The Unintended Consequences of Farm Insurance: A Causal Investigation on Income, Productivity and Input Dynamics

Abstract

Agricultural insurance is a useful tool for managing risk, and many governments offer support to encourage farmers to participate. However, empirical analysis exploring the dynamic effects of participation in these schemes is limited. This study investigates the causal relationship between agricultural insurance participation and farm productivity, income, and input usage over both the short and long term. Using the Italian Farm Accountancy Data Network between 2018 and 2022, the study applies a difference-in-differences approach that allows assessment of the dynamic impact of insurance. The findings reveal that insurance participation has a persistent negative effect on farm income and productivity, particularly in the early years of participation. This decline suggests moral hazard behaviour, where insured farmers reduce entrepreneurial effort. However, no significant long-term changes were observed in fertiliser or crop protection usage, while usage increased immediately after insurance adoption but decreased in subsequent years. The results of this study suggest that while insurance is designed to mitigate income volatility during adverse events, it does not necessarily improve profitability or productivity because of reduced production incentives and higher insurance premium costs. The study highlights the policy challenge of designing agricultural insurance schemes that can improve risk management without weakening productivity growth.

1. Introduction

The role of risk management in agriculture is crucial for ensuring the stability of farm incomes and the economic viability of agricultural operations (Mishra and El-Osta, 2002).

In particular, risk management tools such as crop insurance have gained prominence as they help farmers cope with the financial consequences of unpredictable events. Insurance schemes allow farmers to transfer part of their risk to insurers, thus stabilising their income and reducing the likelihood of catastrophic financial losses. At the same time, inputs can be managed to face the risk, including adapting the quantities of variable inputs such as fertilisers, crop protection chemicals and irrigation, in addition to the adoption and use of specific risk management tools (Iyer et al., 2020; D. R. Just and Just, 2016; Pennings and Garcia, 2004; Pennings and Wansink, 2004). Both insurance and input management will condition income performance.

Efficient, well-designed agricultural policies must not overlook their potential to affect farmers' adoption and application of key production inputs. These decisions, in turn, affect their risk exposure. For example, the European Farm to Fork Strategy (F2Fs) is designed to support sustainable food systems. It includes regulatory and non-regulatory initiatives that could affect how farmers manage variable inputs such as pesticides and fertilisers that are considered potentially harmful to the environment. At the same time, the EU's Common Agricultural Policy has also addressed environmental issues, consistent with F2F, such as climate change and environmental protection. This has become particularly relevant after the adoption of the EU Green Deal (EC 2023; 2019) and the recent Strategic Dialogue on the Future of EU Agriculture (EC 2024).

There is a substantial body of literature examining the relationship between insurance and input use (Deryugina and Konar, 2017; Enjolras and Aubert, 2020; Koenig and Brunette, 2023; Mieno et al., 2018; Pietrobon, 2024; Roberts et al., 2003; Santeramo et al., 2016; Zhang et al., 2023). However, these studies fail to provide a definitive conclusion regarding whether the correlation is positive or negative, nor do they clarify whether the measured effects are short-term, long-term, or permanent. At the same time, the relationship between insurance and production is potentially affected by moral hazard and risk response mechanisms (Aubert and Enjolras, 2014; Goodwin et al., 2004; Koenig and Brunette, 2023; Roberts et al., 2003): insured farmers can, for example, reduce their input use if they see a guaranteed income but in principle could also apply more inputs if encouraged to take riskier decisions. Finally, there are very few studies that regard the causality between insurance, input, and output, especially considering the dynamic and long-term effects (Enjolras and

Aubert, 2020; Mieno et al., 2018; Roberts et al., 2003).

This study fills the gap concerning the causality of agricultural insurance participation on input and output decisions. Insurance participation is measured based on farmers' enrolment in subsidised agricultural insurance programmes under Measure 17.1 of the Rural Development Program (RDP), part of the Common Agricultural Policy (CAP). This measure provides subsidies covering up to 70% of insurance premiums for risks related to climatic events, animal diseases, and other production threats. Participation is indicated as a binary variable, indicating whether a farm received subsidies under Measure 17.1 during a given year. The paper aims to investigate the short and long-term effects of participation in the insurance subsidies, explaining the moral hazard and risk response mechanism using a causality approach. To account for dynamics such as farmers switching into and out of these programs, I utilised advanced Difference-in-Differences estimators capable of handling such heterogeneity.

This study reveals that insurance participation has a negative persistent impact on income, and this decline is significantly greater in the first years of participation, revealing that moral hazard is pervasive and can influence the TFP for a long time. At the same time, moral hazard and risk perception are not directly linked to short-term changes in fertiliser, crop protection, and labour usage; however, they may have a long-term impact on total factor productivity (TFP) and farm-level efficiency as farmers gradually adjust their production practices over time. Conversely, an increase in water usage was observed immediately after adopting insurance, followed by a decrease in later periods, indicating a dynamic and reversible impact.

Overall, it is possible to conclude that while subsidised insurance stabilises income during adverse events, it does not necessarily lead to an increase in profitability or productivity improvements due to reduced production incentives. This result is specific to subsidised insurance schemes, such as those under Measure 17.1 of the RDP, and may differ from outcomes observed with insurance purchased at full market rates, where higher premium costs could influence farmers' risk-taking and input decisions differently.

The paper is structured as follows: Section 2 provides the background and reviews relevant literature. Section 3 presents the theoretical framework. Section 4 describes the data and methodology used in the analysis. Section 5 discusses the results. Finally, Section 6 concludes by outlining the policy implications and limitations of the study.

2. Background and literature review

The role of insurance as a risk management tool is pivotal in agriculture because it allows farmers to cope, especially with risks associated with weather and other external shocks. Insurance participation may influence farmers' decisions regarding input use and production.

The positive role of farm insurance is also recognised by the European Union, which, through Regulation 1305/2013, introduced subsidies to promote agricultural insurance. Italy is one of the EU countries in which there is a high penetration of farm insurance, probably because the farm sector is strongly affected by several weather-related risks. In Italy, support is provided by Measure 17.1 of the National RDP. These subsidies support insurance for crops, livestock, and plants to help farmers mitigate risks from climatic events, animal diseases, and other threats to production, especially relevant in the context of climate change. The measure aims to reduce the cost of insurance premiums by up to 70%. From 2015 to 2022, over one million applications were funded, with around €2 billion in public contributions[1].

2.1 Literature Review

The effect of insurance participation on farm revenue, as discussed in multiple studies, can be both negative or positive. Various pieces of research have shown that taking part in insurance programs can either stabilise or boost farm income by lessening the risks associated with weather conditions or market fluctuations. Kuethe and Morehart (2012), as well as Menapace, Colson, and Raffaelli (2016), discovered that insurance aids farmers in handling external shocks, which ensures a more stable revenue. However, Farrin et al. (2016) and Wąs and Kobus (2018) indicate that insurance could potentially harm farm income due to moral hazard behaviour. According to these authors, the sense of safety provided by insurance may cause farmers to become more risk-taking or cut back on investing in their crops. This lack of effort could result in decreased productivity, reducing

[1] https://www.psrn.it

earnings. Koenig and Brunette (2023) and Zhao et al. (2016) have shown that having insurance does not affect farm income levels alone; other factors at play contribute significantly to determining how much money farmers make each year.

The connection between insurance participation and fertilisers shows a mix of benefits and drawbacks that are varied and intricate. According to Zhang, Yang, and Li (2023) and Mieno, Walters, and Fulginiti (2018), insured farmers might decrease fertilisers due to moral hazard and risk-seeking: farmers might feel less compelled to invest in productivity-enhancing inputs, believing that insurance will compensate for potential losses.

Roberts et al. (2003) provide evidence of how insurance affects even the long-term use of fertilisers by documenting consistent decreases in the rates of application over time. While it seems plausible that insurance could encourage more fertiliser use by motivating riskier, potentially more profitable farming practices, no study has definitively demonstrated this.

The influence of participating in insurance on crop protection[2] use shows mixed outcomes. The studies, such as Enjolras and Aubert (2020) and Zhang et al. (2023), suggest a connection between insurance and crop protection, as insured farmers often focus on boosting yields because they have, or feel they have, a safety net provided by insurance. These authors note an increase in protective strategies among insured farmers. However, Koenig and Brunette (2023) and Roberts et al. (2003) suggest that some farmers may reduce chemical use due to ethical considerations or moral hazard, trusting that insurance will cover potential losses.

Regarding water use[3], research by Deryugina and Konar (2017) and Santeramo et al. (2016) suggest that insured farmers may increase water usage for irrigation as part of risk management strategies. However, these results are in contrast with those of Koenig and Brunette (2023), who do not find a significant impact on insurance.

The impact of insurance on TFP has not received particular attention despite its importance to the agricultural economy. Enjolras and Aubert (2020) suggest that insurance, providing a safety net, can motivate farmers to engage in activities that increase productivity levels and potentially improve TFP growth. Conversely, Pietrobon (2024) suggests that participation in insurance has not led to substantial changes in TFP levels. The change in TFP is a long-term process that depends on a wide range of factors, making it difficult to isolate the specific effects of insurance participation in isolation.

Moral hazard occurs when insured farmers feel secure knowing that any unforeseen losses will be compensated, which may lead to reduced input use or, conversely, riskier investments made with the confidence that potential losses will be covered. Several studies have found moral hazard in insurance participation, including those by Aubert and Enjolras (2014), Babcock and Hennessy (1996), Goodwin et al. (2004), Horowitz and Lichtenberg (1993) and Mieno et al. (2018). These researchers found that by participating in insurance, the farmer tends to reduce the entrepreneurial effort, thereby lowering productivity and yield.

Conversely, risk response theory suggests that farmers could adapt their input use based on their risk preferences and level of insurance coverage. This could lead to changes in the way they use inputs depending on their specific circumstances and behaviour, as indicated in Just et al. (1999). These findings highlight the need to understand these dynamics to promote more efficient farming practices.

A large part of the literature that investigates the relationship between insurance and production relies on static analysis. Mieno et al. (2018) explain the importance of evaluating dynamic aspects to distinguish short and long-term impacts, but only a few studies investigate this aspect concretely (Enjolras and Aubert, 2020; Roberts et al., 2003). As Mieno et al. (2018) demonstrated, farmers are forward-looking and can adjust the current level of input to orient with long-term perspectives. For instance, a farmer might reduce the use of nitrogen-intensive crops in favour of nitrogen-fixing plants in the short term to enhance fertility. This approach may initially lead to lower yields but ultimately improves soil fertility, ensuring greater productivity in the future. This conclusion contrasts with Pietrobon’s (2024) argument that such practices cannot have a major effect. While they do not immediately transform productivity, their contribution lies in gradual improvements to soil health and sustainability rather than dramatic short-term yield increases.

Most of the existing literature focuses on correlation, reporting how insurance is related to output/input

[2] Pesticide consumption in the first 5 countries in Europe is reported in Figure 3 in Appendix A.2
[3] Water use in agriculture in Italy is reported in Figure 5 in Appendix A.2

without disentangling the direction of causality. To the best of our knowledge, only two studies (Enjolras and Aubert, 2020; Roberts et al., 2003) address causality, but they overlook the recent innovation that allows us to consider that farmers enter and exit insurance multiple times during a period.

This research fills the gap in the existing literature, examining how insurance affects aspects of agriculture, such as total revenue and farm net value added (output), as well as inputs, including fertiliser and labour, to understand its nuanced impact after insurance participation. This analysis addresses the complexities arising from the objectives outlined in the European Green Deal, which aim to mitigate income impacts while also reducing input usage levels.

3. Theoretical Framework

Agricultural production is inherently risky due to factors such as weather variability, market fluctuations, and environmental conditions. According to Iyer et al. (2020), Just and Just (2016), Pennings and Garcia (2004) and Pennings and Wansink (2004), farmers typically use several strategies and tools to manage these risks. Two of these have been often studied: insurance and input adjustments.

Researchers have studied the relationship between farmer behaviour, production function and risk. (Di Falco and Veronesi, 2014; Trujillo-Barrera, Pennings, and Hofenk, 2016; Möhring *et al.*, 2020). However, the empirical evidence is inconclusive (see, e.g., Möhring *et al.* (2020) for the pesticide case). To be effective, well-designed agricultural insurance must account for its potential impact on farmers' adoption and application of production function, f.e., through variations in inputs.

The seminal work of Leathers and Quiggin (1991) suggests that crop protection can reduce the risk of income losses and reduce variability, while fertilisers can increase income variability. This piece of evidence is in contrast with Babcock and Hennessy (1996), Horowitz and Lichtenberg (1993), and Smith and Goodwin (2017), which indicate how, in the long term, the results change.

Insurance is developed to maintain a baseline level of the expected utility function. $E\big[u\big(\pi\ (x, s)\big)\big]$, where u is the utility, π is the profit that is a function of input x, uncertainty is s is a function of uncontrolled external input, such as adverse weather conditions or market conditions. While insurance reduces variability, it also influences input levels by altering this utility function. To approximate the expected utility function, we use Taylor expansion (Jondeau and Rockinger 2006; Skoulakis 2012; Azar and Karaguezian-Haddad 2014; Fabozzi, Focardi, and Kolm 2012):

$$\begin{aligned} E\big[u\big(\pi\ (x, s)\big)\big] = u'(E[\pi(x,s)])\frac{\partial E[\pi(x,s)]}{\partial x_i} + \frac{1}{2!}u''(E[\pi(x,s)])\frac{\partial \mathrm{Var}[\pi(x,s)]}{\partial x_i} \\ + \frac{1}{3!}u'''(E[\pi(x,s)])\mathrm{Var}\big(\pi(x,s)\big)\frac{\partial E[\pi(x,s)]}{\partial x_i} \end{aligned} \tag{1}$$

Where, $u'(E[\pi(x,s)])\frac{\partial E[\pi(x,s)]}{\partial x_i}$: represents the marginal utility of expected profit, scaled by the marginal change in expected profit relative to the input level x_i. $u''(E[\pi(x,s)])\frac{\partial \mathrm{Var}[\pi(x,s)]}{\partial x_i}$: accounts for risk aversion (the second derivative of utility), weighted by how the profit variance changes with respect to x_i. Finally, $u'''(E[\pi(x,s)])\mathrm{Var}\big(\pi(x,s)\big)\frac{\partial E[\pi(x,s)]}{\partial x_i}$ captures the farmer's "prudence", which is a higher-order risk preference beyond risk aversion. Prudence measures how a farmer's risk aversion changes as wealth changes.

We can find different cases. If $\frac{\partial E[\pi(x,s)]}{\partial x_i} > 0$ it means that increasing input x leads to a higher expected profit. This indicates that the input is productive and contributes positively to profitability. Conversely if $\frac{\partial E[\pi(x,s)]}{\partial x_i} < 0$ it implies that increasing input x decreases expected profit, possibly due to inefficiencies or diminishing returns. If $\frac{\partial \mathrm{Var}[\pi(x,s)]}{\partial x_i} > 0$, it suggests that increasing input x raises the variability (risk) of profit. This could imply that the input introduces uncertainty into outcomes. If $\frac{\partial \mathrm{Var}[\pi(x,s)]}{\partial x_i} < 0$, it means that increasing input x reduces risk, which might make it more attractive for risk-averse farmers.

$u'''(E[\pi(x,s)])\mathrm{Var}\big(\pi(x,s)\big)\frac{\partial E[\pi(x,s)]}{\partial x_i}$: incorporates higher-order risk preferences (third derivative of utility) multiplied by both the profit variance and the marginal change in expected profit.

When the insurance (I) is introduced, the expected utility function becomes:

$$E\left[u\left(\pi\ (x,s)\right)\right] = u'(E[\pi(x,s)])\frac{\partial E[\pi(x,s)]}{\partial x_i} + \frac{1}{2!}u''(E[\pi(x,s)])\frac{\partial \mathrm{Var}[\pi(x,s)]}{\partial x_i} + \frac{1}{3!}u'''(E[\pi(x,s)])\mathrm{Var}\left(\pi(x,s)\right)\frac{\partial E[\pi(x,s)]}{\partial x_i} \tag{2}$$

The expected profit $E[\pi(x,s)|I]$, variance $\mathrm{Var}[\pi(x,s)|I]$ and high-order effects $u'''(E[\pi(x,s)])\mathrm{Var}(\pi(x,s)|I)$ are conditional on I. In formula (2), the level of input x can depend on insurance participation. Similar to the formula (1), $\frac{\partial E[\pi(x,s)|I]}{\partial x_i} > 0$ means that increasing input x raises expected profits even with insurance. This might occur if insurance encourages risk-taking or higher productivity. Conversely if $\frac{\partial E[\pi(x,s)|I]}{\partial x_i} < 0$ increasing input x we obtain a reduction in expected profit, possibly due to inefficiencies or moral hazard (e.g., reduced effort because losses are covered). At the same time, when $\frac{\partial \mathrm{Var}[\pi(x,s)|I]}{\partial x_i} > 0$, inputs increase profit variability even with insurance, suggesting that the farmer is engaging in riskier practices. If $\frac{\partial \mathrm{Var}[\pi(x,s)|I]}{\partial x_i} < 0$, it means that inputs reduce variability, indicating that insurance stabilises income and encourages safer practices.

We need to investigate how the shift from equation (1) to equation (2) affects profit maximisation, considering that $E[\pi(x,s)|I]$ may be greater than or less than $E[\pi(x,s)]$.

This result is particularly relevant for this investigation because it allows us to understand the effect of insurance on π and input level and the related connection to the total factor productivity.

For example, consider two farmers: one uninsured ($UnIns$) and one insured (Ins). The uninsured farmer uses a level of input x^{UnIns} while the insured farmer uses inputs x^{Ins}.

If moral hazard leads the insured farmer to reduce inputs such that $x^{Ins} < x^{UnIns}$ that can lead to a level of profit $\pi^{Ins}(x^{Ins},s)|I < \pi^{UnIns}(x^{UnIns},s)$.

However, with an indemnity payment from insurance, the insured farmer's total profit may approach or even exceed that of the uninsured farmer: $\pi^{Ins}(x^{Ins},s)|I + Indemnity \gtreqless \pi^{UnIns}(x^{UnIns},s)$ with a low level of variability ($\mathrm{Var}[\pi^{Ins}(x^{Ins},s)|I] < \mathrm{Var}[\pi^{UnIns}(x^{UnIns},s)]$ and less effort to coordinate the input to reach the best performance ($TFP^{Ins} < TFP^{UnIns}$).

This static analysis should be complemented by examining long-term effects, as: $E[\pi^{Ins}(x^{Ins},s)|I + Indemnity]_{short\ term} \neq E[\pi^{Ins}(x^{Ins},s)|I + Indemnity]_{long\ term}$.

To extend this framework into a long-term context for both insured and uninsured farmers, we employ the Bellman equation as proposed by Malikov and Lien (2021). The Bellman equation is a powerful tool for modeling dynamic decision-making over time, as it considers both current and future utility. For uninsured farmers (UnIns) and insured farmers (Ins), their respective value functions can be expressed as follows:

$$\text{Uninsured Farmers: } V_t^{Un}Ins(x_t,s_t) = \max\left\{u\left(\pi_{t(x_t,s_t)}\right) + E[V_{t+1}^{UnIns}(x_{t+1},s_{t+1})]\right\} \tag{3}$$

$$\text{Insured Farmers } V_t^{Ins}(x_t,s_t|I) = max\left\{u\left(\pi_t(x_t,s_t|I)\right) + Indemnity + E[V_{t+1}^{Ins}(x_{t+1},s_{t+1}|I)]\right\} \tag{4}$$

Here, V represents the value function that captures the farmer's total expected utility over time. For insured farmers, the decision-making process also incorporates potential indemnities from insurance in future periods. These equations illustrate how farmers optimise their decisions by balancing immediate utility with future expected gains. The inclusion of insurance modifies the dynamic by introducing indemnities, which may influence input decisions and productivity adjustments over time. By adopting this dynamic framework, we can better understand how insurance participation affects long-term farming behavior compared to uninsured farmers.

Equations (3) and (4) emphasise the importance of conducting a multi-year evaluation to capture the full dynamics of insurance participation. Such an approach provides a more accurate representation of its effects on short-term decisions and long-term outcomes, aligning with insights from Babcock and Hennessy (1996). Consequently, a comprehensive, multi-year investigation is essential to fully assess the implications of insurance on farming practices and productivity.

4. Data and Methodology

4.1 Data Sources

In this study, the Italian FADN (Farm Accountancy Data Network)[4] is adopted, a comprehensive dataset at the farm level. The period analysed is 2018 to 2022 because the measure 17.1 of RDP, even if introduced with the CAP programming period 2013/2020, only had limited participation in earlier years (Figure 1).

We select only the crop farms (specifically the types of farms 1 (Field crops), 2 (Horticulture) and 3 (Permanent crops)). We exclude livestock farming because it can have different risk perceptions due, for example, to different susceptibility to change in weather conditions and risk management through the use of inputs.[5] Specifically, we individuate the treatment as $D = 1$ when the farmers participate in insurance subsidised through the measure 17.1 of Rural Development Program, and $D = 0$ in other cases.

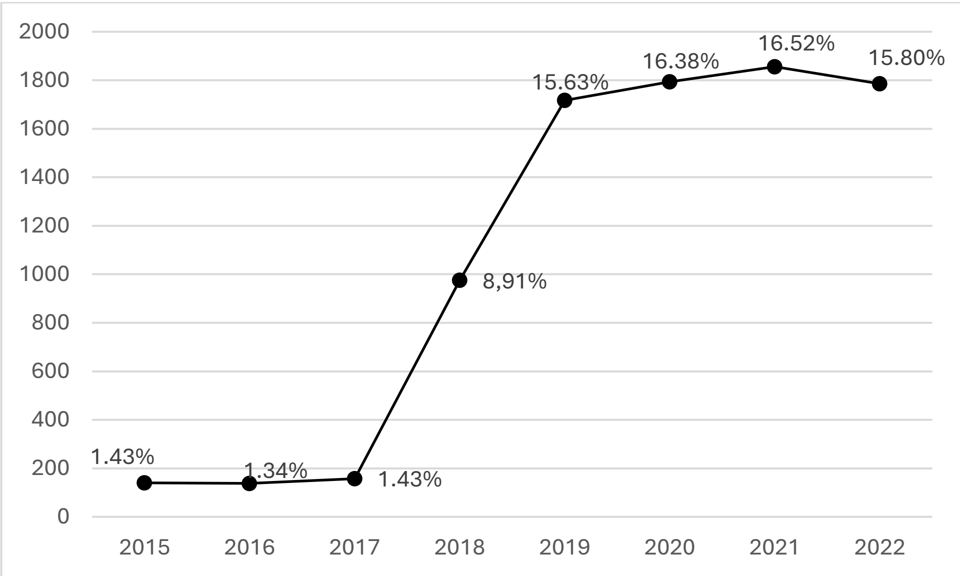

Figure 1 - Participation on Measure 17.1 of RDP in Italian FADN

All economic variables are deflated using specific price indexes (see Appendix A.1 for details). The final dataset comprises 52,235 observations, of which 45,427 are uninsured (i.e., those who do not participate in insurance under Measure 17.1 of the RDP), and 6,808 correspond to farmers who applied for subsidised insurance through Measure 17.1. The comparison of key farm-level variables is reported in Table 1. The difference in means and the Wilcoxon test p-values indicate statistically significant differences across all variables at the 5% significance level.

These farms have high levels of heterogeneity, with a Total Revenue (TR) that indicated that the uninsured farms have a lower mean revenue (€102,003.04) compared to uninsured (€186,067.88), with a difference of -45.18% and the FNVA and Farm Net Income that follow similar patterns, with insured farms showing higher values but significant differences in means (-42.74% and -41.79%, respectively).

The principal inputs show that the insured farms exhibit significantly higher input costs across various categories. Uninsured farms use fewer labour hours on average (3,725 vs. 4,954), with a difference of -24.81%. Crop Protection Costs and Fertiliser Costs are significantly lower in insured farms (€4,499.74 vs. €10,078.94 for crop protection; €6,084.96 vs. €11,186.81 for fertilisers). Furthermore, finally, Water Costs and Water Volume are also substantially lower in insured farms (€518.48 vs. €1,396.89 for water costs; 6,697 m³ vs. 17,134 m³ for water volume).

For capital, insured farms have less Utilised Agricultural Area (UAA) on average (25.44 ha vs 36.09 ha), with a significant difference of -29.51% and also have lower machinery power (-36.02%) and fixed capital (-

[4] The FADN codification of the variable used is reported in Appendix 1

[5] To overcome the problem of differences within the type of farms we take a multiple approach through Propensity Score Matching, Inverse Propensity Weights and variable control.

36.40%). However, uninsured farms allocate a higher proportion of their UAA to nitrogen-fixing plants (+36.70%). Diversification indicators such as the Shannon Index are slightly higher for insured farms (0.866 vs 0.793; -8.32%), suggesting better crop diversification practices among insured farmers. Interestingly, uninsured farms demonstrate better efficiency in some areas. In the case of labour per UAA, uninsured farms utilise labour more intensively per hectare (615 hours/ha vs 334 hours/ha; +84%). Moreover, fertiliser costs per UAA show how uninsured farms spend more on fertilisers relative to their smaller UAA (+113%). Hence, uninsured farms apply more nitrogen per hectare (+30%).

While other figures can be calculated directly by the FADN, for TFP it is necessary to use a specific procedure. In particular, we define TFP as a Solow residual (Solow 1957). Specifically, TFP is derived as the residual from an estimation for the production function where output is regressed – following Ackerberg, Caves, and Frazer (2015)[6] – on capital (K) and labour (L) inputs corresponding to a Cobb-Douglas Production function $Y = \Omega K^{\beta_K} L^{\beta_L}$ or, logarithm formulation (in lowercase the logarithm), $y_{i,t} = \alpha_{i,t} + \beta_k k_{i,t} + \beta_l l_{i,t} + \omega_{i,t} + \epsilon_{i,t}$, where the difference $\omega_{i,t} = TFP_{i,t} = y_{i,t} - \left(\hat{\beta}_k k_{i,t} + \hat{\beta}_l l_{i,t}\right)$. Notably, TFP, reported in logarithms, is 6% lower for insured firms (Table 1).

The comparison hides the complex trade-offs associated with agricultural insurance participation: while insured farms benefit from higher revenue and resource utilisation capacity, they face significantly higher costs that may erode profitability if not managed efficiently. Conversely, uninsured farms operate with lower input levels but demonstrate greater efficiency in resource use per unit area or capital deployed.

[6]The detailed procedure to obtain the value is reported in Appendix A.3

Table 1 - Descriptive Statistics

	Variable	Definition	UnInsured 45427 observations			Insured 6808 observations			Difference I n% (UnInsured - Insured)	Wilcoxon test (UnInsured vs Insured) p.value
			Mean	Standard Deviation	Median	Mean	Standard Deviation	Median		
Other Variables	TR	Total revenue [€]	102003.038	237316.086	44028.000	186067.876	360837.734	95020.500	-45.18%	Sign. <0.05%
	FNVA	Farm Net Value Added [€]	64161.906	152958.256	26798.000	112061.979	227082.583	56439.500	-42.74%	Sign. <0.05%
	FNI	Farm Net Income [€]	43213.737	121755.506	16906.000	74234.307	171755.191	35519.500	-41.79%	Sign. <0.05%
	Labour	Labour [hours]	3725.040	4517.966	2510.000	4954.076	6145.460	3520.000	-24.81%	Sign. <0.05%
	Crop_Prot	Crop Protection cost [€]	4499.738	12417.596	1402.000	10078.941	17607.945	4800.000	-55.36%	Sign. <0.05%
	Fert	Fertilizer cost [€]	6084.957	14903.994	2176.000	11186.812	25958.696	4400.000	-45.61%	Sign. <0.05%
	Water.cost	Water cost [€]	518.480	2960.914	0.000	1396.894	4687.698	0.000	-62.88%	Sign. <0.05%
	Water	Water volume [m^3]	6697.453	33828.645	0.000	17134.896	64667.576	2000.000	-60.91%	Sign. <0.05%
	UAA	Utilised Agricultural Area - UAA [Ha]	25.436	47.050	11.470	36.085	63.499	15.945	-29.51%	Sign. <0.05%
	C_C	Currents Cost [€]	39329.585	109255.307	15141.000	80865.275	174112.848	35488.500	-51.36%	Sign. <0.05%
	Shannon_Index	Shannon Index for diversification	0.793	0.532	0.813	0.866	0.549	0.907	-8.32%	Sign. <0.05%
	Orchards_index	Orchard area on UAA [%]	0.444	0.436	0.323	0.502	0.435	0.540	-11.56%	Sign. <0.05%
	Per_rent	Rented UAA/Total UAA [%]	0.451	0.427	0.368	0.522	0.413	0.555	-13.58%	Sign. <0.05%
	Nitr_fix_Index	Nitrogen-fixing plants/Total UAA [%]	0.147	0.238	0.000	0.107	0.174	0.000	36.70%	Sign. <0.05%
	Irr_Land_Index	UAA under irrigation/UAA [%]	7.927	26.854	0.400	19.834	41.946	5.650	-60.03%	Sign. <0.05%
	Kw_M	kW of Machinery [kW]	172.199	198.766	114.000	269.160	270.948	184.000	-36.02%	Sign. <0.05%
	Fix_K	Fixed Capital [€]	420450.646	2114250.128	176035.000	661082.114	1331351.038	288522.000	-36.40%	Sign. <0.05%
	N	Nitrogen [Kg]	186.140	1895.869	0.000	283.390	2437.515	0.000	-34.32%	Sign. <0.05%
	P_2O_5	Phosphorus [Kg]	134.660	1658.978	0.000	152.468	1111.998	0.000	-11.68%	Sign. <0.05%
	K_2O	Potassium [Kg]	154.255	2604.350	0.000	177.519	981.274	0.000	-13.11%	Sign. <0.05%
	K	Total Capital [€]	522304.382	2187037.130	234820.000	894881.324	1604927.438	436058.000	-41.63%	Sign. <0.05%
Dependent	TR.UAA	Total Revenue/UAA	12195.579	45800.164	3554.036	8167.778	9940.687	5430.655	49.31%	Sign. <0.05%
	FNVA.UAA	FNVA/UAA	7115.583	25180.693	2192.870	5200.233	7026.679	3081.935	36.83%	Sign. <0.05%
	TFP	Total Factor Productivity	6.375	0.839	6.323	6.785	0.628	6.806	-6.04%	Sign. <0.05%
	Labour.UAA	Labour/UAA	615.574	1632.652	244.293	333.922	339.850	233.022	84.35%	Sign. <0.05%
	Crop_Protection.UAA	Crop Protection Costs/UAA	443.758	1823.971	122.803	444.223	454.432	294.577	-0.10%	Sign. <0.05%
	Fert.UAA	Fertilizer Costs/UAA	789.096	4235.597	182.289	369.785	410.120	265.707	113.39%	Sign. <0.05%
	N.UAA	Nitrogen/UAA	14.974	158.787	0.000	11.499	61.321	0.000	30.22%	Sign. <0.05%
	P_2O_5.UAA	Phosphorous/UAA	14.303	163.965	0.000	7.572	33.177	0.000	88.89%	Sign. <0.05%
	K_2O.UAA	Potassium/UAA	17.400	208.117	0.000	10.377	76.611	0.000	67.67%	Sign. <0.05%
	C_C/UAA	Current Costs/UAA	5002.085	24567.553	1201.587	3142.484	4446.519	2112.086	59.18%	Sign. <0.05%
	Crop_Protection.C_C	Crop Protection Costs/Current Costs	0.123	0.111	0.094	0.152	0.093	0.138	-19.36%	Sign. <0.05%
	Fert.C_C	Fertilizer Costs/Current Costs	0.166	0.110	0.157	0.146	0.092	0.134	13.88%	Sign. <0.05%
	Water.cost.C_C	Water Cost/Current Costs	0.013	0.039	0.000	0.015	0.033	0.000	-13.08%	Sign. <0.05%
	Water.UAA	Water Volume/UAA	420.002	1009.507	0.000	588.825	976.049	124.748	-28.67%	Sign. <0.05%

4.2 Identification Strategy

Difference-in-differences (DiD) is used to estimate the causal effects of insurance participation. DiD is a quasi-experimental technique that compares the outcome dynamics between two groups: a treatment group (e.g., farms enrolled in insurance programs) and a control group (e.g. farms not participating in insurance) This approach accounts for variables that could impact both groups equally over time, enabling the evaluation of the impact of participating in insurance programs. An explanation and history of DiD can be found in Cunningham (2021).

DiD allows us to evaluate changes over time in factors that can affect the dependent variable. This method allows for the evaluation of how participation in insurance subsidies through measure 17.1 of the Rural Development Program influences outputs or inputs by capturing both short-term and long-term effects across multiple years following adoption.

A simple DiD is based on Two-Way (Time and Individual) Fixed Effect (TWFE) estimator:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta D_{i,t} + \epsilon_{i,t} \tag{5}$$

where β is the parameter of interest (i.e. the Average Treatment on Treated - ATT), α_i being the individual (farm) time-invariant effect, γ_t time effect, and $\epsilon_{i,t}$ the idiosyncratic error terms. When treatment is heterogeneous, across groups or over time, the TWFE is proved to be biased: estimating the ATT as a weighted average of various late- and already-treated units (Arkhangelsky and Imbens, 2023; Goodman-Bacon, 2021).

The assumption of parallel trends (Parallel Trend Assumption – PTA) is central to the validity of DiD analysis. It posits that, in the absence of treatment, the average outcomes of treated and control groups would have followed the same trajectory over time. This assumption ensures that any observed divergence post-treatment can be attributed to the intervention rather than pre-existing differences or other confounding factors. While critical, this assumption is often untestable directly because counterfactual outcomes are not observed. However, violations can occur due to: (i) factors influencing outcomes differently across groups over time; (ii) treatment assignment depending on time-varying unobservables or past outcomes, leading to deviations from parallel trends; or (iii) other shocks occur contemporaneously with the treatment, affecting one group but not the other.

Recently, to solve this problem, the DiD approach has incurred an improvement that Naqvi (2024), Goldsmith-Pinkham (2024) and Cunningham (2023) call the "DiD-Revolution". Consequently, new estimators have been developed from, among others, Borusyak et al. (2024), Callaway and Sant'Anna (2021), de Chaisemartin and d'Haultfoeuille (2021), Gardner (2022), Sun and Abraham (2021) and Wooldridge (2021, 2022). These estimators, even solving the bias problem of TWFE, relied on "staggered design", considering that a farm remains treated at any time after the treatment. However, this is not the best for the insurance scheme where farmers can be insured and non-insured, alternating each year. At the same time, a staggered design is not suitable for an unbalanced dataset like FADN. Instead, at the base of estimators adopted for staggered design, it is necessary to establish the first year of treatment that in an unbalanced panel can be in a year that is not present on the dataset.

The estimator developed by de Chaisemartin and D'Haultfœuille, 2024 (dCDH24) is adopted to solve these issues. This estimator implements heterogeneity-robust event-study DiD estimators. dCDH24 is specifically designed for cases in which the treatment can be adopted in different periods. Finally, it can handle cases where treatments change multiple times (e.g., farmers might enter – switching-in – and exit – switching-out– insurance schemes). In this case, farmers follow 15 treatment paths, but only one follows a path that is staggered (Table 2). The table represents the treatment dynamics of farmers transitioning between insured (1) and uninsured (0) states over five time periods (ℓ=0,1,2,3,4). In particular, we identify each unique treatment path. Each path represents a unique sequence of transitions between uninsured and insured states over the five periods. There are 15 distinct paths in total[7]. The number of farmers following each specific treatment path is indicated with N. ℓ=0,1,2,3,4: Represents the treatment status of farmers across five periods in particular, with a value of 0

[7] For example: Path 1: Farmers remain uninsured in period ℓ=0, then become insured from ℓ=1 onward. This is the most common path, followed by 259 farmers. Path 5: Farmers start as insured in ℓ=0, then switch to uninsured in ℓ=1, and remain uninsured thereafter. 25 farmers follow this path. Path 15: Farmers are uninsured in all periods except ℓ=3, where they briefly become insured. Only one farmer follows this path.

indicating that the farmer was uninsured during that period and with a value of 1 indicating that the farmer was insured during that period.

Table 2 - Treatment paths (0 is not insured and 1 is insured)

Path	N	ℓ=0	ℓ=1	ℓ=2	ℓ=3	ℓ=4
1	259	0	1	1	1	1
2	76	0	1	1	1	0
3	51	0	1	0	0	0
4	29	0	1	1	0	0
5	25	1	0	0	0	0
6	15	0	1	1	0	1
7	14	0	1	0	1	1
8	12	1	0	1	1	1
9	11	0	1	0	0	1
10	6	1	0	1	0	1
11	5	0	1	0	1	0
12	5	1	0	1	1	0
13	4	1	0	0	1	1
14	3	1	0	0	0	1
15	1	1	0	1	0	0

The dCDH24 estimator is used alongside Inverse Propensity Weights (IPW) to address potential selection bias and ensure that the treatment (insured farms) and control (uninsured farms) groups are comparable. This is important because farms that choose to participate in insurance may systematically differ from those that do not. IPW helps correct for these differences by assigning weights to farms based on their observed characteristics, making the two groups more similar.

The weights are calculated using Propensity Scores (PS), which estimate the likelihood of a farm participating in insurance based on its characteristics. These scores are derived using Entropy Balance (Hainmueller 2012), and extreme values are excluded to ensure the "overlap assumption"—a condition that ensures the characteristics of treated and untreated groups are sufficiently similar for comparison (Sant'Anna and Zhao, 2020; Roth et al., 2023). By applying IPW within a Difference-in-Differences (DiD) framework, we can better balance the two groups, enabling a more accurate estimation of causal effects [8] (Heckman et al., 1997, 1998; Kang and Schafer, 2007; Zeng et al., 2020)[9]. This approach ensures that differences in outcomes between insured and uninsured farms can be attributed to the insurance itself rather than pre-existing differences between the groups.

dCDH24 adopts a bunch of strategies to evaluate the satisfaction of PTA. Using the Joint Test of Nullity of Placebos, it is possible to check whether the pre-treatment differences in the outcome are statistically significant. A non-significant result suggests that the PTA is supported. In the case PTA is not satisfied, it is necessary to include covariates that explain these different trends (in this case, it is called Conditional PTA – cPTA).

5. Results

The results of insurance participation are presented in terms of outcomes, using Total Revenue and Farm Net Value Added (FNVA) per Utilized Agricultural Area (UAA). Subsequently, the evaluation of inputs is provided, considering fertilisers (both expenses and the utilisation in kg of nitrogen, phosphorus, and potassium), crop protection (€), water (m^3), and labour (hours), all measured relative to UAA. Finally, the impact of insurance on Total Factor Productivity is assessed.

5.1 Impact on Total Revenue and FNVA

[8] The procedure to obtain Inverse Propensity Weight is reported on appendix A.4

[9] See Appendix A.6 for the list of control variables adopted. Considering that the unconditional PTA in all the models is not verified, this variable allows verified PTA through a conditional parallel trend.

Table 3 shows and Figure 6 in Appendix A.9 show, the estimated effects of insurance participation on Total Revenue (TR) per UAA (TR/UAA) over different time lags (ℓ).The first year after insurance participation shows a significant decrease in TR/UAA by € 535.78 (Standard Error (SE): 147.38). In the second year, the negative impact on TR/UAA diminishes to €306.87 (SE: €98.99). By the third year, the effect is much smaller at €59.72 (SE: €82.06), indicating a potential recovery or stabilisation. In the fourth year, there is another significant drop in TR/UAA by €241.11 (SE: €95.44). Cumulative Average Treatment on Treated (ATT) shows a significant reduction by €581.65 (SE: €183.04), indicating that insurance participation correlates with a persistent negative impact.

Table 3 – Estimation for Total Revenue/UAA

	Estimate	SE	N	Switchers
ℓ=1	-535.782	147.377	18,214	1,295
ℓ=2	-306.873	98.996	11,748	1,015
ℓ=3	-59.719	82.061	7,238	848
ℓ=4	-241.109	95.444	3,291	516
	Average cumulative (total) effect			
ATT	-581.654	183.044	21,127	3,674
Test of joint nullity of the placebos :	P.Value:			0.080
Test of joint nullity of the effects :	P.Value:			0.000
Test of equality of the effects :	P.Value:			0.000

The test of joint nullity of the placebos (p-value 0.080) suggests that Parallel Trend Assumption (PTA) and the no-anticipation assumption (NAA) are satisfied. Moreover, the test of joint nullity of the effects (p-value 0.000) and the test of equality of the effects (p-value 0.000), respectively, evidence that the impact is relevant and not equal, highlighting the dynamic effect.[10]

Considering the impact of insurance on FNVA in terms of UAA - FNVA/UAA - (Table 4 and Figure 7 in Appendix A.9) allows us to figure out that the first year after insurance participation shows a significant negative impact, with a decrease of €412.64 per hectare (SE 147.67), this negative effect decrease on the second even if with a not significant value of €145.17 (SE = 102.91). The effect remains not significant in the third €101.02 (SE = 92.28), but in the fourth year, with €331.29 (SE = 122.60), the impact returned to be significant, suggesting a potential long-term adverse effect.

Table 4 – Estimation for Farm Net Value Added/UAA

	Estimate	SE	N	Switchers
ℓ=1	-412.642	147.668	18,053	1,276
ℓ=2	-145.172	102.906	11,622	1,006
ℓ=3	-101.021	92.275	7,140	828
ℓ=4	-331.285	122.596	3,259	497
	Average cumulative (total) effect			
ATT	-515.843	215.634	21,015	3,607
Test of joint nullity of the placebos :	P.Value:			0.081
Test of joint nullity of the effects :	P.Value:			0.005
Test of equality of the effects :	P.Value:			0.003

The joint nullity test for placebos (p-value 0.081) shows that the PTA is satisfied. The dynamic impact is instead demonstrated by the joint nullity test for effects (p-value 0.005) and the test of equality of impact (p-value 0.003), rejecting the hypothesis that the effects are equal across periods.

The negative impact on TR/UAA and FNVA/UAA following insurance participation is consistent with some

[10] An in-depth explaination of these tests is reported in appendix A.5

findings in the literature regarding moral hazard and risk response in agricultural insurance programs (Enjolras and Aubert, 2020). In particular, according to Goodwin et al. (2004) and Mishra et al. (2005), moral hazard explains the initial sharp decline in revenue following insurance. On the other hand, Just et al. (1999) suggest that risk response may explain why farmers, once insured, can adapt their input use according to their risk preferences. Finally, while insurance is intended to stabilise income in times of adverse events, it may not always lead to increased revenue, as shown in studies by Farrin et al. (2016) and Wąs and Kobus (2018), which found negative impacts on income levels due to reduced production incentives. The increase in negative impact observed in later years raises concerns about the long-term sustainability of farms participating in insurance programs.

5.2 Impact on Input Usage

5.2.1 Fertilisers

The fertilisation cost per UAA is evaluated (Table 5 and Figure 8 in Appendix A.9). On the overall, the impact is not statistically significant for the periods (ℓ=1: -4.218 (SE 7.220) , ℓ=2 -6.325 (SE 6.778), ℓ=3 0.013(SE 5.597), and ℓ=4 1.276 (SE 6.590)). The cumulated ATT -4.830 (SE 11.940) indicates an overall reduction in fertiliser costs, but this result is not statistically significant.

Table 5 – Estimation for Fertiliser Costs/UAA

Fertilizers Costs /UAA				
	Estimate	SE	N	Switchers
ℓ=1	-4.218	7.220	18,186	1,288
ℓ=2	-6.325	6.778	11,710	1,015
ℓ=3	0.013	5.597	7,222	850
ℓ=4	1.276	6.590	3,303	525
Average cumulative (total) effect				
ATT	-4.830	11.940	21,155	3,678
Test of joint nullity of the placebos :		P.Value:		0.054
Test of joint nullity of the effects :		P.Value:		0.756
Test of equality of the effects :		P.Value:		0.607

By analysing the battery of tests, we can conclude that the PTA assumption is satisfied and that the dynamic effect is not significant.

The breakdown of fertiliser in nitrogen (Table 6 and Figure 9 in Appendix A.9), phosphorus (Table 7 and Figure 10 in Appendix A.9), and potassium (Table 8 and Figure 11 in Appendix A.9) demonstrates that insurance has no short-term impact but, conversely, a long-term effect.

In particular, it is found that in the fourth year for nitrogen (ℓ=4 1.539 (SE 0.667), in the third year for phosphorous (ℓ=3 1.105(SE 0.517)) and in the third and fourth years for the potassium (ℓ=3 1.930 (SE 0.697), ℓ=4 2.028 (SE 0.782)) of insurance participation, the insured tends to increase the consumption of fertilisers. Still, it is necessary to consider that the amount of this increase is very limited.

	Estimate	SE	N	Switchers
ℓ=1	1.066	3.107	18,115	1,285
ℓ=2	-1.294	1.085	11,693	1,012
ℓ=3	0.768	1.256	7,215	849
ℓ=4	1.539	0.667	3,314	525
	Average cumulative (total) effect			
ATT	1.196	2.197	21,136	3,671
Test of joint nullity of the placebos :		P-value:		0.443
Test of joint nullity of the effects :		P-value:		0.072
Test of equality of the effects :		P-value:		0.103

Table 6 – Estimation for N/UAA

	Estimate	SE	N	Switchers
ℓ=1	0.284	1.277	18,146	1,285
ℓ=2	-1.220	0.964	11,711	1,012
ℓ=3	1.105	0.517	7,223	849
ℓ=4	0.966	0.533	3,310	523
	Average cumulative (total) effect			
ATT	0.796	1.347	21,146	3,669
Test of joint nullity of the placebos :		P.Value:		0.084
Test of joint nullity of the effects :		P.Value:		0.243
Test of equality of the effects :		P.Value:		0.399

Table 7 – Estimation for P_2O_5/UAA

	Estimate	SE	N	Switchers
ℓ=1	3.874	4.083	18,135	1,285
ℓ=2	-1.066	1.213	11,710	1,012
ℓ=3	1.930	0.697	7,212	849
ℓ=4	2.028	0.782	3,311	524
	Average cumulative (total) effect			
ATT	3.704	2.333	21,139	3,670
Test of joint nullity of the placebos :		P.Value:		0.812
Test of joint nullity of the effects :		P.Value:		0.001
Test of equality of the effects :		P.Value:		0.033

Table 8 – Estimation for K_2O/UAA

These results demonstrate that there are no moral hazard effects in the use of fertilisers. We can conclude, in line with the study of Mieno et al. (2018), Pietrobon (2024), and Zhang et al. (2023), which found a negative correlation between insurance and fertiliser, that it is the farms that use fewer fertilisers which are more likely to be insured and not that the insurance reduces the level of fertilisers. Moreover, this finding is consistent with the long-term evidence presented by Enjolras and Aubert (2020) and Roberts et al. (2003), who found that the gradual decrease in fertiliser costs over time could reflect a moral hazard phenomenon with farmers adjusting their input decisions as they become more accustomed to the security provided by insurance.

5.2.2 *Crop Protection*

The impact of insurance participation on Crop Protection Costs in terms of UAA (Table 9 and Figure 12 in Appendix A.9) shows that the results have high and persistent variability in the whole period with a consequence that there is no impact on crop protection expenses in comparison with the period before the insurance participation. Indeed, the SE is very high both in the different lags and on the overall ATT effect.

The nullity test for placebos for PTA is satisfied. It is important to note that no significant differences in the effects across different time lags are present.

Table 9 – Estimation for Crop Protection Costs/Utilised Agricultural Area

	Estimate	SE	N	Switchers
ℓ=1	0.576	9.133	18,327	1,313
ℓ=2	0.158	10.432	11,828	1,033
ℓ=3	8.915	6.550	7,278	864
ℓ=4	9.323	8.100	3,316	528
	Average cumulative (total) effect			
ATT	11.781	15.232	21,255	3,738
Test of joint nullity of the placebos :		P-value:		0.102
Test of joint nullity of the effects :		P-value:		0.569
Test of equality of the effects :		P-value:		0.637

These results did not align with the mixed but significant results obtained in the literature (Enjolras and Aubert, 2020; Mieno et al., 2018; Zhang et al., 2023) but confirmed the results of Koenig and Brunette (2023). Even the long-term effect discovered by Roberts et al. (2003) is not confirmed in this case, suggesting that long-term effects may be context-specific. This might explain why our results show increasing estimates over time but with large standard errors.

Farmers show no moral hazard in the use of crop protection, and they do not change the level of pesticide expenses.

5.2.3 *Water*

Table 10 and Figure 13 in Appendix A.9 presents the estimated effects of insurance participation on Water Volume per UAA. The results indicate that in the first period after adopting insurance, there was a significant increase in water usage, with a significant effect of 77.823 cubic meters per hectare (SE = 29.111). In the second period, water usage decreases significantly by -29.241 (SE = 14.774), indicating a reversal of the initial increase. By the third and fourth periods, water usage does not present changes in comparison with the periods previous to the insurance adoption (respectively 9.687 (SE 14.286) and -9.736 (SE = 13.666). The cumulative ATT shows a modest and not statistically significant increase of 17.803 (SE = 28.686). The tests suggest that even in this case, PTA has been satisfied, the dynamic impact is significant, and there are changes across the years following the adoption of insurance.

Table 10 – Estimation for Water Volume/Utilized Agricultural Area

	Estimate	SE	N	Switchers
ℓ=1	77.823	29.111	18,324	1,335
ℓ=2	-29.241	14.774	11,810	1,056
ℓ=3	9.687	14.286	7,290	885
ℓ=4	-9.736	13.666	3,329	543
	Average cumulative (total) effect			
ATT	17.803	28.686	21,385	3,819
Test of joint nullity of the placebos :		P-value:		0.481
Test of joint nullity of the effects :		P-value:		0.002
Test of equality of the effects :		P-value:		0.001

The observed fluctuations in water usage align with existing literature on how insurance participation can influence input decisions through mechanisms such as moral hazard and risk response. Deryugina and Konar (2017) have shown that farmers with insurance may initially increase water usage as they feel more secure in their production decisions and are less concerned about potential losses. This could explain the significant increase in water use in the first period after adopting insurance. However, over time, as farmers adjust to their insured status and potentially face increased costs or environmental regulations, they may reduce water usage, as seen in the second and fourth periods. This pattern is consistent with findings from Koenig and Brunette (2023), who observed that insurance participation does not always lead to sustained increases in input use.

5.2.4 Labour

The impact of insurance on the amount of labour per UAA is not significant, as shown in Table 11 and Figure 14 in Appendix A.9. The results are not significant in all the periods considered, and the result of the cumulative ATT shows that insurance does not change the level of work per UAA.

The PTA is satisfied, and other tests indicate the lack of a dynamic effect.

Table 11 – Estimation for Labour/UAA

	Estimate	SE	N	Switchers
ℓ=1	-12.363	8.805	18,454	1,312
ℓ=2	-8.836	8.290	11,908	1,036
ℓ=3	-7.163	4.003	7,374	872
ℓ=4	-10.199	6.951	3,363	536
	Average cumulative (total) effect			
ATT	-21.077	14.445	21,396	3,756
Test of joint nullity of the placebos :		P.Value:		0.114
Test of joint nullity of the effects :		P.Value:		0.230
Test of equality of the effects :		P.Value:		0.673

Insurance may reduce farmers' incentives to optimise inputs like labour if they feel financially protected against risks (Pietrobon 2024; Goodwin, Vandeveer, and Deal 2004; Mishra, Nimon, and El-Osta 2005), and the lack of significant changes in labour suggests that moral hazard does not play a major role in labour decisions. Considering the risk response, according to Enjolras and Aubert (2020), the results show that farmers might choose to maintain labour efforts if they perceive that insurance allows them to take more calculated risks in production.

5.3 Impact on TFP

The estimation of the effects of insurance participation on Total Factor Productivity (TFP) is shown in Table 12 and Figure 15 in Appendix A.9.

In the first three years after insurance participation, the effect on TFP is estimated to be -0.006 with a standard error (SE) of 0.013 for $\ell = 1$, -0.014 (SE = 0.010) in $\ell = 2$ and -0.012 (SE = 0.008) in $\ell = 3$

suggesting a small and statistically insignificant effect. By $\ell = 4$, the negative impact increases to -0.028 (SE = 0.014), approaching statistical significance but still not conclusive, showing that insurance has a long-term impact on TFP.

The cumulative ATT is -0.036 (SE = 0.018), indicating a cumulative negative impact on TFP, though this result is only marginally significant.

Table 12 – Estimation for Total Factor Productivity

	Estimate	SE	N	Switchers
ℓ=1	-0.006	0.013	18,066	1,296
ℓ=2	-0.014	0.010	11,656	1,023
ℓ=3	-0.012	0.008	7,155	850
ℓ=4	-0.028	0.014	3,255	523
	Average cumulative (total) effect			
ATT	-0.036	0.018	21,066	3,692
Test of joint nullity of the placebos :		P-value:		0.084
Test of joint nullity of the effects :		P-value:		0.243
Test of equality of the effects :		P-value:		0.399

V

The tests that were used demonstrate that the PTA is satisfied and that the impact on TFP is not dynamic.

The results align with some existing studies that have found insurance participation can have mixed or slightly negative impacts on productivity measures like TFP (Cornaggia, 2013; Enjolras and Aubert, 2020). This effect can be generated by the moral hazard where insured farmers reduce their efforts to increase productivity, knowing they are protected from downside risks. The effect, considering the nature of TFP, can be obtained only in the long term. Regarding risk aversion, insured farmers might substitute away from risky but high-return inputs towards safer but less productive practices, thereby reducing overall productivity. Additionally, insured farmers may reallocate resources toward less risky but also less productive activities.

The assessment of the input, income, and productivity shows that the negative impact on profitability is due to expenses for insurance participation itself and not by the increase in feedback or decrease in productivity, showing that, even if the subsidies for insurance play an important role, the expenses are not fully compensated reducing in profitability.

5.4 Robustness check

To ensure the validity and reliability of our findings and clarify the insights gained from our analysis, we perform additional robustness checks using alternative Difference-in-Differences estimators.

Two Difference-in-Differences estimators have been deployed for the sake of the robustness check Sun and Abraham (2021) estimator (SUNAB21) and the estimator developed by Callaway and Sant'Anna (2021) (CS21)[11] (detailed results are reported in Appendix A.7 and A.8). The comparison with these estimators allows for a deeper understanding on the robustness of our approach (dCDH24), according to each estimator's assumptions and the reality of the farms' conversion to organic practice.

SUNAB21 accounts for dynamic treatment effects, allowing for heterogeneity over time, which helps in better specifying models where treatment timing varies. CS21 allows for variation in treatment timing and effects, providing a more flexible model specification. In particular, this estimator is designed to handle heterogeneity across groups and periods effectively. SUNAB21 and CS21 differ from dCDH24, which offers a robust framework for capturing dynamic and heterogeneous treatment effects, addressing potential model specification issues more comprehensively with more robust diagnostics in comparison with other estimators. dCDH24 multiple treatments and varying impacts over time

All methods include placebo tests to verify that estimated effects are not due to pre-existing trends or other factors. The dCDH24 framework explicitly tests these assumptions with detailed placebo analyses.

We adopted similar settings between the estimators, in particular for the control variables that are the same. Still, all the estimators adopted, except for dCDH24, do not take into account the switching-in and switching-off phenomenon.

[11] To use similar assumptions adopted for dCDH24 we adopt not-yet-treated as control group.

We can find that all the estimators give similar values obtained in dCDH24 but more consistent than SUNAB21 and CS21.

They consider that no specific tests are obtained in SUNAB21 for PTA assumptions; conversely, CS21 allows us to take a PTA test. Still, only dCDH24 allows multiple tests regarding the placebo tests and the statistical relevance of the dynamic effect on the whole and between the years.

In summary, SUNAB21 and CS21 have less robustness and consistent outcomes in comparison to dCDH24, which offers more robust frameworks for dealing with complexities such as heterogeneity and dynamic treatment effects. The dCDH24 estimator stands out for its comprehensive handling of these challenges.

6. Summary and Discussion

This study provides insights into the causal relationship between insurance participation under Measure 17.1 of the Rural Development Program (RDP) and farm-level output, inputs and productivity.

Figure 2 reports the summary of the results.

The results indicate a persistent negative impact of insurance participation on both TR and FNVA. Specifically, there is a significant reduction in total revenue per hectare of utilised agricultural area (TR/UAA) in the first year after insurance participation, with a gradual increase over time demonstrating a dynamic impact. However, the cumulative effect remains negative. The initial sharp fall in incomes is consistent with the idea that insured farmers can reduce production intensity because of the perceived security provided by insurance. Similarly, the negative trend on FNVA/UAA after insurance adoption suggests that while insurance may stabilise income during adverse events, it does not necessarily lead to increased profitability in the long term.

These results are in line with Farrin et al. (2016) and Wąs and Kobus (2018): insurance can reduce income levels due to diminished production incentives.

The impact of insurance on input usage presents mixed results. The study finds no significant short-term impact on fertiliser costs per hectare of UAA, but there is evidence of a slight increase in fertiliser use in the long term, particularly considering single nutrient application (i.e. kg of nitrogen, phosphorous, and potassium). These findings align with Enjolras and Aubert (2020) and Roberts et al. (2003), which observe similar long-term impacts. Similar to fertilisers, no significant changes were observed in crop protection costs following insurance participation, in contrast with Enjolras and Aubert (2020) and Zhang et al. (2023), who found increased use of crop protection chemicals among insured farmers. Moreover, immediately after adopting insurance, it is possible to note an increase in water usage, followed by a decrease in subsequent periods, highlighting the dynamic and reversible impact of insurance. This pattern aligns with research by Deryugina and Konar (2017), who found that farmers with crop insurance initially increase water usage as a way to mitigate risks associated with crop failure. This behaviour stems from the safety net effect provided by insurance, which allows farmers to adopt practices they might otherwise avoid due to the increase of variability of potential losses , and consequently, the risk perception. However, over time, these farmers adjust their water use, which is influenced by rising costs or environmental concerns, highlighting a dynamic shift in their resource management strategies. The impact of insurance adoption on labour, consistent with Enjolras and Auber (2020), is not significant, suggesting that farmers do not reduce their labour efforts despite being insured.

Dependent	ATT Cumulative	ℓ=1	ℓ=2	ℓ=3	ℓ=4
Total Revenue /UAA	-	-	-	=	-
FNVA /UAA	-	-	=	=	-
Fertilizers Costs /UAA	=	=	=	=	=
N/UAA	=	=	=	=	+
P_2O_5/UAA	=	=	=	+	=
K_2O/UAA	=	=	=	+	+
Crop Protection Costs/UAA	=	=	=	=	=
Water Volume/UAA	=	+	-	=	=
Labour /UAA	=	=	=	=	=
TFP	-	=	=	=	-

Figure 2 - Summary of results

We can conclude that while moral hazard does not play a major role in reducing input use, insured farmers may gradually adjust their input decisions as they become more accustomed to the security provided by insurance.

Insurance participation has a marginally negative effect over time on TFP. While the initial years show no significant impact, a small but statistically insignificant decline is observed in later years. This demonstrates that a change in TFP requires more time, as production process are updated. This result contrasts with Enjolras and Aubert (2020), who suggest that insurance can encourage risk-taking behaviour and technology adoption, increasing TFP, but is more consistent with other studies, which find no significant change due to offsetting effects of moral hazard (e.g. Cornaggia (2013)). A key limitation of this study regarding the impact of insurance participation on Total Factor Productivity (TFP) lies in the potential influence of unmeasured factors, such as managerial ability or the adoption of new technologies, which may also affect TFP estimates. These unobserved variables could introduce bias into the analysis and make it challenging to isolate the true effects of insurance participation.

7. Conclusions

This study shows that insurance helps farmers manage risks related to external shocks, such as weather and market fluctuations. Concerns have been raised about the effects on economic profitability of participating in current insurance programs due to the costs incurred. This research highlights that even if there is evidence of moral hazard, it does not seem to have a significant overall impact, suggesting that other factors also influence input decisions. Policymakers must create insurance programs that address risk by linking compensation to cultivation methods and performance standards.

One of the key objectives of EU policy is to reduce environmental harm deriving from fertiliser use, crop protection chemicals and water inefficiency. Insurance participation alone may not be sufficient to drive reductions in fertiliser use. Policymakers should consider additional supporting schemes or regulations that encourage sustainable fertiliser use alongside insurance programs. Moreover, the impact of increased water consumption is only related to the first insured year (but not in the following years), showing a dynamic phenomenon. In order to promote efficient water use, policies could introduce water-saving technologies or conditional subsidies tied to efficient water use. These policy recommendations are consistent with a recent study by Dalhaus et al. (2024) which concludes that “focusing on yield stabilisation rather than risk reduction in pesticide use may have adverse effects if not properly managed and accompanied by the right incentives and policies”.

After the evaluation, the long-term effect of insurance participation suggests that while insurance may stabilise income in the short term, it may not lead to lasting improvements in productivity or efficiency of inputs over time.

The presented research has some limits that should be taken into account. First of all, it is based on DiD analysis that could still be affected by hidden variables that could distort results. Furthermore, the conclusions drawn from this study are specific to measure 17 and rely on Italian crop farms. It requires an extension to different crops and countries to create more generable results. In addition, broadening the field of research to include other insurance schemes could improve the general applicability of results. Finally, it is necessary to explore the lasting consequences of insurance involvement in terms of sustainable resource use and climate change resilience.

Future research should aim to explore these dimensions in greater depth to provide a more comprehensive understanding of the mechanisms driving changes in productivity. This would help clarify the broader implications of insurance programs on farm-level efficiency and long-term performance.

In conclusion, this study adds to the comprehension of how agricultural insurance programs can impact farmers behaviour in terms of input use, production and productivity. Though insurance offers benefits in managing risks, it might also result in unintended negative outcomes including lower revenue and productivity. These latter effects support the hypothesis that moral hazard is indeed an issue. These findings emphasise the significance of crafting policies to strike a balance between risk reduction goals and economic sustainability over the long term.

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Appendix

A.1 Variable definition

Table 13 - Variables codification and reference to price index adopt to deflate

Variable	Definition	EU FADN Code	Deflating using: Source	Indicator	Price index
TR	Total revenue [€]	SE206	Eurostat	HICP	HICP - annual data - Base 2015=100
FNVA	Farm Net Value Added [€]	SE415	Eurostat	HICP	HICP - annual data - Base 2015=100
FNI	Farm Net Income [€]	SE420	Eurostat	HICP	HICP - annual data - Base 2015=100
Labour	Labour [hours]	SE011			Not Deflated
Crop_Prot	Crop Protection cost [€]	SE300	Eurostat	Plant protection products and pesticides	Price indices of the means of agricultural production - Base 2015=100
Fert	Fertilizer cost [€]	SE295	Eurostat	Fertilisers and soil improvers	Price indices of the means of agricultural production - Base 2015=100
Water.cost	Water cost [€]	IWATR_V	Eurostat	HICP	HICP - annual data Base 2015=100
Water	Water volume [m^3]	Italian FADN			Not Deflated
N	Nitrogen [Kg]	H_SC_3031_Q			Not Deflated
P_2O_5	Phosphorus [Kg]	H_SC_3032_Q			Not Deflated
K_2O	Potassium [Kg]	H_SC_3033_Q			Not Deflated
TFP	Total Factor Productivity	Calculated			Not Deflated
UAA	Utilised Agricultural Area [Ha]	SE025			Not Deflated
Shannon_Index	Shannon Index for diversification	Calculated			Not Deflated
Orchards_index	Orchard area on UAA [%]	Calculated			Not Deflated
Per_rent	Rented UAA/Total UAA [%]	B_UT_20_A/SE025			Not Deflated
Nitr_fix_Index	Nitrogen-fixing plants/Total UAA [%]	Calculated			Not Deflated
Irr_Land	UAA under irrigation/UAA [%]	IRRAA_X/SE025			Not Deflated
Kw_M	kW of Machinery [kW]	Italian FADN			Not Deflated
Fix_K	Fixed Capital [€]	SE441	FRED	GDP Deflator	Gross domestic product (implicit price deflator) - Base 2015=100
C_C	Currents Cost [€]	SE 275	Eurostat	Materials	Price indices of the means of agricultural production - Base 2015=100
K	Total Capital [€]	SE436 + SE485	FRED	GDP Deflator	Gross domestic product (implicit price deflator) - Base 2015=100

A.2 Input use

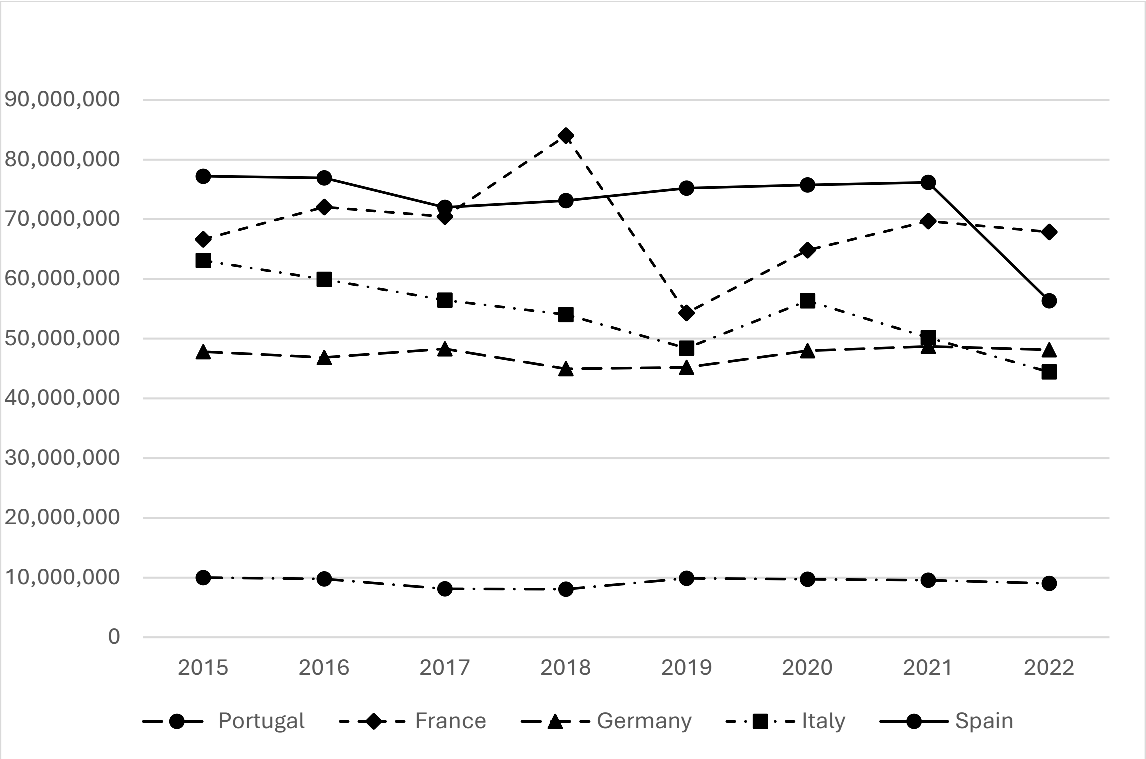

Figure 3 - Pesticide Consumption (kg) – First 5 Countries in Europe

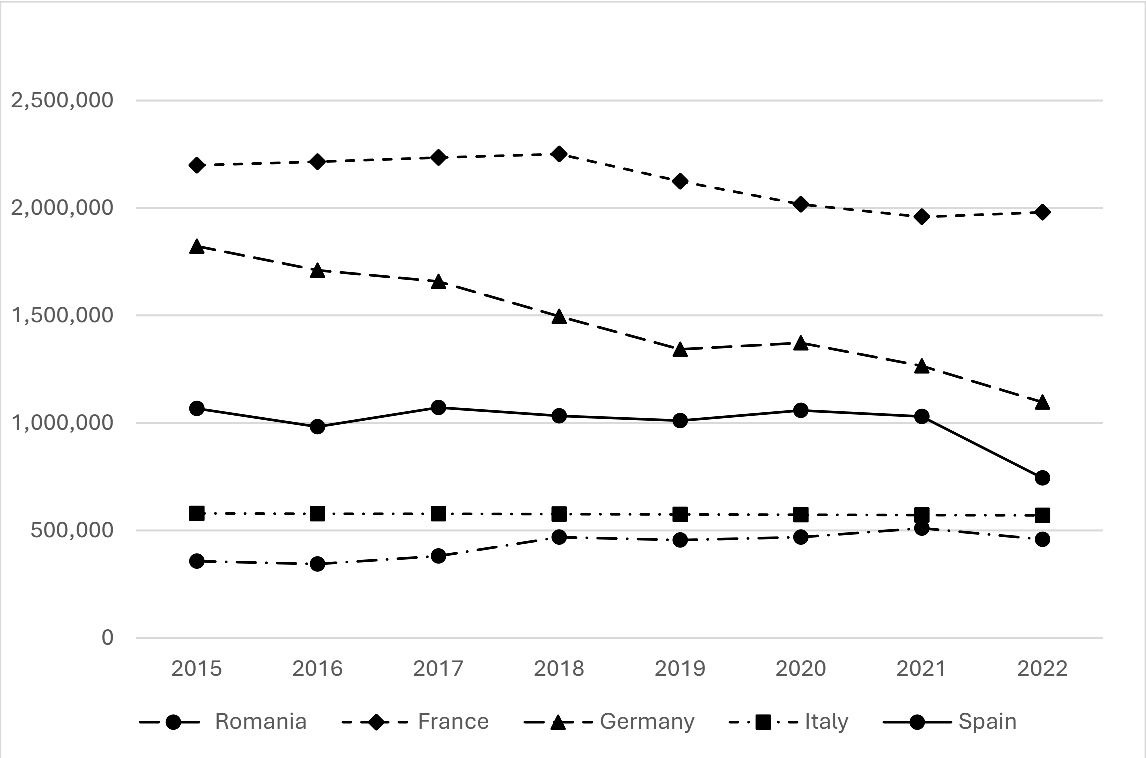

Figure 4 - Consumption of inorganic fertilisers [Kg of nitrogen] - – First 5 Countries in Europe

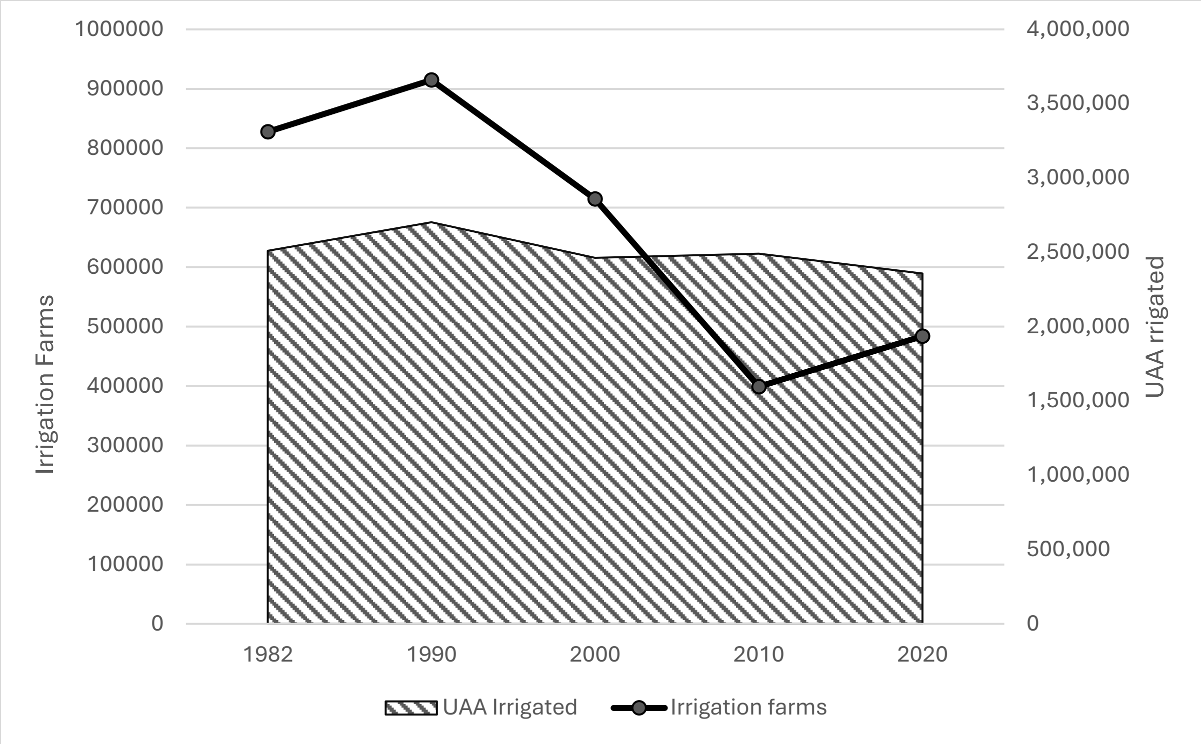

Figure 5 – Water use in agriculture in Italy

A.3 Total factor productivity estimation

Unlike other input and output values, productivity is not directly reported on FADN. The evaluation of this parameter to obtain a correct picture of the phenomenon is pivotal to the impact of insurance participation on input and output.

Moreover, the relationship between inputs and output in production is not directly observable but can be modelled using a production function. Using a Cobb-Douglas production function with two inputs - labor (L) and capital (K) - the output is represented as $Y = \Omega K^{\beta_K} L^{\beta_L}$ where β_K and β_L are the output elasticities of capital and labour, respectively. These elasticities measure how responsive output is to changes in each input, typically with $0 < \beta_K, \beta_L < 1$. The sum of these elasticities ($\beta_K + \beta_L$) i indicates returns to scale. The term Ω represents productivity, which varies across farms due to factors like soil fertility or management practices.

Using a panel dataset and applying a logarithmic transformation, the production function becomes: $y_{i,t} = \alpha_{i,t} + \beta_k k_{i,t} + \beta_l l_{i,t} + \omega_{i,t} + \epsilon_{i,t}$ where the lowercase letters represent the logarithmic transformation of the variables. Estimating the coefficients β_k and β_l using OLS would lead to biased results due to endogeneity: farmers know their total factor productivity (TFP), represented by $\omega_{i,t}$, which is correlated with their input choices.

This violates the assumption that the error term $\varepsilon_{i,t} = \omega_{i,t} + \upsilon_{i,t}$, is uncorrelated with inputs (Marschak and Andrews, 1944; Ackerberg *et al.*, 2007).

Mundlak (1963) addressed this issue by using deviations from the firm-specific mean (the "within" estimator), distinguishing between time-variant inputs (e.g., capital, labour) and time-invariant characteristics (e.g., farm-specific traits). However, Ackerberg et al., (2007) and Olley and Pakes, (1996) showed that this approach fails to fully account for endogeneity because state variables like capital and land are influenced by past decisions. Free-state variables such as labor are more strongly correlated with residual errors, leading to downward bias in estimates. To address this, instrumental variable (IV) methods have been proposed, though identifying valid instruments remains challenging.

Similarly to Biagini, Antonioli, and Severini (2023) in this study, the Control Function Estimator (CFE) is adopted. CFE accounts for TFP as a Markov process. Olley and Pakes, (1996) first implemented this method using investment as a proxy for TFP, but later studies like (Levinsohn and Petrin, 2003) suggested using materials instead, and finally (Ackerberg, Caves, and Frazer 2015) adjusted the estimator of (Levinsohn and Petrin, 2003) reducing bias. In this study, it is used (Ackerberg, Caves, and Frazer 2015) to obtain the production function, and then measure farm-level TFP, we use the Solow residual (Solow 1957) through this difference $TFP_{i,t} = y_{i,t} - (\hat{\beta}_k k_{i,t} + \hat{\beta}_l l_{i,t})$.

We adopt the value is used to evaluate the effect of insurance participation on TFP.

A.4 Calculation Inverse Propensity Weight and application on DiD

Inverse Propensity Weight (IPW) is utilised to address confounding factors, re-weighting the data sample to form a pseudo population with balanced covariate distributions between treated and untreated groups.

The first step is to estimate the propensity score through Entropy Balance (Hainmueller 2012), which is the probability of receiving the treatment D_i given a set of observed characteristics X_i

$$p(d \mid x) = \frac{P(D = d, X = x)}{P(X = x)}$$

Once the propensity scores are estimated, calculate the inverse propensity weights for each individual:

- For treated farmers ($D_i = 1$):

$$w_i = \frac{1}{P(D_i = 1|X_i)}$$

- For untreated farmers ($D_i = 0$):

$$w_i = \frac{1}{P(D_i = 0|X_i)}$$

These weights adjust for the fact that certain individuals are more or less likely to receive the treatment based on their covariates, balancing the groups.

One potential issue with IPW is extreme weights, which occur when propensity scores are very close to 0 or 1. These extreme values can lead to high variance in estimates. The weights have been truncated, excluding the values less than 1st and upper than 99th percentiles (overlap assumption) to address this problem.

The calculated weights are then applied in DiD to create a "pseudo-population" where the covariates are balanced between treated and untreated groups, allowing for an unbiased estimation of the treatment effect.

A. 5 de Chaisemartin and D'Haultfoeuille 2024 (dCDH24) estimator

The motivation for the use of dCDH24 is that it allows for different treatment designs. In this paper, we study treatment-effect estimation using a panel of farms (i), observed at several time periods, indexed by t. Outcomes ($Y_{i,t}$) – i.e., input or output variables – , may be affected by treatment ($D_{i,t}$), but also by i lagged treatments. We define $Y_{i,t}(d_1, \dots , d_t)$ as the value obtained by the farms i with treatment (i.e. insured or not insured) equal to $(d_1, \dots , d_t)$. Using the similar notation of de Chaisemartin & D'Haultfœuille, (2024) we represent the first period when the individual i is treated with F_i. Then Y_{i,F_i-1} is the outcome before the treatment and $Y_{i,F_i-1+\ell}$ is the outcome after ℓ period after the switch. We can obtain the difference between actual-vesus-status-quo (AVSQ) as

$$\delta_{i,\ell} = E\left(Y_{i,F_i-1+\ell} - Y_{i,F_i-1+\ell}\left(D_{i,1}, \ \dots, \ D_{i,1}\right)\right)$$

In other words $\delta_{i,\ell}$ represents the difference between the actual outcome $Y_{i,F_i-1+\ell}$ and the outcome from the farmer that has the same treatment level at time 1 $\left(D_{i,1}, \ \dots, \ D_{i,1}\right)$ but at ℓ is untreated (status quo) $Y_{i,F_i-1+\ell}\left(D_{i,1}, \ \dots, \ D_{i,1}\right)$.

In our case, it is not possible to use the staggered design similar to Callaway & Sant'Anna, (2021) [12] for the peculiarity of treatment with "switching-in" (that change its treatment status from non-insured to insured) and "switching-out" (that changes its treatment status from insured to non-insured) farmers and because, given the unbalanced nature of the panel, it is impossible to define the first year of treatment correctly.

In our case, we have a binary treatment, with "switching-in" and "switching-out" $\forall\ (i,t), D_{i,t} = 1\{E_i \geq t \geq F_i\}, with\ 2 \leq F_i \leq E_i$. A special case is the "one-shot" farm or the farm that is treated for only one period. In our setting, this farm is considered because the treatment can happen even only for one time.

The term $\delta_{i,\ell}$, it is possible to estimate even if we have "switching-in" and "switching-out" farms. dCDH24 estimator, denoted as $DID_{i,\ell}$ compares the change in outcomes for farmers i from the period just before the treatment change ($F_i - 1$) to a later period ($F_i - 1 + \ell$) with the change in outcomes for other farm i that have not yet experienced a treatment change by $F_i - 1 + \ell$ (status-quo) and had the same treatment as farm i in the first period.

$$\mathrm{DiD}_{g,\ell} = Y_{g,F_g-1+\ell} - Y_{g,F_g-1} - \frac{1}{N^g_{F_g-1+\ell}} \sum_{g':D_{g',1}=D_{g,1}, F_{g'}>F_g-1+\ell} \left(Y_{g',F_g-1+\ell} - Y_{g',F_g-1}\right)$$

[12] Note that dCDH24 differs from (Callaway and Sant'Anna, 2021) for many assumptions. For a in-deep tractation see (de Chaisemartin and D'Haultfœuille, 2024)

with $Y_{g,F_g-1+\ell} - Y_{g,F_g-1}$ the difference in outcome of treated farms, $N^g_{F_g-1+\ell}$ as the number of farms g' with the same treatment path as farm g at period t and $\left(Y_{g',F_g-1+\ell} - Y_{g',F_g-1}\right)$ the "status quo" outcome .

The parallel trends assumption (PTA) is key to the validity of the DID estimator. This implies that any differences in outcomes between the treated and control farms are due to treatment and not other factors. De Chaisemartin & D'Haultfœuille, 2024 note that comparing farms with different initial treatments would require a stronger parallel trends assumption that might not hold, especially if there are effects from lagged treatments or time-varying treatment effects. To validate PTA de Chaisemartin & D'Haultfœuille (2024), use the placebo test comparing the outcome trends of switchers (groups that change treatment) and non-switchers (groups that do not change treatment) with the same initial treatment before any treatment changes occur. This helps test whether the assumption holds before the actual treatment changes.

Following the suggestion proposed by de Chaisemartin & D'Haultfœuille (2024), excludes the aggregation of DID estimators, the farms where at time $F_g - 1 + \ell$, group i has experienced both a strictly lower and a strictly higher treatment than its initial treatment level. In such scenarios, the expected difference in outcomes/inputs $\delta_{i,\ell}$, can be expressed as a linear combination of treatment effects with negative weights. This violates the no-sign reversal property, which states that if the potential outcome function is increasing in each argument, then the treatment effect should not be negative. This property, ensuring consistent effect direction, is only valid if all treatments affect energy expenses similarly, which is a strong assumption. Thus, maintaining this property in dynamic models is a minimal requirement compared to static ones.

Our analysis focuses on farms that consistently "switching-in" and "switching-out" in insurance participation, allowing for a clear interpretation of the treatment effects on input/output This approach helps in understanding the true impact of insurance participation on farmers' choices without the confounding effects of inconsistent treatment levels.

For the remaining groups and periods, the treatment change scenarios are categorised into two cases of switchers :

- Scenario 1: A farm adopts insurance (switching-in) in a period F_i and maintains the adoption in subsequent periods. The DID estimator for this farm measures the effect of insurance for ℓ periods on input/output.
- Scenario 2: A farm is insured (switching out) and in the following year does not subscribe insurance contract in the period F_i and continues this trend in subsequent periods. The DID estimator for this farm measures the effect of the exit of the insurance scheme for ℓ periods on input/output. When aggregating, the DID estimator for this farm is multiplied by minus one to align with the effect of participation in the insurance scheme.

To allow dCDH24 to take into account the number of different switchers, $\mathrm{DiD}_{g,\ell}$ is weighted by the total treatment increments from F_i to $F_i - 1 + \ell$ considering switching-in treatment with +1 and switching-out as -1 $S_g = 1\left\{D_{g,F_g} > D_{g,1}\right\} - 1\left\{D_{g,F_g} < D_{g,1}\right\}$ obtaining the weighted $\delta_{g,\ell}$ for each ℓ named δ_ℓ

$$\delta_\ell = \frac{1}{N_\ell} \sum_{g:F_g-1+\ell \le T_g} S_g \delta_{g,\ell}$$

and the weighted $\mathrm{DiD}_{g,\ell}$ for each ℓ named DiD_ℓ

$$\mathrm{DiD}_\ell = \frac{1}{N_\ell} \sum_{g:F_g-1+\ell \le T_g} S_g \mathrm{DiD}_{g,\ell}$$

where

$$N_\ell = \qquad g: F_g - 1 + \ell \le T_g$$

be the number of farms for which there exists a pre- and post-treatment period, and that can be used to calculate $\delta_{g,\ell}$.

It is necessary to adjust DiD estimator for the extent of changes in the treatment normalising DiD estimator in order to calculate the total dose of treatment actually received by the farm g from the period. F_g to the period $F_g + \ell - 1$ (or from $k = 0$ to $\ell - 1$), compared to what would have been received if its treatment status had not changed from period-one level ($D_{g,1}$)

$$\delta^D_{g,\ell} = \sum_{k=0}^{\ell-1} \left(D_{g,F_g+k} - D_{g,1}\right)$$

$\delta^D_{g,\ell}$ is the weighted average of treatment effects across the farms (g) for each time period corresponding to $F_g - 1 + \ell$.

It is possible to obtain the weighted average of $\delta^D_{g,\ell}$ using the switchers' indicator $S_{g,D}$, and considering the total number of farms that have not yet changed $N_{\ell,D}$ obtaining

$$\delta_{\ell}^{D} = \frac{1}{N_{\ell,D}} \sum_{g,D:F_g-1+\ell\leq T_g} S_{g,D}\delta_{g,\ell,D}$$

Finally, the estimator adopted in this investigation is obtained with the weighted sum of $DiD_{g,l}$ weighted for the dose of treatment actually received $\delta_{g,\ell}^{D}$ and δ_{ℓ}^{D}, multiply for absolute value of $\delta_{g,\ell}^{D}$, considering the number of farms for which there exists a pre- and post-treatment period N_{ℓ}:

$$DiD_{\ell}^{n} \coloneqq \frac{1}{N_{\ell}} \sum_{g:F_g-1+\ell\leq T_g} \frac{\left|\delta_{g,\ell}^{D}\right|}{\delta_{\ell}^{D}} \frac{DiD_{g,l}}{\delta_{g,\ell}^{D}}$$

A. 6 Control variables used

Table 14 - Control variables

Dependent	Control variables						
TR/UAA	Shannon_Index	Orchards_index	Per_rent	TR			
FNVA/UAA	C_C.TR	KW_M.UAA	Fix_K.UAA				
TFP	UAA	KW_M	Fix_K.UAA	Shannon_Index	Nitr_fix_Index	Orchards_Index	
Labour/UAA	Shannon_Index	Orchards_Index	Per_rent				
Crop_Protection/UAA	KW_M,UAA	TR	Fert	C_C			
Fertiliser/UAA	Irr_Land_Index	UAA	KW_M	Fix_K.UAA	Shannon_Index	Nitr_fix_Index	Orchards_Index
N/UAA	Irr_Land_Index	UAA	KW_M	Fix_K.UAA	Shannon_Index	Nitr_fix_Index	Orchards_Index
P_2O_5/UAA	Irr_Land_Index	UAA	KW_M	Fix_K.UAA	Shannon_Index	Nitr_fix_Index	Orchards_Index
K_2O/UAA	Irr_Land_Index	UAA	KW_M	Fix_K.UAA	Shannon_Index	Nitr_fix_Index	Orchards_Index
Water.UAA	Irr_Land_Index	UAA	KW_M	Fix_K.UAA	Shannon_Index	Nitr_fix_Index	Orchards_Index

A.7 Robustness Check – SUNAB21

Table 15 - Result using SUNAB21 for TR/UAA - FNVA/UAA - TFP

TR/UAA

	Estimate	SE	LB CI	UB CI
$\ell=0$	-529.000	137.500	-798.500	-259.500
$\ell=1$	946.800	479.200	7.568	1886.032
$\ell=2$	1184.300	424.400	352.476	2016.124
$\ell=3$	1042.600	293.100	468.124	1617.076
$\ell=4$	-111.900	129.000	-364.740	140.940
	Average cumulative (total) effect			
ATT Cumulative	621.416	184.322	260.145	982.688
	Estimate	SE	LB CI	UB CI
Placebo t_{-2}	493.9	188.3	124.83	862.97
Placebo t_{-3}	306.9	383.4	-444.56	1058.36

FNVA/UAA

	Estimate	SE	LB CI	UB CI
$\ell=0$	-631.200	165.100	-954.796	-307.604
$\ell=1$	-46.300	493.800	-1014.148	921.548
$\ell=2$	678.200	468.200	-239.472	1595.872
$\ell=3$	1118.500	343.600	445.044	1791.956
$\ell=4$	25.600	132.100	-233.316	284.516
	Average cumulative (total) effect			
ATT Cumulative	282.677	192.034	-93.709	659.063
	Estimate	SE	LB CI	UB CI
Placebo t_{-2}	132.200	199.200	-258.232	522.632
Placebo t_{-3}	-253.200	419.900	-1076.204	569.804

TFP

	Estimate	SE	LB CI	UB CI
$\ell=0$	-0.007	0.015	-0.036	0.022
$\ell=1$	-0.080	0.049	-0.176	0.016
$\ell=2$	0.107	0.035	0.038	0.176
$\ell=3$	0.050	0.022	0.007	0.093
$\ell=4$	0.054	0.015	0.025	0.083
	Average cumulative (total) effect			
ATT Cumulative	0.019	0.018	-0.0162	0.0538
	Estimate	SE	LB CI	UB CI
Placebo t_{-2}	0.013	0.018	-0.176	0.016
Placebo t_{-3}	-0.031	0.037	0.038	0.176

Table 16 - Result using SUNAB21 for Fertilizers/UAA - N/UAA – P_2O_5/UAA and K_2O/UAA

Fertizers/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	58.600	14.200	30.768	86.432
ℓ=1	16.200	36.800	-55.928	88.328
ℓ=2	-14.100	21.000	-55.260	27.060
ℓ=3	4.880	15.400	-25.304	35.064
ℓ=4	43.200	14.800	14.192	72.208
	Average cumulative (total) effect			
ATT Cumulative	11.465	13.391	-14.782	37.712
	Estimate	SE	LB CI	UB CI
Placebo t_2	-7.710	12.800	-32.798	17.378
Placebo t_3	-20.200	26.200	-71.552	31.152

N/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	3.010	3.160	-3.184	9.204
ℓ=1	-1.500	8.600	-18.356	15.356
ℓ=2	-5.780	3.450	-12.542	0.982
ℓ=3	2.010	1.890	-1.694	5.714
ℓ=4	0.342	1.350	-2.304	2.988
	Average cumulative (total) effect			
ATT Cumulative	-0.459	2.763	-5.874	4.957
	Estimate	SE	LB CI	UB CI
Placebo t_2	2.430	2.630	-2.725	7.585
Placebo t_3	3.230	5.820	-8.177	14.637

P_2O_5/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	1.340	1.340	-1.286	3.966
ℓ=1	-1.270	7.210	-15.402	12.862
ℓ=2	-3.270	2.310	-7.798	1.258
ℓ=3	3.510	1.770	0.041	6.979
ℓ=4	-0.065	1.090	-2.201	2.071
	Average cumulative (total) effect			
ATT Cumulative	-0.079	2.259	-4.507	4.349
	Estimate	SE	LB CI	UB CI
Placebo t_2	1.500	1.980	-2.381	5.381
Placebo t_3	0.055	4.630	-9.020	9.130

K_2O/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	3.990	4.370	-4.575	12.555
ℓ=1	3.190	1.950	-0.632	7.012
ℓ=2	2.590	3.940	-5.132	10.312
ℓ=3	2.320	5.910	-9.264	13.904
ℓ=4	-6.900	3.210	-13.192	-0.608
	Average cumulative (total) effect			
ATT Cumulative	0.303	1.992	-3.602	4.207
	Testing the parallel trends and no anticipation assumptions			
	Estimate	SE	LB CI	UB CI
Placebo t_2	3.190	1.950	-0.632	7.012
Placebo t_3	3.990	4.370	-4.575	12.555

Table 17 - Result using SUNAB21 for Crop Protection/UAA – Water /UAA – Labour/UAA

Crop Protection/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	5.640	10.800	-15.528	26.808
ℓ=1	-34.500	36.100	-105.256	36.256
ℓ=2	-16.500	21.300	-58.248	25.248
ℓ=3	-12.600	31.500	-74.340	49.140
ℓ=4	22.900	11.000	1.340	44.460
Average cumulative (total) effect				
ATT Cumulative	-12.933	12.657	-37.741	11.875
	Estimate	SE	LB CI	UB CI
Placebo t_{-2}	-8.270	14.400	-36.494	19.954
Placebo t_{-3}	-45.000	30.800	-105.368	15.368

Water/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	17.100	31.900	-45.424	79.624
ℓ=1	106.000	174.200	-235.432	447.432
ℓ=2	64.200	47.800	-29.488	157.888
ℓ=3	51.000	33.100	-13.876	115.876
ℓ=4	16.200	33.700	-49.852	82.252
Average cumulative (total) effect				
ATT Cumulative	57.241	53.661	-47.936	162.417
	Estimate	SE	LB CI	UB CI
Placebo t_{-2}	53.000	47.700	-40.492	146.492
Placebo t_{-3}	80.700	111.400	-137.644	299.044

Labour/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	-4.340	5.150	-14.434	5.754
ℓ=1	23.400	19.100	-14.036	60.836
ℓ=2	-0.792	16.400	-32.936	31.352
ℓ=3	29.600	25.100	-19.596	78.796
ℓ=4	3.030	4.840	-6.456	12.516
Average cumulative (total) effect				
ATT Cumulative	10.967	8.138	-4.983	26.917
	Estimate	SE	LB CI	UB CI
Placebo t_{-2}	1.360	7.470	-13.281	16.001
Placebo t_{-3}	-6.410	16.800	-39.338	26.518

Table 18 – Summary of results using SUNAB21

Dependent	ATT Cumulative	ℓ=0	ℓ=1	ℓ=2	ℓ=3	ℓ=4
Total Revenue /UAA	+	-	+	+	+	=
FNVA /UAA	=	-	=	=	+	=
Fertilizers Costs /UAA	=	+	=	=	=	+
N/UAA	=	=	=	=	=	=
P_2O_5/UAA	=	=	=	=	+	=
K_2O/UAA	=	=	=	=	=	-
Crop Protection Costs/UAA	=	=	=	=	=	+
Water Volume/UAA	=	=	=	=	=	=
Labour /UAA	=	=	=	=	=	=
TFP	=	=	=	+	+	+

A.8 Robustness Check – CS21

Table 19 - Result using SUNAB21 for TR/UAA - FNVA/UAA – TFP

TR/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	1565.766	978.176	-362.751	3494.283
ℓ=1	-302.320	786.804	-1853.538	1248.898
ℓ=2	-24000.375	18038.232	-59563.538	11562.787
ℓ=3	-38019.664	15819.655	-69208.805	-6830.523
	Average cumulative (total) effect			
ATT Cumulative	-39169.710	21162.996	-81284.072	2309.762
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	-302.320	786.804	-1853.538	1248.898
Placebo t_{-2}	-302.320	786.804	-1853.538	1248.898
PTA test	p.value		0.241	

FNVA/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	1163.108	2715.798	-5206.802	7533.019
ℓ=1	1294.092	1252.314	-1643.214	4231.398
ℓ=2	1740.458	1409.479	-1565.478	5046.394
ℓ=3	162.734	758.689	-1616.772	1942.240
	Average cumulative (total) effect			
ATT Cumulative	1090.098	1129.031	-1156.674	3302.999
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	-189.288	383.957	-1089.859	711.283
Placebo t_{-2}	779.966	543.463	-494.727	2054.659
PTA test	p.value		0.070	

TFP				
	Estimate	SE	LB CI	UB CI
ℓ=0	-3.827	3.536	-10.758	3.104
ℓ=1	-3.928	4.310	-12.376	4.519
ℓ=2	-4.268	5.887	-15.806	7.270
ℓ=3	-7.059	8.152	-23.038	8.919
	Average cumulative (total) effect			
ATT Cumulative	-4.771	5.480	-15.512	5.971
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	-1.991	5.827	-13.412	9.430
Placebo t_{-2}	-0.068	0.066	-0.197	0.060
PTA test	p.value		0.387	

Table 20 - Result using SUNAB21 for Fertilizers/UAA - N/UAA – P_2O_5/UAA and K_2O/UAA

	Estimate	SE	LB CI	UB CI
Fertizers/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	43.484	17.267	-0.034	87.003
ℓ=1	11.890	23.918	-48.393	72.173
ℓ=2	20.226	34.353	-66.355	106.808
ℓ=3	18.784	36.924	-74.278	111.846
	Average cumulative (total) effect			
ATT Cumulative	23.596	21.601	-18.742	65.934
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	12.911	17.502	-31.200	57.021
Placebo t_{-2}	-80.704	43.581	-190.546	29.137
PTA test	p.value		0.194	
N/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	-2.754	3.763	-11.866	6.358
ℓ=1	-4.741	3.887	-14.156	4.673
ℓ=2	0.653	3.395	-7.570	8.875
ℓ=3	-1.017	4.120	-10.994	8.960
	Average cumulative (total) effect			
ATT Cumulative	-1.965	3.093	-8.028	4.098
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	5.423	2.432	-0.466	11.312
Placebo t_{-2}	-8.124	6.398	-23.618	7.370
PTA test	p.value		0.063	
P_2O_5/UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	0.771	1.528	-2.874	4.416
ℓ=1	-0.475	1.415	-3.850	2.901
ℓ=2	2.426	1.298	-0.671	5.524
ℓ=3	1.169	1.637	-2.737	5.074
	Average cumulative (total) effect			
ATT Cumulative	0.973	1.095	-1.172	3.118
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	3.674	1.913	-0.889	8.236
Placebo t_{-2}	-8.082	6.312	-23.140	6.975
PTA test	p.value		0.34381	
K_2O./UAA				
	Estimate	SE	LB CI	UB CI
ℓ=0	3.052	5.206	-9.261	15.366
ℓ=1	-0.653	1.687	-4.643	3.337
ℓ=2	4.255	1.578	0.523	7.988
ℓ=3	3.159	2.077	-1.754	8.071
	Average cumulative (total) effect			
ATT Cumulative	2.453	1.562	-1.172	3.118
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	2.538	2.227	-2.729	7.806
Placebo t_{-2}	-6.278	5.745	-19.866	7.310
PTA test	p.value		0.108	

Table 21 - Result using SUNAB21 for Crop Protection/UAA – Water /UAA – Labour/UAA

Crop Protection/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	328.134	270.136	-310.803	967.071
ℓ=1	320.310	621.653	-1150.046	1790.667
ℓ=2	1209.545	783.409	-643.404	3062.495
ℓ=3	1682.743	1225.326	-1215.445	4580.932
	Average cumulative (total) effect			
ATT Cumulative	885.183	494.610	-84.252	1854.618
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	4.628	24.566	-53.477	62.732
Placebo t_{-2}	-38.178	55.274	-168.914	92.558
PTA test	p.value		0.295	

Water/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	259.972	216.277	-265.524	785.467
ℓ=1	0.690	63.624	-153.899	155.278
ℓ=2	-27.885	44.691	-136.472	80.702
ℓ=3	-66.542	52.877	-195.018	61.933
	Average cumulative (total) effect			
ATT Cumulative	-62.931	33.298	-128.196	2.333
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	0.690	63.624	-153.899	155.278
Placebo t_{-2}	259.972	216.277	-265.524	785.467
PTA test	p.value		0.061	

Labour/UAA

	Estimate	SE	LB CI	UB CI
ℓ=0	-27.737	12.856	-57.643	2.168
ℓ=1	-35.094	18.882	-79.016	8.829
ℓ=2	-19.469	12.384	-48.277	9.338
ℓ=3	-16.478	20.107	-63.250	30.295
	Average cumulative (total) effect			
ATT Cumulative	-24.694	15.040	-54.173	4.784
	Estimate	SE	LB CI	UB CI
Placebo t_{-1}	6.337	9.951	-16.812	29.486
Placebo t_{-2}	10.851	19.870	-35.370	57.073
PTA test	p.value		0.977	

Table 22 – Summary of results using SUNAB21

Dependent	ATT Cumulative	ℓ=0	ℓ=1	ℓ=2	ℓ=3
Total Revenue /UAA	=	=	=	=	-
FNVA /UAA	=	=	=	=	=
Fertilizers Costs /UAA	=	=	=	=	=
N/UAA	=	=	=	=	=
P_2O_5/UAA	=	=	=	=	=
K_2O/UAA	=	=	=	=	=
Crop Protection Costs/UAA	=	=	=	=	=
Water Volume/UAA	=	=	=	=	=
Labour /UAA	=	=	=	=	=
TFP	=	=	=	=	=

A. 9 Figures of the Event Study

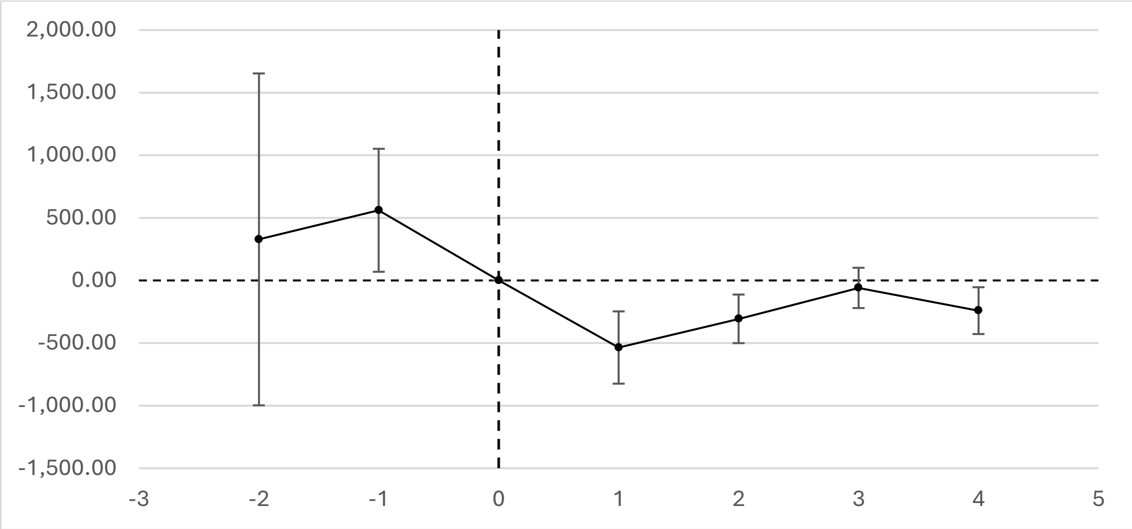

Figure 6 - Event Study for Total Revenue /UAA

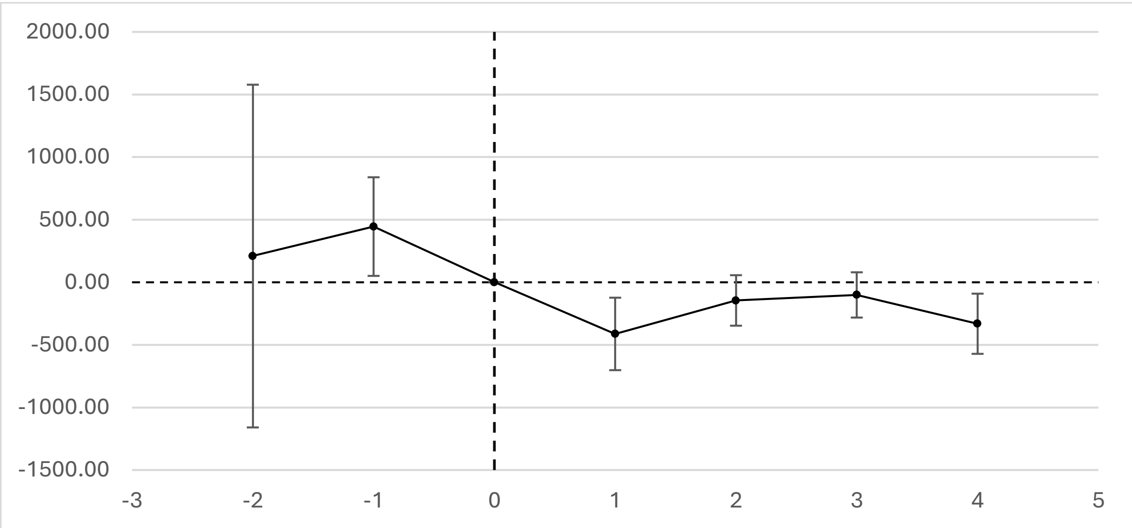

Figure 7 - Event Study for Farm Net Value Added /UAA

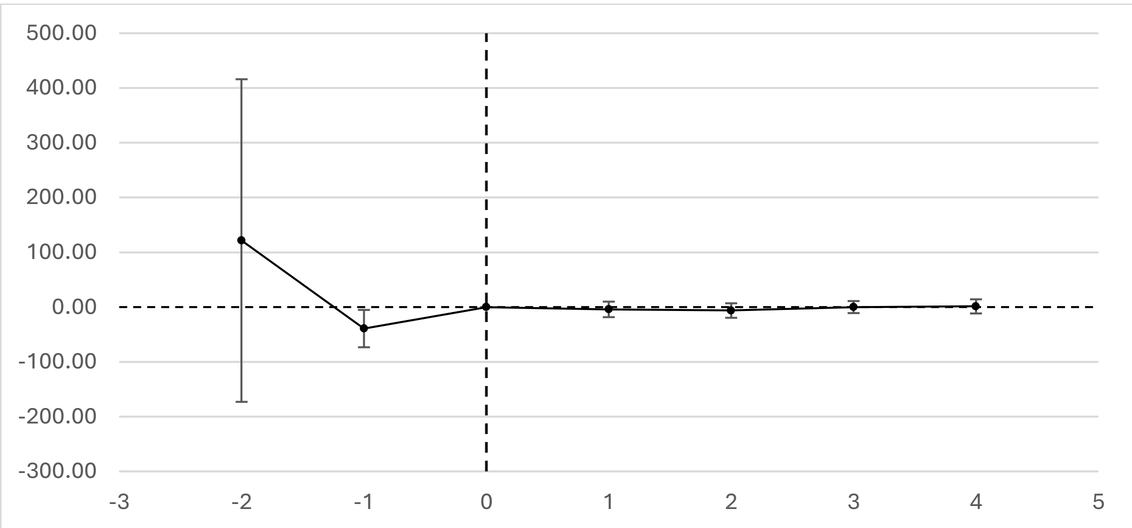

Figure 8 - Event Study for Fertilizer Costs/UAA

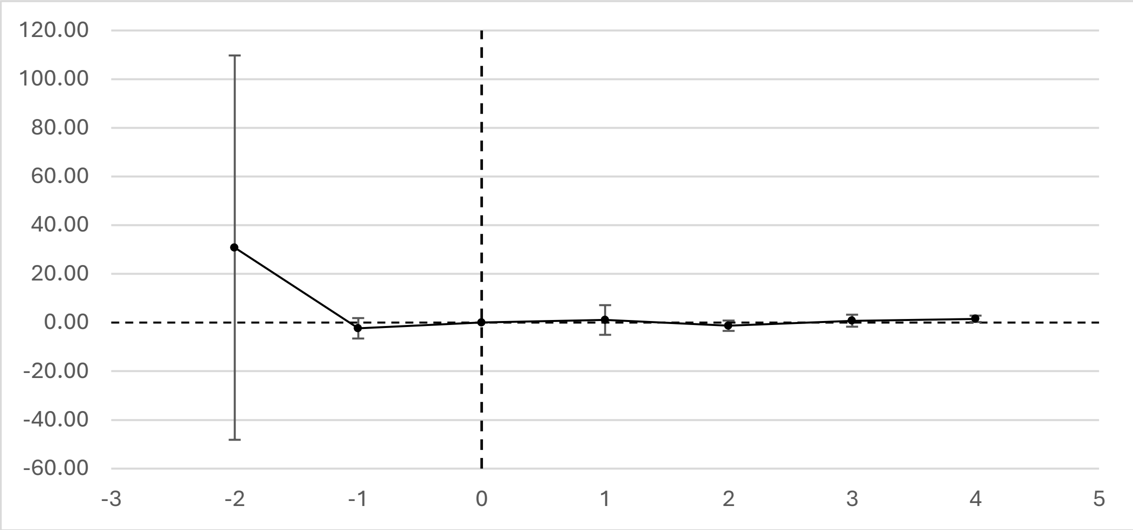

Figure 9 - Event Study for N/UAA

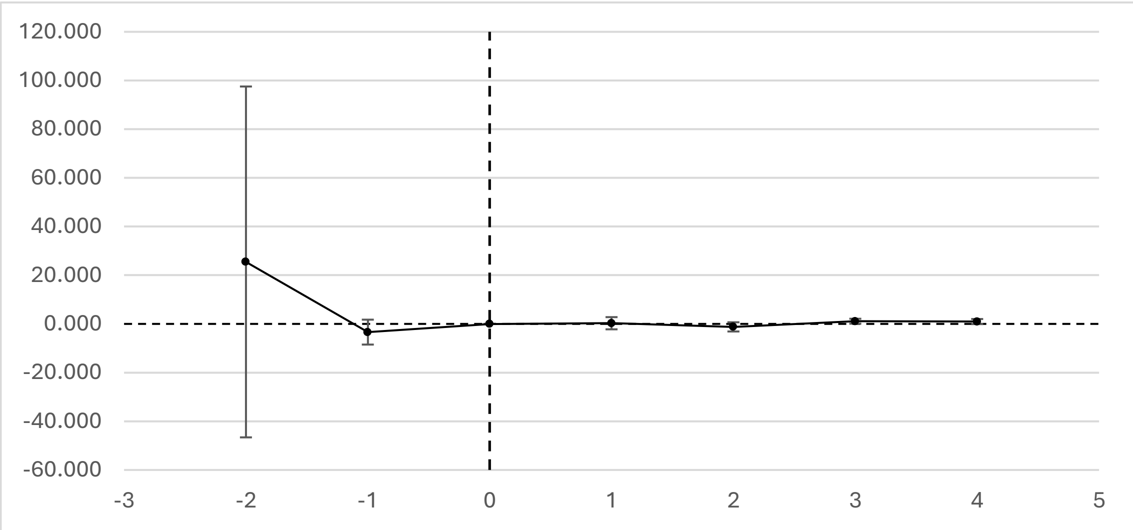

Figure 10 - Event Study for P_2O_5/UAA

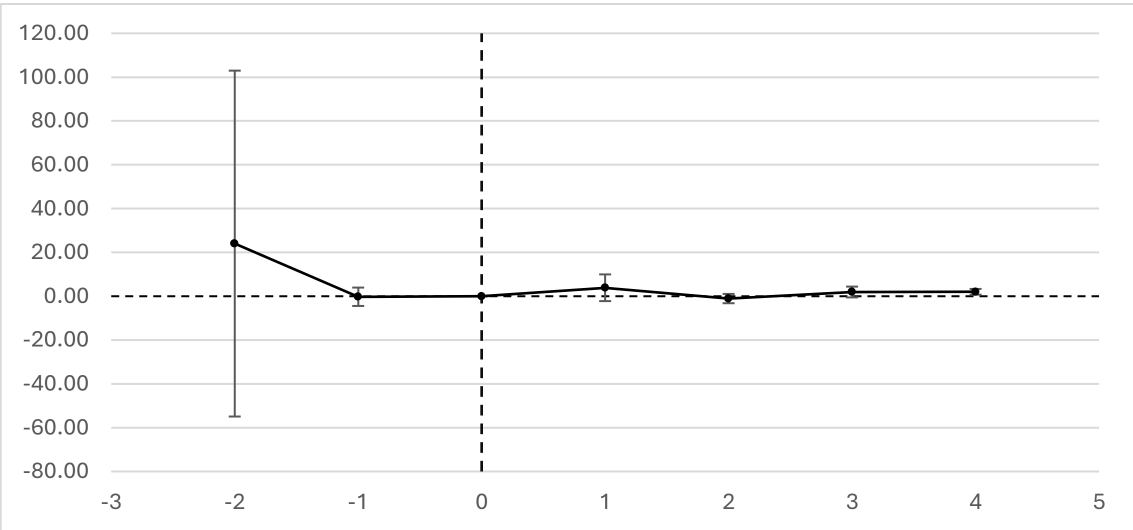

Figure 11 - Event Study for K_2O/UAA

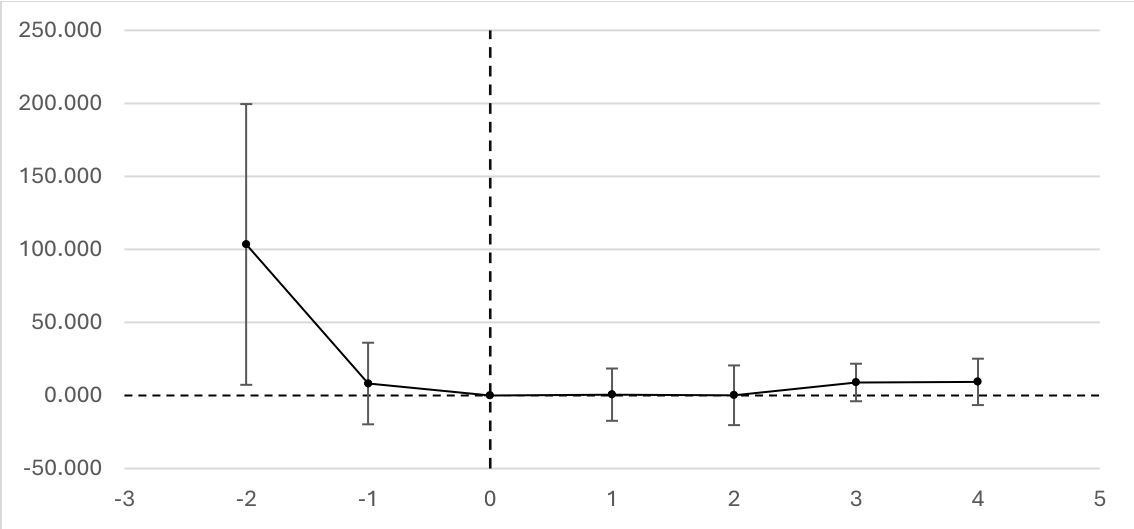

Figure 12 - Event Study for Crop Protection Costs/Utilised Agricultural Area

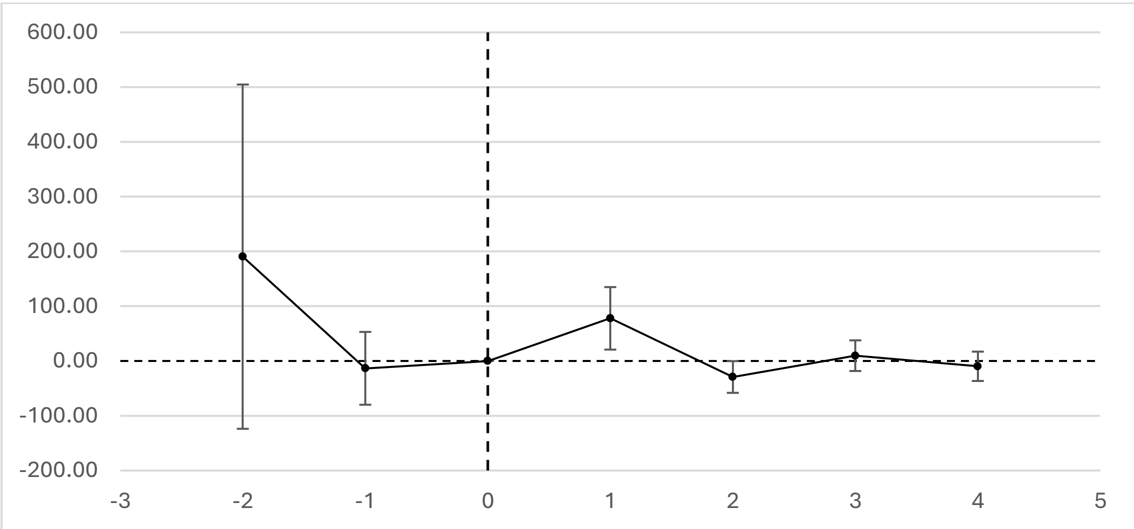

Figure 13 - Event Study for Water Volume/Utilized Agricultural Area

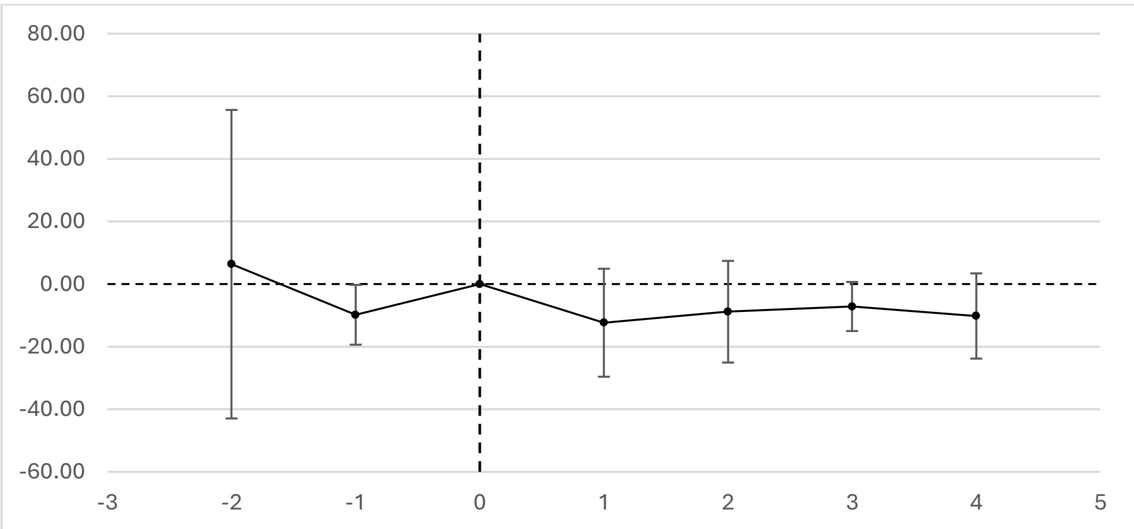

Figure 14 - Event Study for Labour/UAA

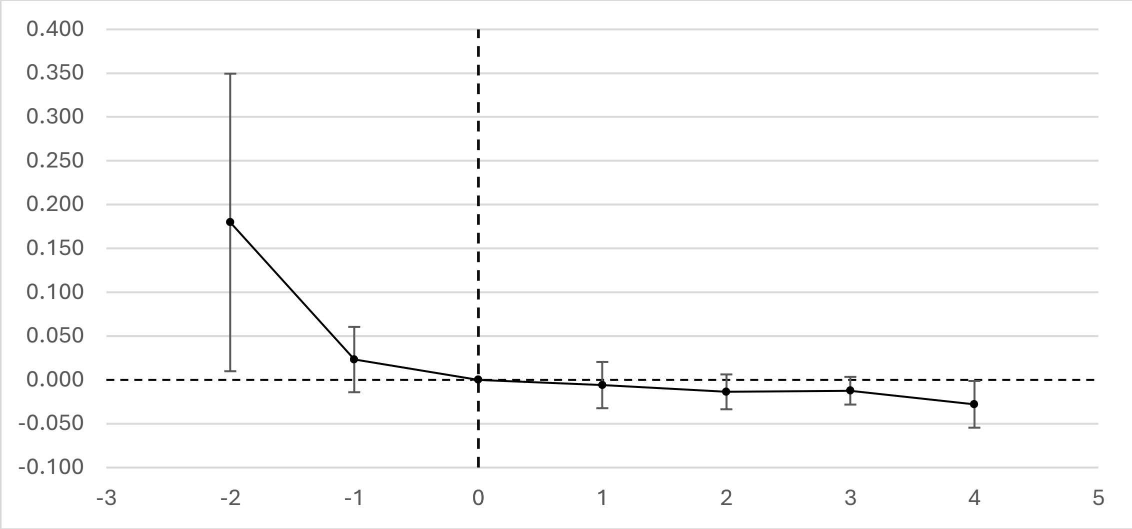

Figure 15 - Event Study for Total Factor Productivity /UAA