Don't Bet the Farm on Crop Insurance Subsidies: A Marginal Treatment Effect Analysis of French Farms

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Farmers face increasing climate risks

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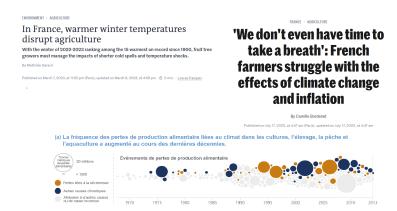


Figure: Sources: Le Monde, GIEC



Yet crop insurance uptake remains extremely low

- Insurance uptake: only 13.3% of farms insured in 2020
- Stable/slight increase: from 12% (2016) to 13,3% (2020)
- Larger farms are more insured than smaller ones
- 30% of surfaces are insured

A paradox since

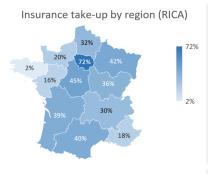
Introduction

 High insurance subsidies: 45%–65% of premiums paid before the 2022 reform

Source: Ministry of Agriculture



No correlation between risk and uptake



Probability of getting hit by a flood/drought in a given year (CCR)

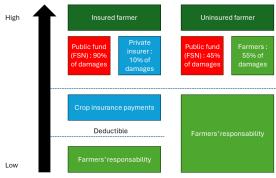


The insurance system in France (until 2022)





The 2023 reform in short





Q1: Impact of crop insurance on the revenue distribution of farmers

Incomes highly variable by nature yet insurance reduces variance

Crop insurance is on average a "good deal"

- Insurance increases average revenue
- Farmers benefit greatly from insuring: +10 20% in expected revenues
- No impact on variance

But this does not mean that every farmer should insure

Heterogeneity in insurance benefits could explain the paradox of underinsurance



Q2: Who benefits the most from insurance?

- No simple links between individual insurance uptake and benefits
 - Larger farms are more insured, yet derive less benefits than smaller farms from their contracts
 - Specialized farms are more insured, yet derive less benefits than diversified farms from their contracts
 - This suggests informational barriers or hidden costs (unobserved)
- Marginal Treatment Effects à la Heckman-Vytlacil: signs of negative selection into treatment
 - Translation: treatment = insured, control = not insured
 - Treatment is NOT randomly assigned, but chosen
 - Hence the instrumental variable methods
- Farmers who would benefit the most are the most reluctant to insurance



Q3: Can increasing insurance subsidies solve the paradox?

- Increasing insurance subsidies does not solve the issue and may even hurt (public finance/tax incidence)
- Farmers who would benefit the most from insurance are highly "resistant" to insurance subsidies
- Farmers with little profits from insurance would be pushed into the insurance market to grab the subsidy
- Windfall gains for many: the unintended beneficiaries
- Targeting the barriers directly
 - Information campaigns
 - Direct help on the paperwork
 - Targeted subsidies
 - Incentives on insurance companies



Contributions

Methodology

- Analysis of heterogeneous treatment effects on both observable and non-observable characteristics
- Probit/interaction and MTE framework ⇒ Never been used in crop insurance literature (ex: Di Falco et al. 2014, Wang et al. 2021)
- Counterfactual analysis of policies

Data: Finer at micro-level (as compared with previous works)

- Continuous instrument ⇒ Enables MTE analysis and large-scale study
- Weather variables AND agronomic indicators



Data sources

Introduction

Farm-level data

- RICA (part of the FADN: Farm Accounting Data Network)
- Pseudo-panel data between 2002 and 2021 for 17,743 individuals with localization
- Floods and droughts on a declarative basis

Weather data

- Reanalysis data from the National Meteorological and Hydrological Services from EU countries
- Temperatures and precipitations at a 0.1 ° lat/long resolution, about 6 × 6 km, every 6 hours
- ⇒ Index of Growing Degree Days

 Sum of out-of-bound for hot and cold days for 3 types of crops (C3, C4, potatoes and roots)

Variable choice: Revenue, insurance, inputs

EBITDA for total impact

- Revenues (including production, costs, subsidies, insurance payments, etc.) before taxes
- 2 measures: gross and net of insurance subsidies
- Insurance: Dummy (0, 1) for insurance status
 1 if more than 20 €/Ha for insurance in a given year

Controls

- Farm characteristics (work hours, total used agricultural surface, fuel and pesticides, agrotourism revenues, cattle, greenhouse, diversification)
- Climate variables (hot and cold GDDs, floods, droughts + lags)
- Two-way fixed effects



IV to deal with endogeneity

- Insurance choice is highly endogenous
- Instrumenting insurance decision through the average insurance subsidy rate and using as dependent variable farmer revenue net of insurance subsidies
- IV: national insurance subsidy rate by year and crop
- Changes every year (French decision until 2015, EU decision after)

IV Average treatment effects

Introduction

Two-way fixed effects + IV (D instrumented) + Antle method of moments:

$$\begin{split} D_{it} &= \alpha + \beta_{11} \mathbb{E}(S|t,c) + \boldsymbol{X_{it}}\beta_{21} + \boldsymbol{\Lambda_{it}}\beta_{31} + \boldsymbol{\Lambda_{it-1}}\beta_{41} + \boldsymbol{\theta_i} + \boldsymbol{\theta_t} + \boldsymbol{\epsilon_{it}} \\ R_{it} &= \alpha' + \beta_{12} D_{it}^* + \boldsymbol{X_{it}}\beta_{22} + \boldsymbol{\Lambda_{it}}\beta_{32} + \boldsymbol{\Lambda_{it-1}}\beta_{42} + \boldsymbol{\theta_i'} + \boldsymbol{\theta_t'} + \boldsymbol{\epsilon_{it}'} \\ \boldsymbol{\epsilon_{it}'^2} &= \alpha'' + \beta_{13} D_{it}^* + \boldsymbol{X_{it}}\beta_{23} + \boldsymbol{\Lambda_{it}}\beta_{33} + \boldsymbol{\Lambda_{it-1}}\beta_{43} + \boldsymbol{\theta_i''} + \boldsymbol{\theta_t''} + \boldsymbol{\epsilon_{it}''} \end{split}$$

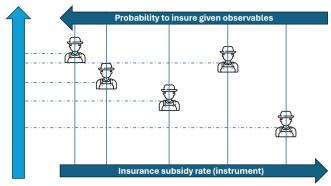
with D_{it}^* the first-stage prediction of D_{it} .

 β_{12} effect of insurance (IV) on Expected income β_{13} same thing on Variance

Estimated via 2SLS (standard)



Heterogeneity (Un)observables



Treatment effect (impact of insurance)



Marginal treatment effects: definition

Introduction

$$\mathsf{MTE}(\boldsymbol{X}, \boldsymbol{\rho}) \equiv \mathbb{E}(R^1 - R^0 | \boldsymbol{X}, U_D = \boldsymbol{\rho})$$

where U_D is the quantile of "resistance to treatment" given \boldsymbol{X} Exploits correlations between willingness to be treated and TE

- Notion based on a model mixing potential outcomes AND a probabilisitic choice model (idiosyncratic value for treatment)
- The IV (subsidy rate) used via the propensity score only
- The most elementary (or atomic) effects one can identify
- All standard estimands of treatment effects are weighted averages of the MTE (Heckman-Vytlacil, 2005)
- For applications, having the MTE enables the exploration of counterfactuals



Introduction Summary Data Empirical Strategy Main Results Policy Analysis Conclusion

Large average impacts of insurance on revenue

	EBITDA with insurance subsidies		EBITDA without insurance subs		
	Mean	Variance	Mean	Variance	
Dummy for crop insurance status (1=insured)	0.226***	-0.000	0.220***	0.000	
Observations	55,371	55,371	55,371	55371	
Weak Ident.	299.154	299.154	299.154	299.154	
Farmer FE	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
Controls	Yes	Yes	Yes	Yes	
Instrument	Yes	Yes	Yes	Yes	
Insurance subsidy rate (1st stage)	0.004***		0.004***		
	(0.000)		(0.000)		

Table: 2nd stage IV log estimations for the impact of insurance on the revenue distribution (NB: All coefficients are elasticities)



Selection into treatment based on observable characteristics (selected variables)

Variable	β1 -	β_0	First s	Selection	
	Coef.	S.E.	Coef.	S.E.	
L. Cold GDDs	0.000	(0.005)	0.015***	(0.005)	N.S.
L. Hot GDDs	-0.042*	(0.022)	0.027*	(0.015)	-
L. Dummy for floods	-0.019**	(0.009)	0.058***	(0.007)	-
L. Dummy for droughts	0.000	(0.009)	0.027***	(0.007)	N.S.
Total work hours (log)	-0.055***	(0.004)	0.011***	(0.003)	-
Farm size (log)	-0.007*	(0.004)	-0.019***	(0.003)	+
Greenhouse dummy	0.154***	(0.026)	-0.180***	(0.014)	-
Cattle dummy	0.101***	(0.011)	-0.127***	(0.005)	-
Crop protection (log)	0.036***	(0.004)	0.074***	(0.002)	+
Rent (log)	0.005***	(0.001)	-0.005***	(0.001)	-
Specialization index	-0.151***	(0.022)	0.273***	(0.011)	-
Subsidies (log)	-0.012***	(0.002)	0.012***	(0.001)	-
General education	0.005*	(0.003)	-0.006**	(0.002)	-
Instrument: Subsidy rate			0.005***	(0.000)	
Observations	56,678		56,6	78	

Table: 1st stage and $\beta_1 - \beta_0$ results for the MTE estimation

Heterogeneity by crop type

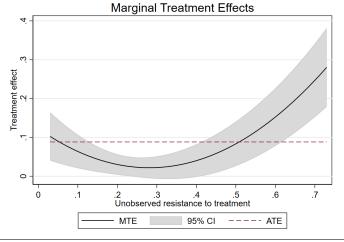
	Cereals	Fruits/Vegetables	Mixed	Vine
Crop insurance status (1=insured)	0.275***	-0.246	0.329***	0.099
	(0.024)	(0.374)	(0.086)	(0.209)
First stage (subsidy on insurance rate)	0.016***	-0.023	0.052***	0.004***
	(0.003)	(0.109)	(0.014)	(0.002)
Observations Weak Ident.	24,598	3,415	18,218	8,784
	188,223	1,275	21,509	4.020
Farmer FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes

Table: 2nd stage IV log estimations for the impact of insurance on revenue distribution by crop type

^{*: 90%} significance, **: 95% significance, ***: 99% significance. Robust standard errors in parentheses.



MTE: Highly heterogeneous effects on the unobservables (Mean)



Left: "good" managers / Mid.: risk averse managers / Right: "bad" managers

Policy design

	Mean
Average subsidy per insured farmer (EUR, baseline)	1061
Average subsidy per insured farmer (EUR, 2 pp increase)	1272
Uptake rate (baseline)	0.25
Uptake rate (2 pp increase)	0.27

Table: Parameters and effects of the counterfactual policy

	Mean
Total budget increase (€M)	103
Number of newly insured farmers	26,000
Indirect benefits of the subsidies (€M)	51
Pure transfers to those already insured (€M)	69
Pure transfers to the newly insured $(\in M)$	34

Table: Aggregate results of counterfactual (scaled up to all farmers in France)

- Counterfactual Policies: Increase propensity scores in the population.
 - E.g. information campaign on insurance benefits or a national-level speech, incentives on suppliers, faster indemnisation, etc.
- MPRTE: estimates the impact of policies targeting the propensity score directly.
 Calculated as the limit of average effect as policy parameter approaches zero
- We use three MPRTE estimators:
 - MPRTE1: Increase using PRTE weights
 - MPRTE2: Fixed upwards shift
 - MPRTE3: Proportional upwards shift

These estimators yield mostly equivalent results, with minor differences in weight composition



MPRTE results

Targeting the propensity score directly appears to be the way to go

Effect	EBITDA (log) net of insurance subsidies	Variance
PRTE	0.027	0.017
MPRTE1	0.087***	0.017
MPRTE2	0.072***	0.017
MPRTE3	0.096***	0.025
Observations	56,905	

Table: MPRTE estimators (parametric)



Summary Data Empirical Strategy Main Results Policy Analysis Conclusion

Conclusions

- Crop insurance benefits most farmers in terms of average revenues
- Impacts of insurance globally positive (hedging behavior)
- Farmers who would benefit the most from insurance are the ones who are insured the least

Policies

- Need to better aim insurance subsidies at smaller farms, rather than a flat increase over the distribution
- The 2023 reform is a good start for simplification but subsidies are strongly increased and still not differentiated by size/turnover
- Better information is needed to encourage insurance
- Timing of subsidies payment to reduce financial barriers

Replicability for the 28 EU countries members of the Farm Accounting Data Network (FADN)



Impacts of insurance on revenue and yields. Try OLS.

Following Antle 1983, Di Falco 2014 and Wang et al. 2021, we use the parametric moments-based approach

$$\begin{split} R_{it} &= \alpha + \beta_{11} D_{it} + \pmb{X_{it}} \beta_{21} + \pmb{\Lambda_{it}} \beta_{31} + \pmb{\Lambda_{it-1}} \beta_{41} + \theta_i + \theta_t + \epsilon_{it} \\ \epsilon_{it}^2 &= \alpha' + \beta_{12} D_{it} + \pmb{X_{it}} \beta_{22} + \pmb{\Lambda_{it}} \beta_{32} + \pmb{\Lambda_{it-1}} \beta_{42} + \theta_i' + \theta_t' + \epsilon_{it}' \end{split}$$

 R_{it} the revenue variable D_{it} the decision to insure (binary) X_{it} the vector of individual characteristics Λ_{it} the vector of climate variables All variables except dummies are expressed in log

OLS results

	EBITDA with	n insur. subsidies	EBITDA w/o	ut insur. subsidies
	(1) Mean	(2) Variance	(3) Mean	(4) Variance
Dummy for crop insurance (1=insured)	0.006***	-0.000	0.005***	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)
Cold OOBs (log)	0.003***	0.000	0.003***	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
L.Cold OOBs (log)	-0.005***	-0.001***	-0.005***	-0.001***
	(0.001)	(0.000)	(0.001)	(0.000)
Hot OOBs (log)	-0.014***	-0.001	-0.015***	-0.001
	(0.003)	(0.001)	(0.003)	(0.001)
Number of floods (log)	-0.006***	-0.000	-0.007***	-0.000
	(0.002)	(0.001)	(0.002)	(0.000)
Number of droughts (log)	0.002	-0.002	0.001	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Observations Farmer FE Year FE Controls	51380	51380	51380	51380
	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	Yes

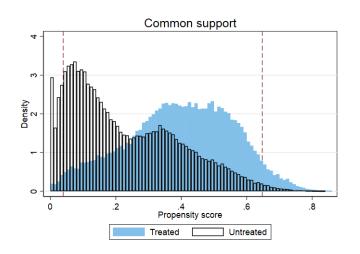
Table: OLS log estimations for impact of insurance on revenue distribution

Continuous effects

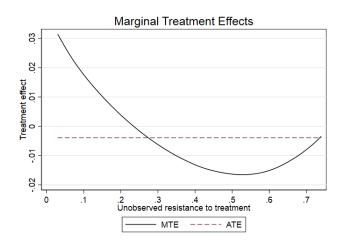
	EBITDA with	insurance subsidies	EBITDA witho	ut insurance subsidies
	(1)	(2)	(3)	(4)
Insurance spending (log)	0.046***	-0.003	0.039***	-0.001
	(0.007)	(0.002)	(0.006)	(0.002)
Observations	69790	69790	69006	69006
Weak Ident.	72.028	72.028	77.879	77.879
Farmer FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes

Table: IV estimations for the impact of insurance on the revenue distribution

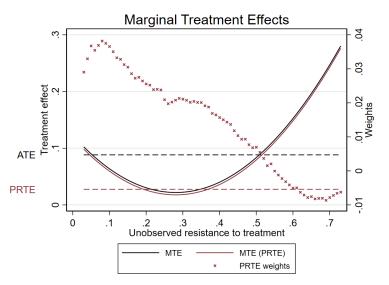
MTE common support



MTE: Highly heterogeneous effects on the unobservables (Variance)



PRTE results: Increasing insurance subsidies seems inefficient



Summary statistics (1/2)

	Mean	SD	Q1	Q2	Q3	Min	Max	Count
Dummy for crop insurance status (1=insured)	0.27	0.44	0.00	0.00	1.00	0.00	1.00	123700
Insurance spending per Ha (EUR/Ha)	24.22	55.91	0.00	2.32	22.81	0.00	450.00	123700
EBITDA with insurance subsidies (KEUR)	85.70	87.45	35.93	64.18	110.31	-504.04	3755.93	123700
EBITDA net of insurance subsidies (KEUR)	85.70	86.94	36.08	64.29	110.32	-504.04	3755.93	122039
Subsidy rate (year, culture)	8.40	9.38	0.00	6.34	15.51	0.00	46.58	123575
Sum of cold GDDs across the year (°C)	49.50	50.78	15.20	33.38	65.54	1.00	582.41	119940
Sum of hot GDDs across the year (°C)	1.06	0.46	1.00	1.00	1.00	1.00	63.79	119940
Number of floods/year	0.07	0.29	0.00	0.00	0.00	0.00	6.00	123700
Number of droughts/year	0.09	0.32	0.00	0.00	0.00	0.00	4.00	123700

Table: Summary statistics for the main variables

Summary statistics (2/2)

	Mean	SD	Q1	Q2	Q3	Min	Max	Count
Number of workers (full-time equiv.)	3922	4262	1600	3200	4600	45	216158	123700
Used agricultural surface (Ha)	104	81	46	85	141	0.32	795	123700
Diversification (1=Not diversified)	0.48	0.28	0.25	0.46	0.67	0.00	1.00	123700
Subsidies received (€)	36949	30564	15750	30834	50784	0.00	1106312	123700
Cattle dummy	0.39	0.49	0.00	0.00	1.00	0.00	1.00	123353
Greenhouse dummy	0.02	0.15	0.00	0.00	0.00	0.00	1.00	123700
Organic dummy (1= at least partial)	0.03	0.17	0.00	0.00	0.00	0.00	1.00	123700
Real costs for gas/oil (€)	6744	6592	2519	4890	8835	0.00	172891	123700
Real costs for pest./fertlzrs (€)	12312	14809	2693	7426	16614	0.00	311599	123700
Agrotourism revenues	77	1292	0.00	0.00	0.00	0.00	147940	123700
Debt	210971	278329	60692	135906	266040	0.00	12118604	123700
Rent	15217	16619	4852	10926	20064	0.00	654873	123700
Main activity : Cereals	0.50	0.50	0.00	1.00	1.00	0.00	1.00	123700
Main activity: Wine	0.12	0.32	0.00	0.00	0.00	0.00	1.00	123700
Main activity: Mixed	0.32	0.47	0.00	0.00	1.00	0.00	1.00	123700
Main activity: Fruits and vegetables	0.06	0.24	0.00	0.00	0.00	0.00	1.00	123700

Table: Summary statistics for the control variables

Channels

2nd stage: θ_2 Effect of channel	Crop protection	Surface	Fertilizers	Specialization
Expenditures for crop protection product per ha (log)	0.29873*** (0.11387)			
Total surface of the farm (log)		1.50487*** (0.38821)		
Expenditures for fertilizers per ha (log)			0.12675*** (0.02880)	
Specialization index (log)				0.30036*** (0.04224)
1st stage: θ_1 Effect of subsidy rate (year, crop)	0.00320** (0.00117)	0.00068*** (0.00016)	0.00752*** (0.00149)	0.00322*** (0.00029)
Observations Weak Ident. Farmer FE	50174 7.460 Yes	50174 16.773 Yes	50174 25.379 Yes	50174 125.919 Yes
Year FE Controls Instrument	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes

Table: Channels IV log estimations on revenue

 \mathbb{E}_0 mean of channel over the full sample of *N* farmers θ_1 first-stage coefficient; θ_2 2nd stage coefficient

 β_{11} the first-stage coefficient for the LATE of subsidies on insurance subscription +1pp in subsidy rate increases the average channel by θ_1 % over the whole sample New mean \mathbb{E}_1 becomes $(1 + \theta_1/100)\mathbb{E}_0)$

Increase concentrated over those who switched to insurance following increased subsidies

From first stage, we know the number of these farmers: is $n = \beta_{11} \cdot N$ The new mean \mathbb{E}_l of the farmers who actually changed their practices is:

$$\mathbb{E}_1 = \frac{(N-n)\mathbb{E}_0 + n\mathbb{E}_L}{N} \text{ hence } \mathbb{E}_L = \frac{N\mathbb{E}_1 - (N-n)\mathbb{E}_0}{n}.$$

To get the treatment effect (TE) on revenue for the switchers in pp:

TE-PP = 100
$$\frac{\mathbb{E}_L - \mathbb{E}_0}{\mathbb{E}_0} \theta_2$$
.

	n	N	θ_1	θ_2	β_{11}	\mathbb{E}_0	\mathbb{E}_1	\mathbb{E}_{L}	$100 \frac{\mathbb{E}_{L} - \mathbb{E}_{0}}{\mathbb{E}_{0}}$	TE-PP
Crop protection	205	50,174	0.00320	0.29873	0.004	103.31	103.31331	104.11913	0.78	0.23
Surface	205	50,174	0.00068	1.50487	0.004	92.97	92.970632	93.124731	0.17	0.25
Fertilizer	205	50,174	0.00752	0.12675	0.004	118.15	118.15888	120.32459	1.84	0.23
Specialization	205	50,174	0.00322	0.30036	0.004	0.46	0.4600148	0.4636253	0.78	0.24

Table: Parameters for the channels computation

Marginal treatment effects: estimation

- Similar to LATE: if subsidies increase a bit, a fraction of people switch to insurance, corrected for propensity changes
- Difference with LATE: subsidies (the IV) can be used for plenty small changes, each leading to a MTE, so we get a function instead of a single number (LATE)
- For instrument not binary but close to continuous
- Identification

$$\mathsf{MTE}(\boldsymbol{X}, \boldsymbol{\rho}) \equiv \frac{\partial E(R|\boldsymbol{X}, \boldsymbol{\rho})}{\partial \boldsymbol{\rho}}$$

 \boldsymbol{X} observable characteristics, p quantiles of resistance to treatment, R observed revenues ($R = DR^1 + (1 - D)R^0$)

• The RHS $E(R|\mathbf{X},p)$ easy to calculate, then numerical differentiation to get the LHS