 1952) to the restrictions on digital markets in recent decades. These historical parallels underscore a fundamental question: under what conditions does regulation stimulate or hinder innovation, and how do firms respond in terms of productivity and technology adoption?

This paper contributes to this discussion by examining the impact of regulatory interventions on productivity and innovation, using agricultural firms as a case study. This tension is particularly relevant in agriculture, where regulations on key inputs such as pesticides, fertilizers, and genetically modified crops can have profound effects on productivity and technological change.

The agricultural sector has long been a cornerstone of Europe's economic and political landscape. The Common Agricultural Policy (CAP), established in 1962, was one of the founding pillars of the European Economic Community (EEC), the predecessor of the European Union (EU). Designed to ensure food security, stabilize markets, and support farmers' incomes, the CAP remains one of the largest budgetary expenditures of the EU, accounting for approximately one-third of the total EU budget in 2023 – amounting to €55 billion – of which France is the largest beneficiary.

Beyond its economic weight, agriculture is also deeply embedded in the political economy of reform in Europe. Recent events, such as the widespread farmers' protests across Western Europe in early 2024, underscore the sector's continued influence. These protests, triggered by rising production costs and concerns over unfair competition linked to free trade agreements, highlight the socioeconomic tensions at the heart of agricultural policy debates, particularly in France.

Richness of French agricultural data. Some recently released agricultural data in France offer an unprecedented level of detail for studying these questions. Unlike standard firm-level datasets, which often provide limited information on inputs, agricultural data offer far greater precision. These datasets capture a comprehensive view of inputs – including machinery, crop types, and chemical inputs – as well as detailed output information, such as the type and quantity of crops sold. This richness stems from exhaustive censuses and surveys, making agricultural data an invaluable resource for identifying economic mechanisms that could be generalized to other sectors. By providing a rare combination of detailed input and output data, the agricultural sector serves as a natural laboratory for economic research on this question, offering insights that are difficult to obtain in other industries, yet whose underlying economic mechanisms can be generalized to broader contexts. To analyze the relationship between pesticide regulation, farm productivity, and innovation, I construct a novel dataset by integrating farm-level balance-sheet data, the CAP Land Parcel Register, and Field Crop Cultural Practices surveys, which offer a detailed inventory of plant protection products used at the farm level. Additionally, I incorporate publicly available data on pesticide authorizations to identify regulatory events.

Case Study. I first consider a typical case: the 2018 European Neonicotinoid Ban. This family of crop protection products is crucial for sugar beet cultivation, which can account for up to 12% of cultivated land in intensively producing counties in northern France, as nearly all sugar beet producers rely on this category of crop protection products. This case study focuses on a product for which no substitutes were available on the market at the time of the ban. Adopting a difference-in-differences approach, I find that land productivity declines more sharply for farms more exposed to the neonicotinoid ban due to their historical reliance on sugar beet cultivation. Furthermore, the results indicate a significant shift in the production function of affected farms, consistent with the idea that the regulation forces farm owners to reorganize their production factors in the short run. Finally, I show that the ban negatively impacts farm labor earnings, primarily driven by a decline in labor demand.

General Case. Next, I examine the broader impact of pesticide bans on agricultural productivity, regardless of the specific product or crop affected. By leveraging the combination of datasets described earlier, I can identify whether a randomly selected farm experienced a pesticide ban on a product it previously used for an economically relevant crop. Using a difference-in-differences approach, I find that land productivity declines for farms exposed to a crop protection product ban. More specifically, the decline is most pronounced when the banned product has no available substitutes, negative but smaller in magnitude when substitutes exist but are limited, and nonexistent when a large number of potential substitutes are available. I then extend the analysis by examining how farms respond to the ban based on whether they had proactively implemented mitigation policies primarily for economic reasons, depending on the number of available substitutes. The findings reveal that when no substitutes are available for the banned crop protection product, mitigation practices fail to offset or even reduce the adverse effects on productivity. However, when substitutes exist in limited quantities, preventive mitigation policies prove highly effective in preserving productivity. Finally, when a large number of substitute products are available, the ban has no discernible impact on land productivity, regardless of whether farms adopted mitigation practices. These results highlight that pesticide bans have a short-term negative effect on farm productivity under two key conditions: (i) when no substitute products are available and (ii) when farms fail to implement preventive mitigation practices in cases where substitute products are scarce. Conversely, regulation can yield positive effects on agricultural productivity, provided that (i) it does not target irreplaceable products and (ii) farms have proactively adopted mitigation measures to facilitate the transition – an outcome that may initially appear counterintuitive.

Indirect effect on innovation. Building on the insights from Schumpeterian growth models and their predictions regarding the interplay between competition and innovation (Aghion et al., 2005), one could anticipate a contrasting effect on innovation. In particular, when a regulatory ban targets an agricultural product with no viable substitute, it generates strong incentives for the agrochemical industry to develop alternative solutions. I present descriptive findings indicating that the impact on innovation fundamentally differs from that on agricultural productivity. If a regulatory shock affects a use for which few or no crop protection products exist, agrochemical firms typically respond by accelerating innovation, leading to an increase in the number of available products for that usage. Conversely, when regulation targets a use with a substantial number of existing crop protection products, it results in a decline in the number of products available on the market. These findings call for more nuanced policy recommendations. Indeed, banning pesticides with few or no substitutes may be fully justified if the objective is to stimulate the development of new, more environmentally friendly alternatives. However, such a strategy should be accompanied by active support policies for farms to help them absorb the transition shock, rather than relying solely on proactive mitigation measures in this context.

Related Literature. This paper builds on a vast literature examining the impact of technological progress in the agricultural sector, particularly the diffusion of new technologies. This includes the adoption of hybrid crops (Griliches, 1957) as well as the spread of agricultural machinery – most notably tractors – and their effects on farm productivity (Gross, 2018; Chabé-Ferret and Enrich, 2021; Manuelli and Seshadri, 2014). It also builds on research highlighting the indirect effects of adopting new agricultural technologies, which can drive broader structural transformations in the economy (Bustos et al., 2016). It also contributes to the literature examining the determinants of agricultural productivity (Gollin et al., 2014a,b; Chen, 2017; Adamopoulos and Restuccia, 2022; Moscona and Sastry, 2022; Boppart et al., 2023), particularly in documenting cross-country differences. I also contribute to the literature linking agriculture and the environment, whether through the lens of climate change or biodiversity. Recent research has examined both how agricultural innovation responds to climate change (Moscona and Sastry, 2023) and the adaptation costs incurred by the agricultural sector in response to climate shifts (Du Puy and Shrader, 2024). More broadly, this paper aligns with the literature documenting the effects of regulation on firms' economic performance (Garicano et al., 2016; Nimier-David et al., 2023) and their innovation outcomes (Aghion et al., 2023).

Outline. The remainder of the paper is structured as follows. Section 2 describes the data and key variables. Section 3 presents a case study on the neonicotinoid ban. Section 4 examines the broader impact of pesticide bans on agricultural productivity. Section 5 provides suggestive evidence on their effects on innovation. Finally, Section 6 concludes.

2 Data

To study this question, I have assembled a wide range of data sources that have recently been made available, allowing for the creation of a unique and novel dataset to study this question. In this section, I present the data sources, define the sample and key variables used in the analysis, and provide summary statistics.

2.1 Data sources

To obtain a comprehensive understanding of the relationship between pesticide regulation, farm productivity, and innovation, I construct a novel and unique dataset. I combine exhaustive farm-level agricultural balance-sheet data and the exhaustive Land Parcel Register with surveys on Field Crop Cultural Practices compiling a detailed inventory of plant protection products used. Finally, I supplement this dataset with publicly available data on plant protection products, including their authorization status by year, to define regulatory events.

Agricultural Benefits Database ("BA"). This database covers the entire population of farms in France's agricultural sector from 1995 to 2023, representing approximately 220,000 farms per year. While the Ficus-Fare database – detailing balance-sheet records for non-agricultural business firms – serves as the benchmark for firm-level studies in France, its counterpart in the agricultural sector, the Agricultural Benefits Database ("BA"), provides detailed information for each farm on total sales, balance-sheet records, total employment, total wage bill, assets by type, and specific expenditure categories. The recent availability of this database offers new perspectives for research on these issues, as previous data sources were limited to thematic surveys, and the relatively small number of farms surveyed made it difficult, if not impossible, to match data across multiple sources. These balance-sheet data are used to construct various measures of production (total production, crop production), productivity (land productivity, labor productivity, etc.) and tangible assets (stock of machines) at the farm level, as well as indicators of remuneration for farm owners and their employees.

Graphical Land Parcel Register. This database covers all French land parcels receiving European subsidies from the Common Agricultural Policy (CAP) between 2015 and 2022, providing highly detailed annual information on parcel size, the crop grown, and the identifier of the farm cultivating the parcel. I use this information to construct precise measures of farm land use allocation across different crop types, allowing me to analyze potential changes in the production function following shocks such as pesticide bans.

E-Phy database. The E-Phy database provides access to detailed information on plant protection products covered by a marketing authorization (AMM) by the *French Agency for Food, Environmental and Occupational Health & Safety (ANSES)*. The dataset files cover approximately 15,000 authorized and withdrawn products since the 1970s. They includes the crop protection product identifier, the date of marketing authorization, the current authorization status (approved or banned), the potential ban date, the active substance content, as well as product uses. Product uses cover three dimensions: the type of crop on which the product can be applied, the target of the product (e.g., insects, fungi), and the application method (e.g., directly applied to seeds, used as a spray). I use this information to define pesticide and active substance ban events.

Field Crop Cultural Practices Survey. The Field Crop Cultural Practices Survey is conducted at the land parcel level for the years 2001, 2006, 2011, 2017, and 2021, covering approximately 20,000 land parcels each year. For each land parcel, the survey provides detailed information on the crop cultivated, the plant protection products applied during cultivation, and the agricultural practices employed (e.g., tillage). This information, in particular, allows for the identification of farms that would be affected by a ban on a specific plant protection product or active substance.

Farm Accountancy Data Network (FADN). The Farm Accountancy Data Network (FADN) is a survey conducted annually in the member states of the European Union according to common rules and principles. In France, data are available from 1968 to 2023, covering approximately 7,000 farms each year since 1988. This survey provides detailed information on farm structures (land area, crop types, and livestock), labor (workforce size, working hours, contract type, etc.), the sociodemographic characteristics of farm managers (age, education, gender, etc.), economic performance indicators (production, intermediate consumption, etc.), and balance sheet components (debt, land, equipment, etc.). The extensive range of information contained in this database makes it the historical reference dataset for micro-level farm studies. However, it only covers around 2% to 3% of all farms each year. Moreover, matching this subsample with the *Field Crop Cultural Practices Survey* results in an even more limited overlap, making it difficult to study the effects of regulatory shocks or policy changes at the farm level. I use this dataset as a secondary data source, particularly to analyze specific farm subsamples over short periods before 2015, when information from the *Graphical Land Parcel Register* is unavailable.

3 The European Neonicotinoids Ban: A typical Case Study

3.1 Institutional Context

Nicotine has been used as a potent insecticide since the 17^{th} century due to its biocidal properties on fruit and horticultural crops. In the 1980s, major global agrochemical companies developed neonicotinoids, a class of neurotoxic insecticides that proved more effective than nicotine due to their systemic action and greater molecular stability. Imidacloprid, the first neonicotinoid, was discovered in 1985 by Bayer and introduced to the market in 1991. This class of biocides experienced rapid expansion in the 1990s, quickly replacing nicotine. By the mid-2010s, neonicotinoid pesticides had become the most widely used class of insecticides worldwide (Simon-Delso et al., 2015), accounting for more than 25% of total global insecticide sales (Bass et al., 2015).

However, several scientific studies have highlighted the harmful effects of neonicotinoids on pollinators and aquatic insects. In 2018, the European Food Safety Authority (EFSA) published a report (European Food Safety Authority, 2018) based on a meta-analysis of 588 studies, concluding that imidacloprid, clothianidin, and thiamethoxam – three widely used neonicotinoids – pose a threat to bees. Following these findings, on April 27, 2018, European Union member states agreed to a total ban on neonicotinoid insecticide use, except within closed greenhouses, with implementation set for the end of 2018. France had anticipated this regulatory shift by banning the use of neonicotinoid-based products and seeds treated with these substances as early as August

2016, with the regulation taking effect on September 1, 2018.

Sugar beet cultivation relies heavily on neonicotinoid seed coatings, which protect the crop from beet yellows virus, a disease transmitted by aphids. This virus causes the leaves to turn yellow, thicken, and become brittle (Figure 1a), leading to significant yield losses. In the most severe cases, yield reductions can reach up to 50%, primarily due to a decrease in beet size (Figure 1b). Moreover, there is currently no truly effective alternative to neonicotinoids for controlling aphids, the vectors of Beet Yellows Virus in sugar beet cultivation, as noted by the French Agency for Food, Environmental and Occupational Health & Safety (ANSES, 2018).

(a) Leaves of sugar beet infected with Beet Yellows Virus

(b) Comparison of the size of a healthy sugar beet (left) and a severely affected one (right) by Beet Yellows Virus

Figure 1. Effects of Beet Yellows Virus on Sugar Beet Cultivation

Observing that several European countries had resorted to derogations under European law to support their sugar beet farmers and the refined sugar production sector, and explicitly stating that "the technical alternatives currently available have proven ineffective",[1] the French government proposed a law, adopted on December 14, 2020, re-authorizing the use of neonicotinoid insecticides exclusively for sugar beet cultivation until 2023. In January 2023, the Court of Justice of the European Union (CJEU) ruled to prohibit any exemptions granted by EU member states to the ban on the marketing and use of seeds treated with plant protection products containing neonicotinoids. Member states that had granted such exemptions, including France, were therefore required to immediately discontinue them.

[1]Press release from the French Ministry of Agriculture and Food, August 6, 2020, https://agriculture.gouv.fr/filiere-betterave-sucre-plan-de-soutien-gouvernemental-pour-faire-face-la-crise-de-la-jaunisse

Sugar beet is primarily cultivated in Northern Europe, including northern France, Germany, the Netherlands, Belgium, and Poland, where the climate is most suitable. Figure 3 presents the share of agricultural land allocated to sugar beet cultivation in 2015 by county (*département* in French). The data reveal that outside the northern quarter of France, most counties cultivate very little to almost no sugar beet. In contrast, in the northern French counties, which account for nearly the entire top 25% of highly intensive sugar beet-producing areas, the share of land used for sugar beet cultivation ranges between 0.39% and 12.24%. Regulations on neonicotinoids thus apply to a specific region where sugar beet cultivation represents a significant share of local agricultural activity.

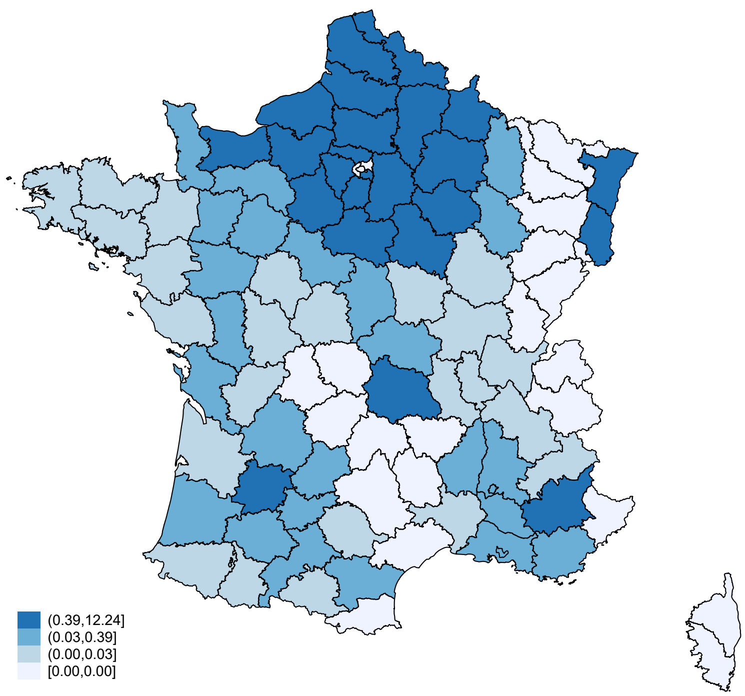


Figure 2. Share of Agricultural Land Allocated to Sugar Beet Cultivation in 2015 (in %)

3.2 Empirical Approach

When a farm is heavily exposed to the neonicotinoid ban, how does it affect land productivity, revenues, production methods, and employment? I now investigate this question in the farm population using a difference-in-differences approach.

The abrupt ban of a crucial plant protection product in a crop representing a significant share of northern France's cultivated land provides a valuable setting for constructing a natural experiment.

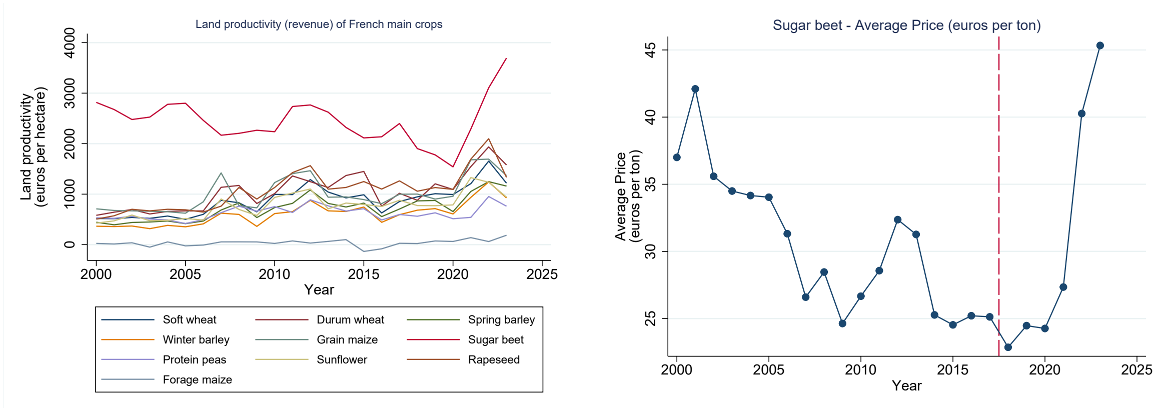
Indeed, a substantial number of farms will be highly exposed to the neonicotinoid ban due to the significant share of their income derived from sugar beet cultivation. However, for this statement to hold, it is essential to first ensure that certain conditions are met.

First, there must be no concurrent shock altering farmers' incentives to produce sugar beet or affecting its profitability. As shown in Figure 3a, sugar beet has been the most profitable crop per hectare among major agricultural crops in France throughout the 2000–2023 period. Its high profitability is precisely why, as early as 1968, the European Union integrated sugar beet production quotas into the Common Agricultural Policy (CAP). A maximum production limit was allocated to incumbent farmers, alongside a guaranteed price, ensuring stable revenues. These production rights could later be resold or reallocated if a farm exited the sector. However, in 2017, the EU abolished these quotas to align the sugar sector with its broader competition framework. One could argue that the near-simultaneous removal of production quotas and the neonicotinoid ban could bias the estimation of the ban's effect. This concern would be particularly relevant if the quota removal had triggered a collapse in sugar beet prices. However, as shown in Figure 3b, while prices declined slightly between 2017 and 2018, the combination of surging global demand—particularly from developing countries—and insufficient global production growth led to a sharp increase in world sugar prices. As a result, the sale price per ton of sugar beet in 2021 exceeded its 2017 level at the time of quota abolition.[2] Ultimately, the removal of quotas granted farms greater production flexibility without discouraging sugar beet cultivation, given the prevailing global market conditions.

Second, sugar beet cultivation must account for a significant share of farm income to ensure that the shock experienced by these farms is substantial enough. As shown in Figure 3, in some counties in northern France, the share of land used for sugar beet cultivation reaches 12%, representing a considerable portion of farm revenue.

Third, it is necessary to either identify which farms use neonicotinoids for sugar beet cultivation or, ideally, ensure that nearly all sugar beet-producing farms rely on neonicotinoids for their crop protection. According to the Field Crop Cultural Practices Survey for the year 2017, 96% of sugar beet-producing farms use neonicotinoids. As a first approximation, our approach will assume that all sugar beet-producing farms use neonicotinoids. However, if some highly intensive sugar beet farms did not use them, this would lead to an underestimation of the magnitude of the effect. Consequently, the estimated results should be interpreted as a lower bound of the true effect.

[2] French Ministry of Agriculture (2024) provides a more detailed analysis of global sugar market supply and demand dynamics over the study period.



(a) Evolution of Price per Hectare for the 10 Main Agricultural Crops in France

(b) Evolution of sugar beet prices

Figure 3. Evolution of Profitability per Hectare and Prices of Major Crops in France

3.3 Identification

Starting from the entire population of French farms, and given that nearly all sugar beet-producing farms use neonicotinoids, I restrict the analysis in the baseline specification to farms that were already producing sugar beet in 2015. This allows for a comparison between farms that, *a priori*, have relatively similar production tools and infrastructure. As a robustness check, I extend the control group to include all farms. I focus on a balanced panel of farms that are present every year from 2013 to 2022 to ensure that the estimated effects are not driven by selection bias or farm exit. To identify the effect of the neonicotinoid ban on agricultural productivity, I adopt a difference-in-differences strategy, considering two groups of farms. Farms for which the land share of sugar beet exceeds the 90th percentile (p90) three years before the ban (in 2015) – and that therefore historically relied heavily on sugar beet production – are classified as exposed and constitute the treatment group. Meanwhile, farms for which the land share of sugar beet is below this threshold form the control group. In the baseline specification, the p90 threshold corresponds to 21% of a farm's cultivated land allocated to sugar beet.

On average, 1,560 exposed farms cultivated 24% of their land with sugar beet in 2015, whereas 14,042 non-exposed farms cultivated only 9%. The samples of exposed and non-exposed farms are described in Table 1. Exposed farms are slightly larger, with an average cultivated land of 159 ha compared to 149 ha for non-exposed farms. They also have higher total production levels and crop production values, suggesting that they are more reliant on crop production. However, their net stock of machines is slightly lower. In terms of productivity, land productivity is marginally higher for exposed farms. Exposed farms also receive slightly higher subsidies. Finally, employment levels are nearly identical, with 1.19 full-time equivalent (FTE) workers in exposed farms compared to 1.18 in non-exposed farms.

	Exposed	Non-exposed
Cultivated land (ha)	159	149
Production (k€)	348	316
Crop production (k€)	297	230
Subsidies (k€)	51	47
Net stock of machines (k€)	140	145
Land productivity (k€ per ha)	2.31	2.25
Employment (FTE)	1.19	1.18
Number of farms	1,560	14,042

Table 1. Characteristics of Farms Exposed and Not Exposed to the Neonicotinoid Ban

Notes: This table presents descriptive statistics for the two groups in 2015, three years before the implementation of the Neonicotinoid Ban.

Indexing farms by i and years by t, the difference-in-differences is specified as

$$log\, Y_{it} = \alpha + \sum_{t=y_0}^{y_n} \delta_t \; IntensiveBeet_{i,t-2017} + \mu_i + \lambda_{ct} + \epsilon_{it}$$

with Y_{it} the outcome of interest, the treatment dummy defined based on the *ex-ante* intensity of sugar beet cultivation $IntensiveBeetCultivation_{i,t-2017}$, farm fixed effects μ_i and city-by-year fixed effects λ_{ct}. The lead-lag coefficient δ_t gives the cumulative dynamic response of the outcome Y_{it} in year t, relative to the base year 2017, which marks the last year before the neonicotinoid ban. I consider a variety of outcomes at the farm level, including total production, land productivity, crop land productivity, wagebill, and employment.

A causal interpretation of the estimates requires the identification condition

$$E[IntensiveBeetCultivation_{i,t-2017} \cdot \epsilon_{it} | \mu_i, \lambda_{ct}] = 0 \quad \forall t.$$

If this holds, one should expect the leads (i.e., $\hat{\delta}_t$ with $t < 2017$) to be statistically insignificant and the point estimates to be close to zero. Although the lack of pre-trends is a necessary condition, it may not be sufficient to guarantee the validity of the identification condition. Indeed, correlated demand and supply shocks may occur simultaneously as farms face the ban. For example, one could argue that the liberalization of the European sugar market, coupled with the end of production quotas, might have led to the closure of several sugar factories in the same year as the ban. This, in turn, could have reduced demand for sugar beet, causing a simultaneous direct negative impact on land productivity for sugar beet producers. However, data on the number of sugar factories do not indicate such a sharp decline. Moreover, agricultural production requires multi-year crop planning to follow crop rotation principles that ensure optimal land use. In this sense, while there is indeed a decline in the share of land dedicated to sugar beet (Figure 5), it remains limited. This provides reassurance that an external shock did not fundamentally alter the production methods of intensive sugar beet producers in the year of the ban.

3.4 Main Results

Productivity. Figure 4 documents the effect on productivity. I find that land productivity declines more sharply for farms that are more exposed to the neonicotinoid ban due to their historical reliance on sugar beet cultivation. Figure 4a presents the difference-in-differences estimation with city-by-year fixed effects. The semi-elasticity of farm land productivity[3] with respect to the neonicotinoid ban is -0.05 after one year, reaching -0.07 after five years, with no evidence of pre-trends. This implies that the land productivity of exposed farms decreased by 7% more than that of less exposed farms after five years. The point estimates are precise; the 95% confidence interval rules out a semi-elasticity above -0.04 or below -0.1 after five years. We observe that the effect is weak and not statistically significant in the first year of the neonicotinoid ban, 2018. In France, farmers sow sugar beet around March and harvest it around October. As a result, the majority of the crop's lifecycle took place before the regulation, which came into effect on September 1, 2018.[4]

Figure 4b examines the response of an alternative measure of land productivity: crop land productivity, defined as the ratio between crop production revenues and total cultivated land. This measure has the advantage of more specifically isolating yields from crop production. However, its denominator does not distinguish between the portion of land actually used for crop cultivation and that used as grassland for livestock for instance. This is why I use land productivity as the main measure. The results are very similar, with a semi-elasticity of approximately -0.06 after two years and -0.1 after five years.

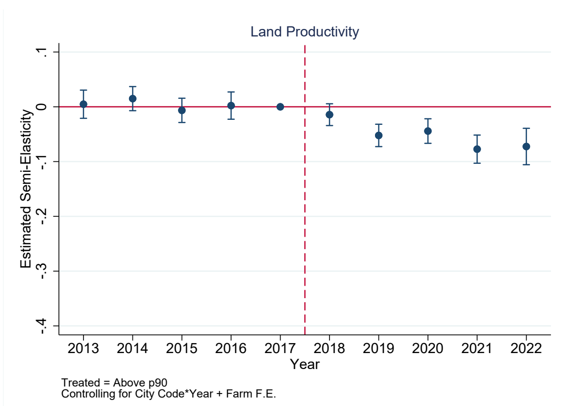
Figure 4c reports the semi-elasticity of total production excluding subsidies. Once again, we observe a negative effect on farms exposed to the ban, with a semi-elasticity of approximately

[3] Land productivity is defined as the ratio between total production (excluding subsidies) and total cultivated land.

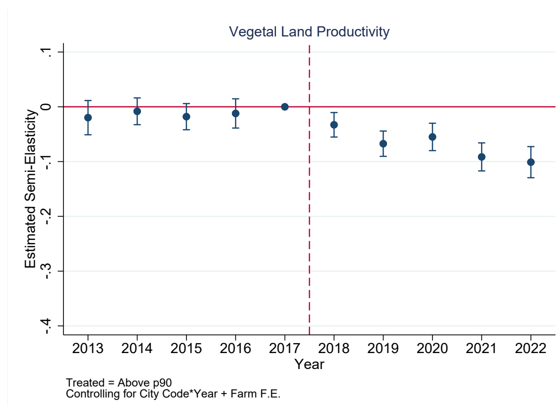
[4] It could be argued that, since the law was enacted in France as early as 2016, farms might have foreseen the regulation and adapted their practices accordingly. However, the lack of pre-trends alleviates this concern, as does the fact that sugar beet remained the most financially rewarding major crop in 2016 (Figure 3a). This issue is explored in greater detail in the next paragraph.

-0.05 after two years and -0.06 after five years. Interestingly, the magnitude of the effect is very similar for total production and land productivity, suggesting that it is primarily the numerator of productivity (total production) that is impacted by the ban, rather than the denominator (total land). Indeed, one might have expected that the sharp decline in revenue would lead farms to downsize after a few years.

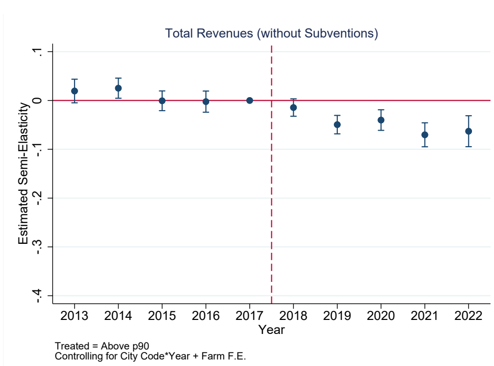
In reality, the opposite effect is observed. Figure 4d shows that total cultivated land increases more for farms that are more exposed to the regulation. However, this growth remains modest, with a semi-elasticity of +0.02 after five years, which is insufficient to offset the decline in production. Furthermore, the fact that exposed farms continue to expand after the ban reinforces the causal interpretation of the results. In fact, one might have argued that these farms were simultaneously experiencing a negative shock, such as the abolition of production quotas in 2017, which could have biased the estimated effects of the ban. However, their expansion instead suggests that the regulatory shock is not correlated with a broader negative shock affecting their entire production structure, as they continue to increase their cultivated area.



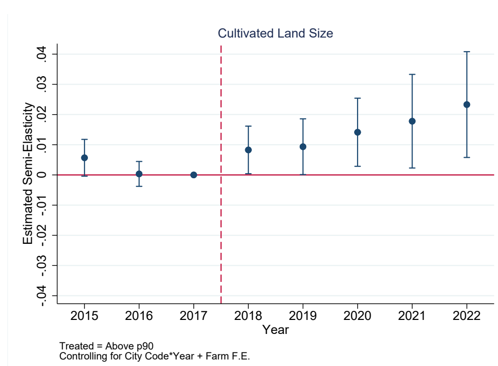
(a) Land productivity



(b) Crop land productivity



(c) Total Revenues (excluding subsidies)



(d) Total Cultivated Land

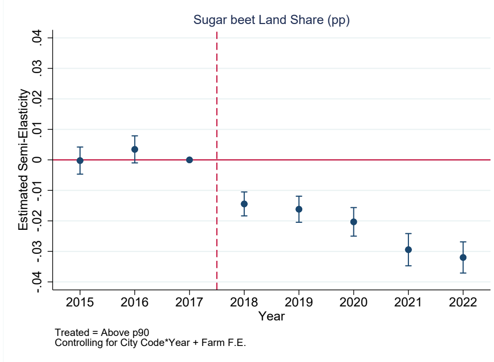
Figure 4. Effect of the European Neonicotinoid Ban on Farm Productivity

Production function and inputs. Figure 5 presents the effects of the regulation on the evolution of the production function. The results indicate a significant shift in the production function of farms affected by the ban, which is consistent with the idea that the regulation forces farm owners to reorganize their production factors in the short run. This disruption leads them to make suboptimal choices regarding crop selection and investments, ultimately explaining the negative effect on productivity observed in the previous section.

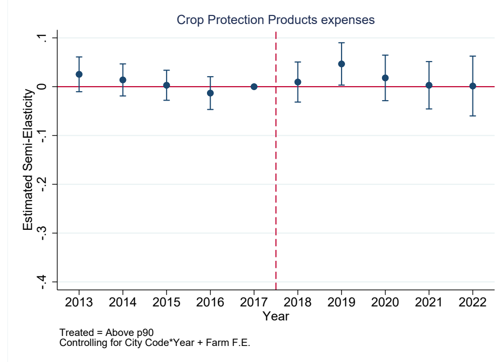
Figure 5a highlights a negative effect of the ban on the land share allocated to sugar beet cultivation. This result suggests that heavily affected farms must immediately adjust their crop allocation starting from the year of the ban. One could argue that, given the law was passed in France as early as 2016, farms may have anticipated the regulation and adjusted their behavior in advance. However, the absence of pre-trends in the land share allocated to sugar beet cultivation between 2015 and 2017 is reassuring in addressing this concern, as is the fact that sugar beet remained the most profitable major crop in 2016 (Figure 3a).

Figure 5b examines the response of expenses on crop protection products and shows that farms more severely impacted by the regulation initially increase their spending on crop protection products in the year following the ban. However, the difference quickly becomes indistinguishable in subsequent years. Additionally, standard errors are large. This finding suggests that, in order to compensate for the ban of the most effective plant protection product, exposed farms increase their use of alternative chemical inputs in the short term, while they gradually reallocate their production resources across different crops.

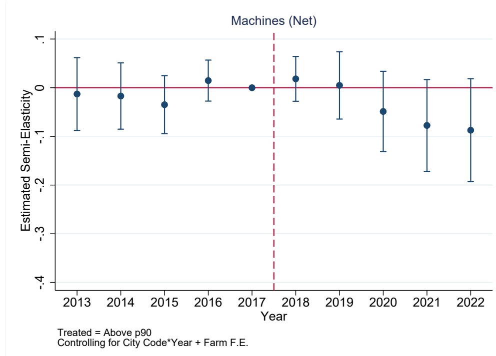
Finally, Figure 5c shows that the net stock of agricultural machinery (e.g., tractors, harvesters) declines more sharply among more exposed farms in the medium run, with no evidence of pre-trends. The difference between the two groups is negligible in the first two years following the pesticide ban but then widens, with a semi-elasticity reaching -0.1 after five years. The estimates for this variable are somewhat noisy, reflecting considerable heterogeneity between farms in both groups. However, the magnitude of the point estimate suggests that the pesticide ban leads to a significant reduction in investment in machinery and equipment, which in turn results in less efficient capital-intensive production factors.



(a) Sugar beet land share



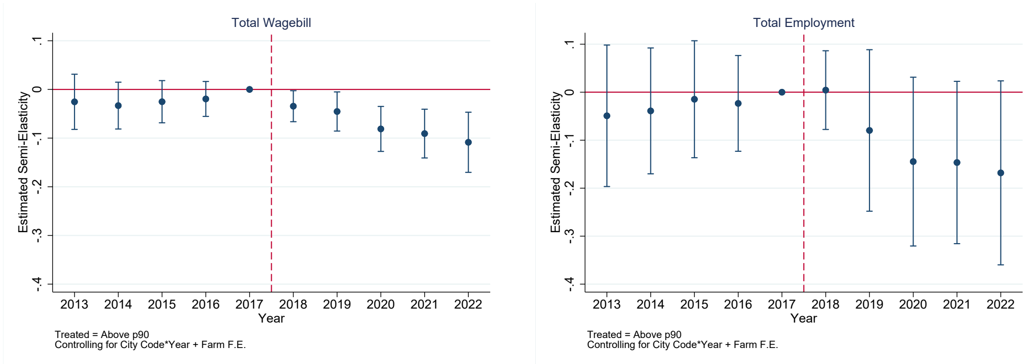
(b) Expenses on crop protection products



(c) Net Machinery Stock

Figure 5. Effect of the European Neonicotinoid Ban on Farm Production Function

Employment and Earnings. Figure 6 presents the estimated effects of the neonicotinoid ban on farm labor demand and earnings. The decline in productivity and the reallocation of inputs and production methods, as described in the previous sections, may lead to a reduction in labor demand for highly affected farms, particularly if they are forced to downsize their production. Figure 6a focuses on total wage bill and shows a decrease following the ban, with a semi-elasticity of -0.04 in the year of the ban, reaching -0.1 after five years. This result indicates that the regulation has a negative impact on farm labor earnings. Finally, Figure 6b shows that this effect is primarily driven by a decline in labor demand, with a stronger reduction in total farm employment for highly exposed farms.



(a) Total Wagebill

(b) Total Employment

Figure 6. Effect of the European Neonicotinoid Ban on Employment and Earnings

3.5 Robustness

I now conduct several robustness checks to assess the overall land productivity response observed at the farm level.

First, I analyze the results using alternative thresholds to define exposure to the neonicotinoid ban, based on the land share of sugar beet cultivation three years before the ban (in 2015). Appendix Figure A1 presents the results using different thresholds to define the investment event (p75, p95, and p99). The semi-elasticities obtained for p75 and p95 are comparable to those in the main specification (p90), while the p99 threshold leads to slightly more negative semi-elasticities, around -0.13 five years after the ban.

Second, Appendix Figure A2 shows that the results remain stable when using alternative specifications with different sets of interacted local fixed effects, i.e. zipcode-by-year fixed effects or county-by-year fixed effects. In both cases, there is no evidence of pre-trends, and the point estimates remain nearly unchanged when considering zipcode-by-year fixed effects. When using county-by-year fixed effects, the estimates become slightly more negative. Since zipcodes and counties are less granular than cities, the estimates are even more precisely estimated than in the main specification. Under the county-by-year fixed effects specification, the effect ranges between -0.11 and -0.09 five years after the ban.

Third, Appendix Figure A3 shows that the estimates remain consistent when balancing the panel over different time horizons.

Finally, one might argue that restricting the sample to farms that were already cultivating sugar beet in 2015 – in both the treatment and control groups – could overestimate the negative effect of the neonicotinoid ban. Indeed, if sugar beet production requires specific capital investments, incumbent sugar beet producers within the control group may face higher adjustment costs than farms that never cultivated sugar beet and were therefore not affected by the ban at all. To address this concern, Appendix Figure A4 extends the analysis to include all farms, regardless of whether they cultivated sugar beet three years before the ban, before defining the treatment group. The estimated effects remain of the same magnitude when defining exposure to the ban using either the p95 threshold or the p99 threshold, corresponding to 16% and 24% of land allocated to *ex ante* sugar beet cultivation, respectively.

Ultimately, this case study shows that regulation appears to have a swift and negative impact on the productivity of exposed farms. However, a key characteristic of this ban is that it left economic agents without any viable substitute to sustain productivity, which is likely to have influenced the outcome. In the next section, we examine the general case through the lens of this insight.

4 Effect of Pesticide Bans on Farm-level Productivity: General Case

In this section, I extend the case study of the neonicotinoid ban to a broader analysis of regulations on the adoption and use of plant protection products. I first present the empirical approach and descriptive statistics for the general case in Section 4.1, followed by the main results on the effect of pesticide bans on productivity in Section 4.2. Finally, I examine the counterbalancing role of mitigation policies in offsetting the negative effects of pesticide bans on farm-level productivity in Section 4.3.

4.1 Empirical approach

Section 3 focused on the ban of a single pesticide family – neonicotinoids – on a single crop – sugar beet. This case study specifically focused on a product with no available substitutes on the market, which, intuitively, may have an impact on the estimated effects. This section considers the general case and raises the following question: what are the general effects of pesticide bans on agricultural productivity? To ensure a homogeneous sample of farms, the analysis is restricted to major field crops, excluding horticulture, viticulture, and greenhouse farming. This restriction allows for the study of a farm dataset with relatively uniform land use, covering the majority of the French territory.

The main challenge is the absence of a comprehensive database in France tracking farm-level use of plant protection products across crops. In the case of neonicotinoid use on sugar beet, I was able to analyze the entire farm population, as nearly all producers relied on these products, making the assumption of widespread neonicotinoid use valid. To more generally document the effect of pesticide bans on farm productivity, I rely on the Field Crop Cultural Practices Survey, which covered approximately 20,000 land parcels in 2017. This dataset provides detailed information on the crop cultivated, all crop protection products used, and the identifier of the farm managing the field. To identify exposure to pesticide bans for each farm, I match these data with the Graphical Land Parcel Register, which covers all French land parcels receiving European subsidies from the Common Agricultural Policy (CAP). This dataset provides information on parcel size, the crop grown, and the identifier of the farm cultivating the parcel. This matching process allows me to focus on a sample of farms engaged in *intensive cultivation* of the surveyed crop two years before the survey (in 2015). Specifically, I define intensive cultivation as meeting two conditions. First, the land share of the surveyed crop in the given field must exceed the national average share allocated to this crop by other French farms, conditional on these farms cultivating the crop. Second, the crop must represent at least 10% of the farm's total cultivated land. These conditions ensure that the surveyed crop has sufficient economic weight to make the information provided in the survey – the use of a specific plant protection product – economically relevant for the focal farm. The first condition ensures that the surveyed farm is highly intensive in the production of the target crop, while the second condition excludes cases where the surveyed crop represents only a minor share of the total land use among all French farms cultivating it, which could otherwise make the first condition insufficient to establish economic relevance. This approach relies on the underlying assumption that a farm growing a given crop applies the same plant protection products across all its fields for that crop.

Using the E-Phy database, which provides detailed information on the market authorization of plant protection products, I identify farms in the sample exposed to a pesticide ban if they used, in 2017, a product whose use on the surveyed crop was prohibited between 2017 and 2018. This approach results in a sample of 863 farms exposed to a pesticide ban on a crop that is economically relevant to them, and 2,304 farms that were not exposed to such a ban on any economically relevant crop. The samples of exposed and non-exposed farms are described in Table 2. Exposed farms are larger, with an average cultivated land of 170 ha, compared to 153 ha for non-exposed farms. They also have higher total production and crop production, suggesting that they are more reliant on crop production. Exposed farms receive slightly higher subsidies and have a larger net stock of machines, indicating greater capital intensity. In terms of productivity, land productivity is slightly higher for exposed farms. Employment levels are also marginally higher in exposed farms, with an average of 1.18 full-time equivalent (FTE) workers, compared to 1.11 FTE in non-exposed farms. Finally, although the sample is smaller and, *a priori*, quite different from the one analyzed in Section 3 and the case of the neonicotinoid ban, the characteristics of farms exposed and not exposed are actually similar between the case study and the general case.

	Exposed	Non-exposed
Cultivated land (ha)	170	153
Production (k€)	332	289
Crop production (k€)	241	167
Subsidies (k€)	52	46
Net stock of machines (k€)	168	146
Land productivity (k€ per ha)	2.19	2.04
Employment (FTE)	1.18	1.11
Number of farms	863	2,304

Table 2. Characteristics of Farms Exposed and Not Exposed to a Pesticide Ban

Notes: This table presents descriptive statistics for the two groups in 2015, two years before the year of the studied pesticide ban.

I adopt a difference-in-differences empirical approach similar to that used in Section 3.3. Indexing farms by i and years by t, the difference-in-differences is specified as

$$log\, Y_{it} = \alpha + \sum_{t=y_0}^{y_n} \delta_t\, ExposedBan_{i,t-2016} + \mu_i + \lambda_{ct} + \epsilon_{it}$$

with Y_{it} the outcome of interest, the treatment dummy defined based on the exposure to the ban of a plant protection product used for an economically important crop for the farm $ExposedBan_{i,t-2016}$. The specification includes farm fixed effects μ_i and county-by-year fixed effects λ_{ct}. The lead-lag coefficient δ_t captures the cumulative dynamic response of the outcome Y_{it} in year t, relative to the base year 2016, which marks the last year before the regulation. In particular, I examine the effects on land productivity at the farm level.

A causal interpretation of the estimates requires the identification condition

$$E[ExposedBan_{i,t-2016} \cdot \epsilon_{it} | \mu_i, \lambda_{ct}] = 0 \quad \forall t.$$

If this holds, one should expect the leads (i.e., $\hat{\delta}_t$ with $t < 2016$) to be statistically insignificant and the point estimates to be close to zero. Although the lack of pre-trends is a necessary condition, it may not be sufficient to guarantee the validity of the identification condition. Indeed, simultaneous demand and supply shocks may coincide with the implementation of a pesticide ban, potentially confounding its effects.

4.2 Results

Average effect on productivity. Figure 7 documents the effect on productivity. I find that land productivity declines for farms exposed to a crop protection product ban. The semi-elasticity of farm land productivity with respect to the ban is statistically significant after five years and reaches -0.03, with no evidence of pre-trends. This implies that the land productivity of exposed farms decreased by 3% more than that of unexposed farms after five years. The standard errors are relatively large compared to the point estimates, making the coefficients only marginally significant at the 95% confidence interval. To my knowledge, this result is novel within the economic literature, as it is the first time that a negative effect of a crop protection product ban on farm productivity is highlighted using a systematic approach and a large sample.

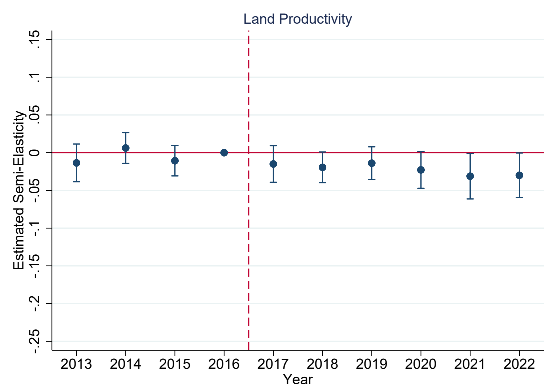
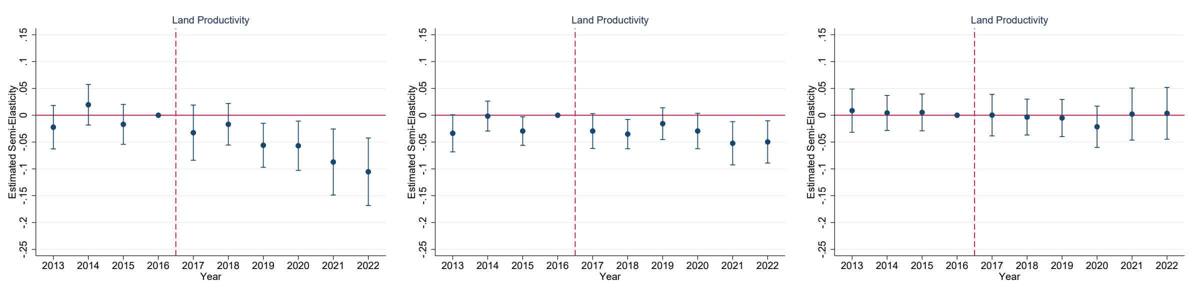


Figure 7. Effects of Pesticide Bans on Farm-Level Productivity

Heterogeneity by degree of substitution. For each plant protection product, the E-Phy database provides highly detailed information on its uses, covering three dimensions: the type of crop on which the product can be applied (e.g. wheat, barley), the target of the product (e.g., insects, fungi), and the application method (e.g., directly applied to seeds, used as a spray). Using this data, I construct a detailed annual database that records the number of crop protection products available for each specific use. This allows me to determine, for each crop protection product used on a given crop, the number of potential substitutes available on the market. I use this information to document the heterogeneity of effects based on the number of substitutes available for the banned crop protection product use, keeping the same control group of farms not exposed to the ban but differentiating the treatment group as follows: (i) Farms where all banned plant protection products have no substitutes; (ii) Farms where all banned plant protection products have between 1 and the median number of substitutes (52); (iii) Farms where all banned plant protection products have more than the median number of substitutes.

Figure 8 presents the difference-in-differences estimation for each of the three treated groups, which include 139, 387, and 266 farms, respectively. In all three cases, there is no evidence of pre-trends. Figure 8a presents the results for farms exposed to the ban where the banned plant protection products had no substitutes. For these farms, land productivity declines more sharply from the second year after the ban, and the effect increases in magnitude over time, reaching a semi-elasticity of -0.1 five years after the ban. This pattern and order of magnitude are comparable to those observed in the case of the neonicotinoid ban on sugar beet cultivation, as shown in Figure 4a. This similarity is expected, as the neonicotinoid ban represents a typical case of prohibiting a crop protection product with no available substitutes. Figure 8b presents the results for farms exposed to the ban with a positive number of potential substitutes, but below the median. In this case, a negative effect on productivity is observed again, but with a semi-elasticity of -0.05 five years after the ban, which is smaller in magnitude than in the case where no substitutes are available. Finally, Figure 8c considers the case of farms exposed to the ban with a number of potential substitutes above the median. Here, a well-estimated null effect is observed.

These results indicate that the slightly negative average effect presented in Figure 7 actually conceals substantial heterogeneity depending on the degree of substitutability of the banned products. While this finding may seem intuitive, it provides a basis for policy recommendations aimed at designing regulations that minimize productivity losses in agriculture. Specifically, for comparable environmental and biodiversity risks, the degree of substitutability of crop protection products should be considered to mitigate the adverse effects of bans.



(a) No substitute available (b) Between 1 and 52 substitutes (c) More than 53 substitutes

Figure 8. Effects of Pesticide Bans on Farm-Level Land Productivity - By Number of Substitutes Available

Robustness. I now perform several robustness checks to evaluate the farm-level land productivity response based on the degree of substitution.

First, Appendix Figure A5 shows that the results regarding the average effect on land productivity remain consistent even if I relax the condition that the surveyed crop must represent at least 10% of the farm's total cultivated land.

Second, Appendix Figure A6 presents the results using an alternative definition of land productivity, where the denominator is the total cultivated land declared under the Common Agricultural Policy (CAP) instead of the total land reported in balance-sheet data. This alternative definition would actually be my preferred measure, but the variable is only available from 2015 onward, preventing an extensive pre-trend analysis. The estimates, however, remain very similar to those obtained in the baseline specification.

Third, Appendix Figure A7 presents the results using crop production revenues as the numerator instead of total revenues (excluding subsidies). Again, the results follow a similar pattern, with slightly more negative effects for farms without available substitutes or with a limited number of substitutes. In contrast, we observe a slightly positive but noisy effect for farms with numerous substitution possibilities.

4.3 Mitigation Practices and the Reduction of Adverse Effects on Productivity

Agricultural production is inherently exposed to multiple sources of uncertainty, including climate variability, soil degradation, pest outbreaks, and evolving regulatory frameworks. When farmers encounter abrupt changes, the associated adaptation costs can be substantial, encompassing yield losses, increased labor demands, investments in alternative methods, and learning costs for new practices. Theoretically, mitigation practices could play a crucial role in reducing these adaptation costs and enhancing resilience in response to such shocks. In the specific context of pesticide bans, mitigation measures can help limit productivity losses and maintain economic viability. For instance, crop rotation and biological pest control can reduce pest pressure naturally, thereby decreasing dependency on chemical solutions. Similarly, precision spraying technologies and resistant crop varieties enable farmers to optimize input use while complying with regulatory constraints. Mechanical weeding, through more frequent interventions, can also serve as an effective alternative pest control strategy. This section aims to examine the extent to which pre-existing mitigation practices implemented by farms help mitigate –or even offset – the effects of the shock.

We can examine this question in detail because the Field Crop Cultural Practices Survey includes a specific section on the implementation of mitigation policies aimed at reducing the use of plant protection products. This section provides information on the types of techniques employed and the reasons for adopting these mitigation practices. The survey identifies three possible motivations: (i) Health reasons, aimed at reducing risks for users of crop protection products or for consumers; (ii) Environmental reasons, focused on protecting the environment and biodiversity (e.g., preventing water pollution); and (iii) Economic reasons, related to reducing production costs by minimizing the use of expensive crop protection products. Additionally, the questionnaire asks respondents to indicate the primary reason for adopting mitigation practices.

We have previously observed that land productivity declines for farms exposed to a crop protection product ban. Therefore, we define the implementation of mitigation practices to counteract productivity loss based on two conditions. First, the primary motivation for reducing dependence on crop protection products is economic. Second, at least one of the other two motivations (health or environmental concerns) is explicitly mentioned as not relevant for this decision. This second condition ensures that we do not include farms equally motivated by all three factors but instead focus specifically on those pursuing an economic objective. Compared to the specification presented in Section 4.1, the control group remains unchanged, while the treatment group is divided into two subgroups: farms implementing mitigation policies primarily for economic reasons and those either not adopting such policies or doing so primarily for non-economic reasons. A separate coefficient is estimated for each subgroup. More precisely, Indexing farms by i and years by t, the specification is as follows:

$$log\, Y_{it} = \alpha + \sum_{t=y_0}^{y_n} \delta_{M,t}\; Mitigation_{i,t-2016} + \sum_{t=y_0}^{y_n} \delta_{NM,t}\; NoMitigation_{i,t-2016} + \mu_i + \lambda_{ct} + \epsilon_{it}$$

with Y_{it} the outcome of interest, a first dummy variable indicating farms exposed to a pesticide ban in 2017 or 2018 that proactively implemented mitigation practices to limit its impact on productivity $Mitigation_{i,t-2016}$, a second dummy variable indicating farms exposed to a pesticide ban in 2017 or 2018 that did not implement mitigation practices in advance $NoMitigation_{i,t-2016}$. As before, the specification includes farm fixed effects μ_i and county-by-year fixed effects λ_{ct}. The lead-lag coefficients $\delta_{M,t}$ and $\delta_{NM,t}$ capture the cumulative dynamic response of the outcome Y_{it} in year t for mitigated and non-mitigated farms, respectively, relative to the last year before the regulation. The advantage of running a single regression is that both groups share the same fixed effects, allowing for a direct comparison of the point estimates. For the baseline specification considering all pesticide bans, 118 farms implemented preventive mitigation practices, while 745 farms did not.

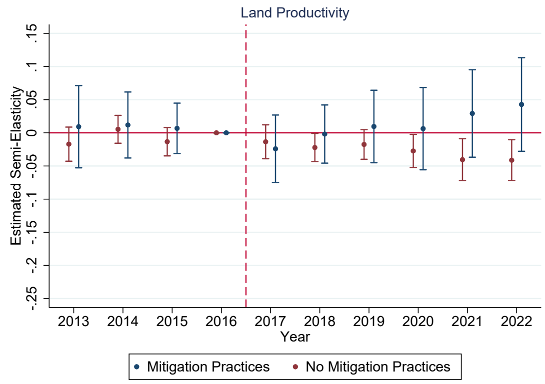


Figure 9. mitigation practices et atténuaiton des effects of Pesticide Bans

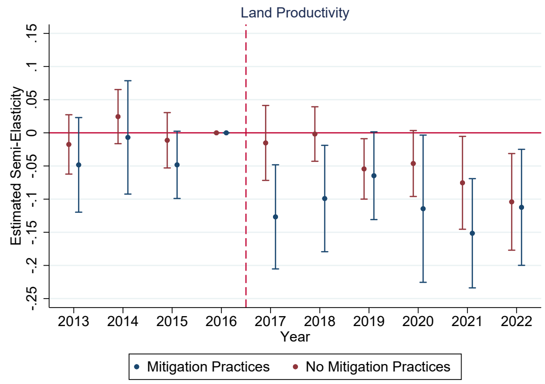
Figure 9 presents the results on productivity. Both subgroups show no evidence of pre-trends. Farms exposed to a pesticide ban without having proactively implemented mitigation practices experience a decline in productivity, whereas those that adopted mitigation measures in advance show no significant effect—or a slightly positive one, if any. However, the standard errors overlap, making it impossible to confirm with certainty that the effects differ significantly by mitigation practices at the 95% confidence level.

To further investigate the extent to which the implementation of mitigation practices helps limit the adverse effects on productivity, I examine the heterogeneity of the effect based on the degree of substitution of the banned crop protection product. Figure 10 presents the estimates for each of the three cases: (i) No substitute available; (ii) Between 1 and the median number of substitutes (52); (iii) More than the median number of substitutes.

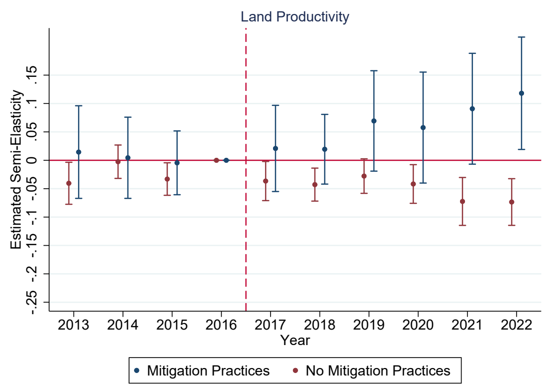
Figure 10a highlights that when no substitute is available for the banned crop protection product, mitigation practices do not reduce the adverse effects on productivity. The decline in productivity is indistinguishable between the two groups, regardless of whether mitigation practices were implemented to limit economic losses.
Figure 10b shows that when substitutes are available on the market but in limited quantity (below the median), preventive mitigation policies fully demonstrate their potential. While the group of farms exposed to the ban without implementing mitigation policies (in red) experiences a 7% decline in productivity relative to the control group five years after the regulation, farms that adopted proactive mitigation strategies (in blue) instead see their land productivity increase by 11% compared to the control group over the same period. The standard errors of the point estimates for the two subgroups do not overlap, confirming that the effects are statistically different at the 95% confidence level.

Finally, Figure 10c shows that when a large number of crop protection product substitutes are available – i.e., when the number of potential substitutes is above the median – the ban has no effect on land productivity, regardless of whether farms implemented mitigation policies or not.

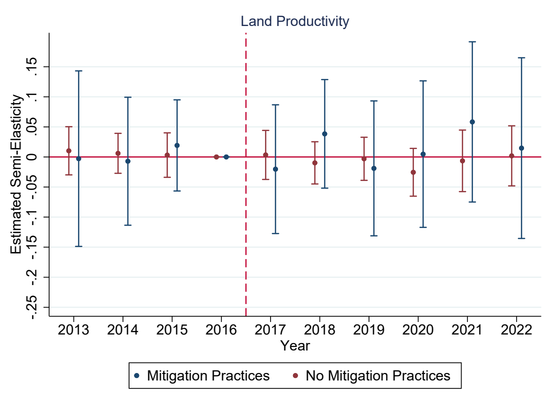
Overall, these results highlight that mitigation policies can be effective in counteracting the adverse effects of regulation on productivity, but only under the essential condition that substitute products are available. When this condition is met, mitigation policies can not only offset the negative impact but may even lead to positive effects following the regulation. This finding conveys a nuanced policy message: regulation can have beneficial effects on agricultural productivity provided that (i) it does not target irreplaceable products and (ii) farms have proactively implemented mitigation practices to facilitate the transition. However, when regulation targets crop protection products with no available substitutes, mitigation practices become entirely ineffective, and the ban systematically results in productivity losses for the agricultural sector.



(a) No substitute available



(b) Between 1 and 52 substitutes



(c) More than 53 substitutes

Figure 10. Effects of Pesticide Bans on Farm-Level Land Productivity - By Number of Substitutes Available

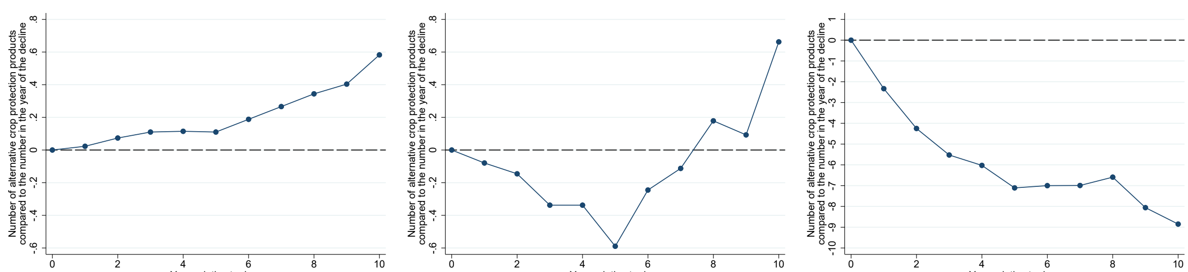
5 Effect of Pesticide Bans on Innovation

Section 4 highlighted that pesticide bans have a short-term negative effect on farm productivity under two conditions: (i) when no substitute products are available and (ii) when farms do not implement preventive mitigation practices in situations where the number of substitute products is limited.

Following the intuition of Schumpeterian growth models and their predictions on the relationship between competition and innovation (Aghion et al., 2005), one might expect an opposite effect on innovation. Specifically, banning a product with no available substitute for an agricultural use creates strong incentives for the agrochemical sector to develop alternatives. Indeed, firms that successfully innovate in this space could gain a temporary monopoly or, at the very least, operate in a market with limited competition for several years, leading to higher profits. From a Schumpeterian perspective, it is precisely the prospect of these high rents that can drive firms to develop new substitutes that are both effective and environmentally sustainable, ensuring approval from regulatory authorities.

Given the available data, tracking the adoption of replacement products or newly developed alternatives by farms affected by a pesticide ban is challenging. The Field Crop Cultural Practices Survey randomly selects a sample of fields in each wave, making it impossible to follow individual farms over time. as a result, I am unable to analyze whether the ban of a crop protection product in the 2000s led to the adoption of a substitute several years later. However, the E-Phy database provides descriptive insights that help document this intuition. To achieve this, I consider all usage types recorded in the database, which cover three dimensions: the type of crop on which the product can be applied, the target of the product (e.g., insects, fungi), and the application method. For each usage type, I count the number of available crop protection products each year. Then, over the period 1990-2022, I identify the year in which the relative number of banned products was the most significant, indicating a regulatory shock for this use. At that point, the number of alternative products ranges between 0 and 170, with a highly skewed distribution. I then classify these cases into three categories: (i) Usages for which the number of available products was below the median (which is 2) at the time of the decline; (ii) Usages where this number is above the median but below the 75th percentile (set at 7) at the time of the decline; (iii) Usages where the number of available products exceeds p75 at the time of the decline.

Figure 11 presents the evolution of the average number of crop protection products available on the market for a given usage, with year 0 representing the year following the regulatory shock, when the relative decline in the number of authorized products was the most significant. Figure 11a shows that when the number of available products the year after the regulatory shock is zero or close to zero, agrochemical companies immediately innovate by developing substitutes, leading to an average increase of 0.6 additional products per usage after 10 years. Figure 11b indicates that when the number of available products the year after the regulatory shock ranges between 2 and 7, agrochemical companies do not innovate in the very short term due to lack of incentives. As a result, the number of products on the market continues to decline for five years, reaching an average decrease of 0.6 products per usage. Then, the incentive to develop substitutes begins to emerge, and the number of products for this usage recovers, eventually surpassing the initial level, reaching 0.6 additional products per usage after 10 years. Finally, Figure 11c examines the case where the number of available products the year after the regulatory shock exceeds 7. In this scenario, since a significant number of alternative products remain available, market competition remains high, reducing incentives for innovation. Consequently, subsequent regulatory measures lead to a continued decline in the number of available products for this usage, resulting in an average decrease of 9 products per usage 10 years after the regulatory shock.



(a) Minimum number of products below median

(b) Minimum number of products between median and p75

(c) Minimum number of products above p75

Figure 11. Effect of Pesticide Bans on Innovation

These descriptive insights suggest that the effect on innovation is the opposite of that on agricultural productivity, which may lead us to reconsider the policy recommendations presented in Section 4. Indeed, in light of this evidence, it may now be fully justified to ban pesticides with few or no substitutes in order to stimulate the development of new, more environmentally friendly molecules for these uses. However, such a strategy should be accompanied by active support policies for farms to help them absorb the transition shock, rather than relying on the effects of proactive mitigation policies in this case.

A natural next step in this analysis would be to leverage a patent database to track how patent filings for active molecules targeting specific uses respond to these regulatory incentives. It would then be valuable to conduct a welfare analysis, weighing the short-term adverse effects on productivity against the medium-term positive effects on innovation, in order to design an optimal policy framework.

6 Conclusion

In this paper, I investigate a core economic question: the conditions under which regulation fosters or impedes innovation and the ways in which firms adjust in terms of productivity and technology adoption. On one hand, regulation can impose constraints on firms and producers, potentially slowing productivity growth. On the other hand, regulation can create economic incentives for innovation by opening new market opportunities, leading to positive long-term effects on sectoral productivity.

I investigate this question in the context of French agriculture. To do so, I construct a novel and unique farm-level dataset, leveraging the richness of recently available annual administrative records. These comprehensive datasets mark a turning point in agricultural research, offering an unprecedented opportunity to study these issues at a granular level and identify the microeconomic mechanisms at play.

I begin by analyzing a typical case – the 2018 European Neonicotinoid Ban – using a difference-in-differences approach. I show that when regulation removes an essential input without viable alternatives, it leads to an immediate and sharp productivity decline, which intensifies over time. I then extend the analysis to pesticide bans more broadly, taking advantage of the generality of the data. The findings are consistent with the case study: When no substitutes are available, abrupt regulation results in a significant productivity decline, which mitigation policies cannot offset; When a limited number of substitutes exist, the impact of regulation depends on farm-level adaptation strategies. If farms fail to implement proactive mitigation practices, the regulatory shock has a negative effect on productivity. However, when farms adopt mitigation practices in advance, the effect of regulation is positive, highlighting the role of strategic adaptation in mitigating economic costs.

While these findings suggest that regulation should be implemented only when viable substitutes exist for the regulated inputs, I also provide preliminary and suggestive evidence on its effects on innovation, offering a different perspective. When a regulatory ban targets an input with no viable substitute, it creates strong incentives for agrochemical firms to develop alternative solutions, leading to the emergence of new products that serve the same purpose while complying with the new regulation. This calls for even more nuanced policy recommendations – suggesting that regulation can be strategically designed to stimulate innovation by targeting inputs with no existing substitutes. However, such policies should be accompanied by active support measures for farms to help them absorb the transition shock, rather than relying solely on encouraging mitigation practices.

These findings do not account for the adverse effects of crop protection products on the environment and biodiversity, which, in turn, can indirectly impact farm productivity – for instance, through climate change or the decline of pollinators. The objective of this paper is not to downplay these crucial externalities affecting global welfare but rather to document the impact of regulation on productivity and innovation.

That said, these findings do not account for the adverse effects of crop protection products on the environment and biodiversity, qui affecte indirectly en retour la productivité des fermes, via le changement climatique ou le manque de pollinisateur par exemple. The objective of this paper is not to downplay these crucial externalities affecting global welfare but rather to document the impact of regulation on productivity and innovation.

A natural extension of these results would be to conduct a welfare analysis, balancing (i) the short-term negative effects of regulation on productivity with (ii) its long-term positive effects on innovation, driven by the economic incentives that regulation creates. Such an approach would provide a comprehensive assessment of the overall impact on well-being.

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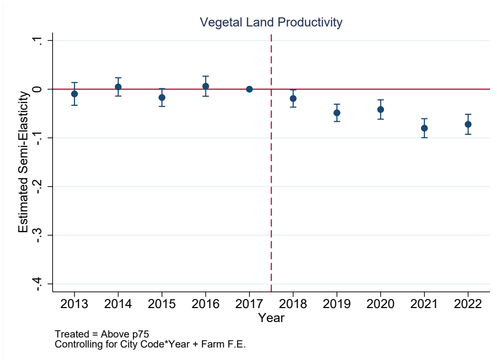
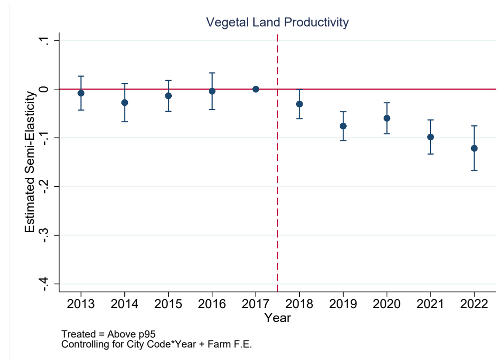
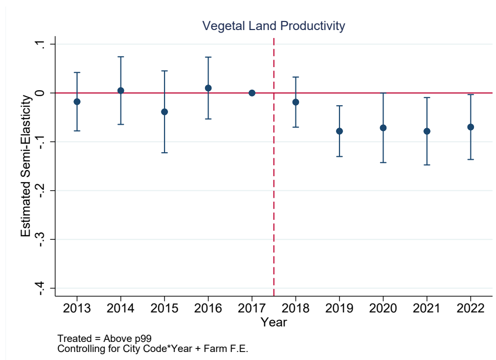
A Appendix Tables and Figures



(a) 75^{th} percentile of sugar beet land share

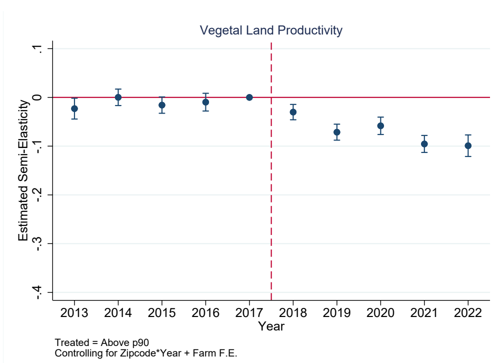


(b) 95^{th} percentile of sugar beet land share

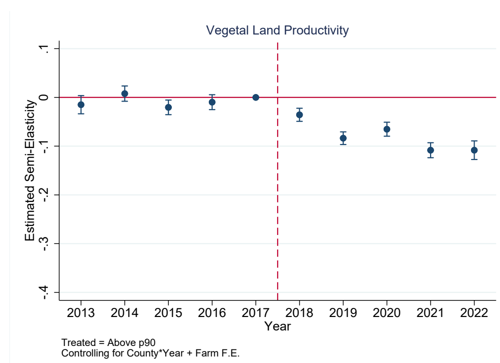


(c) 99^{th} percentile of sugar beet land share

Appendix Figure A1. Effect of the European Neonicotinoid Ban on Farm Productivity with Alternative Thresholds of exposure

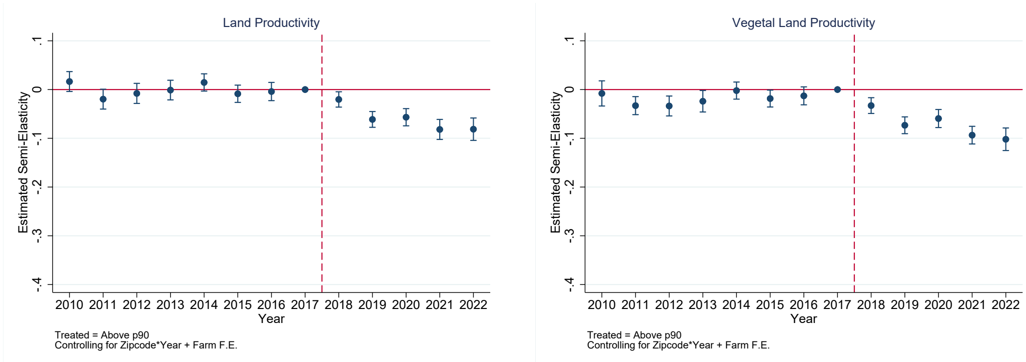


(a) With Zipcode-by-year Fixed Effects



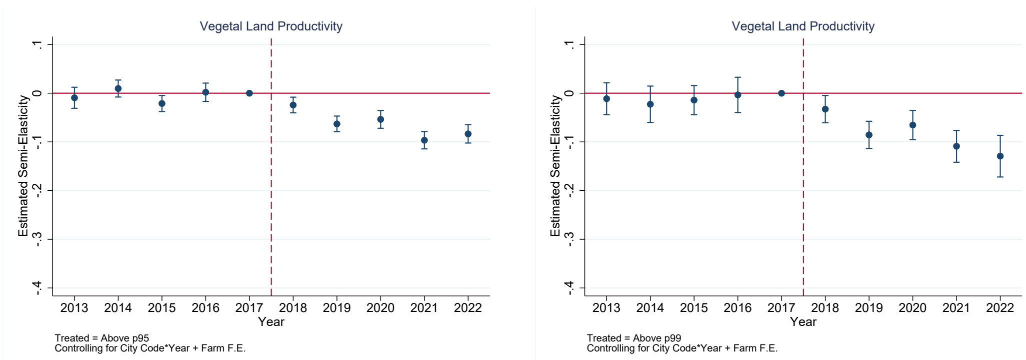
(b) With County-by-year Fixed Effects

Appendix Figure A2. Effect of the European Neonicotinoid Ban on Farm Productivity with Alternative Fixed Effects



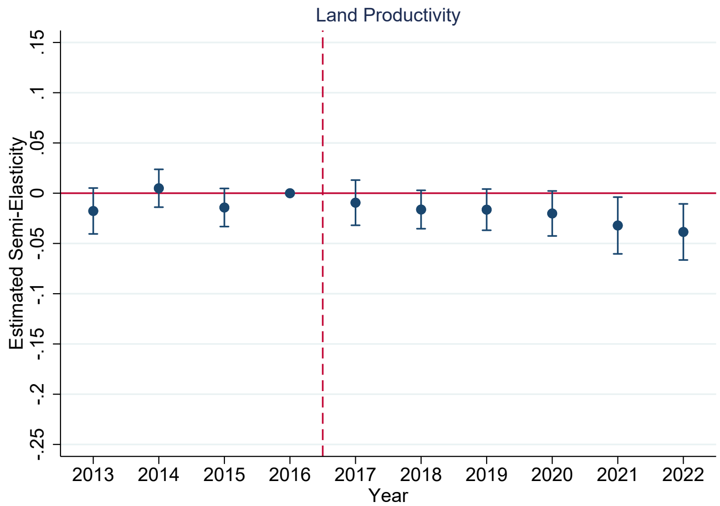
(a) Land productivity (b) Crop land productivity

Appendix Figure A3. Effect of the European Neonicotinoid Ban on Farm Productivity across Balanced Samples

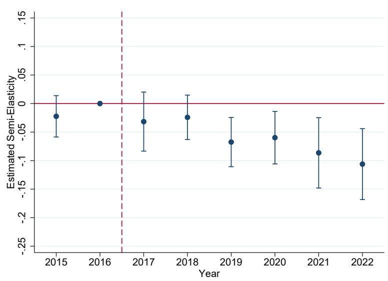


(a) 95^{th} percentile of sugar beet land share (b) 99^{th} percentile of sugar beet land share

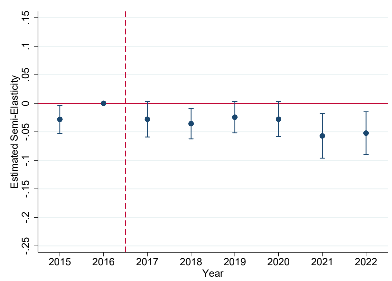
Appendix Figure A4. Effect of the European Neonicotinoid Ban on Farm Land Productivity Beyond Ex-Ante Sugar Beet Producers



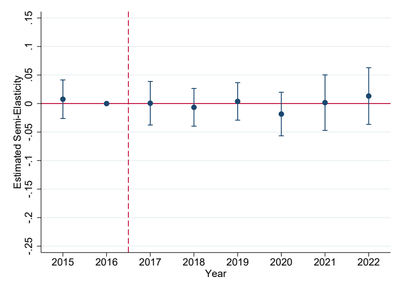
Appendix Figure A5. Effects of Pesticide Bans on Farm-Level Land Productivity with Less Stringent Sample Selection Criteria



(a) No substitute available

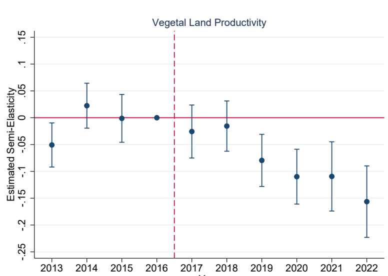


(b) Between 1 and 52 substitutes

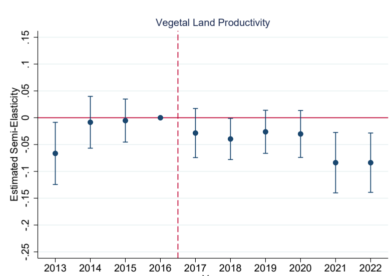


(c) More than 53 substitutes

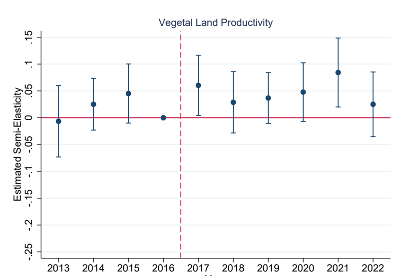
Appendix Figure A6. Effects of Pesticide Bans on an Alternative Measure of Farm-Level Land Productivity - By Number of Substitutes Available



(a) No substitute available



(b) Between 1 and 52 substitutes



(c) More than 53 substitutes

Appendix Figure A7. Effects of Pesticide Bans on Farm-Level Crop Land Productivity - By Number of Substitutes Available