Unintended Environmental Policies:

The Impact of European Agricultural Subsidies on Pollution*

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Abstract: *Government intervention in polluting markets can have unintended environmental consequences. This paper studies how the European Union's Common Agricultural Policy (CAP), one of the world's largest subsidy programs, affects pollution from French grain farms, a market ridden with environmental externalities. Using the 1992 MacSharry CAP reform as a natural experiment to study the role of subsidy designs and levels, a shift-share design combining farm-level administrative data with satellite imagery reveals that a one-standard-deviation increase in reform exposure reduced farm profit by 31%, chemical use by 24% and water pollution by 10%, while accelerating the exit of smaller farms. To unpack the role of subsidies, I estimate a dynamic model of heterogeneous, multiproduct farms. Its estimation reveals a key tradeoff: more efficient farms pollute on average more. The impact of subsidies is then mediated by three channels: changes in farms' input use, and crop mixes (intensive margins), and market selection (extensive margin). Counterfactuals show that while a Pigouvian tax produces the largest welfare gains and is the most efficient policy to reduce chemical use, subsidies are capable of achieving environmental gains while protecting farm profits. My results highlight the tension between economic efficiency, environmental quality, and political constraints in the design of large-scale industrial policy.*

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1 Introduction

Pre-existing regulation and market structure have important implications for the design of environmental policies. The optimal tax on an externality, for instance, may diverge from the Pigouvian rate when it interacts with other taxes or market power (Oates (1991); Bovenberg and Goulder (1996); Preonas (2023)). This paper highlights a related but distinct channel of policy interaction: the unintended environmental consequences of policies that have no explicit environmental objective (Shapiro (2021)).

These unintended consequences are especially salient for distortive industrial policies in polluting sectors. Agricultural subsidies are a primary example. Globally, these policies transfer nearly $750 billion to producers annually (FAO (2024)), significantly distorting production (Adamopoulos and Restuccia (2014)), in a sector causing widespread air and water pollution which is loosely regulated and has proven hard to abate (Bauer et al. (2016); Tschofen et al. (2019)). In spite of their scale, the environmental externalities of these subsidies are not well understood.

This article investigates the environmental impact of the European Union's Common Agricultural Policy (CAP) on the pollution intensity of French grain production. The CAP is the largest EU industrial policy, accounting for 45% of all federal expenses since 1980, with annual spending comparable to the U.S. Farm Bill (Johnson et al. (2010)). Its environmental consequences are an active source of controversy (European Court of Auditors (2024)).

CAP subsidies can impact farm input and crop mixes—and through them individual fertilizer and pesticide use. They can also distort market selection by slowing the exit of less productive farms. The environmental impact of this second channel is determined by the relationship between farms' productivity and pollution intensity. If greater productivity is driven by higher resource efficiency, then the economically efficient allocation of production is also the most environmentally sustainable one (Qi et al. (2021); Ryan and Sudarshan (2021)). On the contrary, a trade-off may exist when high pollution intensity and low costs of production are complementary.

The paper proceeds in two steps. I first use the 1992 MacSharry reform as a natural experiment to provide reduced-form evidence of the subsidies' impact on chemical use, pollution, and market structure. These results then inform a dynamic model of the French grain market, which I use to evaluate the environmental sustainability and economic efficiency of counterfactual subsidy designs and chemical taxes, and to unpack the channels through which they operate. My focus on France allows me to rely on rich administrative data for the analysis, using both a representative yearly panel of producers with precise production and price data, as well as the farm-level French Census of Agriculture.

My analysis begins with the impact of the 1992-95 MacSharry Reform of the CAP, a significant step in the international homogenization of agricultural policy negotiated during the GATT Uruguay Round. The reform replaced grain price support, which was heterogeneous in levels across crops, with more homogeneous land subsidies that are still in place today. Because the reform impacted grain crops in different ways, its design gave rise to

variation in exposure across farms, depending on their pre-reform crop mixes. I use a shift-share design that leverages these pre-determined, farm-specific crop shares as instruments for exposure. Controlling for the endogenous determinants of crop choice, the strategy is similar to a difference-in-difference design where ex ante crop shares conditional heterogeneity drives identification (Goldsmith-Pinkham et al. (2020),Ager et al. (2024)). I find that a one-standard-deviation increase in farm reform exposure led to a 31% decrease in profits and a 24% decrease in chemical use. At the municipality level, this exposure accelerated consolidation, with a one standard deviation increase in average farm exposure decreasing farm population by one unit. It also increased the share of land allocated to cereals by 2%, shifting land away from the more reform impacted oil crops. Leveraging remote sensing data to measure algal blooms (Taylor and Heal (2023)), a direct consequence of fertilizer runoff (Rossi et al. (2023)), I finally find that this same increase in exposure, this time at the county level, led to a 10% decrease in observed water pollution.

The second part of the paper develops an empirical model of the market, which I use to decompose the channels through which different subsidies impact market structure and pollution, as well as to compare their welfare implications. The model builds on the dynamic single agent industry framework of Hopenhayn (1992), and applies it to an agricultural setting with multidimensional productivity types (Hayami and Ruttan (1971)), multiproduct farms in the spirit of Mayer et al. (2014) and capital accumulation as in Clementi and Palazzo (2016). The estimation follows in three steps. First, iso-elastic demand curves are recovered using random local weather shocks as supply shifters (Angrist et al. (2000); Roberts and Schlenker (2013)). Supply is recovered in two times: a production function first, fixed costs and capital adjustment costs second. There are two challenges to the estimation of the production function. First, producers are heterogeneous in both total factor productivity (TFP), and in their ability at using chemicals. Second, farms are multiproduct, but all inputs in the data but land are observed at the farm rather than the farm-crop level. I address the endogeneity issue by using the model's first-order conditions for profit maximization to provide the moments needed to identify the production parameters, and recover the distribution of unobserved productivity shocks, building on Doraszelski and Jomandreu (2018). To account for multiproduct producers, I follow De Loecker et al. (2016) and restrict the estimating sample to single product farms, for which the input to output allocation is known. I control for the induced estimation bias with an extension of the correction developed in turn by Olley and Pakes (1996) and De Loecker et al. (2016). Using the estimated parameters, I can then recover the productivity shocks of both single and multiproduct farms. The estimated elasticity of substitution between chemicals and land generates a positive association between farm efficiency and propensity to pollute. The intuition for this result can be derived from the fact that organic farming usually generates lower yields and compensates with more intensive land use per unit of output. I finally use a simulated method of moments estimator to recover costs of capital adjustment, entry and incumbency. The relative volatility of farm productivity, and its interaction with capital accumulation shapes the

cross-sectional allocation of production across heterogeneous producers, and the selectivity of exit (Collard-Wexler (2013)).

Policy Implications: I use the model for three counterfactual exercises: first to understand the general equilibrium economic and environmental consequences of the policy design shift at the heart of the MacSharry reform, second to highlight how different subsidy designs interact with different channels of equilibrium chemical use, and third to investigate how the subsidies' environmental effects inform the question of agricultural optimal subsidy design.
The first exercise looks at a change from government grain purchasing to a land subsidy, holding government expenditure to post-reform levels. The second design ends up generating larger economic distortions by shifting farm input mix. As such, the policy change slightly increases the average cost of production on the market, and lowers total farm profit as the subsidy is passed through into lower output prices. However, the input choice implications of the land subsidy also lead to positive environmental effects, by lowering chemical use intensity measured as the price constant chemical expenditure to revenue ratio by 2.4% and total chemical use by 3.3%.
In the second exercise, I highlight how a yearly lump sum payment to low-pollution producers achieves environmental gains by retaining these producers on the market, who are not profitable enough to survive under perfect competition. This scheme then reallocates output away from more polluting and profitable farms. Compared to budget-equivalent land subsidies which raises the relative price of chemicals but has little selection effect, the lump sum payments generally do better at lowering chemical use intensity, but worse at lowering total chemical use.
Finally, borrowing a valuation for agricultural chemical pollution from Department of the Commissioner General for Sustainable Development (2011), I identify respectively a 28k€ lump sum payment, a 10% homogeneous land subsidy, and a differentiated (10%,40%) land subsidy for wheat and non-wheat crops, as welfare maximizing conditional on design. They reach respectively a 1%, 1.4% and 2.2% decline in total chemical use, and a marginal value of public funds of 1, 2.9 and 1.6. Across these designs, the differentiated subsidy does best at raising welfare, through larger environmental gains and small effects on farm profit. Without a positive valuation for decreased chemical use, only a small 5% homogeneous land subsidy is found to be welfare improving compared to no intervention. In contrast, the optimal chemical tax achieves a significantly larger (54%) reduction in chemical use, but at the cost of large losses for both producers and consumers. This comparison highlights a central tension to curbing agricultural environmental externalities: direct taxation is the first-best environmental policy, while subsidies protect farm profits but reach much smaller environmental gains.

Related Literature: My paper contributes to the study of optimal environmental policy, which has long stressed the importance of market structure and equilibrium effects (Hotelling

(1931); Oates (1991); Bovenberg and Goulder (1996)). For this paper's purposes, the work of Carlton and Loury (1980) stands out in showing how entry and variation in the number of active firms in a polluting market can make a Pigouvian tax fail. Recent work at the intersection of environmental economics and industrial organization also studies how environmental policies perform at equilibrium, relying on structural methods to tailor empirical models to specific markets (Blundell et al. (2020); Armitage (2023); Rafey (2023); Gowrisankaran et al. (2024)), with a growing focus on dynamic land use in agriculture (Scott (2013); Hsiao (2022); Burlig et al. (2024)). I contribute to this literature by developing a framework that explicitly models and quantifies the dual environmental impact of agricultural subsidies: their effect on production choices within the farm (the intensive margin) and their effect on market structure through farm exit (the extensive margin). Disentangling these channels is critical for policy design. As my analysis shows, the optimal policy depends fundamentally on the empirical relationship between farm productivity and pollution intensity, and whether the largest environmental gains come from changing incumbent behavior or from altering the composition of producers. In contrast to recent papers on dynamic land use, I also have access to rich farm-level administrative data, which allows me to model farms as multiproduct firms accumulating capital. These are important features for my analysis. The first captures how agent-level crop mix decisions impact aggregate chemical use, and the second helps better capture the extent to which farm exit selects on productivity.

While most of the environmental economics literature has focused on the design of policies explicitly targeting the environment, I highlight the relevance of environmental considerations in the design of generic industrial policies within polluting markets. Previous work along these lines has largely documented cases where subsidies had unexpected negative environmental spillovers, such as fuel subsidies that increase emissions and deplete natural resource stocks (Davis (2017); Englander et al. (2023)), or trade protections for carbon-intensive industries (Shapiro (2021)). In contrast, I show that a major subsidy regime can have unintended, positive environmental consequences. Here, I focus on the well-documented case of agricultural pollution (Missirian (2020); Frank (2021); Chabé-Ferret et al. (2021); Taylor (2022); Dias et al. (2023)), measuring fertilizer pollution directly through satellite data (Taylor and Heal (2023); Rossi et al. (2023)). My core theoretical contribution is to embed the longstanding literature on input-biased technical change in agriculture (Hayami and Ruttan (1971); Binswanger (1974); Bustos et al. (2016); Clemens et al. (2018)) within a dynamic, heterogeneous-agent industry model. This approach, similar in spirit to the analysis of the declining U.S. labor share by Oberfield and Raval (2021), allows me to model agricultural intensification and its environmental outcomes as the result of micro-level production decisions.

Finally, this paper contributes to the literature evaluating the welfare consequences of agricultural subsidies. Agricultural subsidies are traditionally understood as generating significant misallocations in the labor market, both across farms of varying efficiency, and across economic sectors, in turn slowing down structural transformation in developing countries (Gollin

et al. (2013); Adamopoulos and Restuccia (2014)). Here I turn my attention to the largely understudied EU CAP. Within a labor misallocation context, any misallocation generated by the CAP likely bears little economic significance, given the relatively small share of EU labor allocated to agriculture. Its impact on input use misallocation, however, is still a relevant question if we turn our attention to land use. Agriculture accounts for 38% of all EU land, making it an industry central to most contemporary environmental questions.[1] While several recent papers have focused on the extensive margin of agricultural land use—the transfer of land out of agriculture into a conservation status (Aspelund and Russo (2024); Grupp et al. (2024); Larsen (2025))—the intensive margin related to the sustainable use of land within agriculture is less understood. In my welfare analysis, I pit the environmental consequences of agricultural subsidies against their better-known effect on economic efficiency, in order to test the general relevance of these environmental effects. I find that, for standard valuations of pollution damages, the magnitude of the environmental benefits from subsidy reform can be large enough to dominate the concurrent effects on economic efficiency, providing a new and consequential dimension to the evaluation of agricultural policy.

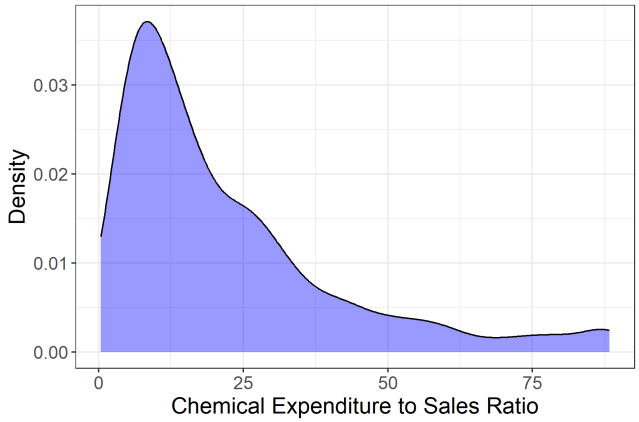
This paper proceeds as follows: section 2 provides background on the Common Agricultural Policy and describes the data. In section 3, I use a shift-share design to evaluate the consequences of the MacSharry reform. Section 4 outlines the structural model and the estimation strategy, section 5 presents counterfactual simulations. Section 6 concludes

2 Context and Data

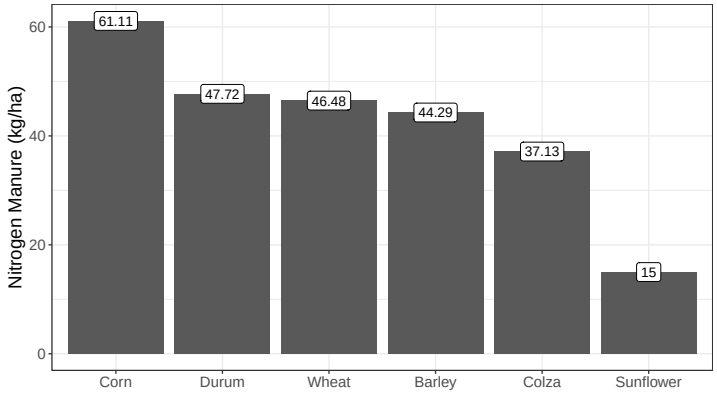
2.1 Determinants of Farm-Level Pollution Intensity

French farm data shows substantial farm-level heterogeneity in the use of chemicals, as illustrated by the 1985-1990 distribution in the farm-level ratio of chemical expenditure to revenue shown in the first facet of figure 1. In this figure, I compute counterfactual revenues for farms using national average prices, in order to focus on the heterogeneity in relative chemical use. This heterogeneity is likely driven by several factors, which will interact with agricultural subsidies at equilibrium in different ways: 1) variation across farms in the price of chemicals relative to other inputs, 2) variation across crops in their chemical requirements interacting with heterogeneity across farms in crop mix composition, and 3) heterogeneity across farms in their efficiency at using chemicals. The first two channels are intensive. Subsidies that change incentives for input use or crop choice will shift the decisions of all the existing producers. The last channel is extensive: subsidies that change the average profitability of the market will move marginal producers inside or outside of the market, and this selection effect will change the average chemical use efficiency of farms according to the empirical correlation between farm profitability and chemical use efficiency.

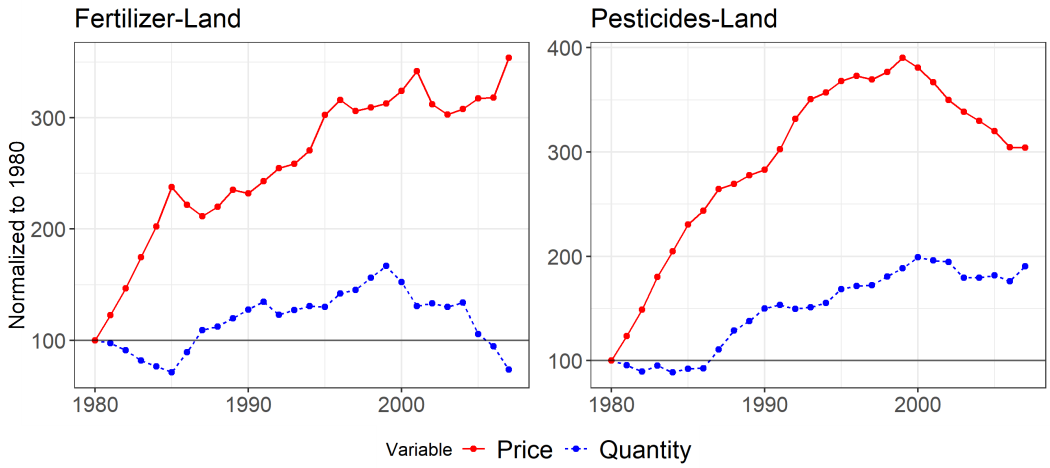
[1] See for Eu land use: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Farms_and_farmland_in_the_European_Union_-_statistics.



(a) Heterogeneity in Chemical Use (1985-1990)



(b) Crop-Specific Nitrogen Use



(c) Relative Input Quantities & Prices

Figure 1: Chemical Use & Farm-Level Determinants

Notes: Figure a) is computed using the FADN panel, and shows the 1985-1990 distribution across farms in the ratio of their chemical expenditures to their total revenue. Revenues are computed here using national average output prices, in order for the ratio to focus on the dispersion of relative chemical use. Figure b) highlights heterogeneity in nitrogen manure use (kg/ha) across crops, computed using the PKGC plot survey. The binscatters of figure c) are computed using combined data from the FADN (input quantities), the INSEE Ipampa price index series (chemical prices), and the Valeur Venale des Terres land price series. Land prices are corrected for the EU land subsidies. I compute input-to-input price and quantity ratios. Inputs are measured as deflated bills for pesticides and fertilizers, and in hectares for land. Prices for chemicals are Laspeyres price indices, while land prices correspond to an average land price in France. All indices are normalized to 100 in 1980.

I provide suggestive evidence for the last two mechanisms in the bottom figures of figure 1. In the first of these two figures, I rely on the PKGC plot-level survey to compute the average amount of nitrogen manure used per hectare across the main crops of the French grain market. The figure illustrates that some crops have higher nitrogen requirements than others: here, everything else equal, a single-crop farm growing corn will use more nitrogen per unit of land than a farm specialized in sunflower. This heterogeneity in crop needs is known to exist for

other categories of chemicals. For example, Carpentier and Rainelli (1997) discusses how cereals rely relatively more on fungicides, a type of pesticides, than other grains.
The last figure of figure 1 provides suggestive evidence for the presence of chemical use efficiency growth over time in the French market. The figure shows the evolution of relative (fertilizer-to-land and pesticides-to-land) input prices against relative input quantities used by farmers. Here, I use farm-level FADN data to compute average fertilizer-to-land and pesticide-to-land input quantity ratios. Prices are measured at the national level, with the price of land adjusted for land-use subsidies. All series are normalized to their 1980 levels. From 1980 to 2000, the relative prices of both fertilizers and pesticides rose substantially (wrt. to land prices), yet farms steadily increased their use of these two chemicals relative to land. This simultaneous increase in relative prices and relative quantities points towards the existence of input-biased technological change increasing the marginal production value of chemicals over time: under input substitutability, profit-maximizing farm would use more of an input that is becoming more expensive if the productivity of that input is increasing.[2] The model will replicate these three mechanisms driving chemical use intensity, and quantify the extent to which different subsidies interact with them. Depending on their design, agricultural subsidies might be able to shift farm intensive production decisions (input mix and crop mix), as well as the average chemical-use efficiency of market incumbents through the farms' extensive market exit decision.

2.2 The Common Agricultural Policy

The Common Agricultural Policy (CAP) was established after World War II to ensure food security, boost production, and support farm incomes (Petrick (2008)). It quickly became the largest policy administered by the EU, accounting for 45% of its total budget since 1980, and reaching over 50 billion euros in annual spending since 2005. As shown in figure 2, the first main CAP subsidy targeting the environment was introduced in 2007, and it remains the case that most of CAP spending is not conditioned on the adoption of sustainable environmental practices. Understanding the environmental impact of these subsidies is hence key to quantify the overall environmental impact of the CAP.
Starting in the 1960s, the cornerstone of the CAP was a joint regime of subsidies and levies designed to generate high internal demand, and higher revenues for farmers. These revenue goals were set through the calculation of crop-specific prices, purposefully computed to be higher than international prices. These price objectives were enforced through different means on the cereal and oil crop market. In the cereal market, they were enforced through three main instruments: government purchasing at floor prices on the secondary market (purchasing mostly from grain elevators), subsidies for exports to the world market, and

[2] I note that the introduction of the EU Nitrate Directive in the late 1990s, which regulated nitrogen use, likely explains the decrease in the fertilizer ratio at the end of the sample period (Chabé-Ferret et al. (2021)). Additional descriptive statistics regarding the role of agricultural production in environmental pollution, and heterogeneity in chemical use across farm size are provided in **??**.

levies on agricultural imports.[3] Import levies were not possible on the oil market due to the 1962 GATT Dillon Round. The EU enforced target prices on the oil market by reimbursing processors for the difference between international market prices and target prices, when they were buying European grains. In both cases, the EU intervened at the level of agricultural intermediaries to maintain EU farm-gate prices above international prices.

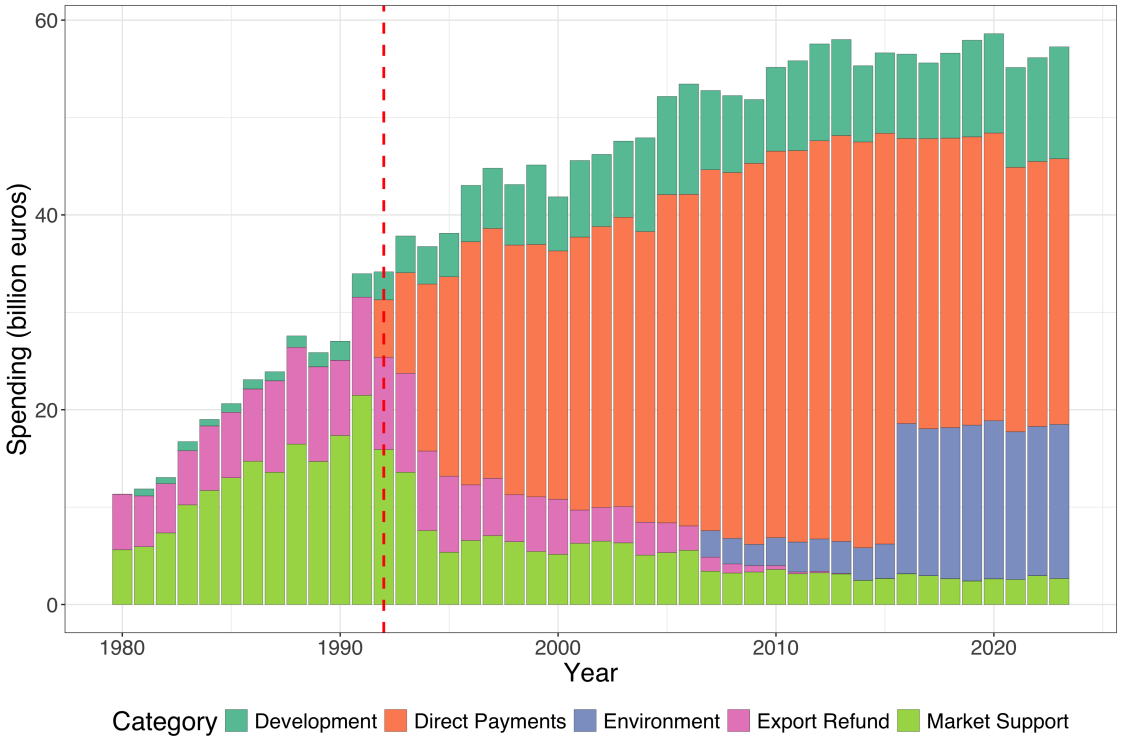


Figure 2: Common Agricultural Policy Spending

Notes: Annual CAP spending data from the EU Commission Directorate General for Agricultural and Rural Development.[4]

Figure 2 shows that up to 1992, government market intervention (market support) and export subsidies (export refunds) accounted for the vast majority of all CAP spending. By the late 1980s, this system proved unsustainable. Figure A1 shows how the EU cereal production steadily outgrew internal private demand, generating an estimated annual 20 million tons surplus of cereals every year since 1983 until the early 1990s. This generated a budgetary crisis and placed the CAP under pressure for reform. The 1992 MacSharry Reform was the response to this crisis, fundamentally altering European agricultural policy, with a shift in the allocation of the overall budget towards direct payments to farmers illustrated in figure 2. The timing and design of the MacSharry Reform were driven by a confluence of powerful forces external to the French agricultural sector, providing a plausibly exogenous source of variation for the first part of my analysis. Internally, the EU faced a budgetary crisis: CAP

[3]Intervention prices were first regionalized, and later harmonized across the Community in the 1970s. They were first set in Unit of Accounts, a fictional common currency introduced for the purpose of the Common Agricultural Policy, later in ECUs, and then euros. For that purpose, specific agricultural exchange rates, called the "green rates", were implemented to prevent within community arbitrage following any re-evaluation of the members' currencies.

spending doubled from 1980 to 1986, and by 1991, expenditures were projected to grow by another 25% in a single year. These fiscal pressures were compounded by the 1992 Maastricht Treaty, which required budgetary discipline in preparation for the monetary union (Moyer (1993)).

Externally, the EU was also pressed for reform. The ongoing GATT Uruguay Round negotiations, which began in 1986, had stalled over the question of agricultural subsidies. The US-led Cairns Group of agricultural exporters insisted that the final treaty regulate not only trade policies but also internal support mechanisms distorting international trade. Given that key member states like France were primary beneficiaries of the subsidy system and opposed cuts, these external pressures were critical in forcing the policy change.

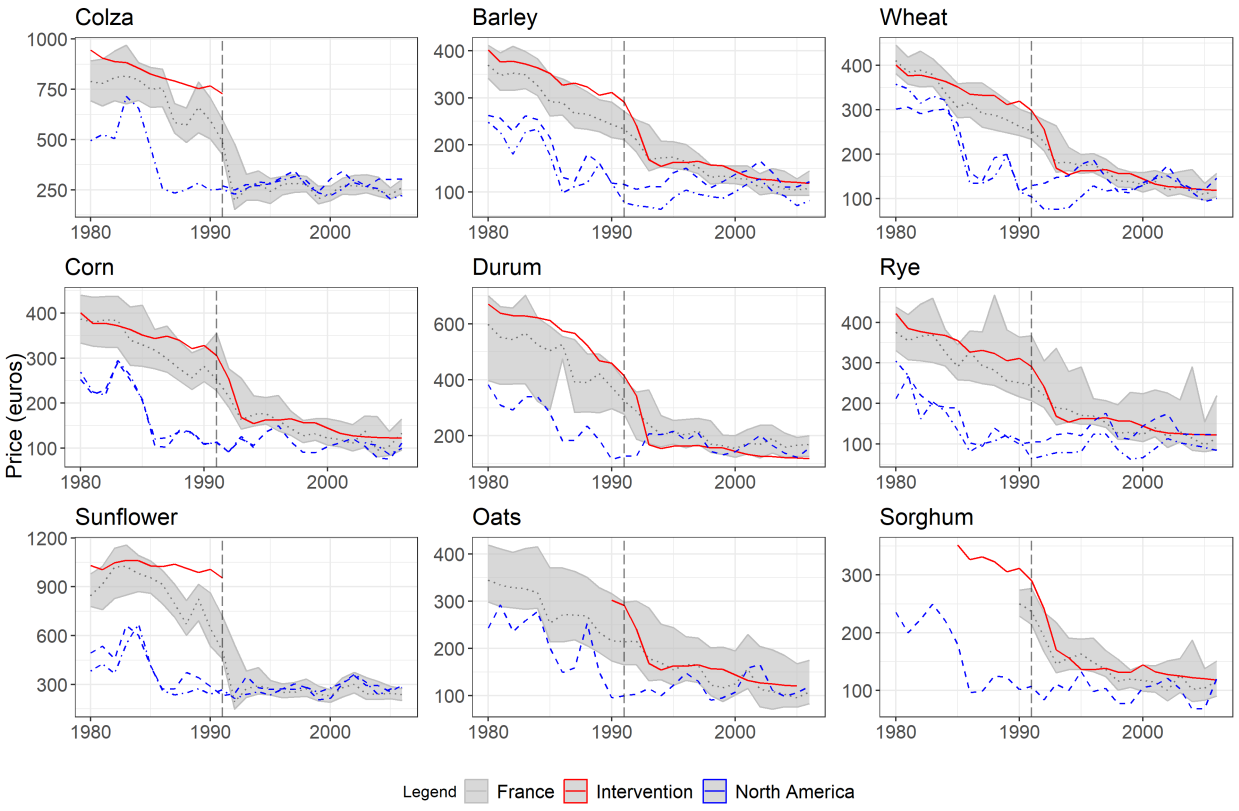


Figure 3: Convergence of French and North American Prices Following the MacSharry Reform

Notes: Evolution of French and North American farm gate prices, as well as EU intervention prices for most cereal and oil crops. French farm gate prices are shown with the grey ribbon, and taken from the FADN. The center dotted line corresponds to the weighted mean, and the edges to the bottom and top 25th and 75th centiles of the distribution of prices. Intervention prices are shown with the solid red line. The data is digitized, taken from the relevant EU directives published over time. U.S. and Canadian farm-gate prices are taken from Faostat, and shown with the dashed and dot-dashed blue lines. All prices are converted into 2020 euros using the relevant exchange rates and correcting for inflation using the Insee's consumer price index.

The reform was announced abruptly, and shifted the policy from a system generating additional demand for EU commodities, to a direct subsidies to farmers lowering their effective

production costs.[5] First, it dismantled the government purchase system by decreasing intervention prices for cereals to international levels, and eliminated target prices and processor subsidies entirely for oil crops. The stated goal of the policy was for EU prices to converge to international levels.[6] Second, to offset the resulting income loss for farmers, the reform introduced a new system of direct payments. These payments were structured as subsidies per hectare of cultivated land, decoupling support from yields. Third, eligibility for these payments was conditioned on a set-aside requirement: that farmers take a fraction of their land out of production, effectively decreasing the rate of land subsidization.

The reform triggered a sharp and heterogeneous decline in French farm-gate prices. Figure 3 provides visual evidence of this shock. Prior to 1992, a large wedge existed between French prices and world market prices (proxied here by North American prices), sustained by the EU's intervention system. The figure shows that following the reform's implementation, this wedge collapsed as French prices converged to the world level.[7] This price shock varied substantially across commodities, meaning the reform's impact depended directly on a farm's pre-existing crop mix.[8] This heterogeneous price shock is the primary source of variation I exploit in the first part of my analysis.

The second component of the reform was the introduction of direct payment.[9] These payments, structured as subsidies per hectare, partially compensated for the loss of price supports. They were calculated using a regionalized historical reference yield, resulting in a more uniform support system across crops than the price supports they replaced.[10]

Finally, the reform's third component was a compulsory set-aside requirement. To receive land subsidies, most farms were required to leave a fixed proportion—initially 10%—of their arable land fallow. The policy did, however, include an exemption for small farms. While I do not exploit this exemption for identification, my empirical specification accounts for a farm's exposure to the set-aside requirement.[11]

The MacSharry reform coincided with a significant acceleration in market consolidation among French cereal and oil crop producers. While a trend of increasing farm size was already present, Figure 4 shows a distinct kink at the time of the reform. Using data from the Census of Agriculture, the top panels show that the growth in average farm size accelerated between 1988 and 2000, and the share of land cultivated by the top decile of

[5] A first reform plan was outlined by the Commission in 1991—it proposed to cut intervention prices for cereals, oil and protein crops to world price levels, and to introduce a progressive compensatory subsidy scheme in the form of marginally decreasing payments per ha. This progressive structure was scrapped with pressure from the member states, to be replaced by the reform described here.

[6] Council Regulation 1766/1992 which introduces the reform states *"the objective can be achieved by lowering the target price to a level representing an anticipated rate on a stabilized world market"*, making very clear the goal of convergence to international prices.

[7] Around the time of the reform, the U.S., Canada and France were by far the largest three exporters of cereals in the world—and North American prices are hence useful points of comparison. See https://ourworldindata.org/grapher/cereals-imports-vs-exports?tab=table&time=1995

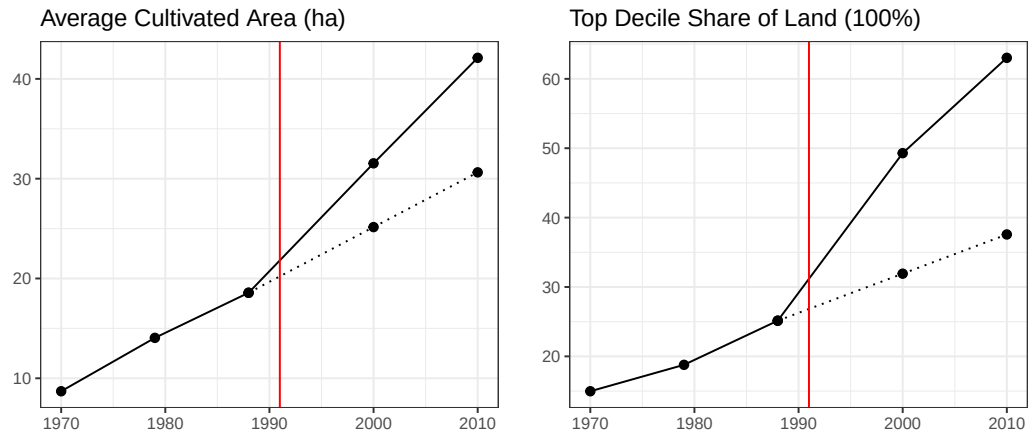
[8] To summarize this farm-level exposure, I construct a land-share-weighted average output price for each farm. Figure A2 shows the result: a sharp, permanent drop of 33% in this farm-level price index between 1991 and 1993.

[9] Figure A3 shows their evolution over time in the FADN data.

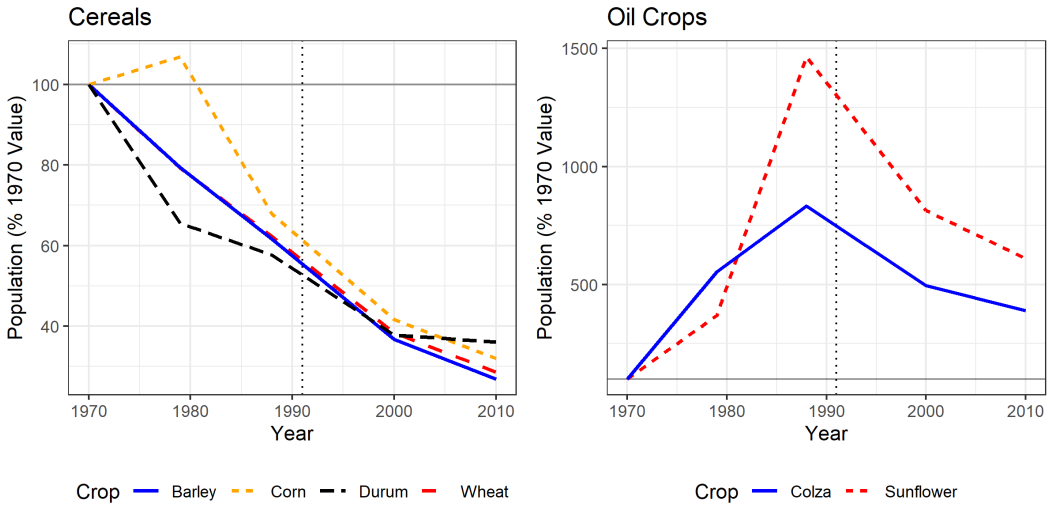
[10] As Figure A4 shows, this effectively homogenized subsidies that were previously highly differentiated by a farm's crop choice.

[11] Specifically, I control for each farm's pre-reform (1991) land use to isolate the primary effects of the price and subsidy shocks from this dimension of the policy.

farms jumped from 25% to 49%.[12]



(a) Farm Growth and Reallocations



(b) Differentiated Farm Exit across Markets

Figure 4: Farm Growth, Reallocations and Exit around the MacSharry Reform

Notes: The data comes from the full count Census of Agriculture for years 1970, 1979, 1988, 2000 and 2010. Average farm size is measured in hectares, and the share of land allocated to the top decile of farms (in size of land) is expressed in percent. These two variables are computed for the set of farms active on the grain market. The evolution of the respective farm populations is expressed wrt. to the 1970 baseline value, in order for the rates to be comparable across crops. The vertical line is for 1991, the last year prior to the reform. The dotted line for the first three figures show the average trend over 1970-1988.

In contrast to the uniform trend in consolidation, producer exit trends differ across crops. The bottom panel of Figure 4 shows that while the number of cereal producers continued its steady, long-run decline with no visible break, the oil crop market experienced a dramatic

[12] As this pattern of consolidation was homogeneous across the cereal and oil crop markets, the figure presents aggregate statistics.

reversal. The number of oil crop producers, which had been increasing prior to the reform, began to decline sharply after 1988. This divergence in exit patterns aligns with the heterogeneous price shocks shown previously in Figure 3. Oil crops, which suffered a much larger drop in profitability, saw a wave of producer exit while cereals did not. This differential response to the reform across crop types provides the core variation for the identification strategy.[13]

2.3 Data

2.3.1 Farm Accountancy Data Network (FADN)

My primary source of farm-level data is the French subset of the European Farm Accountancy Data Network (FADN), a rich panel survey designed to be representative of commercial agriculture in the European Union.[14] The FADN is an ideal dataset for the analysis due to its detail and panel structure. Crucially, while the FADN is a sample (approx. 8,000 farms per year in France), it is designed to capture the vast majority of economic activity. In 2000, the commercial farms it represents accounted for 95% of France's total agricultural production.[15]

The dataset's richness stems from its foundation in farm accounting records. For each farm, it provides annual data on crop-specific sales revenues and volumes, which allows me to recover farm-level output prices. It also contains detailed information on input expenditures (e.g., fertilizer, pesticides), capital stocks, and crop-specific land allocations. Finally, farms are geocoded at the department level for the period of analysis, enabling me to match them with local input prices and weather data.

2.3.2 French Agricultural Census

To analyze market-level dynamics, I leverage the farm-level French Agricultural Census, a unique resource that provides data on the universe of French Farms. The census is fielded approximately every ten years (I use the 1970, 1979, 1988, 2000, and 2010 waves) and covers virtually every agricultural establishment in France.[16]

While the Census lacks the detailed financial data of the FADN, its comprehensive scope makes it ideal for measuring market structure. Its primary variables for my purposes are farm municipality-level location and crop-specific acreage. A key limitation is the absence of a stable farm identifier prior to 1998, which prevents me from tracking individual farms across census waves. I therefore use the repeated cross-sections of the Census to construct

[13] Further evidence in Figure A6 points to an acceleration in farm-level crop specialization during this period, a topic explored in detail alongside the farms' crop mix composition (Table A3) in the structural analysis that follows.

[14] My analysis focuses on France, as many of the datasets I match the FADN to only exist for France.

[15] The FADN's definition of a "commercial farm" has evolved but consistently targets farms that are professionally managed and market-oriented. Prior to 2010, it included requirements on the manager's work hours and a minimum land area of 5ha for non-specialized farms. Since 2010, the threshold is based on a minimum standard production capacity of €25,000.

[16] Farms are defined as production units with independent management that meet a minimum size of .2ha, with exceptions for specific agricultural sub-markets. The original list of establishments filtered with these requirements is built out of a combination of land registries and data from the farmers' family allowances mutual savings societies.

precise, municipality-level measures of net farm exit, the distribution of farm sizes, and aggregate crop-mix composition. Other data sources of data used in this paper are described in appendix B.1.

3 Shift-Share Analysis: Consequences of the MacSharry Reform

3.1 Empirical Strategy

My empirical strategy relies on a shift-share design, where identification is driven by the shares' conditional exogeneity. While the aggregate, crop-specific policy shocks are plausibly exogenous due to their origins in international trade negotiations, these shocks are too few to drive identification. Instead, the design's validity hinges on a conditional exogeneity assumption regarding farms' pre-reform land allocations across different grain crops (Goldsmith-Pinkham et al. (2020)).

Approximating European Policy: The reform altered the entire system of revenue support for grain farms. I summarize the total government support for each crop c in year t as a 'revenue cushion', measured in euros per unit of output. This cushion is the sum of the pre-reform price supports and the post-reform direct subsidies:

$$cushion_{ct} = \underbrace{\mathbb{1}\{Intervention_{ct}\}\left(P_{ct}^{inter} - \overline{P}_{ct}^{I}\right)}_{\text{Price Support}} + \underbrace{\left(\frac{\overline{Sub}_{ct}}{\overline{Yield}_{ct}} - setaside_{ct}\right)}_{\text{Land Subsidy}}.$$

P_{ct}^{inter} is the intervention price for crop c in year t in France, and $\overline{P}_{ct}^{I}$ is the corresponding farm-gate price in North America.

The price support wedge captures the pre-reform system of demand-side government intervention. It is defined as the difference between the EU intervention price P_{ct}^{inter} and the world market price (proxied by North American farm-gate prices), $\overline{P}_{ct}^{I}$, active only when an intervention price exists.[17] The land subsidy captures the post-reform system. It consists of the new land subsidy $\overline{Sub}_{ct}$, converted to a per-output measure by dividing by an average yield, minus the opportunity cost of the compulsory set-aside requirement.[18] Figure A5 plots the evolution of these revenue cushions. The cushions for all major crops decline sharply between 1991 (the final pre-reform year) and 1995 (the final reform implementation year). Critically, the magnitude of this decline varies substantially across crops, with oil crops experiencing a much larger negative shock than cereals. Overall, the reform enforced a convergence in subsidization across crops, as illustrated in Figure A8.

[17] The U.S. and Canada accounted for most of the export market over the 1980s to 2000s, making these prices a relevant reference point for the analysis. I use USA prices but for colza, for which I use Canandian prices—given that the USA was not a significant producer of colza at that time, but Canada was. All these prices are average farm gates prices from Faostat.

[18] I rely on the median and not average subsidies, as the subsidy data recorded in the FADN shows significant mis-measurement. The average subsidy per hectare decreases over time in the FADN, in a pattern that does not match EU policy, while the median value does.

Building the Instrument: I measure each farm's exposure to the reform using a weighted average of these crop-specific shocks, where the weights are the farm's pre-reform land allocations.[19] I define farm j's time-varying average cushion as:

$$Cushion_{jt} = \sum_{c \in \mathbb{C}_{j,t_0}} \frac{s^l_{j,c,t_0}}{\sum_{c'} s^l_{c',t_0}} cushion_{ct},$$

where s^l_{c',t_0} is the share of farm j's land allocated to crop c in the pre-reform period, $t_0 = 1991$. These cropping decisions were made in the fall of 1990, before the reform's design was public. The farm-specific reform exposure instrument Exp_j is then the total change in this revenue cushion over the reform period. This variable captures how hard each farm was hit by the reform, based entirely on its pre-reform state. Its distribution in the sample is shown in figure A10.

$$Exp_j = Cushion_{j,t=91} - Cushion_{j,t=95}.$$

Identifying Assumptions: The recent econometrics literature distinguishes between shift-share designs where identification comes from a large number of plausibly random shocks (Borusyak et al. (2022)) and those where it comes from the interaction between a few dominant shocks and quasi-random exposure shares (Goldsmith-Pinkham et al. (2020)). On top of having a unique year of policy shock, decomposing the variation of the exposure instrument into crop-by-crop sources following the Rotemberg weights of Goldsmith-Pinkham et al. (2020), I find that variation in the Exp_j instrument is dominated by shocks to a few key crops (sunflower, corn, wheat). The many endogenous shocks approach is therefore not a suitable one here.

Consequently, my design follows the identification strategy outlined in Goldsmith-Pinkham et al. (2020). This approach is conceptually similar to a continuous treatment difference-in-differences, where a farm's pre-reform crop mix determines its treatment intensity. The core identifying assumption is that the pre-reform shares, conditional on controls, are not correlated with unobserved, crop-specific trends that would have affected farm outcomes in the 1990s even in the absence of the reform. I will test and discuss the validity of this assumption in the following sections. In appendix B.2, I show very similar results where the instrument is constructed using land shares to aggregate across crops for the land subsidy and set-asides, and output shares to aggregate across intervention prices.

[19] I include the following crops to compute the farm-level cushion: wheat, barley (winter), corn, rye, oats, sunflower, rapeseed, barley (spring), durum, sorghum.

3.2 Farm-Level Analysis

Empirical Design: My primary analysis uses the FADN farm-level panel. I estimate the dynamic impact of reform exposure using the following event-study specification:

$$Y_{jt} = \alpha_j + \eta_{d(j)t} + \sum_{\tau \neq 1991} \theta_\tau Exp_j \mathbb{1}\{t = \tau\} + \sum_{\tau \neq 1991} \delta_\tau X_j \mathbb{1}\{t = \tau\} + \varepsilon_{jt}. \quad (1)$$

Here Y_{jt} is the outcome for farm j in year t, Exp_j is the standardized, farm-specific, time-invariant exposure instrument constructed in the previous section. The coefficients of interest θ_t capture the year-specific causal effect of the reform relative to 1991. The vector X_j contains pre-reform farm characteristics, and $\eta_{d(j)t}$ are department-by-year fixed effects. Standard errors are clustered at the region-by-year level.

The causal interpretation of $\{\theta_t\}_{t \geq 1992}$ hinges on the conditional exogeneity of the instrument. Formally, the identifying assumption is that a farm's pre-reform crop shares are uncorrelated with unobserved factors that would have driven differential growth in the outcome variable post-1991, conditional on the controls. The pre-1992 coefficients $\{\theta_t\}_{t<1992}$ provide a direct test of this assumption, in that they must be non-statistically different from zero.

Threat to Identification and Control Strategy: The primary threat to the identifying assumption is that 1991 crop choices were not random, but rather determined by farm characteristics that could also be correlated with future growth. I structure my strategy, embedded in the inclusion of a farm fixed effect, on the inclusion of controls X_j and department-specific time trends $\eta_{d(j)t}$, to neutralize two main classes of threats which relate to this.

First farm omitted state variables and technology trends. Here the central concern is that a farm's state vector—both observed and unobserved—jointly determines its crop portfolio and its future trajectory. An obvious example is that farms located in fertile land might tend to specialize more, and earn high yields and profits. The farm fixed effects remove the influence of any time-constant unobserved farm confounder. Dynamic elements of the farm state could also bias the results. For example, in a multi-product setting with separate production decisions across production lines, more productive farms are likely also more diverse (Mayer et al. (2014)). To address this, X_j includes a rich set of controls for the farm's pre-reform state. To proxy for unobserved productivity (TFP), which is a key unobserved state variable, I include the farm's 1991 choices of flexible inputs following the logic of the production function literature (Olley and Pakes (1996)). Because farms growing different types of crops are also likely to be more different along unobserved characteristics, it is important to control for the general split of production across crop categories. Finally, it is also key to explicitly account for farm-specific technology adoption paths. Overall X_j contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation across these crops, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984

(the start of my period of analysis) adoption trends in chemicals measured as the evolution in their chemical use.

The second threat comes from spatially correlated shocks. Local soil and climate conditions create strong spatial patterns in cropping, and I do observe systematic variation across space in farm exposure in figure A9. If these local areas are also subject to unobserved, time-varying shocks (e.g., evolving local demand or input prices), these could induce a spurious correlation between the instrument and the outcome. The inclusion of department-by-year fixed effects $\eta_{d(j)t}$ controls for any such shocks that are common to all farms within a department in a given year.

After conditioning on this rich set of controls, the identifying variation comes from sources of specialization that are plausibly orthogonal to the confounding trends of the 1990s. A primary source is stickiness in crop choice. Farms can face significant switching costs related to crop-specific physical capital (e.g., planters, harvesters), human capital, and crop cycles, as discussed by Livingston et al. (2008) and Scott (2013). This stickiness means that initial conditions at entry and past, potentially random shocks to prices or yields can lead to persistent specialization patterns that are uncorrelated with the specific productivity trends of the study period. Similarly, historical factors, such as lumpy investments made decades prior or generational expertise in a specific crop, can create quasi-random variation in the 1991 crop portfolios that my design leverages for identification.

Testing the Design: The event-study coefficients for the pre-reform period provide the primary validation for this strategy. In addition, figure A11 shows balance tests comparing trends for farms with above- and below-median exposure. Pre-reform trends are relatively similar across low and high exposure groups, while there is a sharp drop in sales and profits post 1992 for the high exposure group. Balance tests comparing farms with an above and median crop share, for all crops, show comparable trends pre-treatment (appendix B.2.2). The Rotemberg weights in table A11 show that after the inclusion of controls, the variation in the instrument across farms is driven in a relatively homogeneous way by the main crops of the market. Specifically, the design will make comparisons with farms having relatively large or small shares of corn, wheat, sunflower, spring barley, durum and oats. I note a negative weight associated to colza. However, colza is first associated with little variation in land share across farms, and second, when I decompose the instrument into crop-specific instruments in appendix B.2.4, I see that high colza crop shares in 1991 are associated with similar effects on sales, profit, and chemicals as the ones identified by the aggregate exposure instrument. These two features imply that this negative weight should not bias the interpretation of aggregate farm exposure.

To ensure results are driven by within-farm changes, the analysis is conducted on a balanced panel of farms present from 1985 to 2002, using FADN sampling weights in all regressions.

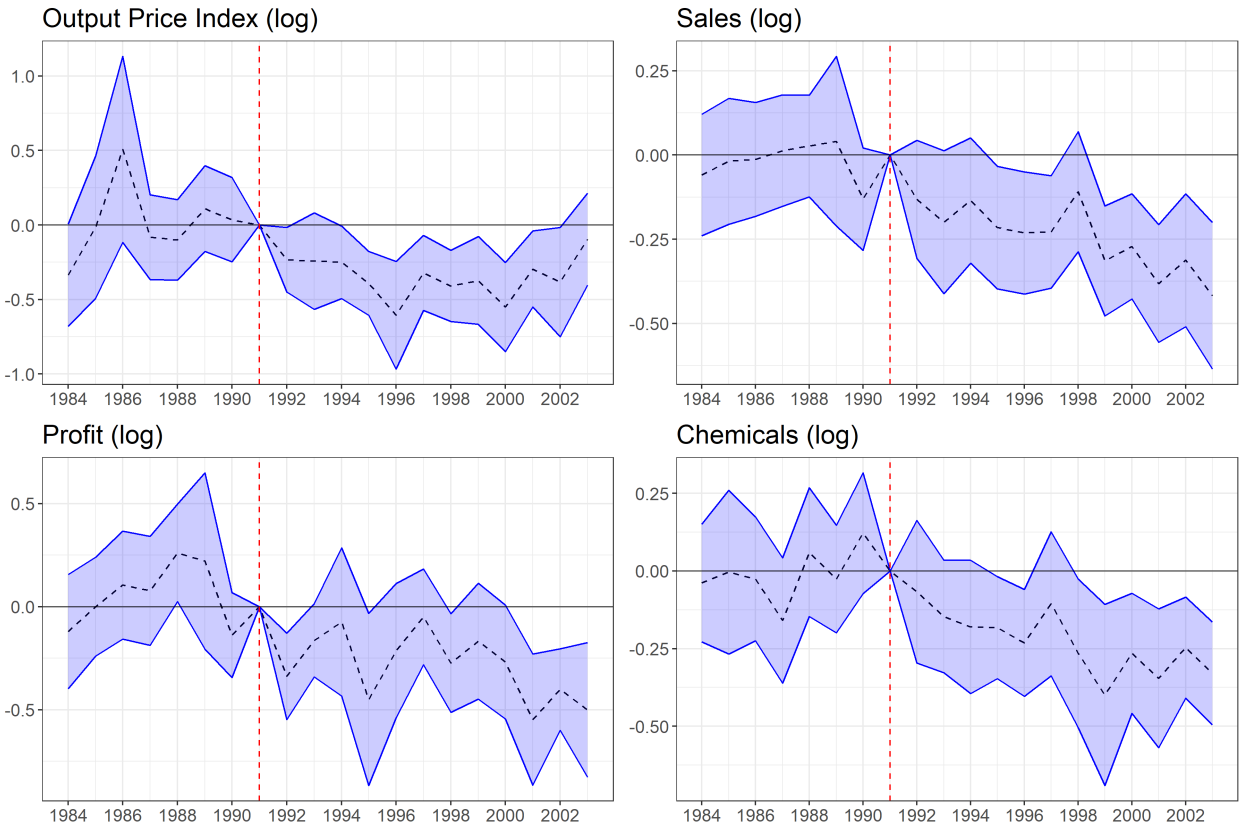


Figure 5: Exposure to the Reform—Farm-Level Event Study

Notes: All event study outcomes are measured as in logs: a farm-level output price index (average price across row crops, using relative areas as weights), total sales, profit measured as value added plus subsidies, and the farms' deflated chemical bill. All coefficients correspond to the year-specific coefficient associated to farm exposure, and give the effect of exposure in that given year. The vector of controls contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984 adoption trends in chemicals measured as the evolution in their chemical use. I add department-year and farm fixed effects, and cluster the standard errors one-way at the region-year level. The table for these results is table A4.

Results: The results of the event-study analysis are presented in figure 5. Coefficients provide the effect of relative additional exposure to the reform, specifically a one standard deviation increase, and do not capture the aggregate effect of the reform. First, the analysis of farm-level output prices serves as a first stage confirming that my instrument is associated with decreased output prices.[20] The top-left panel of figure 5 shows that the pre-reform coefficients $\{\theta_t\}_{t<1992}$ are statistically indistinguishable from zero. This absence of pre-trends supports the core identifying assumption that farms with different ex-ante crop mixes were on parallel paths prior to the reform. From 1992 onwards, the coefficients become sharply negative and statistically significant. By the late 1990s, a one-standard-deviation increase

[20] I measure the farms' output price as the weighted average of its crop-specific prices, using relative land allocations as shares. I use the following crops to compute the average (those for which I observe a balance time series): wheat, winter barley, corn, rye, oats, sunflower, colza, spring barley, durum.

in reform exposure leads to a 22% larger decline in a farm's average output price relative to the 1991 baseline. This estimated effect is consistent with the aggregate 33% price decrease shown in figure A2. As a complement to this first stage, the second panel of figure A12 shows that more exposed farms might also be receiving less land subsidies post-reform, even though the effect is noisy. This pattern is suggestive that the variation I am using stems from both heterogeneity in ex ante exposure to subsidies (a crop mix with more protected crop prices), but also ex post exposure (a crop mix with lower ex post land subsidies per unit), even though most of the variation is driven by price convergence and ex ante price cushions heterogeneity.

The reform had a significant negative impact on farm performance. The remaining panels of figure 5 show that a one-standard-deviation increase in exposure leads to a 23% decrease in total sales and a 31% decrease in profits by the end of the period. These average post-reform effects are taken from the corresponding difference-in-differences estimates presented in table A13. Finally, I find that this economic shock led to a significant reduction in polluting input use. For the average farm, a one-standard-deviation increase in reform exposure causes a 24% decrease in total chemical expenditures. Figure A12 shows that farm-level land use also decreases as a result of increased exposure, though the decrease is smaller than the one in chemicals. This joint but differentiated decrease in input use is indicative that more exposed farms are likely reducing the scale of their production, but might also be changing their input mix composition towards a less chemical-intensive one.

In appendix B.2, I discuss the robustness of the results, and show the sales, profit and chemical-use regressions with crop-specific instruments to test the homogeneity of the reform effects across crops. I also show results with a difference-in-difference framework, and also using the alternative instrument for exposure which combines 1991 land and output shares.

3.3 Municipality-Level Analysis

To study the reform's consequences on market structure—specifically farm exit and the local distribution of land—I turn to the French Census of Agriculture. While the Census lacks the detailed financial data of the FADN, its universal coverage of all French farms makes it the ideal dataset for analyzing extensive margin dynamics. A key feature of the Census data is that individual farms cannot be tracked across waves. Therefore, the analysis must be conducted at a higher level of aggregation. I aggregate the data to the municipality level, the smallest geographic unit available.[21]

My empirical strategy adapts the farm-level design to this repeated municipality-level panel. I measure a municipality's exposure to the reform by taking the average of the farm-level exposure instrument Exp_j across all farms within municipality k in the 1988 Census, denoted $\overline{Exposure}_k$.[22] This measure captures the intensity of the reform's shock for the typical farm

[21] Note there are about 36,000 municipalities in France. I use data from metropolitan France, and results are robust to the inclusion of Corsica.

[22] The distribution of exposure is first winsorized at the 1% level across all of France, before municipality level averages are calculated.

in a locality.[23] The formal specification is an event-study model at the municipality-year level:

$$Y_{kt} = \alpha_k + \eta_{d(k)t} + \sum_{\tau \neq 1988} \theta_\tau \overline{Exposure_k} \mathbb{1}\{t = \tau\} + \sum_{\tau \neq 1988} \delta_\tau X_k \mathbb{1}\{t = \tau\} + \varepsilon_{kt}. \quad (2)$$

where Y_{kt} is the outcome in municipality k and year t. The coefficients of interest $\{\theta_t\}_t$ capture the dynamic effect of local reform exposure. The vector X_k contains a rich set of 1988 municipality-level controls designed to account for initial conditions that could be correlated with both local crop specialization and subsequent consolidation trends. These include moments of the farm size distribution (mean, minimum, maximum and standard deviation), the minimum cultivated area, total municipality-level agricultural area and cultivated area, the average crop count across farms, municipality-level crop evenness and average crop evenness across farms, the fraction of farms in the municipality growing affected crops in 1988, and the fraction of municipality land allocated to cereals (versus oil crops) in 1988. All regressions include municipality and department-by-year fixed effects, resp. α_k and $\eta_{d(k)t}$, and standard errors are clustered at the region-by-year level.

The identifying assumption here is analogous to the farm-level case: conditional on the controls and fixed effects, municipalities with a higher average exposure due to their 1988 aggregate crop patterns were not on a differential trend for farm exit or land reallocation prior to the reform.

In order to test the validity of the design, I show balance tests in appendix B.2.5. These indicate that municipalities with above- and below-median reform exposure exhibit parallel pre-reform trends for the market structure outcome, but with is a slight pre-reform divergence in crop diversity. I explicitly account for this by controlling for the 1988 municipality-level evenness of cropland in all specifications.

The event studies in figure 6 show that the reform triggered significant market consolidation driven by the exit of farms. In 2000, a one-standard-deviation increase in a municipality's reform exposure led to a net decrease of 0.8 farms per municipality, growing to a 1.3 decrease by 2010. This same exposure led to a 0.2% increase in municipality land use evenness. Given that small farms tend to have a less even crop mix, this increase could imply that small farms are the ones exiting the market (see figure A6). I then observe a 2% increase in the land allocated to cereals, away from oil crops. This shift in crop mix parallels the observed change in subsidization across these two categories, as well as the general trends in the number of farms growing each of the two categories shown in figure 4. I show results for additional outcomes in figure A13. Of note, while the average crop count at the farm level goes up as a consequence of the reform, the municipality crop count goes down slightly. This likely implies that post-reform, more exposed municipalities experience an exit of less diverse farms, potentially specialized in the oil crops which underwent the most significant loss in subsidization. Finally, I cannot identify any significant movement in the municipality farm-

[23] Results are similar when using the median of the exposure distribution, as shown in the Appendix.

size distribution (neither for the minimum, average or maximum farm size). A potential interpretation of this result is that farm exit was relatively more driven by pre-reform crop mix composition, than by farm size, and that small farms were sufficiently heterogeneous in their crop mixes. Robustness checks using different methods for aggregating exposure to the municipal level yield comparable results (appendix B.2.5).

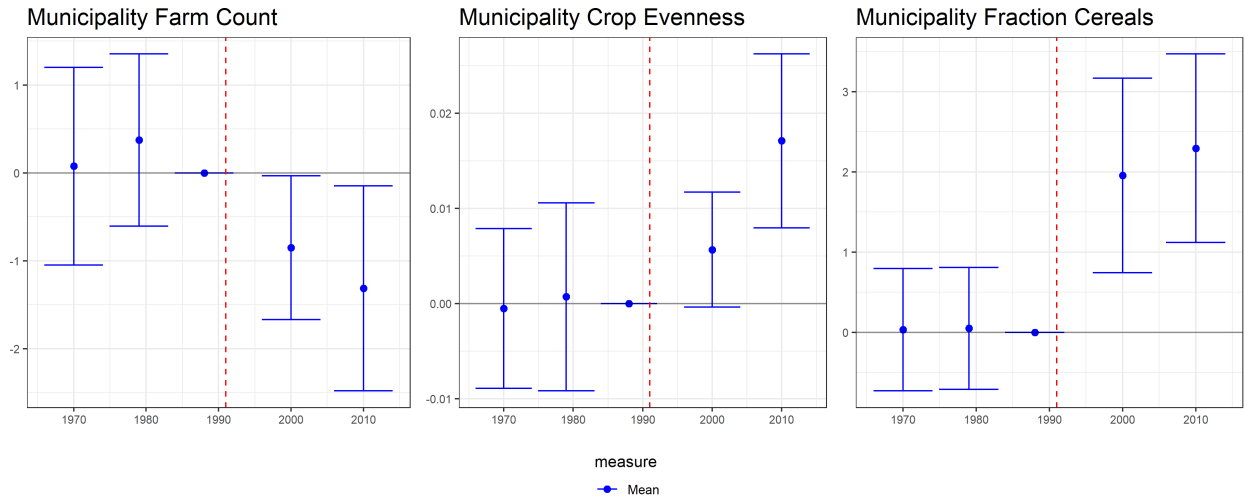


Figure 6: Exposure to the Reform—Municipality-Level Event Study

Notes: This figure gives the results for the municipality-level event study. Outcomes are specified in levels. Farm count corresponds to the number of farms operating in the row crop market within the municipality. Crop evenness is an index for the evenness of the distribution of land across crops, measured as the municipality-level evenness. Fraction cereals gives the fraction of municipality cropland allocated to cereals versus oil crops. The regression includes a series of controls set to their level in 1988 within the municipality, and interacted with a time-varying coefficients, as well as department-by-year and municipality fixed effects. Standard errors are clustered at the region-by-year level. The tables associated to these results are table A5, table A6 and table A7.

3.4 County-Level Pollution

Finally, I connect the reform directly to environmental outcomes by examining its impact on water pollution. Excessive fertilizer use is a primary cause of algal blooms in waterways, a form of nutrient pollution with significant negative consequences for ecosystems and human health (Rossi et al. (2023)). To measure this, I construct a county-year index of algal blooms using Landsat 5 satellite data, following the methodology of Taylor and Heal (2023), which is further detailed in appendix B.1.5. I aggregate the analysis to the county level (approx. 2,000 in France), as municipal boundaries are often too small to reliably overlap with the geographic precision of Landsat 5.

The empirical design mirrors the previous analysis. I estimate an event-study model at the county-year level, using the average 1988 farm exposure within the county $\overline{Exposure_c}$ as the instrument. The specification is analogous to equation (2) but for county fixed effects instead of municipality ones. I include the same set of 1988 census controls aggregated at the county level, in addition to which I add controls for local climate patterns (precipitation

and growing degree days), although results are not sensitive to their addition. To avoid confounding this analysis with the subsequent implementation of the EU Nitrate Directive, I restrict the sample period to end in the year 2001.[24]

The results show a significant reduction in water pollution in areas more exposed to the reform. By 2001, a one-standard-deviation increase in county-level reform exposure leads to a 10% decrease in the algal bloom index relative to its 1991 level. This finding is robust to using the median county level exposure, as shown in figure A25. This provides direct evidence that the reform-induced changes in the agricultural market had a material, positive impact on environmental quality.

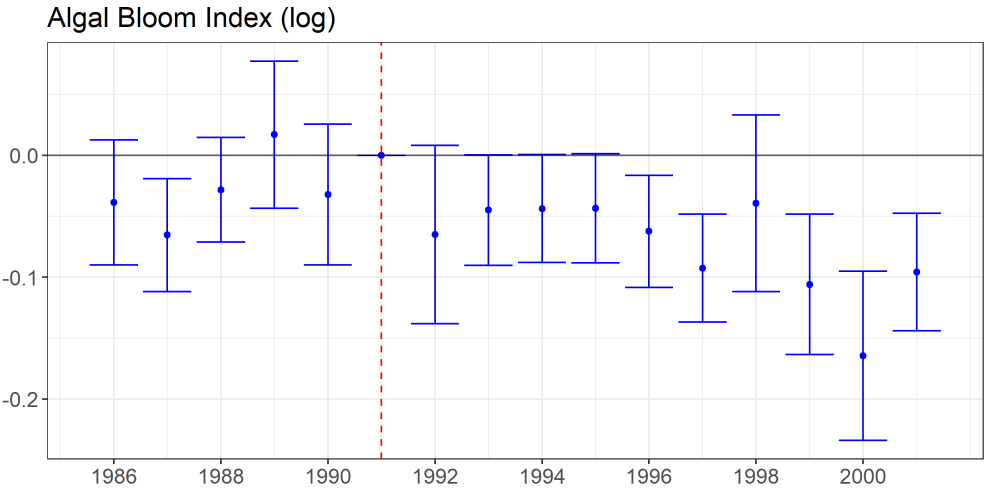


Figure 7: Exposure to the Reform—County-Level Event Study

Notes: This figure gives the results for the county-level event study. The outcome is expressed in log terms, and is a Landsat-5 based index of algal bloom intensity on the within-county water bodies. The regression includes a series of controls set to their level in 1988 within the county (last year of the Census prior to the reform), and interacted with a time-varying coefficients, as well as department-by-year and county fixed effects. Standard errors are clustered at the department-by-year level. The table associated to these results is table A8.

Overall, the results presented in this section indicate that the reform had important effects on market dynamics: it decreased profits, and generated exit of more specialized, oil-crop focused farms. It also reduced the use of chemicals, in so doing also reducing agricultural pollution across France. If the farms that stayed were on average more productive, and either more or less polluting, these reallocations likely had additional consequences for aggregate efficiency and pollution. I investigate this equilibrium effect, as well as that of different subsidy designs using the empirical model I present in the next section.

[24] Chabé-Ferret et al. (2021) analyze the effects of this separate, EU-wide regulation on fertilizer use in France from 2001 onward. The end date ensures the estimates are not contaminated by this later policy.

4 Empirical Model

I develop a dynamic structural model of the French grain farming industry to understand how policy affects chemical use intensity through input choices, productivity, and market structure. I begin by specifying the market environment and the demand for agricultural goods.

4.1 Static Demand

I model the market for several types of grain crops, indexed by c. This aggregation is required for the estimation of the production function, as detailed below. I assume that farms are price takers, and face a downward-sloping iso-elastic aggregate demand curve for each commodity:

$$Q_{ct}^D = exp(\alpha_c + e_{ct}) P_{ct}^{\beta_c},$$

where Q_{ct}^D is the total quantity demanded and P_{ct} is the market price. The parameter $\beta_c < 0$ is the constant price elasticity of demand for crop category c. The term $exp(\alpha_c + e_{ct})$ represents a demand shifter, composed of a crop-category-specific mean intercept α_c and an idiosyncratic, mean-zero demand shock e_{ct}.
While the supply-side focus of the paper justifies a simple demand structure, appendix B.8 discusses an alternative model that incorporates horizontal differentiation across similar grain crops grown by different farms, following the framework of Mayer et al. (2014).[25]

4.2 Supply

On the supply side, I model an industry of heterogeneous farms making dynamic decisions about production, investment, and exit in a competitive market.

Farm State: Farms are characterized by an individual state vector Υ_{jt}. Farms are heterogeneous along two dimensions of productivity, both of which are exogenous to the farm's decisions and follow a persistent stochastic process. The first is ω_{jt}^h, a farm-level TFP shock, and the second is ω_{jt}^{ch}, a shock to the farm's chemical use efficiency. Farms are also characterized by their capital stock K_{jt}. Finally, farms are multi-product producers, and do not produce all crops with the same efficiency. A farm's crop mix at t is denoted $\mathbb{C}_{jt} \subseteq \mathbb{C}$, and is a subset of all the crops sold on the market $\mathbb{C}$. The last element of the set is a time-invariant 'competence ladder' σ_j, which is a farm-specific ranking of crops from most to least efficient. This ladder, drawn upon entry, interacts with the main TFP shock ω_{jt}^h to

[25] This addition allows for price dispersion across producers growing the same crop: high efficiency producers selling a large quantity at a low price, and low efficiency ones selling a small quantity at a high price—in this case, the gains from high production efficiency are larger than in my perfectly competitive model, which hence offers a lower bound for the potential consequences of farm selection. In the monopolistic competition context, a single choke price ensures market clearing across all grains, while in the competitive model a vector of commodity-specific prices is needed, increasing the computational burden of solving for equilibrium. However, my aggregated data is sparse, and likely not sufficient to precisely recover an Ottaviano et al. (2020)-style demand system.

determine crop-specific productivity. Following Mayer et al. (2014), the TFP for crop c is given by $\omega^h_{jct} = \omega^h_{jt}\lambda^{\sum_{n=0}^{dim(\mathbb{C})-1} n\mathbb{1}\{\sigma_j(n)=c\}}$, with n the rank of crop c on farm j's ladder, and $\lambda \in (0,1)$ is a scope parameter governing the strength of specialization.

Market State: In addition to their individual state, all farms face a common aggregate market state Ω_{jt}. I define it as follows: $\Omega_{jt} = \{\mu_t, N^e_t, \{P_{jct}\}_{\mathbb{C}}, \{P^x_{jt}\}_x, P^K_{jt}, Policy_t\}$, where μ_t is the measure describing the distribution of incumbents over the farm state space, N^e_t the mass of entrants, and then vectors of output and input prices, as well as the state of the policy $Policy_t$.

Timing: The sequence of events within a period differs for incumbent firms and potential entrants, as illustrated in Figure 8 and Figure 9. For an incumbent farm, the timing within period t is as follows. First, the state is realized, and farms observe their current productivity shocks $\{\omega^h_{jt}, \omega^{ch}_{jt}\}$, and the aggregate state Ω_{jt}. Second, they make their static production decisions, i.e. choosing variable inputs to produce quantities Q_{jct} for all crops in their mix. Third, they make dynamic decisions. Specifically, they decide whether to stay on the market ($\xi^x_{jt} = 0$), or exit ($\xi^x_{jt} = 1$). If a farm remains on the market, it pays a fixed cost of operation f_k, and chooses its capital stock and crop mix for the next period.

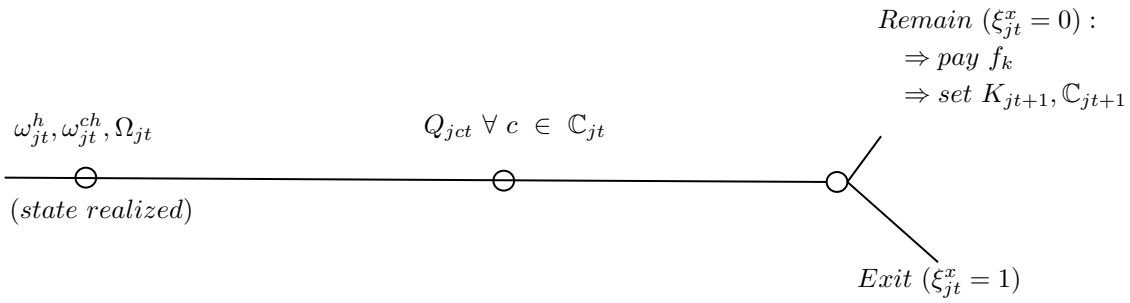


Figure 8: Timing for Incumbent Farms

Short-lived potential entrants face an initial entry period before they can start producing. Observing the aggregate market state Ω_{jt}, potential entrants decide whether to pay a fixed entry cost f_e to enter the market ($\xi^e_{jt} = 1$). Once the entry cost is paid, a farm realizes its initial state vector, including the initial productivity vector ($\{\omega^h_{jt}, \omega^{ch}_{jt}\}$) and a competence ladder (σ_j). After observing its type, a farm can confirm its entry decision, and make initial investment and crop mix decisions, or definitely leave the market.

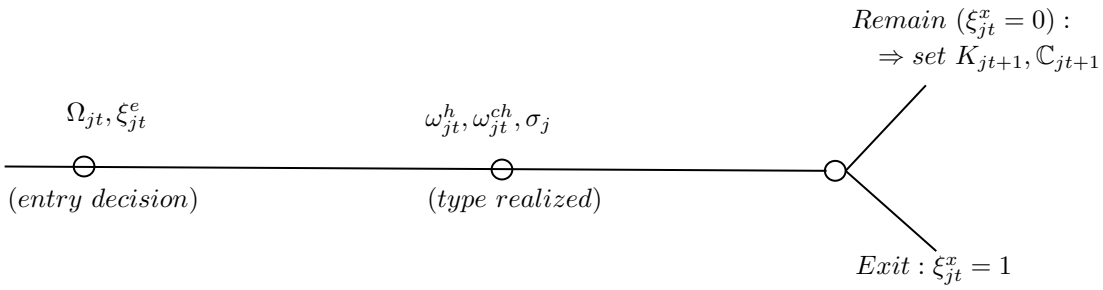


Figure 9: Timing for Entrants

The formal Bellman equations for the incumbent and entrant problems, as well as the law of motion for the distribution of firms and the formal definition of equilibrium, are detailed in appendix B.3.

Production: The production technology is at the heart of the farm's static decision-making. I begin by outlining the core assumptions before specifying the functional forms. I assume that profit maximization occurs independently for each crop in a farm's portfolio. This implies that all flexible inputs (land, labor, chemicals) are chosen for and fully allocated to a specific crop's production line. Conversely, capital (K_{jt}) is treated as a shared input, fully available to all crops grown by the farm without rivalry or cost.[26] This framework deliberately simplifies away certain economies of scope to focus on the primary mechanisms of input substitution and productivity.[27] I discuss and estimate an alternative joint production framework where inputs are shared publicly across products with a penalty in appendix B.5. The production function for quantity Q_{jct} of crop c for farm j at time t is Cobb-Douglas in its main variables:

$$Q_{jct} = e^{\omega^h_{jct}} K_{jt}^{\alpha^c_k} L_{jct}^{\alpha^c_l} \tilde{S}_{jct}^{\alpha^c_s} e^{\varepsilon_{jct}}, \tag{3}$$

with L_{jct} as labor, $\sum_{k\in\{k,l,s\}} \alpha^c_k = 1$, and ε_{jct} is a mean-zero, i.i.d. shock realized after input decisions are made. The key mechanisms of substitution and biased productivity are embedded in the composite input $\tilde{S}_{jct}$, which combines land and chemicals. This composite input is modeled as a constant elasticity of substitution function, in order to allow for flexible substitution patterns and chemical-biased productivity shocks:

$$\tilde{S}_{jct} = \left\{\delta^c_s S^\rho_{jct} + (1-\delta^c_s)\left(e^{\omega^{ch}_{jt}} Chemicals_{jct}\right)^\rho\right\}^{\frac{1}{\rho}}, \tag{4}$$

The CES nest combines land (S_{jct}) with chemicals, with an elasticity of substitution governed

[26] The capital law of motion is $K_{jt+1} = (1-\delta_k)K_{jt} + i_{jt}$, where δ_k is the rate of capital depreciation, and i_{jt} is investment.

[27] The assumption that flexible inputs are fully attributable to production lines is frequent in the literature—implied in single product settings, and formally made in multi-product ones by De Loecker et al. (2016), Orr (2022) or Valmari (2023). I later discuss how this assumption impacts potential economies of scope in the spirit of Panzar and Willig (1981) and Baumol (1977). The assumption that crop-specific profits can be maximized independently from each other captures the assumption of flexible input allocations, of exogenous output prices—unaffected for example by cannibalization concerns of Eckel and Neary (2010) and Nocke and Schutz (2018)—and of limited economies of scope. This also assumes away the overhead costs modeled by Foster and Rosenzweig (2022) for agricultural labor, and enforces that all input prices do not depend on the quantity purchased, and that productivity shocks are exogenous to the size and composition of the crop mix.

by ρ. The chemical-biased productivity shock (ω_{jt}^{ch}) acts as an augmenting shifter for chemical use. As established in the literature (e.g., Doraszelski and Jomandreu (2018)), this structure allows the productivity shock to have a non-neutral effect on input choices. Specifically, an increase in chemical-use efficiency will raise a profit-maximizing farm's chemical-to-land input ratio, as well as chemical-to-output ratio, if land and the chemical aggregate are substitutes ($\rho > 0$). This can be seen by combining the first order conditions related to optimal chemical and land use:

$$log\Big(\frac{Chemicals_{jct}}{S_{jct}}\Big) = \frac{1}{1-\rho} log\Big(\frac{P_{jt}^{s}}{P_{jt}^{ch}}\Big) + \frac{1}{1-\rho} log\Big(\frac{1-\delta_s^c}{\delta_s^c}\Big) + \frac{\rho}{1-\rho}\omega_{jt}^{ch}$$

The production function allows for three different drivers of the chemical-to-land ratio at the farm level: a decreasing relative price of chemicals, a shift in its crop mix towards more chemical-intensive crop, and—if land and chemicals are substitutes—a higher productivity at using chemicals (ω_{jt}^{ch}). While the sign of the first two relations is independent from the value of ρ, the influence of chemical productivity crucially depends on whether $\rho \in]0,1[$, or $\rho < 0$, i.e. whether chemicals and land are substitutes or complements in the production process.[28] The MacSharry reform is likely to play a role along these three dimensions. In appendix B.4, I use simulations to detail the similar role of ρ and ω_{jt}^{ch} in shaping the chemical-to-output ratio of production.

This functional form thus directly models the central trade-off between productivity and pollution intensity that I investigate in this paper. Appendix B.6 extends the production function to include a second CES nest relating pesticides and fertilizers. The coefficients of this extended specification are close to the one found for the simpler design. Additionally, I find that pesticides and fertilizers are complements in production. This implies that their quantities will change in lock-step, and that they can be bundled into a unique chemical input without loss of generality.

Dynamics: The final components of the model govern the farm's dynamic decisions. To make the full dynamic equilibrium model computationally tractable, I introduce a few simplifying assumptions at this stage. These assumptions are used to solve the dynamic programming problem and simulating the model, but were not imposed during the more flexible estimation of the production function itself. First, I abstract from farm-level heterogeneity in crop specialization ability by assuming a homogeneous competence ladder ($\sigma_j = \sigma, \forall j$). Second, input and output prices are assumed to be common across all farms in a given period. This implies that the aggregate state Ω_t is now also common to all farms. These assumptions simplify the farm's state space considerably.

To capture frictions in investment, I introduce convex costs of capital adjustment. The total

[28] For a CES function to be appropriately defined, I need $\rho<1$. This implies that $\frac{1}{1-\rho}$ is always positive.

cost of adjusting the capital stock from K_{jt} to K_{jt+1} via investment i_{jt} is given by:

$$C(i_{jt}, K_{jt}) = P_{jt}^{K} i_{jt} + C_{k}^{Q} K_{jt} \left(\frac{i_{jt}}{K_{jt}} \right)^{2}.$$

The Role of Dynamics: A static model would fail to capture the crucial role of market selection and investment in shaping the industry's response to policy. The dynamic components of the model are essential for two primary reasons.

First, and most importantly, dynamics are necessary to correctly model farm exit and market selection. Farms make forward-looking decisions based on their expectations of future productivity. The central state variables in these decisions are future productivity which is uncertain, and capital, which is costly to adjust and serves as a buffer insulating farms from negative productivity shocks. As shown by Collard-Wexler (2013), this interaction is critical: a farm's exit decision depends not just on how stable its current productivity is, but also on its position in the distribution of capital. Therefore, to correctly account for the selection on productivity that my reduced-form analysis suggests, it is essential to model the interplay between volatile productivity shocks and slow capital accumulation.

Second, these dynamic state variables directly influence the static input choices that determine pollution. A farm's capital stock affects its optimal scale and, potentially, its crop mix. These choices, in turn, determine its demand for chemical inputs. By modeling the slow evolution of capital—a process evidenced by the positive relationship between farm size and age (Figure A14)—the model provides a richer and more realistic picture of the determinants of chemical use, which is crucial for evaluating the environmental impact of different subsidy designs.[29] The dynamic framework also allows me to capture how investment behavior itself responds to the volatility of the economic environment, a key mechanism highlighted by Asker et al. (2014).

4.3 Estimation & Results

For the estimation of the structural model, I simplify the market into two aggregate crop categories: $\mathbb{C} = \{wheat, other\}$.[30] This aggregation is necessitated by the first step of my estimation routine, which identifies the production function parameters using data exclusively from farms that produce only a single crop category. While a methodological requirement, this aggregation is also a reasonable representation of the French grain market. As shown in the Census of Agriculture (Table A3), wheat is the dominant crop, and it is the one most frequently grown in monoculture. Even among the two-thirds of farms that are multi-crop, approximately 90% include wheat in their portfolio.

[29] See Figure A14 showing the relation between farm size (in land use measured in ha) and their age in years of tenure. I show this relation in the 2010 census. The relationship in prior years is heavily impacted by a trend in entry size growth, which biases the overall size-tenure relation. I measure size in land use here, as this is the only available relevant variable observed in the Census.

[30] List of crops in *other* category: sunflower, colza, oats, barley, rye, triticale, corn, sorghum and durum. Finer or different aggregations dramatically reduce the number of single-crop farms available for identification and significantly increase the computational burden of solving the model.

4.3.1 Demand

The primary challenge in estimating the demand equations is that market prices are endogenous, contemporaneously correlated with unobserved demand shocks. To address this, I employ an instrumental variables (IV) strategy, using weather-related shocks that shift crop supply but are plausibly uncorrelated with demand. This approach has a long been used to estimate demand for agricultural commodities (e.g., Angrist et al. (2000), Roberts and Schlenker (2013)).

My set of instruments is constructed from granular weather data. For each relevant region, I construct instruments using both yearly weather realizations, and yearly deviations from local climate averages. The key identifying assumption is that these localized, unexpected weather deviations are orthogonal to aggregate, EU-wide demand shocks for a given crop category. For both specifications, I use national-level data aggregated from the FADN with sampling weights. All regressions include a linear time trend to capture smooth changes in demand, and I compute Newey-West standard errors to account for autocorrelation in the error terms. The resulting demand elasticity estimates are shown in Table A9.

4.3.2 Production Function

The parameters of the production function are estimated in a multi-step process. The estimating equations are derived from the first-order conditions of the farm's static profit-maximization problem.[31]

My estimation strategy is designed to overcome the two main challenges caused by the structure of my data: the allocation of inputs for multiproduct farms and the unobserved productivity shocks that are correlated with input choices. The overall strategy follows the two-step logic of Doraszelski and Jomandreu (2018): the first step is designed to estimate the parameters of the chemical-land nest and recover the chemical-biased productivity shock, while the second step estimates the remaining production function parameters, and recover the distribution of TFP shocks.

Input Observability: The first major challenge is that while crop-specific land use is observed, all other inputs (labor and chemicals) are only measured at the farm level. This makes it impossible to directly estimate a crop-level production function for multiproduct firms.

To address this, my core estimation strategy follows De Loecker et al. (2016) and identifies the production function parameters using data only from single-product farms. For these farms, the input allocation problem does not exist. I then use the estimated parameters and the model's first-order conditions to recover the unobserved productivity shocks for the

[31] Because variable input choices have no dynamic implications in the model, the static first-order conditions are equivalent to those from the full dynamic problem. Independence of crop profits, and the fact that all flexible inputs are fully allocated to product lines finally means that I will be looking at the first order conditions for crop-specific static profit maximization. As frequently done in the production function literature, I assume interior solutions and therefore restrict the estimation sample to observations with non-zero flexible input use (De Loecker et al. (2016)).

full sample of multiproduct farms. A key advantage of my data is that observing crop-specific land allocations allows me to conduct this procedure, while still permitting TFP to be heterogeneous across crops within a farm, an extension to the standard approach.
Using only single-product farms for estimation introduces a potential selection bias, as these farms are likely systematically different from multiproduct farms. For instance, if higher TFP makes it easier to manage multiple crops, then the sample of single-product farms will be negatively selected on productivity (Mayer et al. (2014)).
To correct for this, I extend the selection-correction methodology of Olley and Pakes (1996), and adapted by De Loecker et al. (2016), for my specific context. The procedure explicitly models the farm's choice to be a single-product producer and includes a correction term in the production function estimation. As argued by De Loecker et al. (2016) and Backus (2020), this bias will affect the coefficients of variables correlated with the threshold rule used for the introduction of a second product. Such variables are only present in the second step of my estimation in the form of the farms' capital stocks and chemical productivity. I therefore include the selection correction only in the second step of my estimation routine.[32]

Additional Considerations: Three final data considerations are worth noting. First, a key advantage of the FADN data is that it provides crop-level output in both value and volume, allowing me to use physical quantities in production and avoid the biases associated with using revenue data to measure production (Foster et al. (2008)).
Second, expenditures on chemical inputs must be deflated to recover quantities, while I directly observe labor in hours, and land in hectares. I use national-level price indices for this purpose. Available data suggests minimal regional price dispersion in France, and no dataset is readily available to build representative regional agricultural input prices.[33]
Third, I observe aggregate input bills for both the chemical categories, and cannot address issues of varying consumption basket composition—across farms or across time. Homogeneous input quality updates at the country level might be reflected in prices. Any upgrade in quality that comes with an increase in price not reflected in the national price index—for example a farm starting to buy better and more expensive products—will be manifested as a higher volume of chemicals used rather than an increase in quality. As shown above, a higher chemical-to-land ratio unexplained by varying prices or a change in crop mix will be classified as an increase in chemical productivity. In that sense, the non-Hicksian productivity will not discriminate between input upgrading, learning or changes in farm management that lead to increased chemical use. All these forces will count towards what I measure as increased chemical use efficiency.

[32] De Loecker et al. (2016) argue one should keep observations related to both always single-product firms, and sometimes single product firms when they happen to be single product. I follow their dataset construction guidelines for all my estimation.
[33] These indices are built using an agricultural price survey. However, an initial inquiry ran in 1995 by Insee established that the geographic dispersion in agricultural input prices in France was too small to warrant a geographic stratification of the survey. As such, the survey only achieves representativeness at the country-level. Labor and land prices are observed separately, and specified at the department-by-year level.

First Stage: The first stage aims to estimate the parameters of the nested CES function ($\{\rho, \{\delta_s^c\}_{\mathbb{C}}\}$) and to recover the unobserved chemical-biased productivity shock. The strategy, following Doraszelski and Jomandreu (2018), uses the farm's first-order conditions for land and chemical choice to derive an expression that inverts for the unobserved productivity shock:

$$\rho\omega_{jt}^{ch} = (1-\rho)log\Big(\frac{Chemicals_{jct}}{S_{jct}}\Big) - log\Big(\frac{P_{jt}^{s}}{P_{jt}^{ch}}\Big) - \Big(\frac{1-\delta_s^c}{\delta_s^c}\Big) \tag{5}$$

This equation expresses the unobserved shock ω_{jt}^{ch} as a function of observed data and the structural parameters I wish to estimate. To separate the shock from the parameters, I introduce the assumption that ω_{jt}^{ch} follows a first-order Markov process. This allows me to decompose the shock into its conditional expectation and a random innovation ζ_{jt+1}^{ch}, such that: $\omega_{jt+1}^{ch} = \mathbb{E}[\omega_{jt+1}^{ch}|\omega_{jt}^{ch}] + \zeta_{jt+1}^{ch} = g_{ch}(\omega_{jt}^{ch}) + \zeta_{jt+1}^{ch}$. The innovation ζ_{jt+1}^{ch} is, by definition, mean independent of any information available at time t. By substituting Equation 5 into this expression, and approximating g_{ch} with a high-order polynomial, I can form moment conditions. With $A_{jt}^{z,ch}$ the matrix of valid instruments, the parameters are estimated via a generalized method of moments (GMM) using the following moments:

$$\mathbb{E}\Big[\zeta_{jt+1}^{ch} A_{jt}^{z,ch}\Big] = 0. \tag{6}$$

Second Stage: The second stage relies on the results from the first stage to estimate the output elasticities ($\{\alpha_k^c, \alpha_l^c, \alpha_s^c\}$), and to recover the distribution of TFP shocks. Similar to the first stage, I can rely on the FOC for labor to derive an expression for the TFP shock which depends on parameters and observed variables:

$$\omega_{jct}^{h} = p_{jt}^{l} - p_{jct} - \alpha_k^c k_{jt} - log(\alpha_l^c) + (1-\alpha_l^c) l_{jct} - \alpha_s^c \tilde{s}_{jct}. \tag{7}$$

The standard approach would be to assume the TFP also follows a Markov process, and form moments in a similar was as I did for the first step. However, there is a bias caused by estimating the model on single-product farms. The decision to add or drop a product line is endogenous and likely depends on the farm's state variables, particularly its capital stock and its chemical-use efficiency. Because these variables also appear in the second-stage estimating equation, the selection process induces a correlation between the regressors and the error term, likely biasing the estimates of $\{\alpha_k^c, \alpha_s^c\}_{\mathbb{C}}$.

To address this bias, I explicitly model the selection process and incorporate a correction term, following the logic of Olley and Pakes (1996) as adapted by De Loecker et al. (2016). The true conditional expectation for TFP must account for the information that the farm possessed when deciding to remain a single-product operation. I use Ξ_{jct} for the dummy indicating whether farm j only produces c in t. Under the assumption that the TFP shock follows a first order Markov process, I can then account for the observed truncated TFP

process: $\omega^h_{jct+1} = \mathbb{E}[\omega^h_{jct+1}|\omega^h_{jct}, \Xi_{jct+1} = 1] + \zeta^h_{jct+1}$. I describe in appendix B.7 the correction procedure adapted to this truncated process.

With this correction included, I can build a matrix of instruments orthogonal to the the full residual of the production function, which is composed of the TFP innovation and the idiosyncratic shock to production: $\zeta^h_{jct+1} + \varepsilon_{jct+1}$. I use this to form the moment conditions for the GMM estimation:

$$\mathbb{E}\left[\left(\zeta^h_{jct+1} + \varepsilon_{jct+1}\right) A^{z,h}_{jct}\right] = 0. \tag{8}$$

Estimation: I estimate the parameters for both stages using GMM. Following the approach of Wooldridge (2010) and Doraszelski and Jomandreu (2018), the parameters of the polynomial functions used to approximate the conditional expectation of productivity ($\{g_{ch}(.), g_h(.)\}$) are absorbed and not estimated directly. The validity of the estimation relies on constructing a set of instruments that are orthogonal to the productivity innovations.

The instrument set for the first stage must be correlated with the choice of chemicals and land but uncorrelated with the chemical-use productivity innovation. These will correspond to variables realized prior to the innovation, or taken to be exogenous to the farm-level innovation process such as France-wide agricultural policy. The set includes: a constant (innovation is assumed to be mean zero), pre-determined farm state variables (current and lagged capital stocks), lagged input choices which are correlated with current choices due to persistence but uncorrelated with the current innovation (the lag log ratio of chemicals used to land used), and exogenous factor prices and policy variables (the lag log ratio of chemical and land prices, the current land subsidy, and a measure of current-farm exposure to EU agricultural policy using lagged crop land shares as weights following my shift-share instrument from the reduced-form section).

The instrument set for the second stage must be correlated with the farm's state and input decisions at $t+1$ but uncorrelated with the full residual ($\zeta^h_{jct+1} + \varepsilon_{jct+1}$). The set includes: pre-determined farm state variables (current and lagged capital stock), lagged input and output choices (lagged labor, lagged composite land input, the lag log ratio of chemicals used to land used) and finally exogenous factor prices and policy variables (lag wages, lag land prices, the lag log ratio of chemical and land prices, the lagged farm output price index, current land subsidy, and the same measure of current-farm exposure to EU agricultural policy).

I use Amemiya (1974) GMM weights and a Nelder-Mead minimization algorithm—searching over the space of starting parameters to ensure homogeneous convergence to these values.

Sensitivity of Results to Moments: To understand how specific moment conditions identify the production function parameters, I implement the sensitivity analysis of Andrews et al. (2017). This procedure quantifies the influence of each moment on each parameter estimate, highlighting which assumptions are most critical for my results. The full analysis and results are detailed in appendix B.10.

The analysis reveals that the elasticity of substitution between chemicals and land is identified almost entirely by the moments related to the constant, and to the lag chemical-to-land quantity and price ratios. The procedure provides some clear economic intuition here: for the same lag input price ratio, a higher lag chemical-to-land quantity ratio would be associated with more substitutability between chemicals and land. For the same lag chemical-to-land quantity ratio, a higher input price ratio would imply higher complementarity between land and chemicals. These results reinforce the conclusion from Doraszelski and Jomandreu (2018) that relative input prices are central to identifying the substitution parameters that govern input-biased technological change.

4.3.3 Dynamic Parameters

Three key parameters governing the model's dynamics remain to be estimated: the fixed cost of incumbency (f_k), the convex cost of capital adjustment (C_k^Q), and the fixed cost of entry (f_e). Together, these parameters determine firm survival thresholds, investment behavior, and the equilibrium market size. I estimate these parameters using a Simulated Method of Moments (SMM) procedure, a standard approach for dynamic models (Pakes and Pollard (1989); Gouriéroux et al. (1993); Smith (1993)).

In the first step of the algorithm, I solve the firm's dynamic programming problem to obtain the stationary equilibrium policy functions for investment and exit, under the post-reform subsidy regime. I then simulate a panel of 1,000 farms for T=50 periods, drawing their initial type from the equilibrium distribution. To account for the influence of initial draws on estimation, in this model with endogenous exit, I bootstrap this entire simulation B=100 times, drawing new entrants from the equilibrium entrant distribution to maintain a constant sample size.[34]

I compute a vector of moments from this simulated data $\Phi^s(\Theta)$, with $\Theta = \{f_k, C_k^Q, f_e\}$. The parameter estimates are those that minimize the distance between these simulated moments and their empirical counterparts (Φ^d) calculated from the FADN and Census data:

$$\min_{\Theta} \left[\Phi^d - \Phi^s(\Theta)\right]' W \left[\Phi^d - \Phi^s(\Theta)\right], \tag{9}$$

where W is the weighting matrix. Following Asker et al. (2014), I use the identity matrix for W as the targeted moments are similarly scaled. I proceed to the estimation in two steps: I first run a random grid search algorithm, and then use a simulated annealing algorithm to refine the estimation, starting at the optimum located by the grid search, and setting bounds for the search also derived from the results of the grid search.

[34] Because farms can exit, simply removing initial simulation periods is insufficient to address the initial conditions problem, as is standard in models without exit (Cooper and Haltiwanger (2006); Asker et al. (2014)). Averaging moments across bootstrap replications provides a robust alternative.

Table 1: Moments

Moments for Estimation	Moment	Observed Value	Simulated Value
Auto-Correlation Investment		0.11	0.11
Correlation Investment-TFP		0.050	-0.046
Coef. Variation in Tenure		0.64	0.82
Coef. Variation in Profits		0.75	0.80
S^2 (Measure of Fit)			0.96
Untargeted Moments	Moment	Observed Value	Simulated Value
Price (wheat)		158 €/t	164 €/t
Price (other)		184 €/t	242 €/t
Supply (wheat)		36.8 million t	41.4 million t
Supply (other)		27.5 million t	22.6 million t
Chemical Expenditure to Revenue Ratio		27.5 %	23.6 %

Notes: The coefficient of variation in tenure is computed in the 2000 Census of Agriculture, which is the first census post-reform for which land subsidies are effective. All other targeted moments are computed using the FADN survey over the 1995-2007 period. The auto-correlation in investment tracks the correlation in investment rates within farms over time, the correlation between investment and TFP the correlation between farm investment and productivity levels. The coefficients of variation in tenure and profits capture the spread in farm tenure and profits within the market at equilibrium. [35]

The credibility of the SMM estimates rests on the targeted moments being sufficiently informative about the parameters. Formally, following Gouriéroux et al. (1993), identification requires that the function mapping parameters to moments, $\Phi^s(.)$, is injective (a relevance condition), and that my simulation procedure provides a consistent estimate of this function. My use of bootstrapping and large simulated panels is designed to ensure the second condition holds.

While all moments are used to estimate all the parameters, the relevance condition is best discussed by going through the respective use of each moment in estimating the targeted parameters.[36] The parameters governing firm behavior—the fixed cost of operation (f_k), the capital adjustment cost (C_k^Q), and the cost of entry (f_e)—are identified by moments describing the stationary distribution of farms. I target four such moments from the FADN data, listed in Table 1. The within-farm autocorrelation of investment and the correlation between investment and productivity measured as TFP are primarily informative about the capital adjustment cost. Without adjustment costs, investment would track productivity shocks closely, and have little serial auto-correlation. Convex costs force firms to smooth their investment over time, creating higher autocorrelation and weakening the contemporaneous link to productivity.

The cross-sectional coefficients of variation in profits and farm tenure are primarily informative about the fixed cost of operation. A higher fixed cost truncates the profit distribution

[35] The S^2 measure corresponds to: $S^2 = 1 - \frac{(x-\hat{x})'(x-\hat{x})}{x'x}$, with x the vector of observed moments and $\hat{x}$ the vector of predicted moments, replicating the measure of fit of Asker et al. (2014) used in a similar exercise.

[36] Their distribution is shown in Figure A16.

from below and raises the productivity threshold for survival, leading to shorter average tenures and a less dispersed tenure distribution. Under the zero-profit condition, the fixed cost of entry equates the expected value of entry, which depends both on expected tenure and expected profit. These moments capture the intensity of selection in the market.

4.3.4 Results

I present the main parameter estimates in Table 2. Table A10 provides the values for the additional model parameters that I calibrate directly from the FADN or external sources. The jointly estimated parameters confirm the central economic trade-off motivating this paper. As shown in Figure A27, the model implies that more profitable farms are also more pollution-intensive. In the context of the model's competitive market, profitability is a direct proxy for efficiency, meaning there is a positive relationship between a farm's underlying productivity and its chemical use per unit of land.

Recovered Elasticity of Substitution: The key parameter governing this trade-off is the elasticity of substitution between land and chemicals. which is estimated to be of is $\sigma = 1.47$. This indicates that land and chemical inputs are substitutes in production. This estimate aligns well with the literature on agricultural technical change. Land-chemical substitutability is consistent with the broad history of post-WWII agriculture, where technological progress was characterized by new, high-yield seed varieties that substituted away from land by requiring more intensive chemical use (Hayami and Ruttan (1971), McGuirk and Mundlak (1991)). The magnitude of my estimate is comparable to other key elasticities found in agriculture, such as the elasticity of 1.71 between labor and capital estimated for U.S. agriculture by Kislev and Peterson (1982).
Interpreted through the lens of the biased agricultural technical change theory of Hayami and Ruttan (1971), the high degree of substitutability between land and chemicals can be seen as evidence of input-biased technological change. Rather than simple substitution along a fixed isoquant, it represents a shift in the production function technology itself, where an increase in chemical-use efficiency allows for a fundamental shift in production techniques. This is precisely the mechanism my model is designed to capture.[37]

Fixed Costs: I obtain a yearly fixed cost paid by incumbents of $11,400$€, Industry estimates of administrative costs for the average wheat farm in my sample place these around $9,400$€ (Guillermet (2015)). The fixed cost of entry is estimated to be $517,000$€. Industry estimates set the initial investment value to enter the agricultural market to be of $250,000$€ for a small farm, and between $500,000$€ and 1 million € for a large farm.[38]

[37] A rich literature discusses the precise definition of substitution elasticities with more than two inputs. My estimate for σ corresponds to the Hicks-Allen elasticity, which is constant for a CES function. This differs from the Allen-Uzawa partial elasticities used in some of the earlier literature on input-biased technical change (e.g., Binswanger (1974)), making direct numerical comparisons difficult. I discuss this in detail in Appendix appendix B.4.

[38] See https://www.agri-france.com/reprendre-une-ferme/.

Table 2: Estimated Model Parameters

Coefficient	Parameter	Estimate	Std. Error
Demand Parameters			
Demand constant (wheat)	α_{wheat}	22.08	(1.69)
Demand constant (other)	α_{other}	20.10	(1.97)
Demand elasticity (wheat)	β_{wheat}	-0.89	(0.27)
Demand elasticity (other)	β_{other}	-0.58	(0.32)
Production Function			
Substitution Land-Chemicals	ρ	0.32	(0.15)
Land Share (Wheat)	δ_s^{wheat}	0.35	(0.19)
Land Share (Others)	δ_s^{other}	0.40	(0.28)
Labor Share (Wheat)	α_L^{wheat}	0.29	(0.20)
Labor Share (Others)	α_L^{other}	0.49	(0.18)
Land-Nest Share (Wheat)	α_S^{wheat}	0.17	(0.14)
Land-Nest Share (Others)	α_S^{other}	0.29	(0.14)
Capital & Fixed Costs			
Convex Adjustment Cost	C_k^Q	2.50	(0.44)
Fixed Cost of Incumbency (€1K)	f_k	6.64	(2.91)
Fixed Cost of Entry (€1K)	f_e	58.1	(11.1)

Notes: For demand, the parameters come from IV regressions of aggregate quantity sold on prices, using local weather deviations as supply shocks. Standard errors are corrected for auto-correlation using the Newey-West procedure. For the production function, the parameters are obtained from a two-step estimation, each step performed by GMM. The estimation is run on the FADN French sample restricted to 1980-2007. Observations prior to 1980 are removed, as they do not contain output price data. Observations post-2007 are removed, to focus on a period with significant variation in EU agricultural subsidies, both across time and across crops. I keep farms observed for at least three periods in a row[39]*, and that produce either only crops in the wheat group, or in the other crops group. I remove farms that are not observed with positive input values for the set of considered inputs (land, labor, capital, fertilizers, pesticides). standard errors are obtained using a block bootstrap procedure, where I draw all the observations related to a farm at a time, using $B = 1000$. For capital and fixed costs, parameters are obtained using a simulated method of moments. Because of the computation burden, and the fact that the production function is run on a protected server containing the administrative data, while the numerical model is solved for on a high-performance computing cluster, standard errors for the simulated method of moments do not account for estimation error in the production function parameters or the demand estimation.*

5 Pollution-Inclusive Welfare Evaluation of Agricultural Subsidies

5.1 A Simplified MacSharry: Budget Equivalent Government Purchasing vs. Land Subsidies

In this first counterfactual exercise, I model the conceptual change in subsidization at the heart of the MacSharry reform: moving from demand support via direct government pur-

[39]This is done to smooth potential measurement issues, and follows from De Loecker et al. (2016) and Doraszelski and Jomandreu (2018).

chasing of commodities, to a land subsidy which reduces the farmers' costs of production. To capture the consequences of the change in subsidy design, I model a government expenditure-constant change from one policy to the other. Using a 32% land subsidy value for 1995, this implies a government purchase of 0.9 million tonnes of grain on the market, which I split equally between the two commodities. Table 3 shows the consequences of the policy change.

Table 3: Government Purchasing vs. Land Subsidization (Budget Equivalent)

Panel A	Market Outcomes							
	Expenditure	Wheat P	Other P	Wheat Q	Other Q	Avg. Profit	Cost/Unit	Chemical Share*
Government Purchasing	191.4 M€	164 €/t	246 €/t	41.9 Mt	22.3 Mt	52.2 k€	145.8 €	34.6 %
Land Subsidy	191.6 M€	164 €/t	242 €/t	41.4 Mt	22.1 Mt	53.1 k€	147.5 €	33.8 %
Panel B	Welfare Implications							
	Consumer Surplus		Total Profit		Chemical Expenditure		Pollution Damage	
Δ Level (%)	+ 103 M€		-223 M€ (- 8.3%)		-137 M€ (-3.2%)		[-809 M€,-274 M€] (-3.3 %)	
Panel C	Decomposing the Change in Chemical Expenditure							
	Change (%) ≡		Crop-Level (Within) +		Crop Mix (Within) +		Reallocation (Across)	
	-3.3%		-2.29%		+0.073%		-1%	

Notes: * The chemical share, which corresponds to the ratio of the chemical expenditure to revenue, is computed holding prices fixed to pre-reform level in order to only capture the change in chemical-use intensity. I recover the equilibrium under a 32% land subsidy, and then perform a bisection to find the level of government purchasing for which government expenditure is equivalent. This table compares these two equilibria.

Reform Evaluation: The first effect of the policy change is to decrease output prices. Because government purchasing is modeled as symmetric across the two markets, it ends up playing a larger role on the market with the highest crop price, which is here the second crop. The price decreases generated by the move to a land subsidy are concentrated on that second crop. Because farms are multi-product producers, and because of decreasing returns to scale and the absence of crop-specific fixed costs, all farms produce some amount of the two crops. This implies that the new zero-profit condition can be reached with an asymmetric price decrease, where only one of the two crops is impacted.

Second, the reform leads to a decrease in production. Here the decrease us of 1% on both markets. This decrease in production is driven by market exit, and a decrease in the mass of producers on the market. The farms that stay on the market increase their volumes of production slightly, and consequently reach slightly larger profits. They do so because they benefit from the decrease in costs of production which is not fully translated into decreases in output prices.

Overall, this change of subsidization has a negative effect on production efficiency, but a positive one on environmental outcomes. While keeping farm selection at the same level, the land subsidy distorts input choices from the efficient level (the average cost per unit goes up by 1%), but also distorts input choices away from the polluting input which is now relatively more expensive. As a consequence, the output-price-constant ratio of chemical expenditure-to-farm-revenue is reduced by 2.4%. The total use of chemicals is decreased

further, by an overall 3.3%. This larger decrease stems from the reduced overall production volume. I decompose this total change in chemical use, using a modification of the decomposition formula of De Loecker and Collard-Wexler (2015) (see appendix B.9).[40] This decomposition highlights that decreases in total chemical use are in part driven by changes in farm-crop-specific input mixes holding scale constant (-2.3%), and in part by decreases in total production and reallocations (-1%).

Focusing on consumer surplus and total farm profit, this change in subsidization is only evaluated as positive if we account for the environmental gains from reduced chemical use. Losses in farm profit are about twice as large as gains in consumer surplus from reduced output prices. This calculation does not account for any additional policy objectives, such as supporting the revenue of small farmers or guaranteeing food security. If we account for the decreases in chemical use, evaluated using low and high marginal costs of agricultural pollution from the French Department of the Commissioner General for Sustainable Development (2011), these welfare gains become positive, and are raised by a value between 274 M€ and 809 M€.

A change in the model introducing crop-specific fixed costs would give rise to more specialized producers in the model, and would likely accentuate reform-driven price decreases for both crops. The actual MacSharry reform also included an end to export subsidies and import levies, which should have further decreased output prices, and which I do not model. Finally, the fact that I only model the French market, rather than the whole EU market, might hide reallocations in production happening across countries, where larger reform-induced farm exit of low efficiency producers might also decreases output prices and costs of production.

5.2 Which Channels Relate Subsidies to Chemical Use?

The empirical model allows for three different channels to impact chemical use on the market: 1) a first intensive margin of input choice, 2) a second intensive margin of crop choice, 3) an extensive margin of farm selection. For the first channel, shifts in relative input prices will change the farms' choices of inputs for the production of any given crop. For the second channel, changes in input prices and in output prices will change the farm's crop mix. Finally, changes in the relative profitability of the market given a farm's type will select farms in and out of the market. This selection mechanism will interact with the positive correlation between farm profitability and chemical use intensity established for the French market in section 4. On top of these three channels, subsidies will also increase expected profit at entry, and through the zero profit condition, decrease equilibrium output prices and the farms' scale of production.

In this sub-section, I compare a budget equivalent series of two different farm subsidies in order to highlight how subsidies end up interacting with these different channels. The first of these two subsidies is the land subsidy introduced post-MacSharry reform and still in

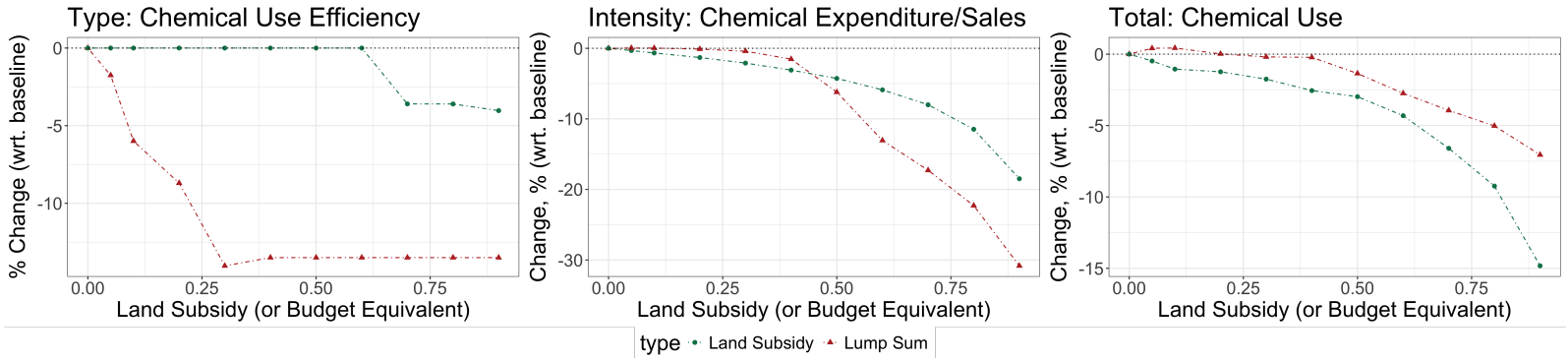
[40] Because the set of farms existing at equilibrium is identical across the two equilibria, the reallocation terms includes the last two terms shown in subsection B.9, on top of the pure reallocation third one.

place in the EU today. The second is a lump sum payment to low chemical use efficiency producers who cannot survive on the market in the no-intervention equilibrium, i.e. a subsidy scheme where the government pays a yearly lump sum to farms whose ω_{jt}^{ch} is sufficiently low. These producers can be considered as organic or low pollution types, kept out of the market because of the positive correlation between farm efficiency and pollution intensity. While the land subsidy will play mainly along the intensive input choice margin by shifting the relative price of chemicals and land, the second will play along the extensive margin of selection, allowing for low efficiency but also low pollution farms to remain on the market and shifting more production towards these more sustainable producers. Through large changes in output prices, that second subsidy will also impact the farms' production scale and crop mix. Figure 10 illustrates equilibrium chemical use under these two series of subsidies.

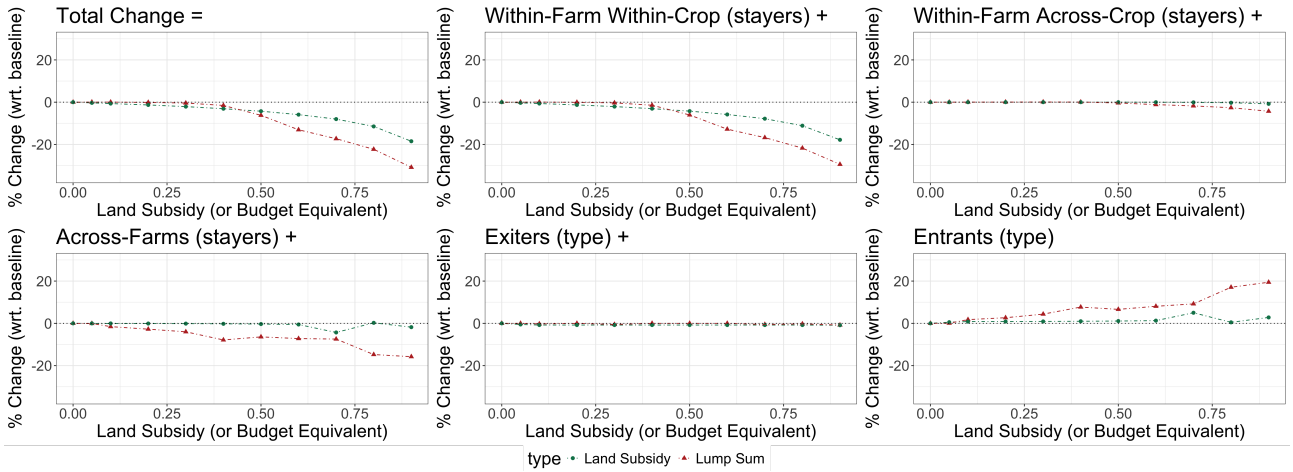
Panel a) of figure 10 shows first the effect of subsidies on farm selection along the chemical use efficiency dimension: how subsidies, by shifting the survival threshold at which farms exit the market, end-up changing the average chemical use efficiency on the market. Figure 10 then shows the subsidies' impact on the intensity of chemical use, and on total chemical use. The first figure of panel a) illustrates that higher lump sum payments do allow for lower chemical use efficiency farms to remain active on the market, in turn lowering market average chemical use efficiency. Figure A18 gives the average chemical expenditure to sales ratio of farms active both in the no-intervention equilibrium and in any given lump sum equilibrium (stayers), and compares it to the average ratio of farms that are only active under the lump sum payment (entrants).[41] Entrants have systematically a lower intensity of chemical use. This implies that the lump sum payment, by reallocating production towards these more sustainable farms, should reduce the overall intensity of chemical use. On the contrary, the land subsidy has a small effect on selection, first null until the subsidy becomes larger than 0.60, after which it also slightly lowers the average chemical use efficiency of the market. As such, the land subsidy will mostly impact chemical use through changes in relative input prices, while the lump sum payment will mostly have an effect through selection.

The rest of panel a) indicates the effects of subsidies on relative and aggregate chemical use. For this exercise, I keep output prices constant to no-intervention levels, in order to focus on the changing intensity of chemical use in the production process. Figure 2 of panel a) shows that for large levels of intervention, the lump sum payment achieves a larger reduction in the intensity of chemical use than the budget-equivalent land subsidy. However, figure 3 shows that the land subsidies always leads to a larger decrease in total chemical use, reaching a 15% decrease wrt. no intervention for a 0.90% land subsidy, compared to a 7% decrease with the equivalent lump sum payment.

[41] As in previous parts of the paper, I measure the intensity of chemical use with the average chemical expenditure to sales ratio. This measure is more readily interpretable than a chemical quantity to output quantity ratio, and allows for aggregation across crops.



(a) Effects on Chemical Use



(b) Decomposing Changes in Chemical Use Intensity

Figure 10: Land Subsidy vs. Lump Sum Payments to Low Chemical Use Efficiency Farms

Notes: These figures describe equilibrium chemical use outcomes under a series of respectively increasing land subsidies, and budget-equivalent lump sum payments paid to low chemical use efficiency producers who cannot survive under the baseline no-intervention equilibrium. In the first panel, the first figure tracks the average chemical use efficiency in the market, which is a marker of the effects of market exit in selecting farms along their efficiency at using chemicals. The second and third track resp. the intensity of chemical use measured with the chemical expenditures to sales ratio (keeping output prices constant to baseline levels). In the second panel, the first figure shows the evolution of the chemical expenditure to sales ratio, which is then decomposed using the accounting formula described in appendix B.9. The decomposition of the change in total chemical use is shown in figure A17.

Using the accounting equivalence outlined in appendix B.9, panel b) of figure 10 decomposes the intensity of chemical use into: changes within farm and within crop in chemical expenditure ratio, changes within farm in the allocation of production of total revenue across crops, market share reallocations across stayers, and resp. the impact of farm exit and of farm entry. This decomposition is useful to understand the relative strength of the two subsidy regimes, and the mechanisms through which they operate.
Most of the land subsidy effect goes through the first channel, with farms responding to shifting relative input prices by adapting their crop mix towards more intensive land use and lower chemical use. The lump sum payment, on the contrary, has an effect first by significantly lowering output prices and increasing demand, and second through selection. With respect to the first channel (within-farm within-crop), it decreases output prices as expected profit at entry rises monotonically with higher lump sum payments. As a consequence, all stayers reduce their scale of production, and a relative lack of adjustment in capital stock implies that this smaller scale of production comes with higher flexible input efficiency and less chemical use per unit of output. Second, the lump payment decreases the market share of the stayers and reallocates production across stayers as production scale falls. Within stayers, production is reallocated towards larger and more polluting farms as prices drop. Third, it gives a positive market share to low chemical use intensity farms. As shown in figure A18, these entrant farms have a lower chemical use intensity than the stayers. The effect of decreased stayer market share and reallocations within stayers is shown on figure 4 of panel b), and the entry of new farms is shown in figure 6. The decomposition of the change in total chemical use is shown in figure A17.

5.3 Optimal Policy Design

In this last counterfactual exercise, I compare the welfare implications of a series of agricultural subsidies and of a chemical tax. Conditional on a valuation for the damages caused by agricultural chemical use, I perform a grid search that identifies the optimal subsidy or tax level within each design, and then compare these optimal intervention across designs. I use this comparison to ask two questions: how do the environmental implications of these subsidies change our understanding of their optimality (within and across designs), and conditional on our valuation of environmental pollution, what is the extent to which these subsidies can substitute for the direct taxation of chemicals? Figure 11 plots the welfare implications of these optimal subsidy and tax levels.

Optimal Subsidies: Using a valuation for the damages caused by agricultural chemical pollution from Department of the Commissioner General for Sustainable Development (2011), I find that both a positive level of land subsidy, land subsidy differentiated by crop, and of a lump payment to low chemical use efficiency producers can generate welfare gains compared to the no-intervention equilibrium. My search identifies an annual 28k€ lump sum payment to sustainable producers, a homogeneous 10%, and a differentiated $(10\%, 40\%)$ land subsidy

schemes as welfare optimal within their design. Their generated welfare gains and marginal value of public funds (MVPF) measured as consumer surplus, total profit and environmental gains over government expenditure, are resp. of 119M€ and MVPF of 1.6 for the differentiated land subsidy, 75M€ and 2.9 for the homogeneous land subsidy, and 9.6M€ and 1 for the lump sum payment.

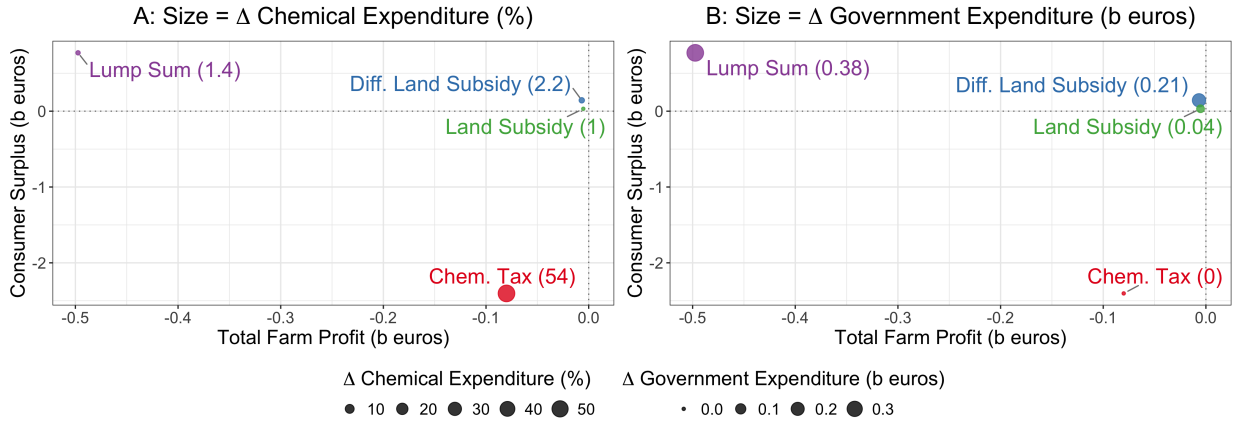


Figure 11: Comparison of Welfare Maximizing Policies

Notes: This figure plots the welfare implications of different optimal subsidy and taxes. Within each design, a grid search is performed over the range of possible intervention levels, and the welfare optimizing level is selected. The welfare criterion used for this is composed of consumer surplus, total farm profit, government expenditure and environmental gains from reduced chemical use. The marginal cost of agricultural chemical pollution is taken from Department of the Commissioner General for Sustainable Development (2011). The figure plots the difference in consumer surplus, total farm profit and government expenditure relative to the no-intervention equilibrium. The change in chemical expenditure is expressed in percent, also compared to the no-intervention equilibrium.

Out of these three designs, the differentiated land subsidy does best overall, reaching the largest decrease in chemical use (2.2% compared to baseline), while also increasing consumer surplus slightly and being relatively inexpensive, with a cost of 40M€. Compared to the homogeneous land subsidy, it subsidizes land use for the land intensive crop more, reaching higher decreases in chemical use at a relatively constant cost to consumers. The lump sum payment does best for consumer surplus, but at a relatively high cost for producers.

In a case where environmental pollution is not valued, only a small homogeneous 5% land subsidy can generate positive, albeit very small, welfare gains. No level of lump sum payment to producers can generate positive welfare gains. Within the set of previously identified optimal policies, the optimality ranking is also shifted, with the homogeneous land subsidy becoming the dominating subsidy. In that sense, the unintended environmental consequences of these agricultural subsidies are meaningful, capable of overturning their welfare effect, and changing our understanding of which subsidies should be optimally implemented. As highlighted previously, this comparison does not account for additional goals of subsidies which could be added additively to the welfare criterion, for example a reduction in agricultural profit dispersion.

Subsidy vs. Tax: A second natural question is whether an optimal land subsidy can be an efficient substitute to a direct tax of chemicals. Figure 11 plots the optimal chemical tax next to the optimal subsidies.[42] This comparison yields a straightforward take-away: a chemical tax is significantly more efficient at reducing total chemical use: the optimal tax reduces chemical expenditure by 54%, compared to 2.2% of the optimal subsidy. This reduction is achieved at zero cost for the government. For the chosen valuation of agricultural chemical pollution, it also reaches a 2.1 billion euros welfare gain. However, this tax achieves these gains at a significant costs, both for consumers and producers. Indeed, it significantly raises output prices and decreases quantity. Within this framework, subsidies are poor substitutes for the direct taxation of chemicals. This taxation, however, has a significant negative effect on economic surplus measured as consumer surplus and total farm profit.
When government expenses are not valued in welfare, both land subsidy designs can reach a 15% decline in total chemical use, which puts them closer to the environmental gains of a chemical tax. In that sense, such agricultural subsidies can be considered as partial substitutes to a chemical tax which would be paired with direct subsidies to consumers, aimed at reducing its negative incidence on consumer surplus.

6 Conclusion

In this paper, I study the effect of EU Common Agricultural Policy (CAP) subsidies on environmental pollution within the French grain market. I document large equilibrium effects of EU subsidies, and a fundamental trade-off in the market: within the French grain sector, higher farm productivity is positively correlated with pollution intensity.
To establish these results, I first use the 1992 MacSharry CAP reform as a natural experiment. A shift-share analysis demonstrates that the reform significantly decreased the profitability of French agriculture, led to the exit of small farms, and to a reduction in both chemical use and water pollution.
To better understand and quantify the equilibrium consequences of agricultural subsidies, I then develop an empirical model of the industry. The model rationalizes the correlation between profitability and chemical use intensity, showing that it stems from the elasticity of substitution between land and chemicals in production (estimated at 1.47), combined with heterogeneity across producers in their efficiency at using chemicals in production.
My results show that both policies targeting the extensive margin by supporting the survival of low-pollution producers, and policies aimed at shifting the relative price of chemicals and land, can be effective at reducing both the intensity of chemical use, and aggregate chemical use. Finally, I show that while these subsidies have meaningful environmental externalities which can transform our understanding of their welfare consequences, they remain poor substitutes for a direct tax on chemicals.

[42] The tax considered here is paired with a direct lump sum repayment to producers. This tax is relatively more generous to producers even though harder to implement practically, as it limits distortions to production to input choice, and does not additionally tax producers.

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Appendix for online publication:
An Empirical Model of Agricultural Subsidies with Environmental Externalities

A Additional Figures and Tables

A.1 Figures

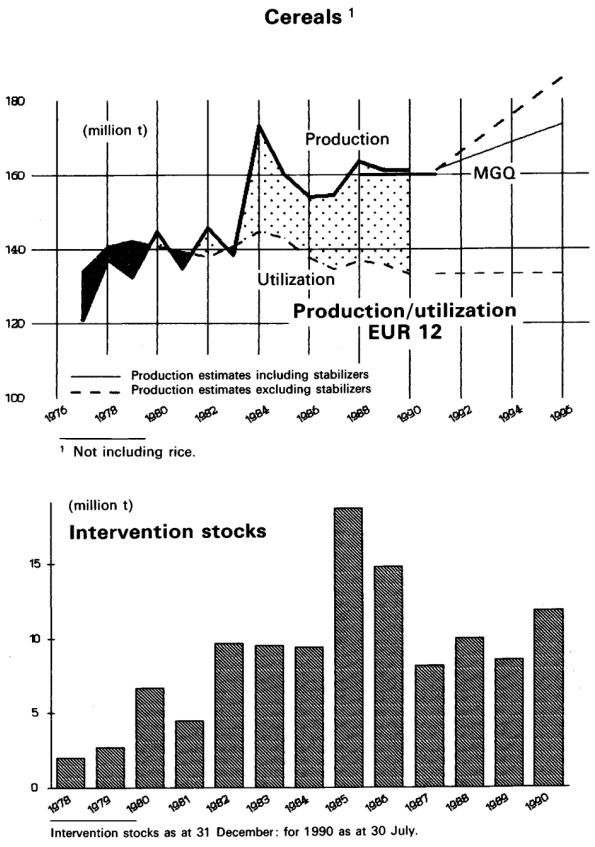


Figure 12

Figure A1: Intervention on the Cereal Market

Notes: This figure taken from a 1990 report of the European Commission describes the growing gap between supply and demand for cereals in the European Union, as well as the evolution of the stock of cereals purchased by the governmental agencies following the purchasing guarantee set on the market. The figure comes from the 1990 The Agricultural Situation in the Community report. The report can be accessed via the University of Pittsburgh at https://aei.pitt.edu/31386/1/CM5890934ENC_002.pdf .

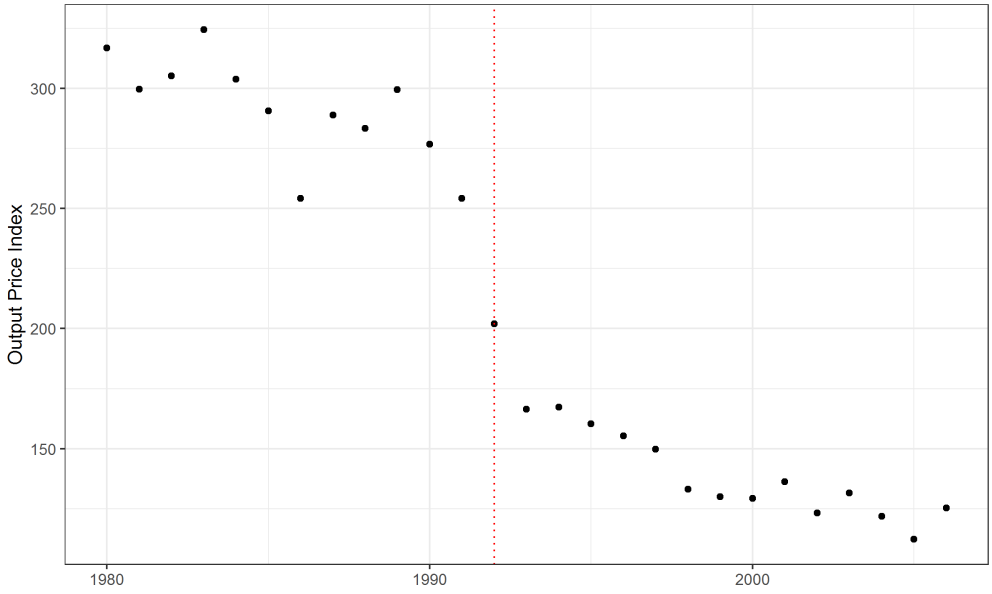


Figure A2: Average Farm Price

Notes: Binscatter for a farm-level average output price, computed over oil and cereal crops, using relative land shares as weights.

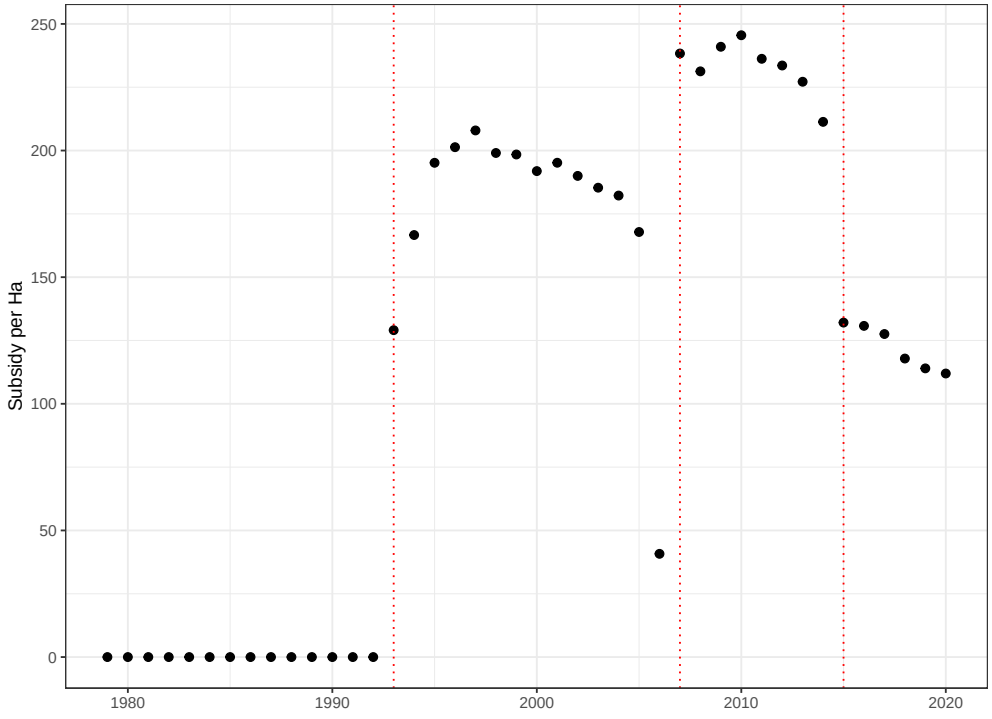


Figure A3: EU Land Subsidies under the CAP

Notes: I show a binscatter for the land subsidies given under the CAP, as observed in the FADN survey of farms. Each vertical red line indicates a reform of the subsidization scheme, the first one corresponding to the MacSharry reform.

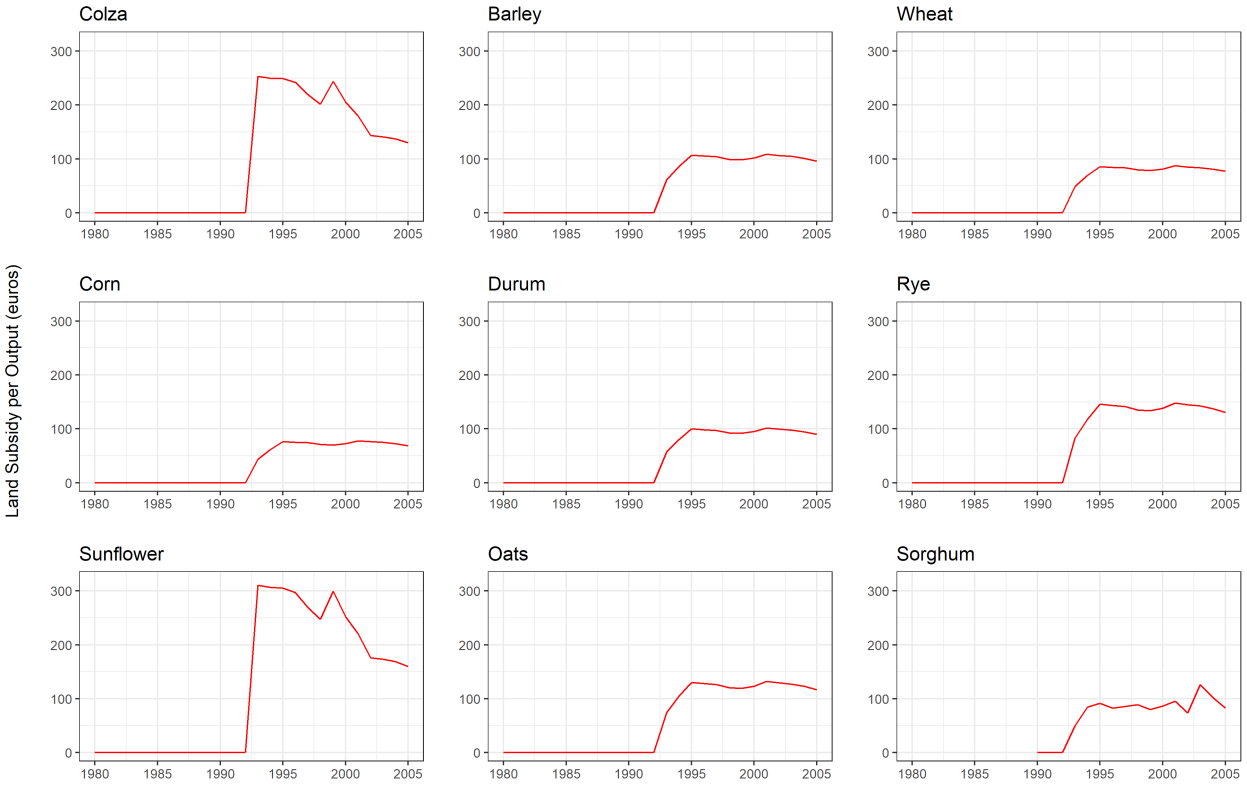


Figure A4: EU Land Subsidies per Crop under the CAP

Notes: The figure shows the evolution of the average land subsidy per unit of output over time, as measured in the FADN. I measure the average subsidy per hectare for cereals and oil crops, dividing the farms' total subsidy for each crop category, by their land allocated to each category. I then divide this measure by the average crop-specific yield observed in France in that year, in order to recover a subsidy per unit of output. Subsidies per land are relatively stable across years, while yields increase, making it so that subsidies slightly decrease over time absent any policy adjustment.

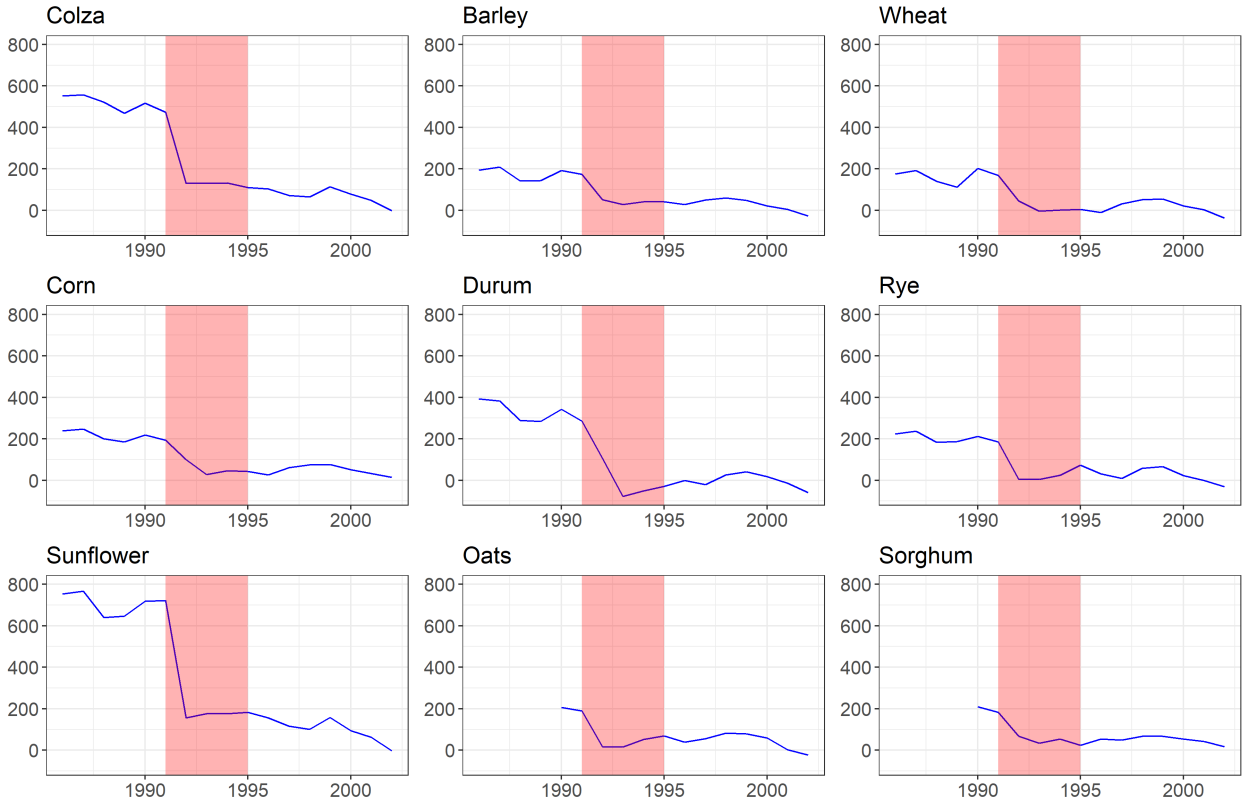


Figure A5: EU Subsidization per Unit of Output—Heterogeneity in Losses around the Reform

Notes: The figure plots crop-specific EU subsidies per unit of output over time, using data from the FADN, and digitized time series of EU intervention prices over time, as well as U.S. and Canadian farm gate prices from Faostat. The shaded area is for 1991-1995, going from the last year pre-reform to the last year of the reform. Data on oats and sorghum is only introduced in 1990 in the FADN.

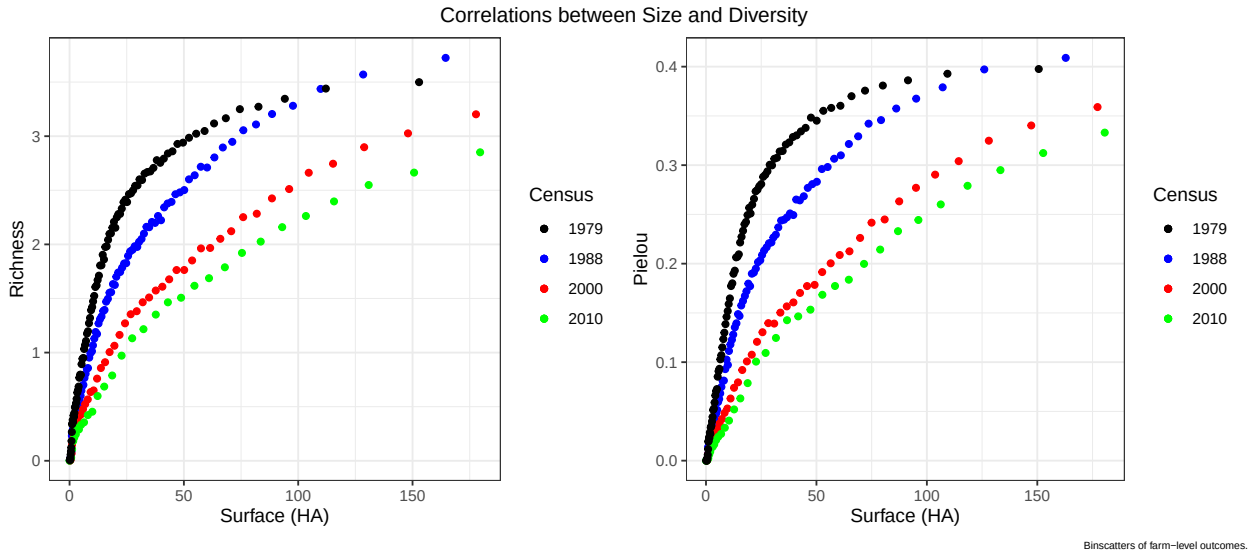


Figure A6: Evolution of Farm Crop Diversity

Notes: These binscatters are computed using data from the Agricultural Census. I take into account the maximum number of crops which can be tracked over the 1970-2010 waves of the Census, which are: wheat, durum, barley, oats, rye, corn (grain), corn (seeds), sorghum, rice, beetroot, rapeseed, sunflower, soy. Crop richness is a simple count measure of the number of crops being grown in a given farm. The Pielou index in a measure of how evenly land is allocated across the crops grown within a farm[43].

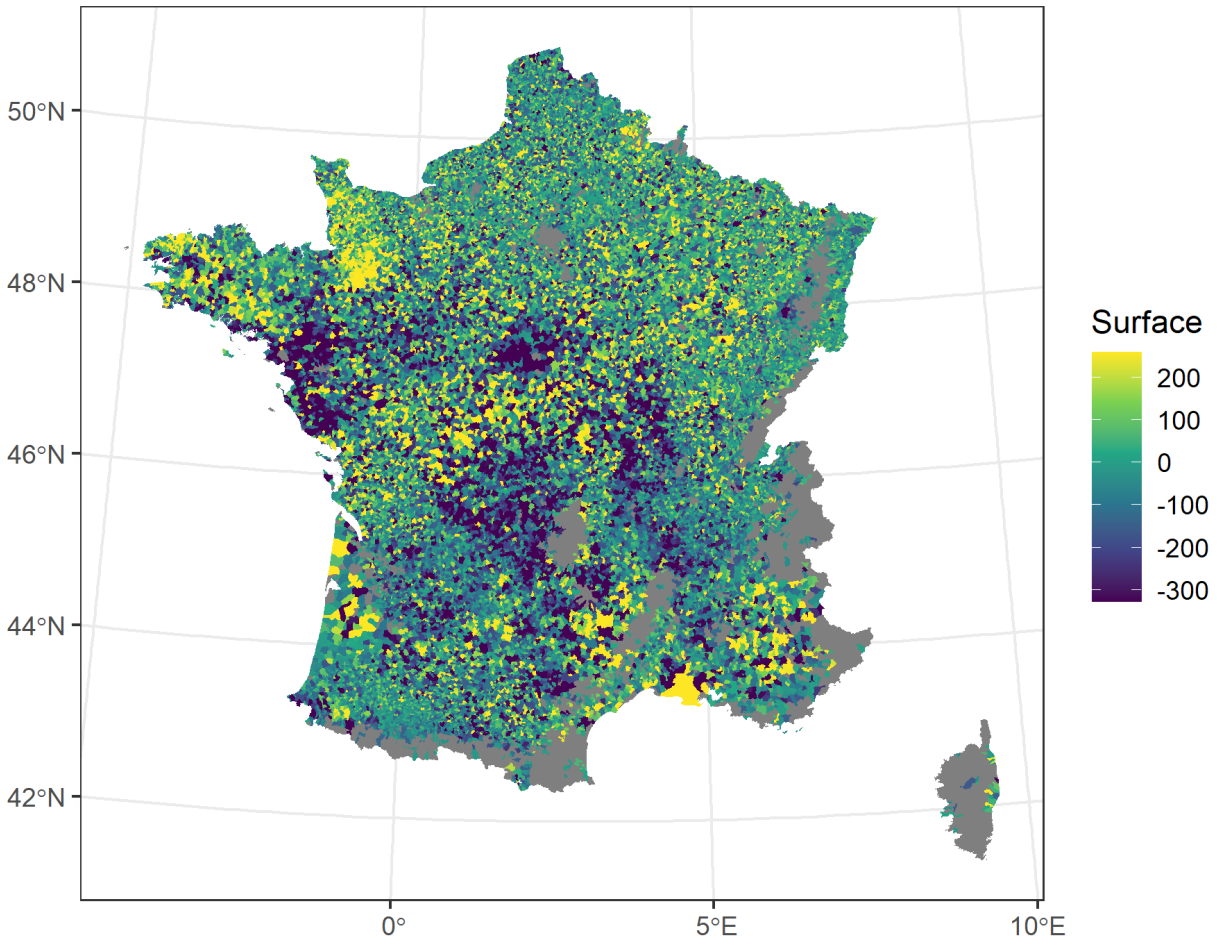


Figure A7: Evolution of Village-level Total Agricultural Area

Notes: This map shows the evolution of within-village total agricultural area between 1988 and 2000. I use the data from the relevant waves of the French Agricultural Census. Decreases in agricultural area mainly happen in the center of France around the Massif Central, as well as in Vendée and possibly lower Brittany.

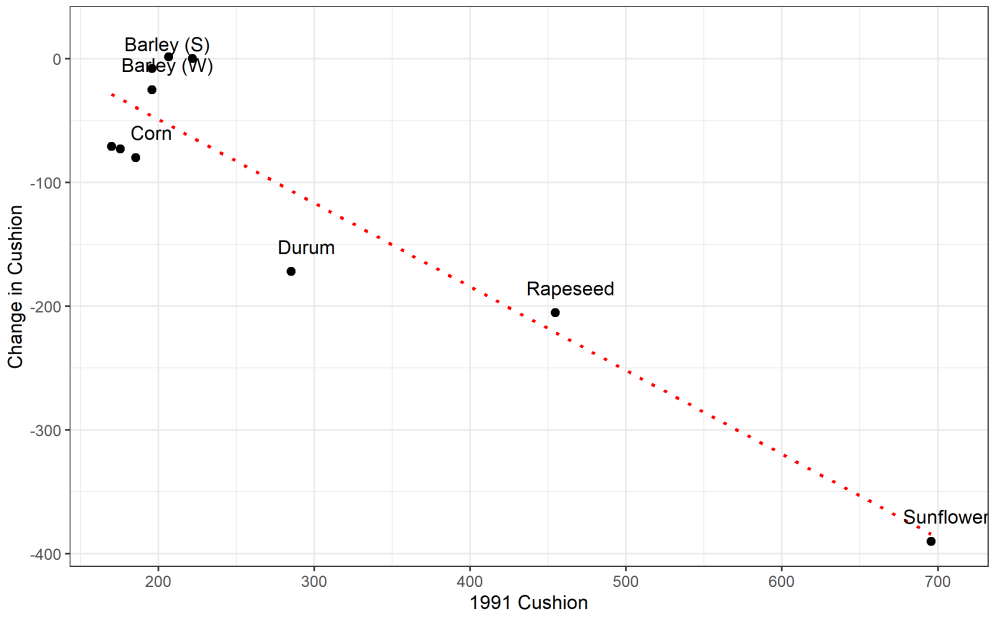


Figure A8: Convergence of Crop Cushions Post Reform

Notes: The figure illustrates the convergence of crop cushions post reform. Here the cushion is the French average of the crop-specific cushions in the relevant year, computed according to the formula outlined in **??**. *The change in cushion is the change observed between 1991 and 1995, corresponding to the period of the MacSharry reform.*

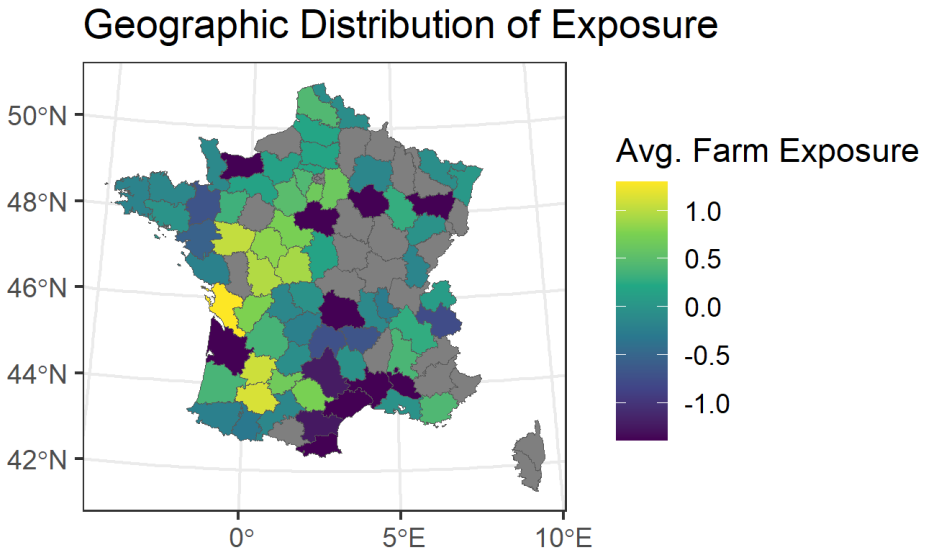


Figure A9: Department Weighted Averages of Farm-Level Exposure

Notes: The figure shows the geographic distribution of the standardized measure of farm-level exposure. The exposure is computed using data from the FADN, and department-level averages are computed using the extrapolation weights provided there. I plot the geographic variation of the standardized exposure here.

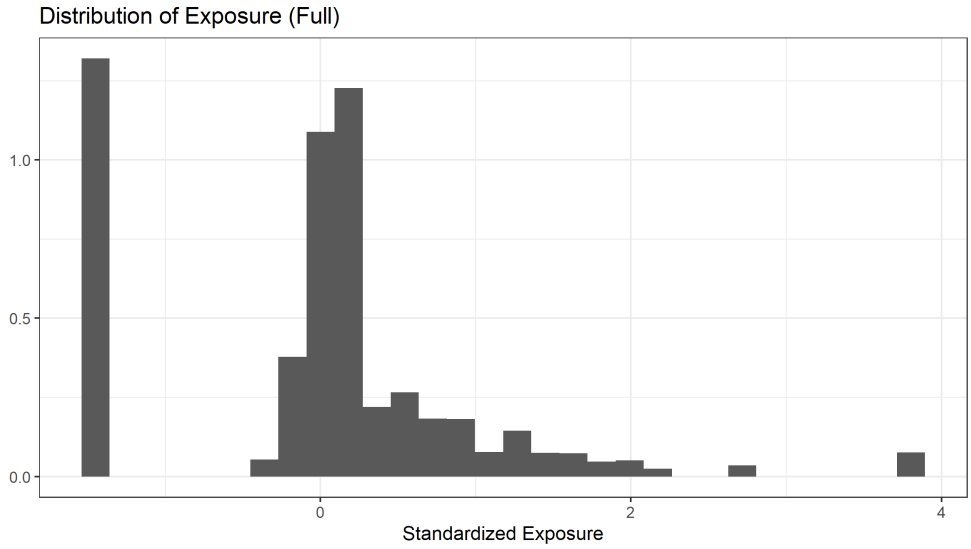


Figure A10: Distribution of Farm-Level Exposure

Notes: The figure shows the distribution of the standardized measure of farm-level exposure (the preferred instrument). The exposure is computed using data from the FADN.

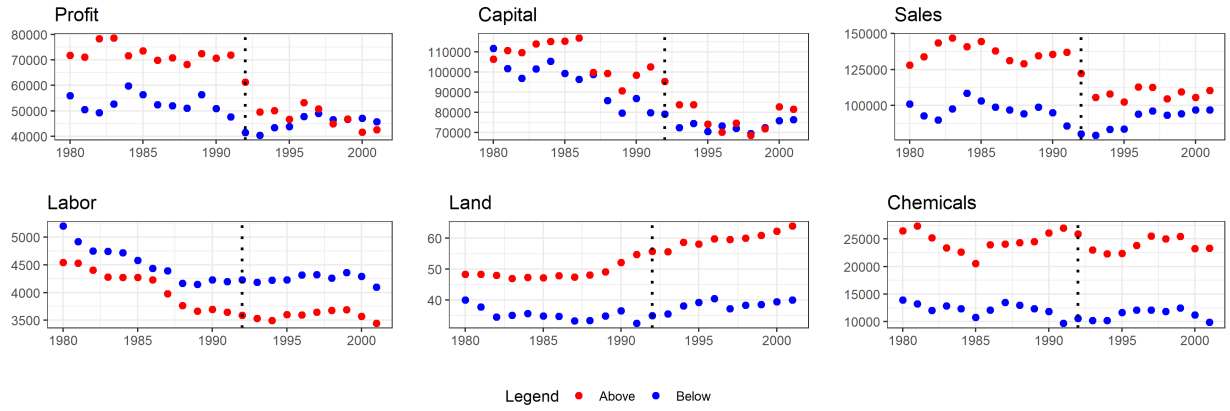


Figure A11: Balance in Levels and Trends

Notes: These binscatters are computed using data from the FADN, and use sampling weights to compute bin-specific averages within each category. Profit corresponds to total farm profit, capital is the sum of total farm value in buildings and machinery, sales is total sales. All of these values are computed in 2020 euros. Labor is total labor in hours per year, and land total utilized agricultural area in hectares.

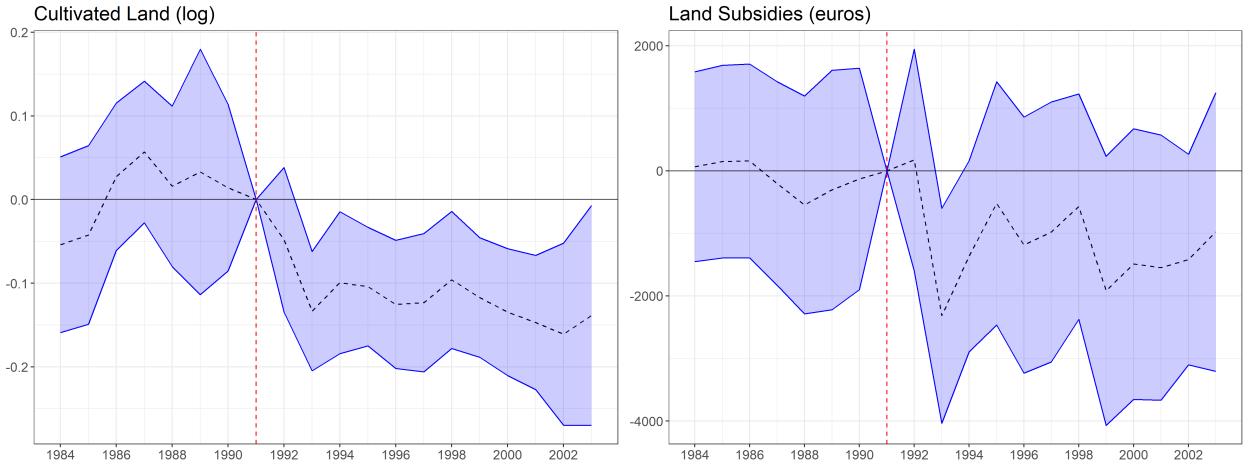


Figure A12: Exposure to the Reform—Farm-Level Event Study (Additional results)

Notes: The outcomes of the event studies are the following: the amount of land cultivated within the farm in log terms, and the amount of subsidies received from the land subsidy post-MacSharry reform in euros (this measure is 0 for all farms up to 1992, which is why it is measured in levels). All coefficients correspond to the year-specific coefficient associated to farm exposure, and give the effect of exposure in that given year. The vector of controls contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984 adoption trends in chemicals measured as the evolution in their chemical use. I add department-year and farm fixed effects, and cluster the standard errors one-way at the region-year level.

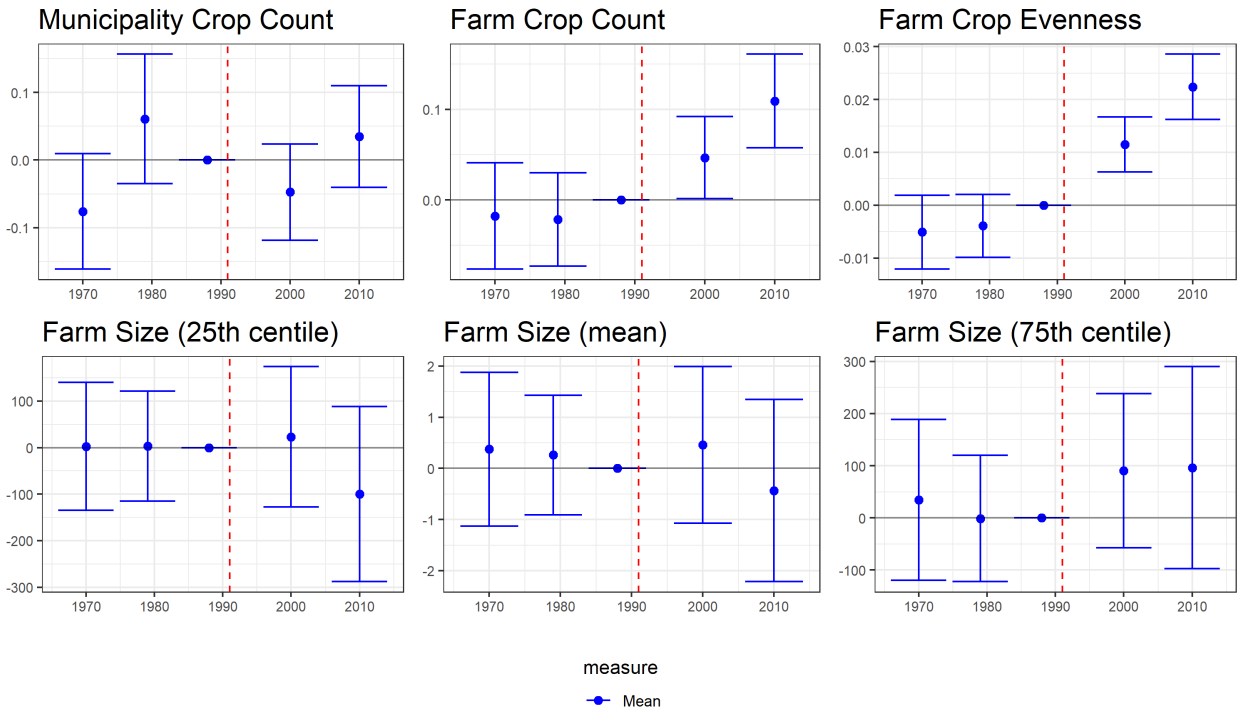


Figure A13: Additional Municipality Level Results

Notes: This figure gives the results for the municipality-level event study. Outcomes are the following: the number of crops grown within the municipality, the number of crops grown in the average farm within the municipality, the evenness of land allocation across crops for the average farm, the 25th, mean and 75th centile of the farm size distribution, measured in ha cultivated land. The regression includes a series of controls set to their level in 1988 within the municipality, and interacted with a time-varying coefficients, as well as municipality and department-by-year fixed effects. Standard errors are clustered at the region-by-year level.

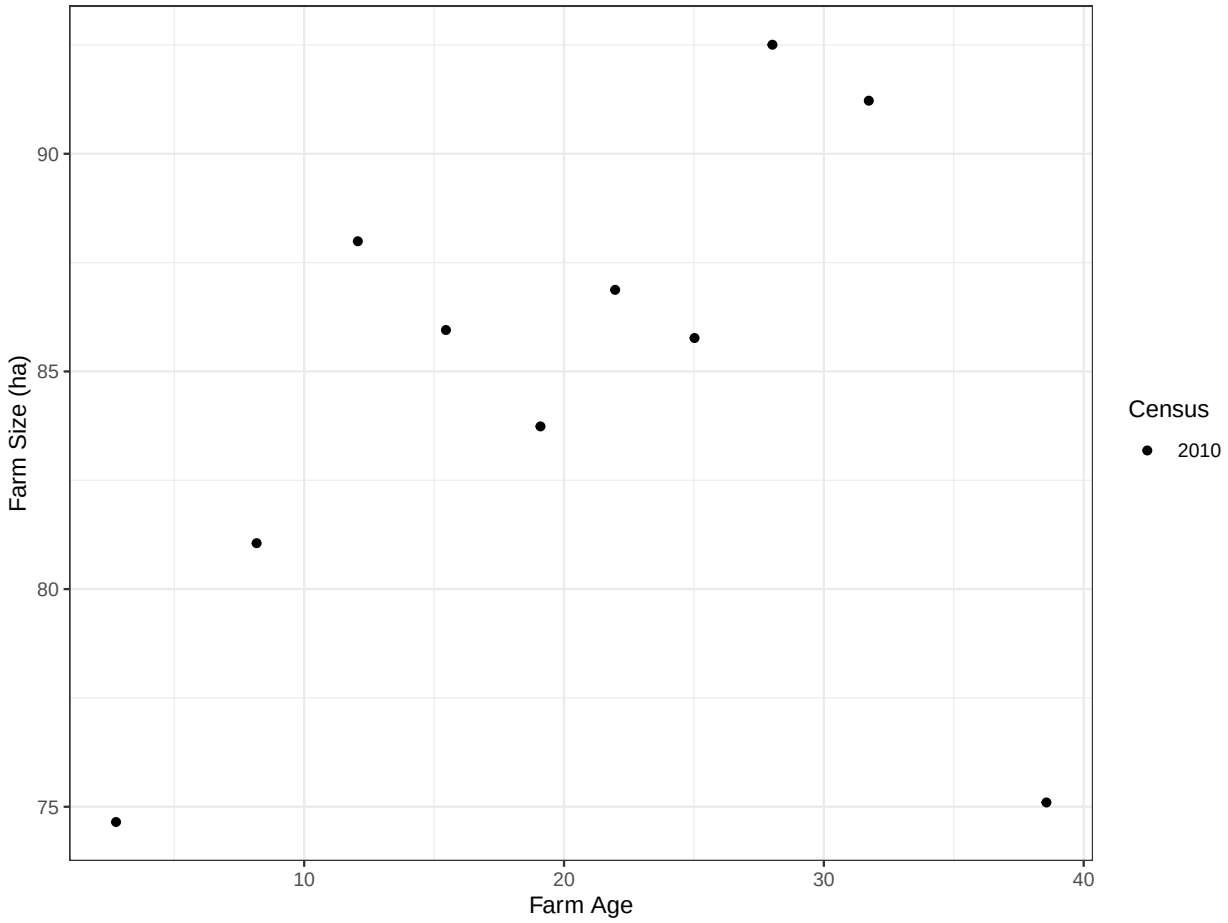
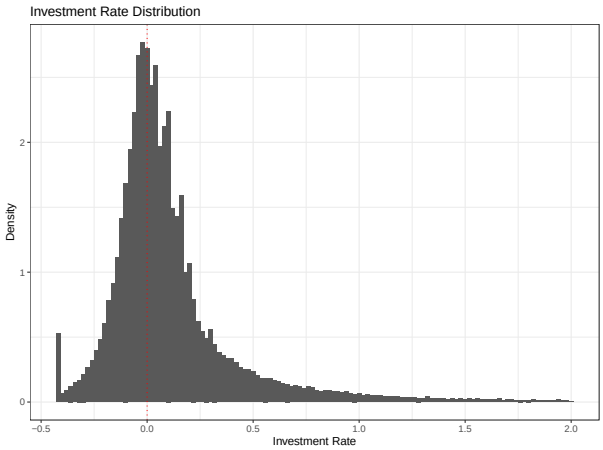
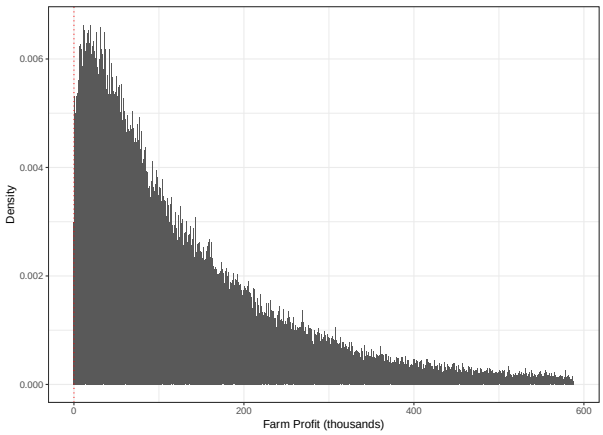


Figure A14: Relation between Farm Size and Farm Age in the 2010 Census

Notes: The figure shows a binscatter showing the relation between farm size and farm tenure, as observed in the 2010 French agricultural census. I use the 2010 Census to capture this relation, as the total number of farms ceases to decrease as quickly between 2000 and 2010, and one can interpret the market as relatively more stable than in the previous decades. In previous waves of the Census, older farms had likely entered the market under very different conditions, and were more likely to be small non-commercial farms with different management styles.

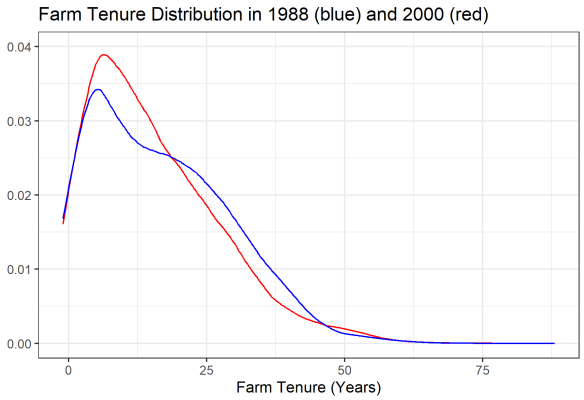


(a) Distribution of Investment Rates (FADN)



(b) Distribution of Profits (FADN)

Figure A15



(a) Distribution of Tenure (Census)

Figure A16

Notes: I plot the distributions from which I obtain the moments used for the simulated method of moments estimation routine. The investment rate is recovered as the difference between lagged depreciated capital using an 8ppt depreciation rate, and the current capital level. Profits are directly observed in the data, as well as farm tenure. The first two graphs are obtained from FADN data, while the last one is built with 1988 and 2000 Census data.

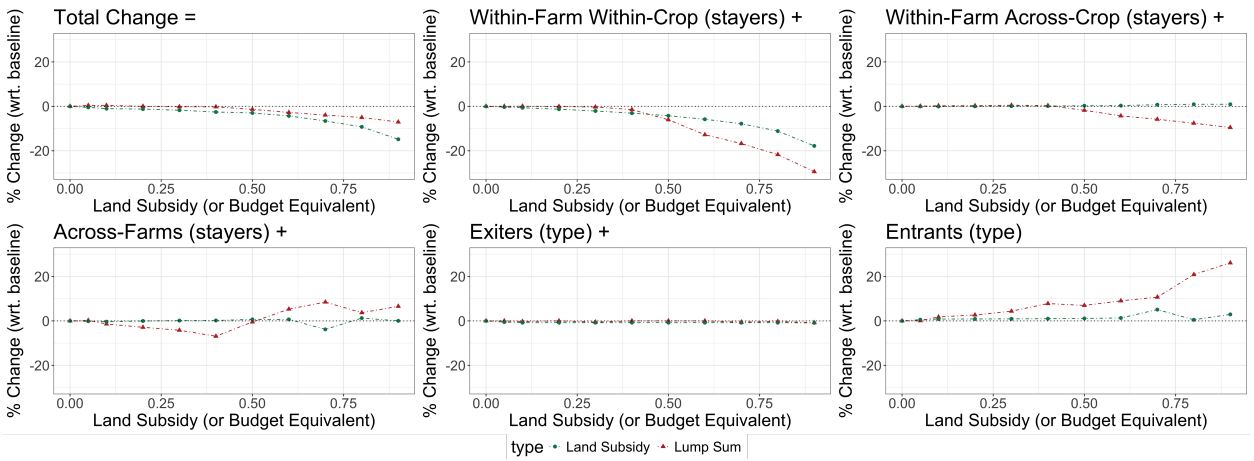


Figure A17: Relation between Farm Size and Farm Age in the 2010 Census

Notes: These figures describe the evolution of total chemical use under a series of respectively increasing land subsidies, and budget-equivalent lump sum payments paid to low chemical use efficiency producers who cannot survive under the baseline no-intervention equilibrium. The first figure shows the evolution of total chemical expenditures, which is then decomposed using the accounting formula described in appendix B.9.

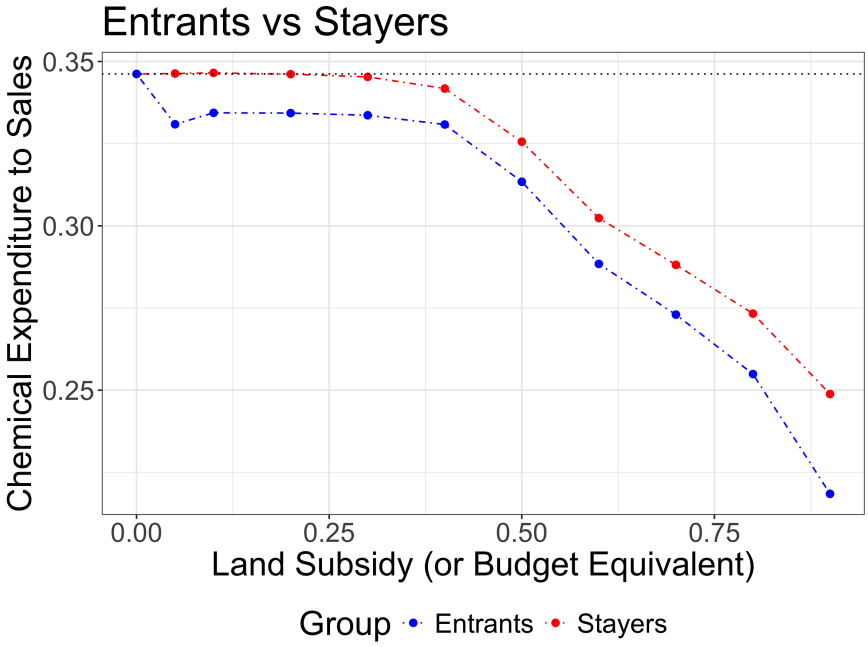


Figure A18: Relation between Farm Size and Farm Age in the 2010 Census

Notes: This figure shows the average chemical expenditure to sales ratio of stayers vs entrants for different levels of lump sum payments.

A.2 Tables

Table A1: Descriptive Statistics - Farm-Level Dataset

Statistic	N	Mean	St. Dev.
Output Volume—Sum (t)	308,984	179	303
Output Volume—Wheat (t)	191,357	149	204
Output Volume—Corn (t)	95,925	116	205
Output Volume—Sunflower (t)	36,263	31.0	33.9
Output Price Index (€/t)	169,219	213.3	94.8
Farm Surface (ha)	308,982	71.0	67.6
Capital (€)	308,984	128,136	167,984
Total Labor (hours)	308,982	4,406	3,739
Profit (€)	308,984	161,577	264,342
Phytosanitary (expenses in €)	268,893	8,071	11,066
Fertilizer (expenses in €)	268,893	16,040	17,643

Table A2: Agricultural Market Trends

Panel A	All Farms (0/1)								
	Year	Farms (K)	Total Farm Surface (K ha)	Total Cultivated Land (K ha)	Avg. Farm Surface	Avg. Cultivated Land	Gini (all land use)	Gini (cultivated)	Land Share of Top 10^{th} Decile
	1970	1583	29905		18.8		0.58		0.23
	1979	1257	29497		23.4		0.58		0.29
	1988	1006	28596		28.4		0.5816		0.37
	2000	653	27856		42.6		0.61		0.62
	2010	519	27833		53.6		0.62		0.73
Panel B	Row Crops Farms (1/1)								
	Year	Farms (K)	Total Farm Surface (K ha)	Total Cultivated Land (K ha)	Mean Farm Surface	Mean Cultivated Land	Gini (all land)	Gini (cultivated)	Land Share of Top 10^{th} Decile
	1970	1035	25984	9006	25.1	8.7	0.49	0.66	0.15
	1979	823	25882	11568	31.4	14.0	0.48	0.66	0.19
	1988	602	23828	11189	39.5	18.6	0.48	0.65	0.25
	2000	352	22885	11106	64.9	31.5	0.48	0.63	0.49
	2010	261	21828	10980	83.7	42.1	0.46	0.60	0.63

Notes. The data is computed using the full count agricultural census for years 1970, 1979, 1988, 2000 and 2010. The average farm size and total agricultural land are both computed in hectares, and the total agricultural area for France corresponds to the sum of all total used agricultural areas at the farm level. Cultivated land for row crop farms is computed for the largest set of row crops that I can track across the years of the Census: wheat, durum, barley, oats, rye, corn, sorghum, rice, beetroot, rapeseed, sunflower and soy. The Gini-Coefficient is computed at the country level, for the distribution of farm size.

Table A3: Crop Mixes within French Farms

Year	Only Wheat	Non-Wheat Only	Wheat +	Other +	Only Barley	Only Corn	Only Oats	Only Rye	Only Sunflower	Only Colza
1979	0.041	0.19	0.64	0.14	0.048	0.11	0.011	0.0071	0.00020	0.00040
1988	0.094	0.18	0.64	0.092	0.054	0.085	0.014	0.011	0.0058	0.0023
2000	0.13	0.19	0.62	0.066	0.045	0.096	0.013	0.0051	0.0090	0.0022
2010	0.14	0.17	0.63	0.063	0.046	0.079	0.0078	0.0057	0.0078	0.0042

Notes. The data is computed using the full count agricultural census for years 1970, 1979, 1988, 2000 and 2010.

Table A4: Farm-Level Shift Share Results

Dependent Variables:	Price Index (log)	Sales (log)	Profit (log)	Chemical Expenditure (log)
Model:	(1)	(2)	(3)	(4)
Variables				
$Exposure_j \times 1984$	-0.336*	-0.059	-0.120	-0.038
	(0.179)	(0.093)	(0.139)	(0.101)
$Exposure_j \times 1985$	-0.015	-0.019	0.000	-0.003
	(0.246)	(0.096)	(0.120)	(0.137)
$Exposure_j \times 1986$	0.508	-0.013	0.105	-0.025
	(0.325)	(0.086)	(0.130)	(0.105)
$Exposure_j \times 1987$	-0.082	0.013	0.077	-0.159
	(0.145)	(0.084)	(0.138)	(0.106)
$Exposure_j \times 1988$	-0.100	0.027	0.261**	0.061
	(0.140)	(0.078)	(0.122)	(0.109)
$Exposure_j \times 1989$	0.110	0.041	0.222	-0.026
	(0.179)	(0.128)	(0.217)	(0.089)
$Exposure_j \times 1990$	0.036	-0.131*	-0.138	0.122
	(0.154)	(0.078)	(0.107)	(0.103)
$Exposure_j \times 1992$	-0.233**	-0.131	-0.338***	-0.067
	(0.110)	(0.092)	(0.100)	(0.119)
$Exposure_j \times 1993$	-0.242	-0.199*	-0.163*	-0.146
	(0.181)	(0.108)	(0.091)	(0.096)
$Exposure_j \times 1994$	-0.250*	-0.135	-0.074	-0.180
	(0.148)	(0.096)	(0.187)	(0.112)
$Exposure_j \times 1995$	-0.391***	-0.215**	-0.450**	-0.183**
	(0.119)	(0.093)	(0.216)	(0.087)
$Exposure_j \times 1996$	-0.606***	-0.231**	-0.214	-0.232**
	(0.170)	(0.093)	(0.166)	(0.097)
$Exposure_j \times 1997$	-0.322**	-0.228***	-0.049	-0.105
	(0.131)	(0.085)	(0.120)	(0.120)
$Exposure_j \times 1998$	-0.409**	-0.109	-0.273**	-0.265**
	(0.181)	(0.091)	(0.123)	(0.125)
$Exposure_j \times 1999$	-0.372**	-0.314***	-0.167	-0.399***
	(0.172)	(0.084)	(0.147)	(0.152)
$Exposure_j \times 2000$	-0.551***	-0.271***	-0.268*	-0.265**
	(0.168)	(0.081)	(0.143)	(0.102)
$Exposure_j \times 2001$	-0.295**	-0.382***	-0.547***	-0.346***
	(0.150)	(0.092)	(0.170)	(0.121)
$Exposure_j \times 2002$	-0.383**	-0.312***	-0.401***	-0.246***
	(0.190)	(0.101)	(0.105)	(0.085)
$Exposure_j \times 2003$	-0.094	-0.418***	-0.500***	-0.330***
	(0.156)	(0.110)	(0.161)	(0.088)
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Department-Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,929	2,978	2,945	2,978
R^2	0.95	0.95	0.90	0.95

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. The event study outcomes are the following: a farm-level output price index (average price across row crops, using relative areas as weights), total sales, profit measured as value added plus subsidies, farm profit and the farms' deflated chemical bill. All coefficients correspond to the year-specific coefficient associated to farm exposure, and give the effect of exposure in that given year relative to the effect in 1991. The vector of controls contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984 adoption trends in chemicals measured as the evolution in their chemical use. I add farm and department-year fixed effects, and cluster the standard errors one-way at the region-year level. The figure for these results is figure 5.

Table A5: Municipality-Level Shift Share Results: Farm Count

Dependent Variable:	Farm Count	
Model:	(1)	(2)
Variables		
$Exposure_k$ (mean) × 1970	0.076	
	(0.57)	
$Exposure_k$ (mean) × 1979	0.38	
	(0.50)	
$Exposure_k$ (mean) × 2000	-0.85**	
	(0.42)	
$Exposure_k$ (mean) × 2010	-1.31**	
	(0.59)	
$Exposure_k$ (median) × 1970		0.81
		(0.75)
$Exposure_k$ (median) × 1979		0.90
		(0.58)
$Exposure_k$ (median) × 2000		-0.93*
		(0.50)
$Exposure_k$ (median) × 2010		-1.29*
		(0.70)
Fixed-effects		
Municipality	Yes	Yes
Department-Year	Yes	Yes
Fit statistics		
Observations	147,157	147,157
R^2	0.95	0.95

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. This table gives the results for the municipality-level event study. Farm count corresponds to the number of farms operating in the row crop market within the municipality. The regression includes a series of controls set to their level in 1988 within the municipality, and interacted with a time-varying coefficients, as well as municipality and department-by-year fixed effects. Standard errors are clustered at the region-by-year level. The figure for these results is figure 6.

Table A6: Municipality-Level Shift Share Results: Crop Mix Evenness

Dependent Variable:	Crop Evenness	
Model:	(1)	(2)
Variables		
$Exposure_k$ (mean) × 1970	-0.001	
	(0.004)	
$Exposure_k$ (mean) × 1979	0.001	
	(0.005)	
$Exposure_k$ (mean) × 2000	0.006*	
	(0.003)	
$Exposure_k$ (mean) × 2010	0.017***	
	(0.005)	
$Exposure_k$ (median) × 1970		0.004
		(0.003)
$Exposure_k$ (median) × 1979		0.004
		(0.004)
$Exposure_k$ (median) × 2000		0.003
		(0.003)
$Exposure_k$ (median) × 2010		0.012***
		(0.004)
Fixed-effects		
Municipality	Yes	Yes
Department-Year	Yes	Yes
Fit statistics		
Observations	147,157	147,157
R^2	0.80	0.80

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. This table gives the results for the municipality-level event study. Crop evenness is an index for the evenness of the distribution of land across crops, measured as the municipality-level evenness. The regression includes a series of controls set to their level in 1988 within the municipality, and interacted with a time-varying coefficients, as well as municipality and department-by-year fixed effects. Standard errors are clustered at the region-by-year level. The figure for these results is figure 6.

Table A7: Municipality-Level Shift Share Results: Fraction Cereals

Dependent Variable:	Fraction Cereals	
Model:	(1)	(2)
Variables		
$Exposure_k$ (mean) × 1970	0.033	
	(0.388)	
$Exposure_k$ (mean) × 1979	0.050	
	(0.388)	
$Exposure_k$ (mean) × 2000	1.96***	
	(0.62)	
$Exposure_k$ (mean) × 2010	2.29***	
	(0.60)	
$Exposure_k$ (median) × 1970		0.030
		(0.445)
$Exposure_k$ (median) × 1979		0.042
		(0.444)
$Exposure_k$ (median) × 2000		1.78***
		(0.655)
$Exposure_k$ (median) × 2010		2.47***
		(0.813)
Fixed-effects		
Municipality	Yes	Yes
Department-Year	Yes	Yes
Fit statistics		
Observations	147,157	147,157
R^2	0.64	0.64

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. This table gives the results for the municipality-level event study. Fraction cereals gives the fraction of municipality cropland allocated to cereals versus oil crops. The regression includes a series of controls set to their level in 1988 within the municipality, and interacted with a time-varying coefficients, as well as municipality and department-by-year fixed effects. Standard errors are clustered at the region-by-year level. The figure for these results is figure 6.

Table A8: County-Level Shift Share Results: Algal Blooms

Dependent Variable:	Algal Bloom (log)	
Model:	(1)	(2)
Variables		
Exposure X Year 1986	-0.039	-0.019
	(0.026)	(0.022)
Exposure X Year 1987	-0.065***	-0.046**
	(0.024)	(0.021)
Exposure X Year 1988	-0.028	-0.016
	(0.022)	(0.018)
Exposure X Year 1989	0.017	0.030
	(0.031)	(0.026)
Exposure X Year 1990	-0.032	-0.017
	(0.030)	(0.027)
Exposure X Year 1992	-0.065*	-0.056*
	(0.037)	(0.034)
Exposure X Year 1993	-0.045*	-0.029
	(0.023)	(0.019)
Exposure X Year 1994	-0.044*	-0.021
	(0.023)	(0.019)
Exposure X Year 1995	-0.044*	-0.022
	(0.023)	(0.019)
Exposure X Year 1996	-0.062***	-0.039**
	(0.024)	(0.018)
Exposure X Year 1997	-0.093***	-0.072***
	(0.023)	(0.019)
Exposure X Year 1998	-0.039	-0.030
	(0.037)	(0.030)
Exposure X Year 1999	-0.106***	-0.081***
	(0.029)	(0.025)
Exposure X Year 2000	-0.164***	-0.136***
	(0.035)	(0.031)
Exposure X Year 2001	-0.096***	-0.078***
	(0.025)	(0.023)
Exposure Measure	$Exposure_c$ (mean)	$Exposure_c$ (median)
Fixed-effects		
County	Yes	Yes
Department-Year	Yes	Yes
Fit statistics		
Observations	25,764	25,748
R^2	0.87	0.87

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. This table gives the results for the county-level event study. The outcome is a Landsat-5 based index of algal bloom intensity on the within-county water bodies. Algal blooms are generally caused by the over-fertilization of agricultural land. The regression includes a series of controls set to their level in 1988 within the county (last year of the Census prior to the reform), and interacted with a time-varying coefficients, as well as county and department-by-year fixed effects. Standard errors are clustered at the region-by-year level. The figure for these results is figure 7.

Table A9: Demand Results

Dependent Variables:	Log Quantity (Wheat)	Log Quantity (Other)
Model:	(1)	(2)
Variables		
Constant	24.39***	22.40***
	(1.691)	(1.966)
Price (log)	-0.8903***	-0.5785*
	(0.2750)	(0.3168)
Fit statistics		
Observations	28	28
R^2	0.79	0.63

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. I obtain estimates of total quantity sold and average prices for France for the two crop categories using the FADN and its sampling weights. I then run regressions of quantities on prices, instrumenting the prices with weather shocks in order which should shift supply but not demand. I include a linear time trend in all regressions, and use the Newey-West correction for serial auto-correlation.

Table A10: Model Parameters

Coefficient	Parameter	Value
Other Estimated Parameters		
Competence Ladder	λ	.80
Baseline TFP	μ	.58
Auto-Correlation TFP	ρ_h	.71
Shape TFP Pareto Distribution	σ_h	.12
Location TFP Pareto Distribution	δ_h	0
Auto-Correlation Non-Hicksian shock	ρ_{ch}	.83
Shape Non-Hicksian Pareto Distribution	σ_h	.16
Location Non-Hicksian Pareto Distribution	δ_h	0
Calibrated Parameters		
Time Preference	$\frac{1}{1-r}$	.9
Capital Depreciation	δ_k	.08
Price Capital	p_k	1
Price Land	p_s	1.77
Price Chemicals	p_c	4.15
Price Labor	p_l	.5

Notes: I use the recovered productivity shocks to estimate these other estimated parameters. Specifically, I demean TFP shocks, and use the average as an estimate of μ. Demeaned TFP shocks are used to compute the following parameters. The competence ladder corresponds to the average ratio of the highest crop TFP to lowest crop TFP within a farm, across farms and years. The Pareto distribution parameters are recovered across farms and years, and the auto-correlation in both shocks are computed using within-farm variation. For the additional calibrated parameters, the rate of time preference follows from the modelling choice of Scott (2013), the rate of capital depreciation is set to 8%, the price of capital is normalized to 1—and such that one unit of capital accounts for a stock of 1,000€ in capital. The relative price of land, to chemicals to labor follows from estimates of per-hectare expenses in each category for wheat in France in Guillermet (2015), and their ratio to the cost of capital is normalized so that the average type farm in the model has the average observed labor to capital ratio in the FADN.

B Appendix

B.1 Data Description

B.1.1 Intervention Prices

For the purpose of this paper, and to the best of my knowledge, I created the first database of agricultural commodities' EU intervention prices covering the end of the 1960s to the early 2000s when intervention was completely removed. Intervention prices denominated in ECUs, euros or francs were gathered from the yearly and sometimes commodity-specific directives published by the European Union over that period of time. When prices were denominated in ECUs, I used the CAP-specific exchange rate which was then used to translate ECUs to each member state's currency. I similarly gathered data on commodity-specific land subsidies, which I later combine with farm-specific land subsidies as recorded in the FADN.

B.1.2 Input Prices: Indices and Price Surveys

Input prices are drawn from the IPAMPA agricultural input price indices, and from the Enquête sur l'observation des Prix des Consommations Intermédiaires nécessaires aux Agriculteurs (EPCIA), the price survey used to develop the IPAMPA. I use the IPAMPA indices for pesticides and fertilizers interpolated by INSEE back to 1980.
The EPCIA has been run since 1996, and provides price data for pesticides and fertilizers. Its sample is based on a 1995 survey, which helped identify a sample of products representing 50% of the total sales within their product category. The sampling of establishments selling these products was done based on the establishments' respective market share within that product category. Finally, within a product and establishment, the series chosen corresponded to the product's most frequent sales conditions. As such, series are good, company and mode of sale specific. When series disappear, they are replaced with their closest equivalent. The EPCIA is made of 4165 series, sold by 250 companies. The EPCIA is aggregated into national and regional price indices using 1990 plutocratic weights, and the following index of category-specific month-to-month price evolution:

$$i_t = i_{t-1}\left(\prod_i^n \frac{P_{i,t}}{P_{i,t-1}}\right)^{\frac{1}{n}} \tag{10}$$

I also recover agricultural hourly wages from the continuous labor survey "Enquête Emploi", which is a survey fielded for a sampled set of households, each household being drawn once and then followed for the next six trimesters. I consider the hourly wage data provided by workers whose occupation is classified as that of an agricultural worker or farmer.

Finally, I use land prices taken from the Land Market Value survey (Valeur Venale des Terres), a yearly and department-level survey, which is fielded every year by the statistical

services of the French departmental administration for agriculture and forestry. These are based on data provided by the public company in charge of land management (SAFER), which authorizes agricultural land purchases and consolidations when transactions surpass a given threshold. This data is then complemented by data provided by local notaries, and several local administrations. I use this data for 1994-2015. The data was digitized from scanned data catalogues for the first years of the series.

B.1.3 Plot Level Data

I use the "Pratiques Cultures sur les Grandes Cultures" or PKGC (Agricultural Practices for Field Crops) survey, a plot-level dataset, to highlight the heterogeneitya cross crops in their use of nitrogen.[44] It is important to note that this dataset is a repeated cross-section, not a panel.

B.1.4 Weather Data: Realizations and Forecasts

Our realized climate data comes from the European Centre for Medium-Range Weather Forecasts (ECMWF)'s ERA5 reanalysis product. ERA5 gives hourly estimates of climate data, out of which I use precipitation and temperature (temperature 2m above the surface of the Earth). ERA5 combines observational weather data with model-based data into a 0.25*0.25 gridded dataset.
I extract that data at the French department level, cropping the grid with department shapes, and averaging the data using simple area weights. Using the time separability assumption common in the literature, I aggregate the hourly data into growing-season observations [45]: growing degree days (GDD) and heat degree days (HDD) for temperature[46], and total precipitation for rainfall. In order to match the forecast dataset, I only use 4 daily measurements of temperature to compute the GDDs and HDDs, specifically at midnight, 6h, 12h and 18h.

The forecast data is taken from ECMWF's SEAS5 seasonal forecasting system. Forecast are produced on the first of each month for the following 5,160 hours [47]. For temperature, they are produced at a 6h interval, and give an instantaneous prediction of temperature, while for rainfall, they give the accumulation of rainfall every 24h. As such, the rainfall forecasts for the second day of the month will be the following: a 24h ahead forecast, a 30 to 32 days ahead forecast produced on the first day of the previous month, and so on until the

[44] Plots surveyed are selected among the farms that benefit from the European Union's Common Agricultural Policy. The survey focuses on land plots defined as the set of contiguous land for which the same crop is cultivated, with homogeneous agricultural practices (fertilizer and pesticide use for example). For each crop, the survey selects the minimum number of regions covering at least 95% of that crop's production, and within each region the minimum set of departments accounting for at least 90% of the region's production. Within departments, the survey selects farms with at least .1 hectare cultivated, and less than 200ha. A unique plot is selected within each farm. For the waves that we study, around 20,000 plots are sampled each time.

[45] I use an extensive definition of the agricultural growing season for France, running from October of the previous year, to July of the current one.

[46] Growing degree days are computed over the $[4°, 30°]$ degree interval, and heat degree days sum the realized temperature above 30°C.

[47] ECMWF provides an ensemble of 25 forecasts, which I average.

lead value exceeds 5,160 hours. Temperature forecasts work in a similar way, but are just produced with more granular time steps.

The main issue for my purpose is that given that forecasts are produced every first of the month, different days within a month will not be provided a forecast with the same lead. I would ideally like to build the forecast-equivalents of the growing-season aggregates for realized weather, for different lead times. For example, the rainfall forecast for the growing season, with a constant one-month lead throughout the season (or the equivalent of the farmer's knowledge about rainfall one month in advance throughout the growing season). I approximate this by bundling together forecasts produced one calendar month ago (the one month lead for the rest of the paper), produced two calendar months ago, up to five months ago. As such, the forecasts that I aggregate into growing season observations are not homogeneous in terms of lead value, but are the closest equivalent of it that I can get.

Similarly to the weather realization data, I extract the gridded data into department-level observations, using area weights.

B.1.5 Landsat 5 Remote Sensing Data

Both the remote sensing indices are based on Landsat 5 imagery. Landsat 5 was a low orbit satellite jointly managed by the U.S. Geological Survey and NASA, and ran between 1984 and 2013. Its unusual longevity making it a good source of data to build long time series. It had a repeat cycle of about 16 days, and was equipped among else with a Thematic Mapper (TM) and a Multi-Spectral Scanner.

Our algal bloom index follows the methodology of Taylor and Heal (2023). For every year between 1985 and 2001, I filter Landsat data for images taken between June and August, which I crop for surface water and treat for clouds and cloud shadows. I then run the following function on each pixel:

$$Bloom = NIR - 1.03 * SWIR \tag{11}$$

NIR corresponds to the near infrared band of Landsat 5 (.77 to .90μm), and SWIR to the shortwave infrared band (1.55 to 1.75μm). In both cases, these come from atmospherically corrected surface reflectance data produced by the Landsat TM series. The index is then averaged across the selected months of the year, and averaged over surface water area at the county level.[48]

Our measure of edge density follows recent remote sensing work developed for agricultural field delineation, and specifically the general procedure outlined in Watkins and van Niekerk (2019). I use the following workflow. I first create three composite images per year, respectively for the periods January-April, May-August and September-December. Clouds and cloud shadows are masked, and images are averaged within each period. I then use first a Gaussian filter, and then a Canny edge detection filter using four bands: red, blue, green and

[48] There are 2,054 counties in France, making them much smaller geographic entities than U.S. counties, and the smallest geographic entity above villages (communes).

near infrared. I then aggregate the resulting edge image across bands, and across seasons within the year. Filtering per season prior to running the filter allows to account for varying landscape patterns within the year, and for example to better differentiate fields that might have different seasonal patterns but might be similarly green during some time of the year. I finally filter the images to remove human settlements, and compute the resulting average edge density per county. Very roughly, this procedure should give an index of landscape fragmentation, and should correlate with the homogenization of landscapes driven by increasing field size and an increased encroaching of agriculture on previously non-agricultural land.

B.2 Robustness and Additional Results for the Reduced Form Analysis

I start this robustness section by showing the Rotemberg weights for the shift-share instrument, following the formula provided by Goldsmith-Pinkham et al. (2020). I compare them to the weights obtained when including all controls. This comparison highlights the role of controls in shifting the source of the variation used to identify the effect of farm reform exposure. I then provide a more in-depth analysis of the conditional parallel-trends assumption driving the difference-in-difference design. I show trends in the same set of variables as shown in Figure A11, but for farms with a higher or lower crop shares—and this for the main crops that drive the variation in the shift-share instrument—as given by the value of the Rotemberg weights. Finally, I provide the complete set of results in a difference-in-difference format, and give the shock-by-shock regression results, in order to decompose potential heterogeneity in treatment across crop-mix composition.

B.2.1 Rotemberg Weights

I give the Rotemberg weights below—with and without the inclusion of the controls used in the farm-level regressions. This has the advantage of both showing what cross-crop variation is used for identification, and how this variation is influenced by the controls.

Table A11: Rotemberg Weights: With Controls

Crop	Weight	Shock	Variance Land Share
Corn	0.308	151	0.117
Wheat	0.29	164	0.0307
Sunflower	0.289	540	0.0829
Spring Barley	0.116	128	0.0151
Durum Wheat	0.109	314	0.0237
Oats	0.0438	121	0.00573
Winter Barley	0.0104	133	0.0105
Sorghum	0.00515	160	0.000096
Rye	-0.0382	113	0.0336
Colza	-0.135	362	0.0105

Notes. The weights are computed after residualizing the instrument on the fixed effects used in the farm-level regressions. These Rotemberg weights are obtained when using only land shares to measure farm exposure. The shock column indicates the value of the crop-specific shock, and the share variance corresponds to the variance observed in the FADN sample of the crop-specific share.

The weights vary in a quite striking way as I include controls. With their inclusion, I move from an instrument which is essentially a difference-in-difference with a continuous treatment for the share of land allocated to sunflower in 1991, to one comparing farms growing relatively more or less of the main crops of the market: corn, wheat, sunflower, spring barley, durum wheat and oats. Wheat, corn and barley being the most planted crops in France, this seems like a source of variation yielding more representative results. I note however that some negative weights also appear in the process, specifically for colza, which is associated with a high shock but limited variation across farms in 1991 land use. This negative weight could raise issues in the case of heterogeneous treatment effects. I will investigate the possibility of heterogeneous treatment effects, following the recommendations of Goldsmith-Pinkham et al. (2020), by dis-aggregating the instrument into crop-by-crop instruments.

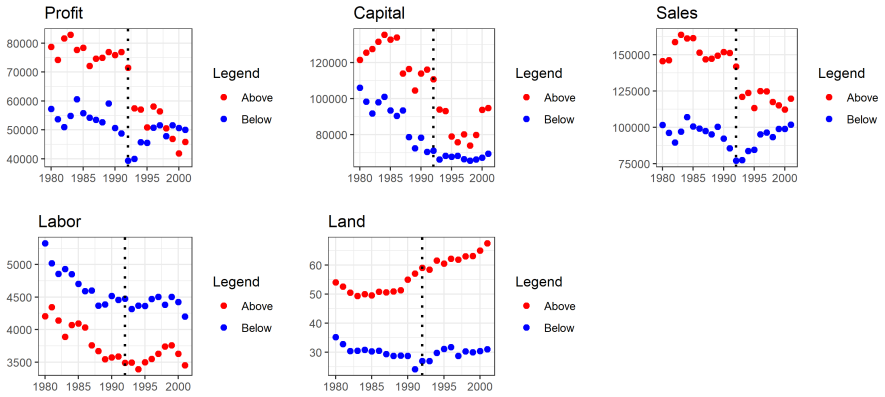
Table A12: Rotemberg Weights: Without Controls

Crop	Weight	Shock	Variance Land Share
Sunflower	0.584	540	0.117
Durum Wheat	0.126	315	0.0307
Corn	0.122	151	0.0830
Wheat	0.0820	164	0.0151
Rapeseed	0.0530	362	0.0237
Rye	0.0130	113	0.00570
Spring Barley	0.00800	128	0.0105
Winter Barley	0.00800	133	0.000100
Oats	0.00200	121	0.0337
Sorghum	0.00200	160	0.0105

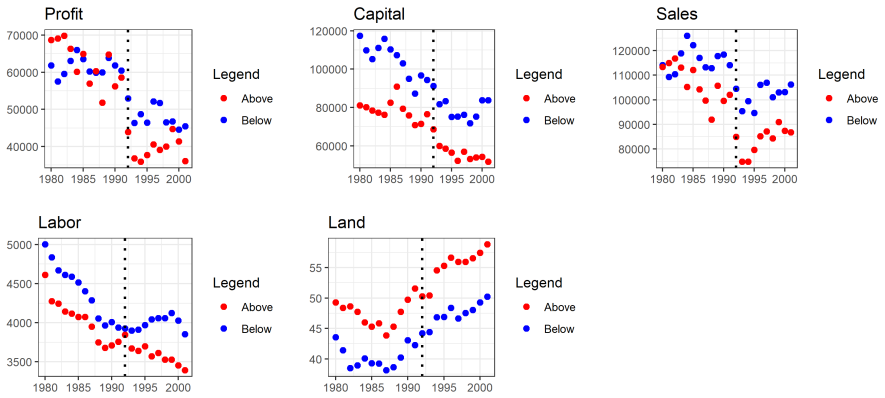
Notes. The weights are computed after residualizing the instrument on the fixed effects used in the farm-level regressions. These Rotemberg weights are obtained when using only land shares to measure farm exposure. The shock column indicates the value of the crop-specific shock, and the share variance corresponds to the variance observed in the FADN sample of the crop-specific share.

B.2.2 Balance Tests: Across Crop Shares

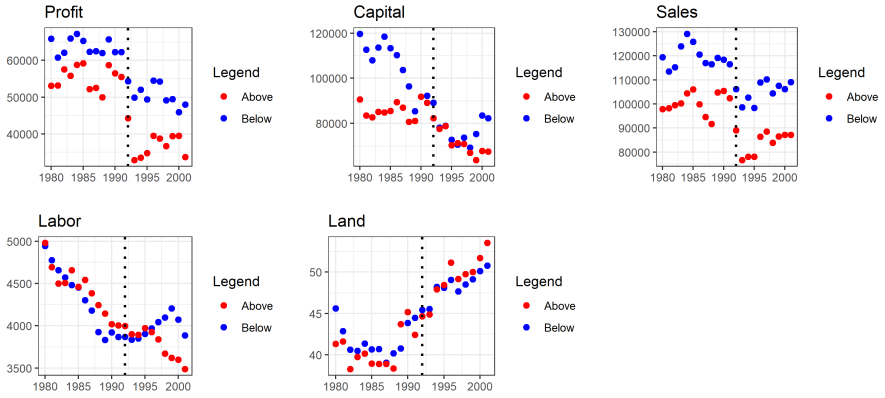
Next, I show the balance tests across farms with an above and below median share of wheat, corn, winter barley, rye, sunflower and colza. when looking at these comparison, one should keep two things in mind. The first thing is that everything else equal, I expect larger farms to have lower crop shares than smaller ones, as they tend to be more diverse—and this to be especially the case for the most common crops like wheat or corn. The second, is that this heterogeneity in crop shares should otherwise correlate with local production structures—Pierre (2004) describes the difficulties of starting to grow a given crop when the local distribution system is not already in place. Crop choice should also correlate with local climatic and soil conditions. The graphs are then useful in order to understand the extent to which these factors can change the levels and dynamics across farms. I note that because I look at impacts on outcome growth rates, rather than outcome levels—differences in levels are not worrisome. The main threat to identification lies with the presence of unobservables that are linked with heterogeneity in exposure, and which affect farm-level growth. The following elements stand out: across all crops, capital is the one variable that differs the most in trends across groups prior to the reform—making it a necessary control in the design. Profit, sales and labor show relatively comparable trends prior. Trends in land use also show some notable differences in the cases of rye and colza. While the differences for rye are quite significant, I also know from the previous Rotemberg weights that rye plays an almost absent role in the variation of the shift-share instrument, and hence should not drive results too much. Differences in colza are potentially more important, again justifying the control for the share of production coming from oil crops pre-reform.



(a) Balance Tests - Wheat



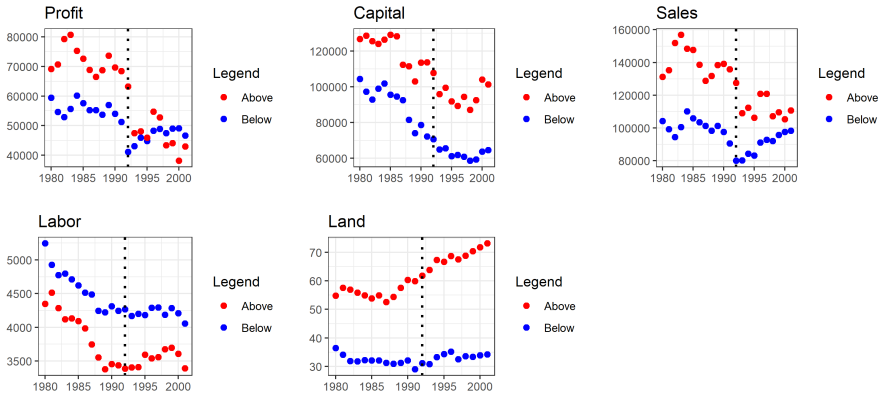
(b) Balance Tests - Sunflower



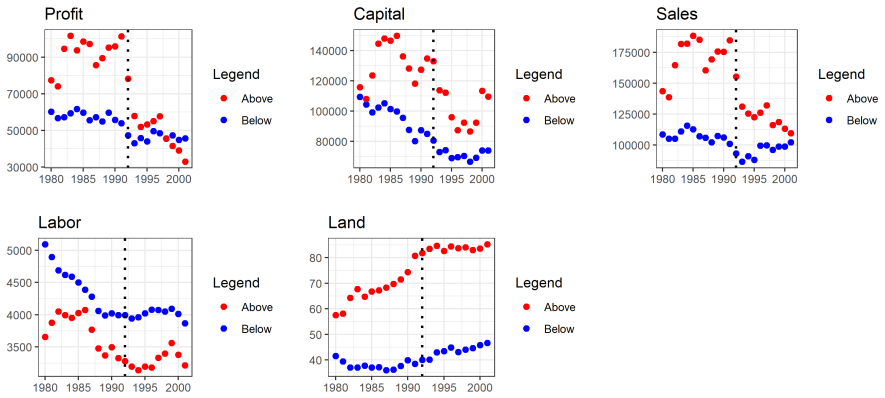
(c) Balance Tests - Corn

Figure A19: Trends per Category

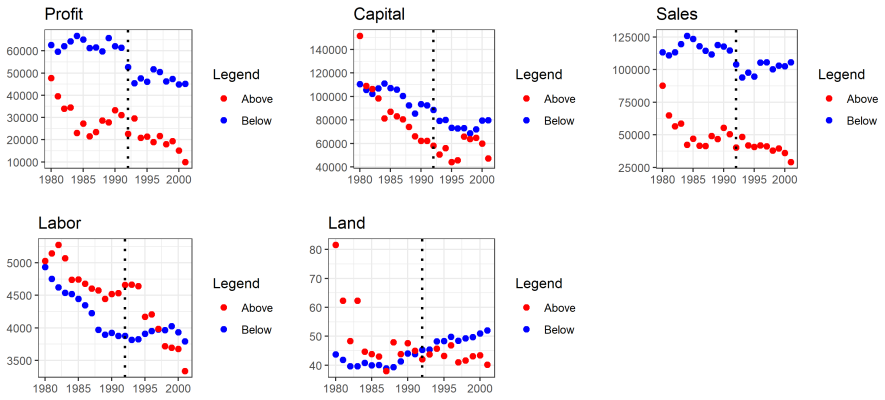
Notes: The figures show the trends of relevant farm characteristics for the bottom and top third of farms in terms of their share of land allocated to the relevant crop in 1991.



(a) Balance Tests - Barley



(b) Balance Tests - Colza



(c) Balance Tests - Rye

Figure A20: Trends per Category (continued)

Notes: The figures show the trends of relevant farm characteristics for the bottom and top third of farms in terms of their share of land allocated to the relevant crop in 1991.

B.2.3 Additional Farm-Level Results

It is useful to recast event study design in a pure difference-in-difference design in order to recover a unique coefficient summarizing the effect of the reform. I can do so using a modified estimating regression of the following form:

$$Y_{jt} = \alpha_j + \eta_{d(j)t} + \beta^1 Exp_j Post_t + X_j Post_t \Gamma^1 + \varepsilon_{jt}. \tag{12}$$

I also run this design with an alternative construction of the exposure instrument, where price intervention shocks are averaged across crops using output-based weights, and land subsidy ones using land weights. In both cases, results match the ones obtained using the event study design.

Table A13: Difference-in-Difference Results

Dependent Variables:	Price Index (log)	Sales (log)	Profit (log)	Chemical Expenditure (log)
Model:	(1)	(2)	(3)	(4)
Variables				
$Exposure_k \times Post_t$	-0.221***	-0.229***	-0.306***	-0.245***
	(0.074)	(0.043)	(0.067)	(0.049)
Mean Outcome in Level	224	109k	50k	17k
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Department-Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,929	2,978	2,945	2,978
R^2	0.94	0.94	0.87	0.94

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Outcomes are the following: a farm-level output price index (average price across row crops, using relative areas as weights), total sales, profit measured as value added plus subsidies, and the farms' deflated chemical bill. All coefficients correspond to the period-specific coefficient associated to farm exposure, and give the effect of exposure in that given year. The vector of controls contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984 adoption trends in chemicals measured as the evolution in their chemical use. I add farm and department-year fixed effects, and cluster the standard errors one-way at the region-year level.

Table A14: Difference-in-Difference Results (Alternative Instrument)

Dependent Variables:	Price Index (log)	Sales (log)	Profit (log)	Chemical Expenditure (log)
Model:	(1)	(2)	(3)	(4)
Variables				
$Exposure_k \times Post_t$	-0.179***	-0.233***	-0.324***	-0.236***
	(0.058)	(0.041)	(0.069)	(0.048)
Mean Outcome in Level	224	109k	50k	17k
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Department-Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,929	2,978	2,945	2,978
R^2	0.94	0.94	0.87	0.93

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Outcomes are the following: a farm-level output price index (average price across row crops, using relative areas as weights), total sales, profit measured as value added plus subsidies, and the farms' deflated chemical bill. All coefficients correspond to the period-specific coefficient associated to farm exposure, and give the effect of exposure in that given year. The vector of controls contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984 adoption trends in chemicals measured as the evolution in their chemical use. I add farm and department-year fixed effects, and cluster the standard errors one-way at the region-year level. Exposure is computed using land shares for land subsidies, and output shares for price intervention.

B.2.4 Independent Instruments

Table A15: Heterogeneity in Crop-Specific Effects

Dependent Variables:	Sales (log)	Profit (log)	Chemical Expenditure (log)
Model:	(1)	(2)	(3)
Variables			
$Wheat_j \times Post_t$	-0.0026***	-0.0031***	-0.0032***
	(0.0007)	(0.0008)	(0.0008)
$WinterBarley_j \times Post_t$	0.0003	-0.0001	-0.0009
	(0.0011)	(0.0019)	(0.0014)
$Corn_j \times Post_t$	-0.0024***	-0.0020*	-0.0025***
	(0.0009)	(0.0011)	(0.0009)
$Rye_j \times Post_t$	-0.0052***	0.0006	-0.0023
	(0.0015)	(0.0024)	(0.0024)
$Sunflower_j \times Post_t$	-0.0030***	-0.0060***	-0.0017
	(0.0007)	(0.0017)	(0.0012)
$Colza_j \times Post_t$	-0.0037***	-0.0079***	-0.0025**
	(0.0008)	(0.0021)	(0.0011)
$Durum_j \times Post_t$	-0.0056***	-0.0054*	-0.0054***
	(0.0015)	(0.0031)	(0.0018)
$Sorghum_j \times Post_t$	0.0212***	0.0775***	0.0080
	(0.0079)	(0.0209)	(0.0126)
$SpringBarley_j \times Post_t$	-0.0002	-0.0013	-0.0008
	(0.0006)	(0.0010)	(0.0008)
$Oats_j \times Post_t$	-0.0007	-0.0045**	0.0016
	(0.0010)	(0.0022)	(0.0014)
Fixed-effects			
Farm	Yes	Yes	Yes
Department-Year	Yes	Yes	Yes
Fit statistics			
Observations	2,978	2,945	2,978
R^2	0.94	0.88	0.94

Clustered (Region-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. I show the heterogeneity of the difference-in-difference results across crop-specific shocks. The instrument is decomposed in multiple crop-specific instruments. I include the crop shares in levels, but do not show the coefficients in the table. The vector of controls contains the following elements: farm 1991 capital stock, total labor used, total land use, their chemical use, the number of crops they grew and the evenness of their land allocation, their fertilizer-to-land and pesticides-to-land ratios, the share of their production which corresponds to oil crops (colza and sunflower), and the farms' 1983-1984 adoption trends in chemicals measured as the evolution in their chemical use. I add farm and department-year fixed effects, and cluster the standard errors one-way at the region-year level.

I decompose the shift share instrument into crop-specific instruments. Each crop-specific instrument corresponds to the crop-specific change in subsidization between 1991 and 1995, interacted by the land share allocated to that crop by the farm in 1991. The regression is otherwise similar to the difference-in-difference regressions presented previously. The coefficients for the instruments interacted with the post-1991 dummy isolate the effect of crop-specific exposure to the reform after the reform happened. All crop-specific instruments but sorghum have negative effect on sales, and almost all of these are statistically significant. Sorghum is similarly the one coefficient with a positive effect for profit, and for chemical use. This means that the shift-share instrument hides some degree of heterogeneity in terms of the effects of exposure. I note however, that sorghum production in France corresponds to about 1.5% of the overall production of the grain market, and hence does not correspond to a very significant share of the market. The crop-by-crop results otherwise describe a high level of homogeneity in the consequences of exposure to the reform.

B.2.5 Municipality-Level Results

In this section, I first present balance tests comparing municipality with relatively more and relatively less exposure to the reform, and then the distribution of the measure of exposure used for the municipality-level design. I end by showing the shift-share results using different aggregate measures to go from farm to municipality.

Starting with balance tests, I show the trends (averages for each wave of the census) for six municipality characteristics, splitting them nationally between municipalities with a median exposure above or below the French median in 1988. Trends are overall similar, apart from the evenness variable. In the estimation design, I control for this evenness, both at the municipality and farm level.

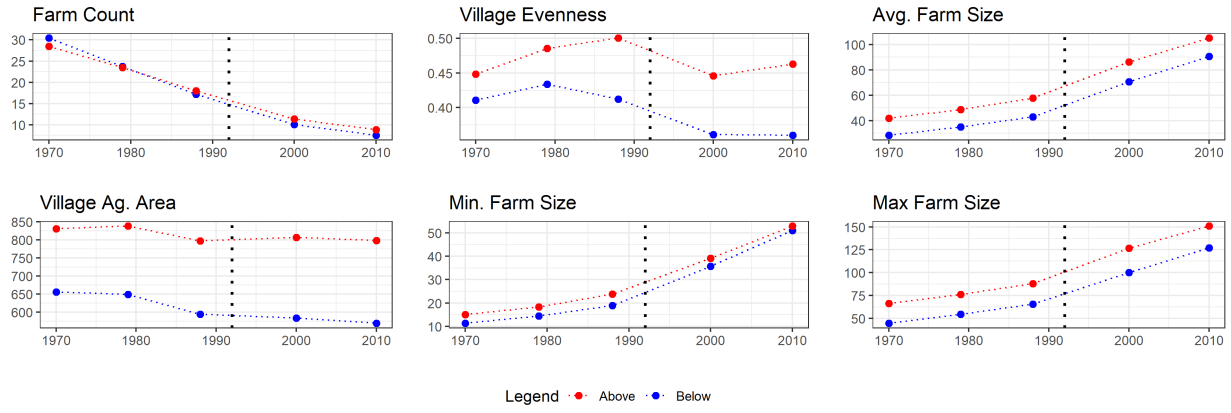


Figure A21: Municipality-Level Trends

Notes: This figure gives the evolution of municipality level outcomes over time, for the group of municipalities for which median exposure is above or below the median exposure in France as a whole.

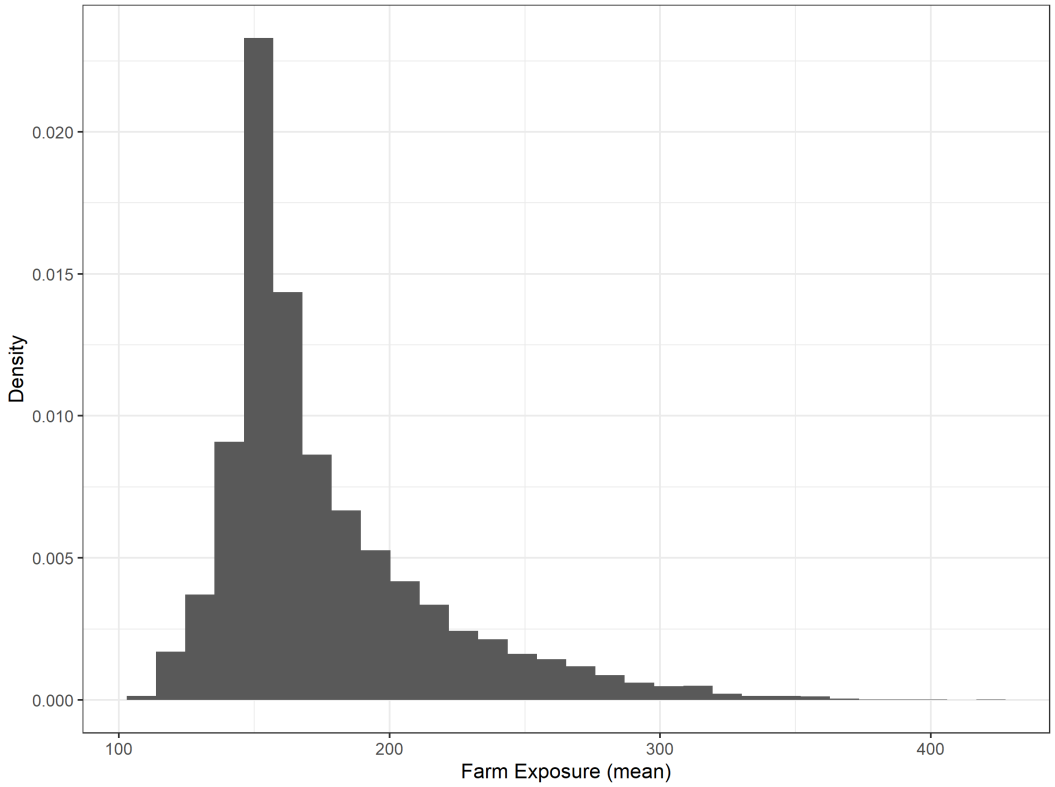


Figure A22: Distribution of Median Exposure

Notes: This figure gives the distribution of the municipality-level exposure to the MacSharry reform.

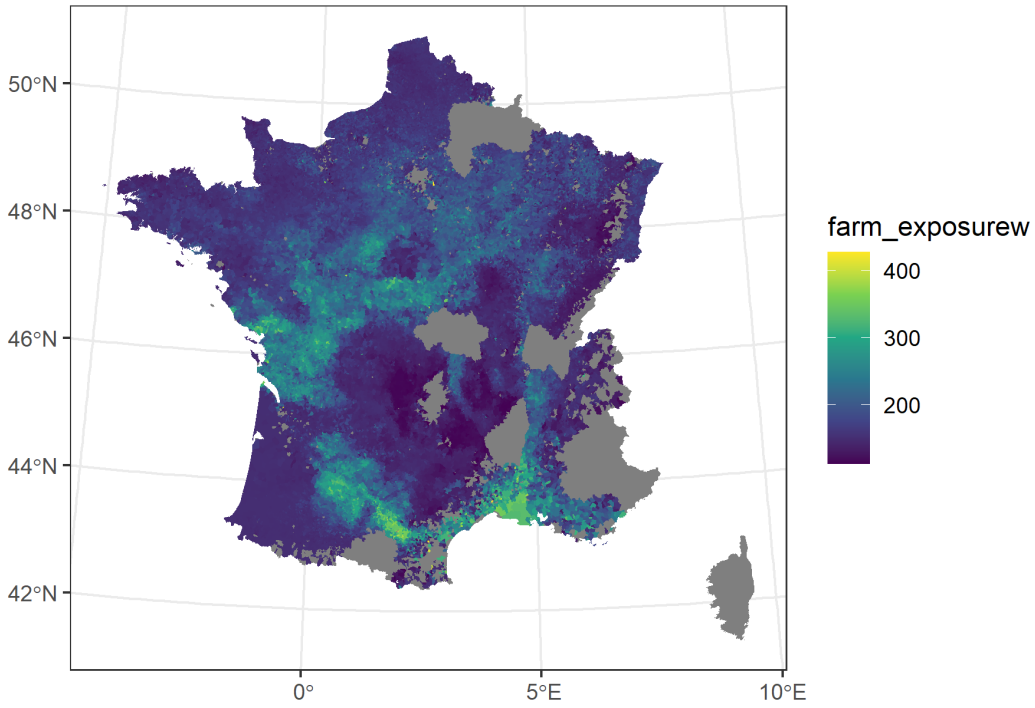


Figure A23: Geographic distribution of Mean Exposure

Notes: This figure gives the distribution of the municipality-level exposure to the MacSharry reform.

Next, I show the distribution of median municipality exposure. As mentioned previously, all the measures of municipality-level exposure are computed after winsorizing the farm-level measure of exposure in the Census for the bottom and top 1ppt values. Exposure is mostly distributed between 100 and 200€ per output unit, with a large right tail which likely corresponds to municipalities which have some of their land allocated either to colza, durum and sunflower, which are the crops with a shock value higher than 100 € per unit. These are mostly located in two areas of France, as shown in Figure A23, along the Mediterranean coast, as well as the main grain region of France around the Beauce region below Paris.
Finally, I show the shift-share results using median farm exposure within the municipality, rather than the average. This measure of exposure is more robust to outliers. Results are similar as the ones obtained using the average value.

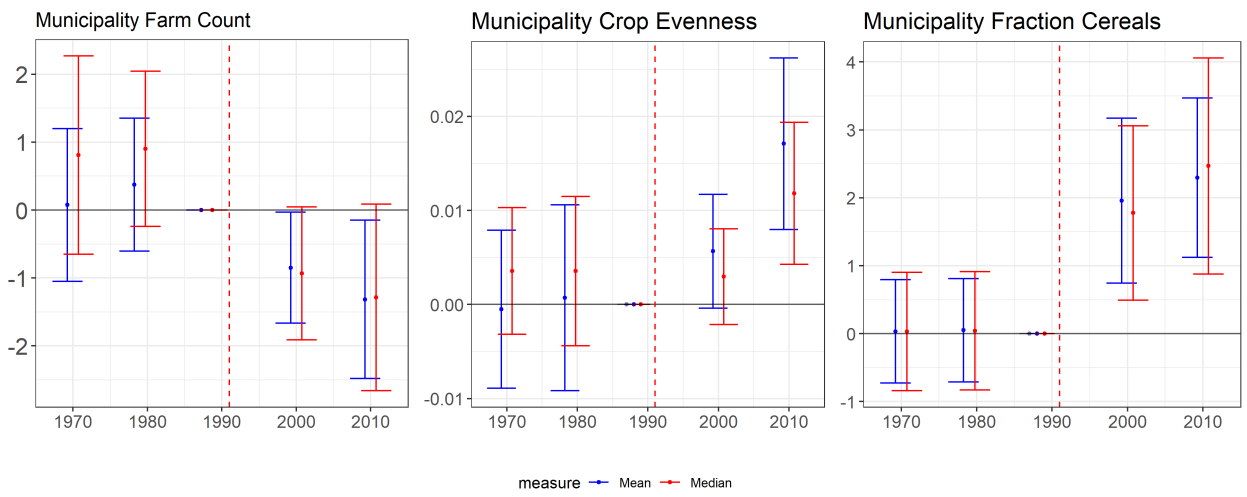


Figure A24: Municipality-Level Outcomes

Notes: This figure gives the results for the municipality-level event study. Farm count corresponds to the number of farms operating in the row crop market within the municipality. Crop evenness is an index for the evenness of the distribution of land across crops, measured as the municipality-level evenness. Fraction cereals gives the fraction of municipality cropland allocated to cereals versus oil crops. The regression includes a series of controls set to their level in 1988 within the municipality, and interacted with a time-varying coefficients, as well as municipality and department-by-year fixed effects. Standard errors are clustered at the region-by-year level.

B.2.6 County-Level Results

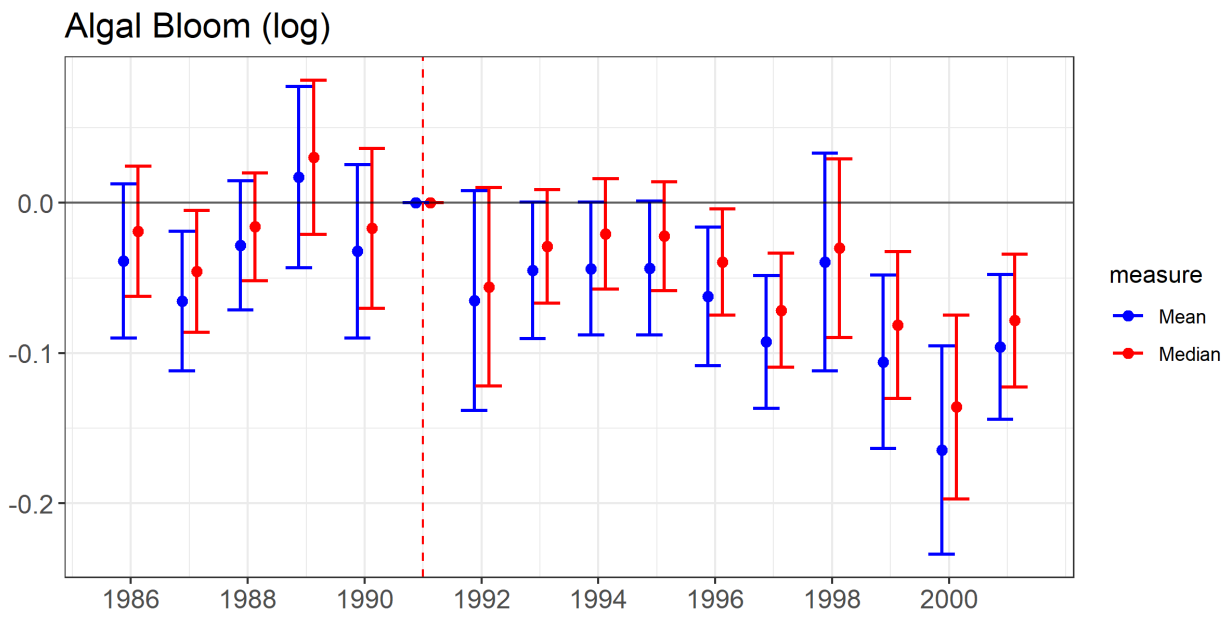


Figure A25: County-Level Algal Blooms

Notes: This figure gives the results for the county-level event study. The outcome is a Landsat-5 based index of algal bloom intensity on the within-county water bodies. The regression includes a series of controls set to their level in 1988 within the county (last year of the Census prior to the reform), and interacted with a time-varying coefficients, as well as county and department-by-year fixed effects. Standard errors are clustered at the department-by-year level. The table associated to these results are Table A8.

B.3 Model Details

I start with the Bellman decisions describing the farms' decisions—both incumbent and entrant farms—which correspond to the general outline of the model from section 4.2. The incumbent's decision can be characterized by:

$$V(\Upsilon_{jt};\Omega_{jt}) = \underset{\{X_{jct}\}_{\mathbb{C}_{jt}},\xi^x_{jt},K_{jt+1},S^o_{jt+1},\mathbb{C}_{jt+1}}{max} \underbrace{\Pi_{jt}}_{\text{Static Profit}} - \underbrace{C(K_{jt},K_{jt+1})}_{\text{Capital Adjustment}}$$
$$+\xi^x_{jt}\underbrace{\left[(1-\delta_k)K_{jt}P^K_{jt}\right]}_{\text{Scrap Value if Exit}} + (1-\xi^x_{jt})\underbrace{\left(\beta\mathbb{E}\left[V(\Upsilon_{jt+1};\Omega_{jt+1})|\Upsilon_{jt},\Omega_{jt}\right]-f_k\right)}_{\text{Expected Value of Continuation}}$$

And I can further write static profit as:

$$\Pi_{jt} = \sum_{c\in\mathbb{C}_{jt}} \underbrace{\left[P_{jct}Q_{jct} - P^L_{jt}L_{jct} - (1-\tau^c_s)P^S_{jt}S_{jct} - P^F_{jt}F_{jct} - P^P_{jt}Pest_{jct}\right]}_{\text{Crop Specific Profit: } \pi_{jct}}$$

The entrant's problem takes the form:

$$V_e(\Omega_{jt},f^e_t) = \underset{\xi^e_{jt},\xi^x_{jt},K_{jt+1},S^o_{jt+1},\mathbb{C}_{jt+1}}{max} \mathbb{E}\Bigg[\xi^e_{jt}\Bigg\{-f^e_t - \underbrace{C(0,K_{jt+1})}_{\text{Capital Adjustment}}$$
$$+(1-\xi^x_{jt})\underbrace{\beta\mathbb{E}\left[V(\Upsilon_{jt+1};\Omega_{jt+1})|\Upsilon_{jt},\Omega_{jt}\right]}_{\text{Expected Value of Continuation}}\Bigg\}|\Omega_{jt},f^e_t\Bigg]$$

After the simplifying assumptions regarding the homogeneity of σ_j, the ownership of land and on input and output prices, I can further write the transition operators which describe the evolution of entrant and incumbents farms as: $\phi_t(\omega',\omega^{ch'},K',\mathbb{C}'|\omega,\omega^{ch},K,\mathbb{C})$ and $\phi_{e,t}(\omega',\omega^{ch'},K',\mathbb{C}'|\omega,\omega^{ch})$. They require the additional introduction of the transition operator $J^h(.|.)$ and $J^{ch}(.|.)$ for both shocks, and of the policy functions κ^k for incumbent capital investment, $\kappa^{\mathbb{C}}$ for crop choice, and κ^k_e for entrant capital investment. These transition operators now write as:

$$\phi_t(\omega',\omega^{ch'},K',\mathbb{C}'|\omega,\omega^{ch},K,\mathbb{C}) = J^h(\omega'|\omega)J^{ch}(\omega^{ch'}|\omega^{ch})\mathbb{1}\{K'=\kappa^k(\omega,\omega^{ch},K|\Omega_t)\}*$$
$$\mathbb{1}\{\mathbb{C}'=\kappa^{\mathbb{C}}(\omega,\omega^{ch},K|\Omega_t)\}\mathbb{1}\{\xi^x(\omega,\omega^{ch},K|\Omega_t)=0\}$$

I note that crop choice is a dynamic decision simply because of the timing assumption—which allows me to address the selection bias induced by focusing on single crop farms for estimation—but crop choice has no impact on a farm's transition. The current state of a farm's crop mix in a given period has no bearing on the dynamic decisions made by the farm

regarding the next period, including its crop mix decision. The analogue transition operator for entrants writes $\phi_{e,t}(\omega', \omega^{ch'}, K'|\omega, \omega^{ch})$:

$$\begin{aligned}\phi_{e,t}(\omega', \omega^{ch'}, K', \mathbb{C}'|\omega, \omega^{ch}) =& J(\omega'|\omega)J^{ch}(\omega^{ch'}|\omega^{ch})\mathbb{1}\{K' = \kappa_e^k(\omega, \omega^{ch}, 0|\Omega_t)\}* \\ & \mathbb{1}\{\mathbb{C}' = \kappa^{\mathbb{C}}(\omega, \omega^{ch}, 0|\Omega_t)\}\mathbb{1}\{\xi^x(\omega, \omega^{ch}, 0|\Omega_t) = 0\}\end{aligned}$$

Once I have defined these, I can then define the law of motion for the measure μ_t. $G_1(.)$ and $G_2(.)$ are the distributions from which entrants draw resp. their original TFP and chemical productivity. With N_t^e the mass of entrants, the allocation of farms over the market space is then fully described by the measure μ_t, whose transition operation $T(.)$ can be written as:

$$\begin{aligned}\mu_{t+1}(\omega', \omega^{ch'}, K', \mathbb{C}') = & \int \phi_t(\omega', \omega^{ch'}, K', \mathbb{C}'|\omega, \omega^{ch}, K, \mathbb{C})d\mu_t(\omega, \omega^{ch}, K, \mathbb{C}) + \\ & N_t^e \int\int \phi_{e,t}(\omega', \omega^{ch'}, K', \mathbb{C}'|\omega, \omega^{ch})dG_1(\omega)dG_2(\omega^{ch})\end{aligned}$$

With all these elements, I can finally define the stationary equilibria on which I will focus as follows. I look at stationary competitive equilibria composed of the tuple of $\Omega^\star = \{\mu^\star, N^{e,\star}, f^{e,\star}, \{P_c^\star\}_{\mathbb{C}}, \{P^x\}_x, P^K, Policy\}$ such that—for a given policy state and given input prices:

- $V^e(\Omega^\star) \leq 0$, and $V^e(\Omega^\star) = 0$ if $N^{e,\star} > 0$. (**Zero Ex-Ante Profit**)
- $\mu^\star = T(\Omega^\star)$. (**Stationary Market**)
- $P^\star$ s.t. $Q_c^S(\Omega^\star) = Q_c^D(P_c^\star) \ \ \forall c \in \mathbb{C}$. (**Output Market Clearing**)
- $f^{e,\star}$ s.t. $f^{e,\star} = Q^{e,\star}(\mathbb{M}(\mu^\star))^{-1}$. (**Entry Goods Market Clearing**)

B.4 Role of Chemical-Biased Productivity Shocks

The relation between the chemical-to-output ratio (at the production optimum) and the chemical-biased productivity shock ω_{jt}^{ch} will also depend on ρ in the same way as the land-chemicals ratio.

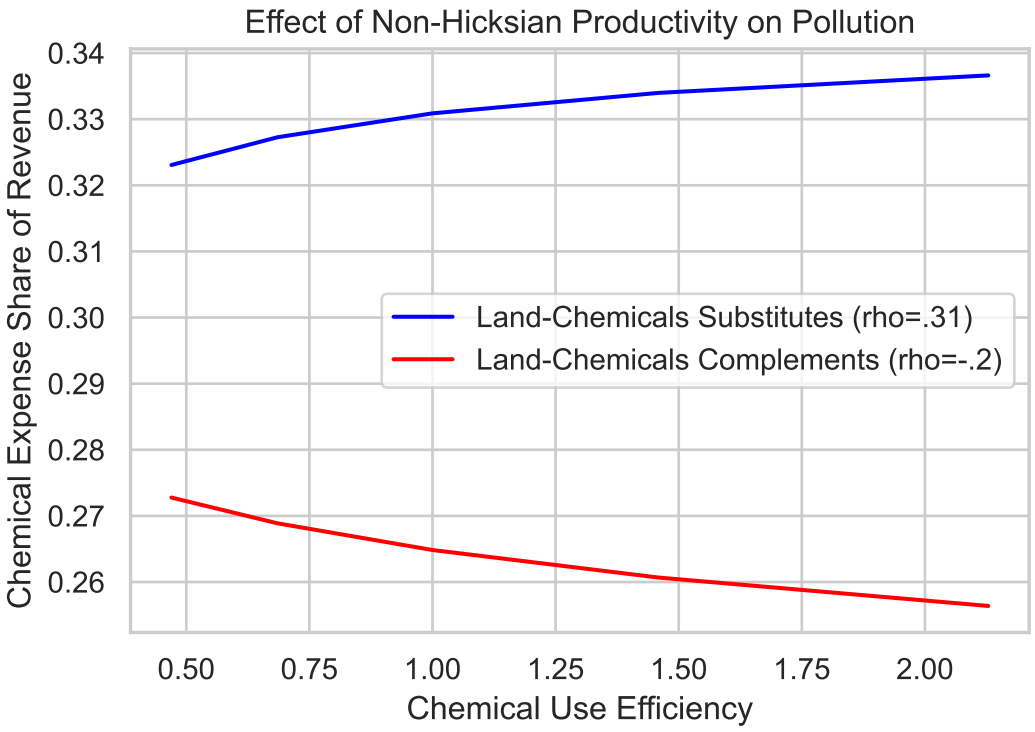


Figure A26: Relation Between Pollution Intensity (Chemical Expense as a Fraction of Revenue) and Chemical-Efficiency

Notes: This figure shows the effect of non-Hicksian productivity shocks on firms' chemical-to-output ratios at their optimal production level. I use simulations to shows the effect of changing the parameter of substitution between land and chemicals from land and chemicals being substitutes, to them being complements.

I finally get the following relation between farms' profitability and pollution intensity. In the competitive model, profitability is also a direct measure of efficiency, and hence I have a positive relation between farm efficiency and pollution intensity. To facilitate the aggregate at the farm-level, I show pollution intensity as the ratio of the amount of chemicals used over the value of production.

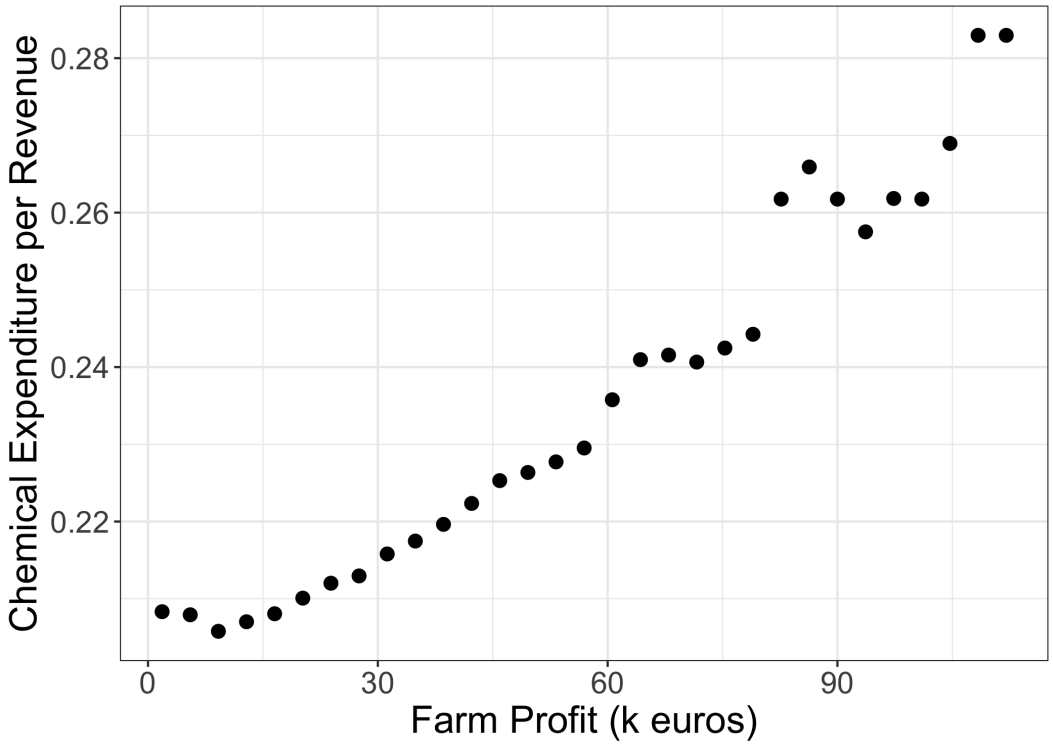


Figure A27: Relation Between Pollution Intensity and Profitability

Notes: This figure shows the relation between farm profitability and pollution intensity (measured as the chemical expenditure over revenue) recovered at the equilibrium of the model.

B.5 Joint Production Estimation Framework

Here I describe an alternative joint production framework, for which I also provide estimates. This approach combines the work of Dhyne et al. (2022) and of Doraszelski and Jomandreu (2018). From the first, I use the idea that inputs can be shared across product lines, and that the parametrization of a firm-level transformation function will define the degree of penalization that accompanies this sharing of inputs. I then draw from Doraszelski and Jomandreu (2018) to model and estimate non-hicksian shocks, within that multi-product production framework. Because the recovery of non-hicksian shocks relies heavily on the first-order conditions taken from the firm-level optimization problem, I move away slightly from the exact specification used by Dhyne et al. (2022).

In effect, consider a firm j which produces the set of crops $\mathbb{C}_{jt}$ within a production period t. The firm is endowed with product-specific input-neutral shocks $\tilde{\omega}_{jct}$. I write the transformation function as:

$$f_{jct} = exp(\tilde{\omega}_{jct}) g_{jct}^{\gamma_{cc}} \prod_{c' \in \mathbb{C}_{jt}, c' \neq c} g_{jc't}^{\gamma_{cc'}}$$

Here f_{jct} is the quantity of crop c produced. That quantity depends on a specific TFP shock, and on product-specific functions g_{jct} which are evaluated at the level of inputs used for each

crop grown in the season. The parameters γ_{cc} parametrize the rivalry or complementarity in production from jointly producing c and c', and potentially sharing some inputs across these two product lines. I keep the functions g_{jct} fairly general for the moment, and parametrize them further later. One additional set of assumptions I make is that:

$$g_{jct} = g_c(K_{jt}, L_{jt}, Fert_{jt}, Pest_{jt}, S_{jct}, \omega^p_{jt}, \omega^f_{jt})$$

This means that each function g_{jct} depends on the firm-level chosen amounts of capital K_{jt}, labor L_{jt}, fertilizer $Fert_{jt}$, pesticides $Pest_{jt}$, on a crop-specific chosen amount of land S_{jct}, and on firm-level pesticide and fertilizer productivity shocks that I denote ω^p_{jt} and ω^f_{jt}. This implies that all inputs but land are selected at the firm-level, and shared across product-lines according to the γ matrix. I also consider that the g_c function only varies across crops, but not periods or farms, and that these two non-hicksian shocks fully account for the heterogeneity in these functions across farms. This assumption of land being a crop-specific input, while others are shared with the same penalty γ allows me to derive an estimating equation to recover the non-hicksian shocks.

With this specification, the firm-level profit is as follows:

$$\Pi_{jt} = \left(\sum_{c \in \mathbb{C}_{jt}} P_{jct}(f_{jct}, D_{jct}) f_{jct} - P^S_{jt} S_{jct} \right) - P^L_{jt} L_{jt} - P^F_{jt} Fert_{jt} - P^p_{jt} Pest_{jt}$$

Taking $\{L_{jt}, Fert_{jt}, Pest_{jt}, S_{jct}\}$ as flexible inputs, their setting will only impact within period profit. I write $P_{jct}(f_{jct}, D_{jct})$ for the inverse demand function, known to the farmers, which depends on the volume produced and sold f_{jct}, and a demand shock D_{jct}. Writing X_{jt} for any of the public inputs $\{L_{jt}, Fert_{jt}, Pest_{jt}\}$, I get the following expression:

$$\frac{\partial \Pi_{jt}}{\partial X_{jt}} = 0 \Leftrightarrow P^X_{jt} = \sum_{c \in \mathbb{C}_{jt}} \frac{\partial g_{jct}}{\partial X_{jt}} g^{-1}_{jct} \sum_{c' \in \mathbb{C}_{jt}} \gamma_{cc'} f_{jc't} P_{jc't} \left[1 - \frac{1}{\eta_{jct}} \right]$$

I denote by η_{jct} the absolute value of the elasticity of demand. I then look at land, the only private input in this set-up:

$$\frac{\partial \Pi_{jt}}{\partial S_{jct}} = 0 \Leftrightarrow P^S_{jt} = \sum_{c' \in \mathbb{C}_{jt}} P_{jc't} \left[1 - \frac{1}{\eta_{jct}} \right] \gamma_{cc'} \frac{\partial g_{jct}}{\partial S_{jct}} g_{jct} f_{jc't}$$

Combining these two equations, I get:

$$\frac{P^X_{jt}}{P^S_{jt}} = \sum_{c \in \mathbb{C}_{jt}} \frac{\frac{\partial g_{jct}}{\partial X_{jt}}}{\frac{\partial g_{jct}}{\partial S_{jct}}}$$

This relation is quite intuitive, the relative allocation of inputs has to be such that the ratio of their marginal impacts on production across production lines equals the ratio of their

prices.
To go further, I assume a specific shape for the g_{jct} function[49]. I take:

$$g_{jct} = K_{jt}^{\alpha_k} L_{jt}^{\alpha_L} \left\{ \delta_s^c S_{jct}^{\rho} + \delta_p^c \left[e^{\omega_{jt}^p} Pest_{jt} \right]^{\rho} + \delta_f^c \left[e^{\omega_{jt}^f} Fert_{jt} \right]^{\rho} \right\}^{\frac{\alpha_s}{\rho}}$$

Without relying on a translog specification, this is the simplest specification which allows me to model non-hicksian productivity shocks. I note that the heterogeneity in the g_{jct} across crops only relies on the $\{\delta_s^c, \delta_f^c, \delta_p^c\}_c$ parameters. Because I are mostly worried about variations in crop-composition impacting the chemicals-to-land ratios at the farm-level, this is the main form of heterogeneity I are interested. A more expansive heterogeneity could specify crop-specific elasticities ρ_c, which I assume away here.
With this parametrization, I obtain the following estimating equation, where small cap letters represent logs, with $x \in \{pest, fert\}$:

$$p_{jt}^x - p_{jt}^s = \rho \omega_{jt}^x + (\rho - 1) x_{jt} + log\Big(\sum_{c \in \mathbb{C}_{jt}} \frac{\delta_x^c}{\delta_s^c} S_{jct}^{1-\rho} \Big)$$

This equation mirrors the first stage estimating equation from Doraszelski and Jomandreu (2018), adapted to the parametrized multi-product setting. Here, the input ratio can either be affected by variations in the input price ratio, by changes in the establishment's production mix, or by changes in the etablishment's profficiency in using input x in the production process. Similarly to them, when the inputs of interest are substitutes, and holding everything else constant, an increase in ω_{jt}^x will increase the ratio of x_{jt} to land.

I propose to recover the $\{\delta_s^c, \delta_f^c, \delta_p^c\}_c$, and ρ in a first estimation step, and to recover the remaining parameters in a second step. To simplify the estimation process, I assume that $\gamma_{cc} = 1$, and $\gamma_{cc'} = \gamma$, and verify post-estimation that $\gamma_{cc'} \in]-\frac{1}{dim(\mathbb{C})}, 0[$ to guarantee that the second order conditions from the optimization problem are met.

First Step: I specify a structure for the two input-biased productivity shocks. For each of them, I assume an AR(1) structure such that, with ζ_{jt+1}^x an exogenous i.i.d. innovation shock:

$$\omega_{jt+1}^x = \mathbb{E}[\omega_{jt+1}^x | \omega_{jt}^x] + \zeta_{jt+1}^x = g^x(\omega_{jt}^x) + \zeta_{jt+1}^x$$

I take $g^x(.)$ to be a third-order polynomial. I use the following moments, with A_{jt}^1 the matrix of instruments:

$$\mathbb{E}[(\zeta_{jt}^p + \zeta_{jt}^f) A_{jt}^1] = 0$$

Our instruments match the production function literature, and correspond to lagged firm-level observables presumably uncorrelated to the productivity innovations, as well as the

[49]Note that this framework can also accomodate a full CES specification. Given the difficulty of estimating the parameters within a CES nest, I keep the CES structure to a minimum - the land nest being itself estimated within an equation which is linear in part of the parameters.

current values of farm-level land prices and hourly agricultural wages.

Second Step: For the second step, I take the log of the production function, and re-order the elements to get:

$$\tilde{\omega}_{jct} = log(f_{jct}) - \left(\sum_{c' \in \mathbb{C}_{jt}} \gamma_{cc'} \right) \left[\alpha_K k_{jt} + \alpha_L l_{jt} \right] - \sum_{c' \in \mathbb{C}_{jt}} \gamma_{cc'} \tilde{s}_{jc't}$$

Where $\tilde{s}_{jc't}$ is the log of the land-fertilizer-pesticide nest, which I can compute using the estimates from the first step. Now, I use crop-specific policy cushions, as well as land prices and agricultural wages as instruments denoted A^2_{jt} in a GMM estimation, with moments:

$$\mathbb{E}\left[\tilde{\omega}_{jct} A^2_{jt} \right] = 0$$

I obtain the following results:

Table A16: Joint Production - Parameters

	Coefficient	se
α_k	0.2415	0.0006
α_l	0.4812	0.0015
α_s	0.0931	$2.2e^{-5}$
γ	-0.0904	0.00013
ρ	0.3886	0.00073
δ_f - Cereals	0.2428	0.0027
δ_f - Oil/Protein	0.2916	0.0034
δ_f - Industrial	0.0282	0.0002
δ_p - Cereals	0.1789	0.0025
δ_p - Oil/Protein	0.2925	0.004
δ_p - Industrial	0.1024	0.002

Standard errors from the second step are corrected for the two-step procedure, following Doraszelski and Jomandreu (2018), and the coefficients associated to the input-biased productivity processes are concentrated out, and not estimated. I note a negative value for γ indicating that the more you share the public inputs across production lines, the less a given crop will benefit from that input (either because of an increase in scope, or an increase in the scale of the other product's production levels). I also note that $\rho \in]0, 1[$, indicating that land, pesticides and fertilizers are substitutes in production, which was expected.

B.6 Extended Production Function

The production function for quantity Q_{jct} of crop c for farm j at time t remains Cobb-Douglas in its main inputs:

$$Q_{jct} = e^{\omega^h_{jct}} K^{\alpha^c_k}_{jt} L^{\alpha^c_l}_{jct} \tilde{S}^{\alpha^c_s}_{jct} e^{\varepsilon_{jct}}, \tag{13}$$

with L_{jct} as labor, $\sum_{k\in\{k,l,s\}} \alpha_k^c = 1$, and ε_{jct} is a mean-zero, i.i.d. shock is realized after input decisions are made. The key mechanisms of substitution and biased productivity are embedded in the composite input $\tilde{S}_{jct}$, which combines land and chemicals. This composite input is now modeled as two nested constant elasticity of substitution functions, in order to allow for flexible substitution patterns and chemical-biased productivity shocks:

$$\tilde{S}_{jct} = \left\{\delta_s^c S_{jct}^{\rho} + (1-\delta_s^c)\left(e^{\omega_{jt}^{ch}}\left\{\delta_p^c Pest_{jct}^{\rho_2} + (1-\delta_p^c)Fert_{jct}^{\rho_2}\right\}^{\frac{1}{\rho_2}}\right)^{\rho}\right\}^{\frac{1}{\rho}}, \tag{14}$$

This function has two layers. The inner nest combines pesticides ($Pest_{jct}$) and fertilizers ($Fert_{jct}$) into a chemical aggregate, with an elasticity of substitution governed by ρ_2. The outer nest then combines physical land (S_{jct}) with this chemical aggregate, with an elasticity of substitution governed by ρ. The chemical-biased productivity shock (ω_{jt}^{ch}) still acts as an augmenting shifter on the entire chemical aggregate.

The second step of the estimation is similar to the one used in the main estimation procedure described in the paper. I obtain the following results:

Table A17: Alternative Production Function (Additional Nest)

Coefficient	Parameter	Estimate	Std. Error
Substitution Land-Chemicals	ρ	0.3425	(0.2033)
Substitution Fertilizers-Pesticides	ρ_2	-1.8104	(1.0575)
Land Share (Wheat)	δ_s^{wheat}	0.3952	(0.2457)
Land Share (Others)	δ_s^{other}	0.5001	(0.3285)
Pesticide Share (Wheat)	δ_p^{wheat}	0.1189	(0.0924)
Pesticide Share (Others)	δ_p^{other}	0.0438	(0.1007)
Labor Share (Wheat)	α_L^{wheat}	0.1124	(0.2148)
Labor Share (Others)	α_L^{other}	0.3835	(0.2723)
Land-Nest Share (Wheat)	α_S^{wheat}	0.7785	(0.0832)
Land-Nest Share (Others)	α_S^{other}	0.3240	(0.0792)
N		7625	
Unique Farms		2671	
N - Group 1		2511	
N - Group 2		5114	

Notes: The parameters are obtained from a two-step estimation, each step performed by GMM. The estimation is run on the FADN French sample restricted to 1980-2007. Observations prior to 1980 are removed, as they do not contain output price data. Observations post-2007 are removed, to focus on a period with significant variation in EU agricultural subsidies, both across time and across crops. I keep farms observed for at least three periods in a row[50], and that produce either only crops in the wheat group, or in the other crops group. I remove farms that are not observed with positive input values for the set of considered inputs (land, labor, capital, fertilizers, pesticides). standard errors are obtained using a block bootstrap procedure, where I draw all the observations related to a farm at a time, using $B = 1000$.

[50]This is done to smooth potential measurement issues, and follows from De Loecker et al. (2016) and Doraszelski and Jomandreu (2018).

Recovering Input Allocations: As discussed in subsection 4.3, I estimate the production parameters on single crop-group firms, following De Loecker et al. (2016). Because I observe farm-crop level land allocations, knowing the parameters of the production specification, I can then recover both input allocations and hicksian and non-hicksian productivity shocks for multi-product firms. The production function has the following shape:

$$Q_{jct} = e^{\tilde{\omega}^h_{jct}} K_{jt}^{\alpha^c_K} L_{jct}^{\alpha^c_L} \left\{ \delta^c_s S^{\rho}_{jct} + (1-\delta^c_s) \left(e^{\omega^{ch}_{jt}} \left[(1-\delta^c_p) Fert^{\rho_2}_{jct} + \delta^c_p Pest^{\rho_2}_{jct} \right]^{\frac{1}{\rho_2}} \right)^{\rho} \right\}^{\frac{\alpha^c_S}{\rho}}$$

With: $\tilde{\omega}^h_{jct} = \omega^h_{jct} + \varepsilon_{jct}$

Drawing from the first-order conditions, I can write the following relation between pesticides and fertilizers:

$$Fert^{1-\rho_2}_{jct} = \frac{P^P_{jt}}{P^F_{jt}} \frac{(1-\delta^c_p)}{\delta^c_p} Pest^{1-\rho_2}_{jct} \tag{15}$$

I can use the relation to recover a relation between land and pesticide allocations:

$$\frac{P^s_{jt} S^{1-\rho}_{jct}}{\delta^c_S} = \frac{P^P_{jt}}{\delta^c_p (1-\delta^c_s)} \left(e^{-\omega^{ch}_{jt}} \right)^{\rho} Pest^{1-\rho}_{jct} \left[(1-\delta^c_p) \left(\frac{P^P_{jt}(1-\delta^c_p)}{P^F_{jt}\delta^c_p} \right)^{\frac{\rho_2}{1-\rho_2}} + \delta^c_p \right]^{1-\frac{\rho}{\rho_2}}$$

For farms producing the two crop groups, I can then take the ratio of this expression for their two crop categories c and c':

$$\frac{Pest^{1-\rho}_{jct}}{Pest^{1-\rho}_{jc't}} = \frac{S^{1-\rho}_{jct}}{S^{1-\rho}_{jc't}} \frac{\delta^c_p (1-\delta^c_s) \delta^{c'}_s}{\delta^{c'}_p (1-\delta^{c'}_s) \delta^c_s} \frac{\left[(1-\delta^c_p) \left(\frac{P^P_{jt}(1-\delta^c_p)}{P^F_{jt}\delta^c_p} \right)^{\frac{\rho_2}{1-\rho_2}} + \delta^c_p \right]^{\frac{\rho}{\rho_2}-1}}{\left[(1-\delta^{c'}_p) \left(\frac{P^P_{jt}(1-\delta^{c'}_p)}{P^F_{jt}\delta^{c'}_p} \right)^{\frac{\rho_2}{1-\rho_2}} + \delta^{c'}_p \right]^{\frac{\rho}{\rho_2}-1}}$$

Once I have estimated the parameters of the production function, the right hand side of this expression is fully known. As I know total farm pesticide use, I can then recover the volumes of pesticide used for each of the crops that they grow. I can then use Equation 15 to recover the fertilizer allocations as well. With these, I can construct the crop-specific land nest values, and use the outer Cobb-Douglas shape of the production function to recover crop-specific labor allocations, from these crop-specific land nests.

B.7 Selection Correction for the Production Function Estimation

I need to account for selection while building moments for the second step of the estimation procedure. Using $\Xi_{jct} = 1$ a dummy for the fact that j only produces crop c in period t, I want to build moments based on the following corrected process:

$$\omega^h_{jct+1} = \mathbb{E}[\omega^h_{jct+1} | \omega^h_{jct}, \Xi_{jct+1} = 1] + \xi^h_{jct+1} \tag{16}$$

With I_{jt} the farm's information set at the end of period t, I want to base the moments on

the following derivation—with $\overline{\omega}^h_{jcc't+1}$ the threshold used at the end of period t to decide on the inclusion of crop c' on top of c. Here c is the ex-ante most profitable crop to grow in period t, and c' the second (out of two crops). I use a competence ladder, which means that there will be a strict relation between the farm's TFP between c and c'. I also note that because demand and input prices play a role in crop choice—the core competence of a farm might not always match the identity of the unique crop it grows.

$$\begin{aligned}
\xi^h_{jct+1} + \varepsilon_{jct+1} &= q_{jct+1} - \alpha^c_k k_{jt+1} - \alpha^c_l l_{jct+1} - \alpha^c_s \tilde{s}_{jct+1} - \mathbb{E}[\omega^h_{jct+1} | I_{jt}, \Xi_{jct+1} = 1] \\
&= q_{jct+1} - \alpha^c_k k_{jt+1} - \alpha^c_l l_{jct+1} - \alpha^c_s \tilde{s}_{jct+1} - \mathbb{E}[\omega^h_{jct+1} | \omega^h_{jct}, \overline{\omega}^h_{jcc't+1}] \\
&= q_{jct+1} - \alpha^c_k k_{jt+1} - \alpha^c_l l_{jct+1} - \alpha^c_s \tilde{s}_{jct+1} - g_h(\omega^h_{jct}, \overline{\omega}^h_{jcc't+1})
\end{aligned}$$

Where moving from line 1 to 2 relies on the first-order Markov process assumption, and the definition of the threshold $\overline{\omega}^h_{jcc't+1}$.[51] I can then specify $g_h(.)$ as a polynomial of its two terms. While Equation 7 provides an expression for ω^h_{jct}, I also need one for the threshold $\overline{\omega}^h_{jcc't+1}$. For this I derive an expression for the conditional probability of producing only crop c as a function of farm productivity and its state, focusing on the crop-addition threshold.[52] The competence ladder structure means that the threshold for the production of the second crop c' can be expressed using the farm's observed TFP shock for crop c combined with its competence ladder σ_j—specifically by its rank on the farm's ladder $\sigma_j^{-1}(c)$, as well as additional variables that influence the value of the threshold—input and output prices, capital stock and chemical productivity:

$$\begin{aligned}
\mathbb{P}\Big(\Xi_{jct+1} = 1\Big) &= \mathbb{P}\Big(\omega^h_{jct} \leq \overline{\omega}^h_{jcc't+1}(\omega^{ch}_{jct}, K_{jt+1}, S^o_{jt+1}, \sigma_j^{-1}(c), \Omega_{jt}) | \overline{\omega}^h_{jcc't+1}(.), \omega^h_{jct}\Big) \\
&= h(\overline{\omega}^h_{jcc't+1}(.), \omega^h_{jct}) \\
&= h(\omega^h_{jct}, \omega^{ch}_{jct}, K_{jt+1}, S^o_{jt+1}, \sigma_j^{-1}(c), \Omega_{jt}) \\
&= h(\{X_{jct}\}, \omega^{ch}_{jct}, K_{jt+1}, S^o_{jt+1}, \sigma_j^{-1}(c), \Omega_{jt}) \\
&= SP_{jt}
\end{aligned}$$

Equation 7 is used to move from the third to the fourth line. While I do not observe $\sigma_j^{-1}(c)$, I approximate it by the interaction between the farm's location and a dummy for the crop it produces—assuming competence ladders are determined by local soil and climatic factors. As in Olley and Pakes (1996) and De Loecker et al. (2016), under some regularity conditions on the density of ω^h_{jct}, I can invert SP_{jt}, which is first recovered non-parametrically, to obtain a proxy for the threshold that I use in the polynomial approximation of $g_h(.)$.

[51] Because of the assumed competence ladder structure, firms face a unique TFP process that propagates across their crops. The process g_h is similar across crops as a direct consequence of this.

[52] The threshold for not including crop c as well corresponds to the usual selection issue outlined by Olley and Pakes (1996) when no production is equated with exit, and is addressed in the usual way by keeping an unbalanced panel of farms.

B.8 Monopolistic Competition

An alternative to perfect competition is to adopt a monopolistic competition framework—which preserves the single agent setting—but allows for price dispersion and some horizontal differentiation across goods. While agricultural products are commodities usually thought of as homogeneous, exogenous local conditions can lead to similar crops having different moisture or nutrient content, making them more or less suitable for different uses. In that sense, a model with differentiated products might be preferable. Monopolistic competition can also allow for mark-ups that vary across producers, and along with changes in market structure.

I adopt for this section the quadratic demand of Melitz and Ottaviano (2008). The demand structure goes as follows: in a closed economy, a representative consumer has the following utility at period t:

$$U_t = q_{0,t} + \alpha \int_{i\in\Omega} q_{i,t}^c di - \frac{1}{2}\gamma \int_{i\in\Omega} (q_{i,t}^c)^2 di - \frac{1}{2}\eta \Big(\int_{i\in\Omega} q_{i,t}^c di \Big)^2 \tag{17}$$

$q_{0,t}$ corresponds to the quantity of outside good consumed. Agricultural varieties $i \in \Omega$ are differentiated. α and η control the substitution between differentiated varieties and the outside good, while γ accounts for the degree of differentiation across varieties. Here, I note that two varieties can be two types of corn grown by two different farms, or wheat and corn grown by the same farm. I discuss next a clustering of the agricultural market, where each market correspond to a crop type, and firm produce different varieties within each crop market.

I take the outside good to be the numeraire. This preference structure implies the following demand for variety i - with $\overline{p}_t$ the average price of agricultural varieties on the market, and M_t the mass of consumed varieties:

$$q_{i,t} = \frac{\alpha}{\eta M_t + \gamma} - \frac{1}{\gamma} p_{i,t} + \frac{\eta M_t}{\eta M_t + \gamma} \frac{1}{\gamma} \overline{p}_t$$

I see that M_t and $\overline{p}_t$—market-level statistics on which atomistic farms have no individual impact—determine the characteristics of the demand curve faced by farms. From this relation, I can also derive a choke price p_t^{max} above which farms will not face any positive demand.

Estimating Demand: I use the following expression to recover the parameters of demand. From now on I denote by m the crop grown, to match the competence ladder structure that I introduce next. Because crops are differentiated in the model, each of a farm's variety is uniquely produced by that farm.

$$q_{mt} = \frac{1}{\gamma}\alpha - \frac{1}{\gamma} p_{mt} - \frac{\eta}{\gamma} Q_t$$

I take for Q_t total agricultural production sold in France, approximated using the weighted sum of sold output in the FADN, for the set of crops that I consider. q_{jmt} and p_{jmt} are respectively the quantity sold, and associated price, for each variety produced by a farm in a given period. I estimate the following regression using a two-stage least squares strategy, with exogenous shocks to firm supply as instruments. Specifically, I use local realized and forecasted weather shocks as supply shocks.

$$q_{jmt} = \beta_0 + \beta_1 p_{jmt} + \beta_2 Q_t + \varepsilon_{jmt}$$

I recover the following parameters. I only use data post-2003 for the estimation, in order to obtain demand parameters that are not impacted by intervention pricing.

Table A18: Demand - Parameters

Coefficient	Parameter	Estimate	Std. Error
Substitution with Numeraire	η	1.32e-07	6.92e-08
Substitution within Varieties	γ	3.19e-02	1.01e-02
Substitution with Numeraire	α	203.5	71.42

Notes: I recover the parameters from a 2SLS regression, using FADN data fro 2003-2020, and using realized and forecasted weather data constructed at the department-year level as supply shocks. The realized weather data is constructed from the ECMWF ERA-5 hourly weather data series, and the forecasts come from ECMWF SEAS-5. Both are aggregated into growing season observations.

The standard errors for the transformed parameters are computed using the delta method. This yields a decreasing choke price over time, which drops significantly around the time of the reform.

Extension to Differentiated Crop Markets: It is useful to extend the model to account for different agro-ecological zones, for which different crops are more or less suitable. Doing so can allow me to draw some conclusions on the impact of different policy designs on respectively the localisation of agriculture, and on the evolution of local crop diversity and pollution.

The first step in developing a model with differentiated locations is to extend the demand system to allow for differentiated crop markets. In the previous version of the model, all the varieties produced within and across farms were considered as different agricultural varieties. Translated to the data, this meant that two farms growing wheat would grow different agricultural varieties, to the same extent that one farm growing corn and wheat would also grow two differentiated varieties. All the agricultural commodities were then facing the same choke price, and the same aggregate demand. I now differentiate the crop markets. Specifically, agricultural varieties c can now be located in different crop markets k. There are K crop markets, and their set is represented by $\mathbb{K}$, with $k \in \mathbb{K}$. Demand takes

the following form:

$$U_t = q_{0,t}^c - \frac{1}{2}\gamma \int_{i\in\Omega} (q_{i,t}^c)^2 di - \frac{1}{2}\eta\Big(\int_{i\in\Omega} q_{i,t}^c di\Big)^2 + \sum_k \alpha_k \int_{i\in\Omega_k} q_{i,t}^c di \tag{18}$$

This corresponds to the simplest way in which I can introduce some heterogeneity in demand across crop types. Extending the notation to M_k, the mass of produced and consumed varieties in market k, and $\overline{p}_k$ their average price, each crop market will have the following choke price:

$$p_{max}^k = \alpha_k - \eta \frac{\sum_k M_k(\alpha_k - \overline{p}_k)}{\Big(\eta \sum_k M_k\Big) - 1}$$

Quite simply, the choke prices will vary across crop markets in an additive way according to the variation in the $\{\alpha_k\}_k$.

Firms will now relate to these differentiated markets according to what I call their crop schedule, or a permutation of $\mathbb{K}$. Farm j will be endowed by a time-constant schedule σ_j, which relates the rank of their varieties grown to a specific crop market—and hence to a specific residual demand curve. The first crop grown by a farm is now $\sigma_j(0)$, and two farms with different schedules will then have differentiated core competences. There are $K!$ such possible schedules, and a farm draws its schedule at random upon entry, from a uniform distribution over the set of possible schedules. Entrants then do not decide which market to enter, but are endowed with a schedule randomly. While the firm dynamics literature allows for a wider range of assumptions regarding the market-directedness of entry, such as Nocke (2006) where entrepreneurs enter a unique targeted market to produce a unique product, or Klette and Kortum (2004) where innovation happens randomly in a new market across a continuum, the assumption allows for a smooth integration of differentiated markets within the Mayer et al. (2014) multi-product setting. Here, firms keep producing an integer amount of products, specifically they produce at a maximum K goods, and given the continuum of producers, I preserve the atomicity of each of them, and the single agent framework.

Our model then follows the same structure as the one previously outlined, although the zero profit condition now sets a set $\{p_{max}^k\}_k$ of choke prices. Given the additive structure of the choke prices, a unique zero profit condition at entry is sufficient to define the K different choke prices.

The Bellman equation characterizing an incumbent's problem can now be written as follows:

$$\begin{aligned} V(\delta_{jt}, K_{jt}, \sigma_j; \{p_{max}^{kt}\}_k) = & \max_{\mathbb{C}_{jt}, \{S_{jct}, X_{jct}, L_{jct}\}_{c\in\mathbb{C}_{jt}}, \zeta_{jt}, K_{jt+1}} \sum_{c\in\mathbb{C}_{jt}} \Pi_{jct} \\ & - C(K_{jt}, K_{jt+1}) + \zeta_{jt} P^K (1-\delta_k) K_{jt} \\ & + (1-\zeta_{jt}) \frac{1}{R} \Bigg\{ \int\int V(\delta_{jt+1}, K_{jt+1}, \sigma_j; \{p_{max}^{kt+1}\}_k) dJ\big(\delta_{jt+1}|\delta_{jt}\big) dF\Big(\{p_{max}^{kt+1}\}_k | \{p_{max}^{kt}\}_k\Big) - f_c \Bigg\} \end{aligned}$$

Where I note $\mathbb{C}_{jt} = \{\sigma_j(0), ..., \sigma_j(M_{jt} - 1)\}$, for M_{jt} the farm's scope in the given period. F is now extended to account for the evolution of the complete choke price vector, rather than the unique one. However, given the additive structure of the choke price heterogeneity, F retains the same dimension as previously, and only models the evolution of a slightly different object.
The entrant's problem now has to account for the drawing of one's crop schedule as well. I write the entrant's Bellman as follows:

$$V^e(\{p^{kt}_{max}\}_k) =$$
$$\max_{\zeta^e_{jt}} \zeta^e_{jt} \left\{ \max_{K_{jt+1}} \frac{1}{R} \int\int\int\int V\big(\delta_{jt+1}, K_{jt+1}, \sigma_j; \{p^{kt+1}_{max}\}_k\big) dJ\big(\delta_{jt+1}|\delta_{jt}\big) dF\big(\{p^{kt+1}_{max}\}_k|\{p^{kt}_{max}\}_k\big) dG(\delta_{jt}) dU(\sigma_j) \right.$$
$$\left. - P^K K_{jt+1} - f_e \right\}$$

Here, I denote by $U(.)$ the uniform distribution over the different crop schedules, which corresponds to the set of K-cycles, without repetition.
Again, I can follow the notation of Hopenhayn and Rogerson (1993) to write the law of motion which describes the evolution of the market. I denote this measure by μ, a measure defined over the three dimensions that characterize the state of a farm—meaning productivity, capital and crop schedules. I denote by $\phi_\sigma(\delta', K'|\delta, K)$ the probability of transition from state (δ, K) to (δ', K'), for a farm with crop schedule σ. With $\kappa(\delta, K, \sigma; \{p^{kt}_{max}\}_k)$ the investment policy function, and $\zeta(\delta, K, \sigma; \{p^{kt}_{max}\}_k)$ the incumbency policy function, I have:

$$\phi_\sigma(\delta', K'|\delta, K) = J(\delta'|\delta)\mathbb{1}\{K' = \kappa(\delta, K, \sigma; \{p^{kt}_{max}\}_k)\}\mathbb{1}\{\zeta(\delta, K, \sigma; \{p^{kt}_{max}\}_k) = 0\}$$

And for an entrant, it is also useful to denote the transition probability:

$$\phi^0_\sigma(\delta', K'|\delta) = J(\delta'|\delta)\mathbb{1}\{K' = \kappa(\delta, K = 0, \sigma; \{p^{kt}_{max}\}_k)\}\mathbb{1}\{\zeta(\delta, K = 0, \sigma; \{p^{kt}_{max}\}_k) = 0\}$$

The stationary measure then solves, with N_e the mass of entrants, $\forall\ (\delta', K', \sigma)$:

$$\mu(\delta', K', \sigma) = \int\int\int \phi_\sigma(\delta', K'|\delta, K) d\mu(\delta, K, \sigma) + N_e \int\int \phi^0_\sigma(\delta', K'|\delta) dG(\delta) dU(\sigma)$$

This relation defines an operator T for the evolution of the state measure μ.

I can then write the mass of produced varieties in each crop market, and their respective average price:

$$M_k = \int\int\int \mathbb{1}\{c_k \in \mathbb{C}(\delta, K, \sigma)\}\ d\mu(\delta, K, \sigma)$$
$$\overline{p}_k = \frac{1}{M_k} \int\int\int \mathbb{1}\{c_k \in \mathbb{C}(\delta, K, \sigma)\} p_k(\delta, K, \sigma)\ d\mu(\delta, K, \sigma)$$

With $\mathbb{C}(\delta, K, \sigma)$ the crop mix of a farm with this given type, derived from that farm's scope $M(\delta, K, \sigma)$ combined with its crop schedule σ. I also denote by $p_k(\delta, K, \sigma)$ the optimal price for crop k, set by a farm of type (δ, K, σ) actually producing this crop k.

The stationary equilibrium of this differentiated demands model is then a tuple formed by choke prices $\{p^k_{max,\star}\}_k$, a stationary measure $\mu^\star$, and an equilibrium mass of entrants $N^\star_e$ such that:

- $V^e(\{p^{k,\star}_{max}\}_k) \leq 0$, and $V^e(\{p^{k,\star}_{max}\}_k) = 0$ if $N^\star_e > 0$.
- $T\left(\mu^\star, N^\star_e, p^{k,\star}_{max}\}_k\right) = \mu^\star$.
- $p^{k,\star}_{max} = \alpha_k - \eta \frac{\sum_j M_j(\alpha_j - \overline{p}_j)}{\left(\sum_j \eta M_j\right) - 1}$.

B.9 Decomposition

I propose a slight modification of the dynamic decomposition of Olley and Pakes (1996) and De Loecker and Collard-Wexler (2015) to highlight the role of different channels in driving the evolution of total chemical use on the market. I write evolution of market-level total chemical use between t and $t+1$, with $\mathcal{A}$ the set of farm types for which the equilibrium mass is positive across both equilibria, $\mathcal{B}$ the set of exiters, and $\mathcal{C}$ the set of entrants:

$$
\begin{aligned}
\Delta Chemicals = &\sum_{j \in \mathcal{A}} Q_{jt} \left(s_{jc_1 t} \Delta \frac{C}{Q}_{jc_1} + s_{jc_2 t} \Delta \frac{C}{Q}_{jc_2} \right) \\
&+ \sum_{j \in \mathcal{A}} Q_{jt} \left(\Delta s_{jc_1} \frac{C}{Q}_{jc_1 t} + \Delta s_{jc_1} \Delta \frac{C}{Q}_{jc_1} + \Delta s_{jc_2} \frac{C}{Q}_{jc_2 t} + \Delta s_{jc_2} \Delta \frac{C}{Q}_{jc_2} \right) \\
&+ \sum_{j \in \mathcal{A}} \left(\Delta Q_j \frac{C}{Q}_{jt} + \Delta Q_j \Delta \frac{C}{Q}_{j} \right) \\
&- \sum_{j \in \mathcal{B}} Q_{jt} \frac{C}{Q}_{jt} \\
&+ \sum_{j \in \mathcal{C}} Q_{jt+1} \frac{C}{Q}_{jt+1}
\end{aligned}
$$

I write $\frac{C}{Q}_{jtc_2}$ for the chemical-to-output ratio of farm j in period t for crop c_2, s_{jtc_1} denotes the output share of crop c_1 in farm j at t, and Q_{jt} is for total output. The first line of the decomposition is for within-farm within-crop changes in chemical intensity associated with changes in input price ratios. The second line is for changes in chemical-use intensity coming from reallocations of production within the farm. The last line is for cross-farm reallocations, as well as changes in production volumes.

Changes in the chemical expenditure to sales ratio can be obtained with a comparable decomposition, where farm revenue market share replaces production volume, and where

the chemical-per-output ratio is replaced by the farm-crop specific of farm specific chemical expenditure ratio.

B.10 Sensitivity Analysis for the Production Function Estimation

I rely on the work of Andrews et al. (2017) to discuss the role of the identifying assumptions regarding instrument exogeneity in driving the estimation of the production function parameters. I first summarize the purpose and implementation of their method, and then describe the estimates and their implications for the sensitivity of the estimates to instrument exogeneity.

The purpose of the method developed by Andrews et al. (2017) is to recover the sensitivity of model parameters to the moments used in structural estimation, and in this extending the omitted variable bias formula to structural cases. They propose to recover a matrix they call the "sensitivity" matrix, which maps the relation between the parameters of the model, and the moments used for their estimation. When combined with alternative assumptions about instrument validity—recasted as the impact of alternative assumptions on moment values—this sensitivity matrix allows to predict the impact of alternative assumptions on the estimated parameters. In other words, this analysis aims at shedding light on the role of identifying assumptions in driving estimation.

I denote by $\hat{\theta}$ the parameter vector minimizing the criterion function:

$$\hat{g}(\theta)'\hat{W}\hat{g}(\theta)$$

In this case, $\hat{\theta}$ can the the estimate for the first stage and second stage of the production function estimation. For any a in the set A of alternative assumptions, they define a local perturbation of the model in the direction of a such that the estimate $\hat{\theta}$ has first-order asymptotic bias—where Λ is the sensitivity matrix:

$$\mathbb{E}[\tilde{\theta}(a)] = \Lambda\mathbb{E}[\hat{g}(a)]$$

An alternative assumption a should be interpreted as an alternative assumption regarding the relation between the chosen instruments and the structural errors for resp. the first and second step of estimation. The sensitivity matrix can be written as:

$$\Lambda = -\left(G'WG\right)^{-1}G'W$$

Where W is the probability limit of $\hat{W}$, the weight matrix used in the GMM criterion, and G is the Jacobian of the probability limit of $\hat{g}(\theta)$ evaluated at the true parameter vector θ_0. Λ serves as a local approximation to the mapping from moments to estimated parameters.

I provide an estimate of ΛK for each of the estimation step for the production function, where K is a weighting matrix, which weights the sensitivity matrix by the inverse of the standard deviation of the relevant instruments. The values for the constant are standardized by the standard deviation of the structural error, in order to have a similar interpretation. As Andrews et al. (2017) discuss, their units of Λ are contingent on the units of the different moments—which means it will vary across moments depending on the values of the instruments I interact with the GMM structural errors. As such, this weighting ensures that Λ elements can be read as the effect of a one standard deviation violation of the given moment condition on the asymptotic bias in $\hat{\theta}$. I present and discuss below the estimates of ΛK for each estimation step.

Table A19: Sensitivity for First Step

	Constant	Lag Chemicals-Land Ratio	Capital	Lag Capital	Lag Chemicals-Land Price Ratio	Land Subsidy	Farm Exposure
ρ	-1.1668	0.3049	-0.0000	-0.0000	-0.1032	0.0000	0.0000
δ_s (group 1)	-2.3655	0.4831	-0.0000	-0.0000	-0.6012	0.0000	0.0000
δ_s (group 2)	-0.6842	0.2653	-0.0000	-0.0000	0.2287	0.0000	0.0000

Table A20: Sensitivity for Second Step

	Constant	Capital	Lag Capital	Lag Labor	Lag Wage	Lag Land Price
α_l (group 1)	-0.0006	-0.0000	0.0000	0.0000	0.0000	0.0000
α_s (group 1)	0.0005	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
α_l (group 2)	0.0002	0.0000	-0.0000	0.0000	-0.0000	-0.0000
α_s (group 2)	-0.0002	-0.0000	0.0000	0.0000	0.0000	0.0000
	Lag Chemicals-Land Ratio	Lag Land Composite	Lag Chemicals-Land Price Ratio	Lag Output Price Index	Land Subsidy	Farm Exposure
α_l (group 1)	0.0001	0.0000	-0.0022	-0.0000	0.0000	-0.0000
α_s (group 1)	-0.0003	0.0000	0.0015	0.0000	-0.0000	0.0000
α_l (group 2)	-0.0000	-0.0000	0.0009	0.0000	0.0000	0.0000
α_s (group 2)	0.0001	0.0000	-0.0006	-0.0000	0.0000	-0.0000