Adverse selection and choice frictions in crop insurance against climate risk*

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Abstract

Despite the increased frequency of extreme weather events and large premium subsidies, the use of climate-related crop insurance contracts in European countries remains low. We investigate the economic factors behind these low coverage rates by linking Italian administrative data on insurance purchases and damage claims to high-frequency georeferenced data on weather events. We focus on two potential explanations: inefficient pricing of insurance contracts due to adverse selection and choice frictions that create a wedge between the value of insurance and actual demand. To identify adverse selection, we leverage a 2014 reform that lowered the cap for premium subsidies in EU countries. This policy caused a reduction in demand and an increase in average costs for insurers, indicating adverse selection. Regarding frictions, we document through a staggered difference-in-differences design that firms are more likely to buy insurance when faced with "salient" extreme events, suggesting that farmers are imperfectly informed about the value they assign to insurance. We conclude by discussing how current price subsidies may be less effective than insurance mandates in light of these uncovered market failures.

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1 Introduction

The frequency and intensity of climate extremes has strongly intensified in recent decades and it is expected to further increase in the coming years.[1] The Secretary-General of the World Meteorological Organization has recently declared that extremes such as heatwaves, flooding, hailstorms and drought are becoming the "new norm".[2] To cope with these risks, insurance against various types of extreme events represents one of the most important financial risk-management tools adopted by farmers. Consequently, government-subsidized premia emerged as a dominant type of support for agriculture and absorbs a significant part of the public budget. In the United States, the annual average cost for the Federal Crop Insurance Program is approximately \$8.5 billion,[3] while in Europe the programmed total public expenditure under the 2014-2020 Financial Framework amounted to €2.2 billion (European Commission, 2017). Despite high subsidization and the fact that the benefits of crop insurance have been extensively documented (Cole and Xiong, 2017), farmers' propensity to rely on insurance is highly heterogeneous across areas and remains low in many European countries (Santeramo and Ford Ramsey, 2017; European Commission, 2017).[4]

A classic hypothesis for why insurance coverage could be low is that buyers and sellers of insurance have asymmetric information on risk and its consequences. In a market with hidden information, insurers cannot price-discriminate based on risk. In this context, high-risk farmers are more likely to buy insurance contracts, driving low-risk ones out of the market. This form of *adverse* selection leads to inefficiently low equilibrium coverage (Akerlof, 1970; Einav et al., 2010a). Another hypothesis behind low coverage is that farmers are subject to choice frictions, i.e. they do not recognize the true value that insurance offers them and therefore buy less insurance than they should. In other words, frictions create a wedge between the true insurance value – that is relevant for welfare – and willingness to pay as revealed by demand (Spinnewijn, 2017; Handel et al., 2019).

In this paper we are the first to test for the presence of both adverse selection and choice

[1]According to the IPCC a climate extreme is defined as "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable. For simplicity, both extreme weather events and extreme climate events are referred to collectively as climate extremes." (Field et al., 2012, p.5). A more exhaustive definition can be found in Section 3.1.2. of Seneviratne et al. (2012)

[2]See "Climate change: Extreme weather events are 'the new norm' ". BBC News, 31st October 2021.

[3]Source (2013-2022): USDA Risk Management Agency, Summary of Business Reports 5/1/2023. Accessed at: https://www.rma.usda.gov/-/media/RMA/AboutRMA/Program-Budget/22cygovcost.ashx?la=en

[4]The system of incentives for agricultural insurance, however, is not without limitations. For instance, in the American insurance market, Annan and Schlenker (2015) show evidence of moral hazard: farmers participating in the subsidized insurance program are discouraged from adopting climate adaptation strategies, leading to increased crop losses.

frictions in the Italian crop insurance market, and discuss their policy implications. Our empirical analysis uses administrative data on insurance coverage, premiums, and damage claims at the municipality level, combined with a high-resolution database of extreme weather events. Adverse selection and choice frictions are often cited as justifications for substantial government interventions. However, despite the critical need to promote risk-coping strategies in agriculture in response to increasing climate variability and substantial public spending in this area, we know very little about the impact of these market failures. Our paper is a first attempt to fill this gap.

To test for adverse selection, we exploit a 2014 EU-wide reform that lowered the cap on government premium subsidies from 80% to 65%, causing a sudden and exogenous price variation. Insurance coverage fell by about 37% in the four years following the reform. We use this exogenous variation to test whether firms willing to pay the higher post-reform premia are *negatively* selected, meaning they are riskier on average, as indicated by their ex post insurance claims.[5] Although the subsidy cap change was uniformly applied, municipalities with lower initial insurance coverage were less affected by the reform than those with higher coverage. Intuitively, this is because insurance coverage has a natural zero lower bound. Following Deryugina and Konar (2017) and Hackmann et al. (2012), we use the share of insured firms in the year before the reform as an instrumental variable for the change in insurance coverage between pre- and post-reform years. We find an increase in average costs following a drop in the share of insured firms, indicating adverse selection: farmers with a higher willingness to pay end up claiming more damages and costing more to insurers (Einav et al., 2010a).

Identifying choices that are inconsistent with true preferences requires knowing the utility function that the farmer is maximizing. In the absence of this information, we rely on an indirect test. Specifically, we study the evolution of insurance demand around extreme weather events using a staggered difference-in-differences design. Absent frictions, specific extreme events should not impact demand, which should only vary with the underlying climate risk distribution. However, our results indicate otherwise: the number of insured firms sharply responds to extreme events in a way that cannot be explained by underlying changes in risk, as the climate changes slowly. We interpret this as evidence that farmers are imperfectly informed about the value they assign to insurance contracts or that they do not act upon this information, creating a gap between value and demand. Furthermore, we show that average costs do not change in the years after extreme events, and we discuss how

[5] This approach follows a long tradition in the literature on insurance markets. See Einav and Finkelstein (2023) for a recent survey.

this suggests that salience frictions play a significant role in reduced insurance uptake.

We conclude by discussing the policy implications of our results. Subsidizing insurance premia is common in EU countries. Crop insurance policy has been part of the Common Agricultural Policy (CAP) since 2010, with many European countries offering substantial subsidies – co-financed by the EU – to encourage its use (ISMEA, 2018). Adverse selection and the presence of frictions suggest that insurance uptake is below the social optimum and that policy interventions can be desirable. Given that choice frictions make market demand less responsive to prices, the current reliance on subsidies to premia as the most common policy tool may not effectively incentivize demand or mitigate adverse selection. Therefore, it may be reasonable to consider *insurance mandates* as an alternative policy tool. However, the costs and benefits of mandates should also be carefully evaluated. While mandates eliminate adverse selection by requiring all firms to buy insurance, they can still lead to inefficiencies: transactions occur for firms where the marginal cost of insuring exceeds the private value of insurance. Further research is needed to quantify the slope of demand curves and the social costs associated with insurance mandates.

We make several contributions to the literature on crop insurance markets and on the importance of choice frictions in insurance markets with asymmetric information. First, this paper relates to the extensive literature documenting selection in insurance markets. Previous contributions have primarily focused on health insurance (Einav et al., 2010a; Hackmann et al., 2012; Einav et al., 2013), while the closest yet distinct setting to ours is house insurance against natural disasters such as hurricanes or floods (Wagner, 2021; Bradt et al., 2021; Gibson and Mullins, 2020). To the best of our knowledge, we are the first to test for adverse selection in the crop insurance market using plausibly exogenous and quasi-experimental price variation (see Einav and Finkelstein (2023) for a recent survey of empirical applications of these tests in insurance markets).[6] Second, we contribute to a recent literature highlighting the role of choice frictions in insurance markets. Recent empirical work has emphasized specific behavioral frictions such as inattention (Chang et al., 2018a), inertia (Handel, 2013), risk underestimation (Barseghyan et al., 2013), economic frictions such as liquidity constraints (Karlan et al., 2014; Casaburi and Willis, 2018), lack of trust and limited salience (Cole et al., 2013), and scarce financial literacy among low-educated farmers, particularly in developing countries (Cole et al., 2017). Our empirical results show that choice frictions are a relevant

[6]Earlier studies on the crop insurance market relied on regression adjustments to estimate the relationship between price, demand, and cost (Just et al., 1999; Makki and Somwaru, 2001, among others). The Italian crop insurance market has been studied by Santeramo et al. (2016), who find that geography, firm size, and profitability are important predictors of insurance demand, and by Porrini et al. (2019), who use regional data to show that insurance reimbursements positively impact profitability. However, we are the first to study this market using quasi-experiments and by explicitly considering sources of market imperfections.

feature in one of the largest European agricultural insurance markets.

The rest of the paper is structured as follows. Section 2 describes the institutional setting, Section 3 describes the data and how we build our variables of interest. In Section 4 we present our methodology and results on adverse selection. In Section 5 we do the same for choice frictions. Section 6 concludes by discussing our findings and their policy implications.

2 Institutional setting: subsidized insurance

Italy represents a suitable case to study market failures in the agricultural insurance sector. First, alongside Spain, Italy represents the largest European government-subsidized crop insurance market (Santeramo and Ford Ramsey, 2017), amounting to approximately 7 billion euros. In addition, Italy is already among the most critically affected countries by global warming in Europe and is disproportionately experiencing the impact of extreme weather events. Since 2004 the Italian government has introduced very generous subsidies (up to 80% of the premium) for the purchase of insurance contracts against adverse weather events.[7] The annual public expenditure for these subsidies amounts to around 400 million euros. Nearly 80% of the subsidized contracts receive financing from the European Commission. This implies an average expenditure of 25 euro/hectare and 215 euro/farmer (ISMEA, 2018). At the geographical level, more than 80% of the insurance market is concentrated in the Northern areas, in which nearly 90% of the cultivated land is insured. However, the overall policy take-up is relatively weak, with subsidized farmers accounting for only 19% of the total gross production and 9% of the total agricultural lands.

Subsidized insurance covers three distinct categories of adverse events: i) catastrophes or infrequent perils (drought, ice formation and flood), ii) frequent perils (hail, excess snow, excess rain, extreme wind) and iii) additional adversities, also known as *garanzie accessorie* (hot wind and temperature fluctuations).[8] To apply for a subsidy, farmers have to send their expression of interest before the plantation season. After the expression of interest, eligible farmers need to fill an Individual Insurance Plan (PAI) which defines the insurance contract and includes the historical yields on which the compensation is calculated. Subsidy eligibility is based on a series of basic requirements: farmers must be active in the agricultural sector and must own an updated cultivation plan, on which all the cultivated areas must be well identified.[9]

[7] The first government subsidies were introduced in 2004 with the Legislative Decree No. 102/2004. Additional details and historical background can be found in Appendix A1.

[8] Source: Mipaaf, PAAN (2015)

[9] Source: http://www.psrn-network.it/wp-content/uploads/2018/06/opuscolo_A5_web_final.pdf

In our analysis, we exploit changes in the maximum amount of the subsidized premium, which was initially set at 80% of the premium price. In 2014, the Article 37 of EU Regulation no. 1305/2013 lowered the subsidy maximum to 65% of the insurance premium due. This change in the subsidized price allows us to run in Section 4 an explicit empirical test for the presence of adverse selection in the Italian insurance market.

3 Data and measurement

Insurance data: Information on insurance contracts comes from the *SicurAgro* database, an administrative dataset released by *Ismea*, an Italian agency part of the Ministry of Agriculture, which provides services to the agricultural sector. The data span the 1998-2018 time window and has information on insured values, number of insured firms (since 2004), premia and damage claims at the municipality level.[10] Ideally, we would like to restrict our analyses to the set of municipalities where crops are cultivated. Unfortunately, we do not know of any database at the municipality-by-year level that contains this information for the Italian agricultural sector. As a second best, in our baseline analysis, we restrict ourselves to the set of municipalities which appear at least once in the *SicurAgro* database, *i.e.* that have at least one year with a positive insured value. Our restricted sample considers 5,365 municipalities out of 7,954.[11] To obtain a measure of the share of insured firms in a given municipality, we divide the number of insured firms in the *SicurAgro* database by the number of agricultural firms taken from the 2010 Agricultural Census. Figure 1 Panel (a) plots this share in each municipality included in our sample. While we observe that insured farms are by and large present in most Italian municipalities, shares are significantly higher in the Po Valley, with peaks of 100% in some areas. This is not surprising as this area has a high number of farms adopting intensive agriculture and accounts for more than one third of national agricultural production (Angelini et al., 2010). We present summary statistics for all the relevant variables from this dataset in Table A1.

Extreme weather events: We merge the Sicuragro database with extreme weather event data from the European Severe Weather Database (ESWD), compiled by the European Severe Storms Laboratory. This dataset encompasses several climate extremes and provides the information needed to build our weather shocks.[12] Each event entry includes precise

[10]For some of the early years we also observe the subtotals by type of insured risk. This information is not available in the later periods, when our weather variables are available. For this reason, we ignore this dimension.

[11]We define the list of municipality codes on 30th of June 2018, and we use it to harmonize the municipality data over time.

[12]These extremes include tornadoes, severe winds, large hail, heavy precipitations, funnel clouds, gustnadoes,

geographic and temporal information. We focus specifically on three types of events that might have a direct potential impact on agricultural production: large hail, severe wind and heavy precipitations.[13] Furthermore, considering the variability in reporting rates over time, particularly in the earlier periods when reporting networks may have been limited, we focus on events reported since 2010.[14]

ESWD data allow the identification of extreme and localized events such as hail, which are often missed using standard weather measures such as precipitations and wind speed. Italy's vulnerability to extreme weather is highlighted by over 2,800 extreme weather events, recorded from 2010 to 2018.[15] Figure 1 Panel (b) illustrates the geographical distribution of extreme hail, wind, and rain events within the Italian municipalities included in our sample. We observe a relatively higher concentration of events in Northern Italy.

Temperatures and precipitations: For some of the analyses, we complement the ESWD database with more standard weather data collected from the Agri4Cast database of the European Commission. Specifically, we select minimum and maximum temperatures, wind speed and total rain precipitations. The data are available at the daily frequency on a regular grid of 25×25 km.

Other data: We merge the *SicurAgro* database to the Population Census from the National Institute of Statistics (Istat). From the Census we gather information on socio-demographic characteristics of each municipality in 2011. We provide more details on the variables in Section A2.

4 Testing for adverse selection

An insurance market suffers from adverse selection whenever consumers that have higher willingness to pay are also costlier to insure and insurers cannot price-discriminate such differences in costs. Such selection would imply that the average and marginal cost curves of insurance companies are a decreasing function of coverage (Einav et al., 2010b). Given that both insurers and farmers observe the history of weather events, adverse selection may not seem a concern in the context of crop insurance against climate risk. However, farmers'

lesser whirlwinds, heavy snowfall/snowstorms, ice accumulation, avalanches, and damaging lightning.

[13] The dataset is compiled based on events signaled to ESDW by external sources. However, very few events (less than 1%) do not undergo plausibility checks before entering the database.

[14] The European Severe Storm Laboratory (ESSL) acknowledges that "reporting rates can change over time."

[15] Over the past decade, the frequency of extreme weather events has increased. Figure A1 illustrates the annual count of weather extremes included in our analysis. The upward trend is particularly pronounced for large hail and extreme wind, whereas heavy precipitations exhibit a more erratic pattern.

ability to cope with extreme events may still constitute private information, thus leading to adverse selection. Alternatively, adverse selection could arise from the inability of insurers to tailor contracts to specific subgroups of the firms population, which generates dispersion in climate risk among the farms that are offered a given contract (Finkelstein and Poterba, 2014). Regardless of its specific microfoundation, in what follows we want to estimate empirical relationships of the type:

$$\Delta C_i = \alpha + \beta \Delta S_i + \epsilon_i, \tag{1}$$

where ΔC_i is the change in insurers' average costs in municipality i, over a given time window. Average costs are defined as the value of total damage claims over total insured values. ΔS_i is the change in the share of firms in municipality i that are insured, over the same time window. ϵ_i is an error term. Adverse selection would imply $\beta < 0$, as a larger insurance take-up in a municipality leads to a decrease in average costs.

Estimating (1) by OLS could produce biased results. In the context of crop insurance, farmers could buy more insurance in anticipation of higher future claims ("reverse causality") or there could be unobserved factors in ϵ_i driving both higher demand and more claims in a given area. To isolate a change in demand that is not related to the potential evolution of average costs, we exploit a large EU-wide reform occurring in 2014 (EU Regulation 1305/2013). The change in regulation decreased the *maximum* subsidy that national governments could provide to insured firms, from 80% to 65% of the premium. Importantly for us, the timing of the EU-wide reform is unlikely to be related to cost determinants in Italy, making it suitable to estimate causal effects. The reform induced a large and sharp reduction in coverage that is visible from the aggregate data. In Figure 2 Panel (a) we show that from 2014 – the first post-reform year – to 2017 the total number of insured firms decreased from a peak of ≈ 160,000 to ≈ 100,000, *i.e.* a 37.5% decline.[16] In the presence of adverse selection, firms that remain insured even after the reform should be riskier and costlier to insure. As a consequence, insurers' average costs should increase in the years following the reform. Panel (b) shows that average costs slightly increase around the year of the reform compared to their pre-trend, and especially so in 2017. This year is particularly important for our analysis due to its high frequency of extreme events.[17] Unlike other insured events, such as health shocks, the distribution of weather extremes is characterized by certain years with a high concentration. These are the periods where we expect to observe a greater dispersion in average costs, and where the effects of changes in insurance take-up become detectable.

[16]A reform going in the opposite direction (an increase of the cap to 70%) was passed in 2018, which is why we conduct our analysis up to 2017 (included).

[17]The data show that the notable increase in 2017 values is not driven by a few outliers, but rather by a general shift in the distribution of average costs.

To provide a more systematic analysis, we build on Deryugina and Konar (2017) and exploit the fact that municipalities with higher initial insurance coverage should be more affected by a price change compared to those with lower initial coverage.[18] As a consequence, in the presence of adverse selection, areas with high initial coverage should exhibit larger increases in average costs, as their demand contracts the most. Conversely, if willingness to pay is unrelated to costs, we would expect no differential evolution in average costs across areas with different initial coverage. Figure 2 Panel (c) and (d) visually represent this variation. We categorize municipalities into four equally spaced bins based on their share of insured firms in 2013, one year before the reform.[19] Then, we plot the evolution of the average share of insured firms (the "first stage," Panel (a)) and the average costs (the "reduced form," Panel (b)) in each bin. Darker lines indicate bins with a higher 2013 share of insured firms. A few things are worth noticing: first, in Panel (a), municipalities with a higher share in 2013 did not exhibit any discernible trend in the years leading up to the reform, but then displayed a comparatively larger drop in insurance coverage, particularly noticeable in 2016 and 2017. Second, in Panel (b), the darker lines representing bins with a higher 2013 share showed stronger increases in average costs in 2017, with less pronounced patterns in the previous years. As anticipated, the potential effects of insurance take-up become evident in 2017 when the frequency of extreme events is sufficiently high. Specifically, these patterns suggest the presence of adverse selection, as areas where insurance demand declined the most experienced a greater increase in average costs.

We test this more formally by estimating first-differenced equations like in (1), at different time horizons, always instrumenting the pre vs post-reform change in the share of insured firms with the 2013 share of insured firms. One may be concerned that our instrument captures underlying trends in the take up of insurance or costs at the municipality level. The graphical evidence in Figure 2 should mitigate this concern, as no differential pre-trends are visible across categories. However, following Deryugina and Konar (2017), in our regressions we also flexibly account for pre-trends by adding growth rates of the share of insured firms in previous years as controls. Moreover, since many of the high-coverage municipalities are in the North of the country, we also include 20 NUTS-2 region fixed effects to only exploit within-region variation in the instrument. Each of our first-stage equations takes the form:

$$\Delta^k S_i = \gamma_p + \delta_1 S_{i,2013} + \sum_{t=2009}^{2013} \theta_t \cdot \text{Growth}_{it} + \nu_i, \tag{2}$$

[18] A similar approach, albeit with some differences, is employed in Hackmann et al. (2012).

[19] The categories are: (i) [0,25%), (ii) [25%,50%), (iii) [50%,75%), and (iv) [75%,100%].

where $\Delta^k S_i$ is the change in the average share of insured firms between 2013 (pre-reform) and the post-reform year $k = \{2014, 2015, 2016, 2017\}$. $S_{i,2013}$ is the share of insured firms in 2013, one year before the reform is implemented; γ_p are region fixed effects; Growth_{it} are the yearly growth rates of the share of insured firms between years t and $t-1$ in the same municipality (starting from t =2009). Each of our second-stage equations is as follows:

$$\Delta^k C_i = \alpha_p + \beta_k \Delta S_i + \sum_{t=2009}^{2013} \lambda_t \cdot \text{Growth}_{it} + \epsilon_i, \tag{3}$$

where the Δ^k operator is the same as before and α_p are region fixed effects. We run our regressions on a balanced panel of all municipalities that appear for at least one year in the *SicurAgro* data and we weight observations by the number of agricultural firms in each municipality as reported by the 2011 Agricultural Census.

Table 1 reports the 2SLS estimates of β_k for years $k = \{2014, 2015, 2016, 2017\}$, together with 95% confidence intervals. We show various specifications that progressively add controls for past demand growth and region FEs. The β_k coefficients are always negative with the exception of the first year in two of the specifications. In years 2014 to 2016, when there are fewer extreme events, the coefficients are very imprecisely estimated, and only marginally significant in 2016. However, the coefficient is negative and strongly significant in 2017, the year with the highest frequency of weather extremes, in line with the graphical evidence in Figure 2. Notably, this result holds after the inclusion of the growth controls (columns (2) and (4)), mitigating concerns that our results are driven by pre-existing trends. Also, it is robust to the inclusion of region fixed effects, which control for heterogeneous trends in demand across different regions (columns (3) and (4)). The point estimate in 2017 for our preferred specification (column (4)) implies that a 10 percentage point reduction in the share of insured firms leads to a 1.1 Euro cent per Euro insured increase in average costs. This increase is sizeable given that in 2013 the mean average cost stood at 3.86 Euro cents.

Table 1 also provides a summary of the relevant first stage coefficients (Panel (b)) and Kleibergen and Paap (K-P) F-statistics (Panel (c)). The first stage estimates have the expected sign: municipalities with higher shares of insured firms witnessed larger decreases in demand following the reduction of the subsidy. K-P F-statistics are always above conventional threshold levels.

5 Testing for choice frictions

Testing for the presence of choice frictions is conceptually harder than testing for adverse selection: to argue that an agent is not maximizing an objective function, one must be able to observe such function in the first place (Allcott and Greenstone, 2012). Since we are unable to observe all the different benefits and costs related to insurance purchases and how firms weight them, we can only rely on *indirect* tests.

In settings without frictions, demand reflects the value that agricultural firms assign to insurance, which solely depends on the probability distribution of weather events, risk preferences, and idiosyncratic risk. Absent changes in these factors, demand should not respond to specific climate *realizations*. Demand responses following weather events suggest that firms know their insurance value only imperfectly, indicating a wedge between demand and value. It is important to note that choice frictions do not necessarily imply irrational behavior. Even if demand responses result from rational Bayesian updating about the climate, demand still fails to reflect the welfare-relevant value for insurance. To test for the presence of choice frictions, we employ a staggered difference-in-differences design, examining the evolution of insurance demand before and after extreme weather events. A similar idea is exploited in Chang et al. (2018b), who study health insurance demand after days of high air pollution.

Insurance demand could respond either through Bayesian learning or because firms pay attention to risks that become more salient after an extreme event. We propose a new test to distinguish between these mechanisms in the context of insurance, using the dynamics of average costs post-event. Assuming the event is a signal on firms' risk but not on their risk preferences, Bayesian marginal buyers should be costlier to insure than the average in the uninsured pool but less costly than the average insured buyer. Conversely, inattentive marginal buyers should not differ in cost from current buyers if inattention is orthogonal to risk and risk preferences. Thus, average costs should *change* after the event under Bayesian learning but remain constant under inattention.[20] In other words, if costs remain flat after the event, firms are selecting based on characteristics uncorrelated with risk, supporting the saliency explanation. We show that insurance demand persistently reacts to extreme events. While average costs initially rise due to damage from the event, they return to pre-event levels, indicating that saliency rather than Bayesian updating may drive our results, consistently with Chang et al. (2018b). At the end of Section 5.a we also discuss why another

[20] There is a knife-edge case where the pool of marginal buyers is as risky as the existing insured pool. However, under adverse selection, the average riskiness of the insured pool is already higher than in the uninsured pool, so this should be ruled out.

friction, credit constraints, is inconsistent with our evidence.

5.a Event studies with extreme weather events

In this section we provide a test for frictions by studying how demand changes in response to extreme weather events. We implement a staggered difference-in-difference design that exploits heterogeneity in the exact timing of extreme weather events across Italian municipalities. Thanks to the ESWD database, we gather information on all municipalities that ever experience a large hail, severe wind or heavy precipitation event in the 2010-2015 period. In our analysis, we also include a pure control group that never experiences an extreme weather event of this kind during the observation window.

To investigate the dynamics and check for pre-trends, we analyze the evolution of insurance demand, premia and average costs four years before and up to three years after the event.[21] Our main estimating equation is:

$$\log y_{it} = \alpha_i + \gamma_t + \sum_{k=0}^{3} \beta_{ik} \cdot \mathbf{1}(t - E_i = k) + \epsilon_{it}, \tag{4}$$

where α_i are municipality fixed effects, which control for any time-invariant difference between treated and control municipalities; γ_t are calendar year fixed effects, which control for common time-varying unobservables; $\mathbf{1}(t - E_i = k)$ are dummies that capture time relative to the date of the extreme weather event E_i. The coefficients β_{ik} are potentially heterogeneous treatment effects of the extreme weather event on municipality i at horizon k after the event. We use the Borusyak et al. (2021) imputation estimator, which solves negative-weighting issues highlighted in the recent econometric literature (Goodman-Bacon, 2021) and has desirable efficiency properties. To study heterogeneous treatment effects, we compute the average municipality-level treatment effects among the municipalities in each subgroup of interest. We cluster standard errors at the municipality level, to allow for serial correlation in the outcomes at the municipality level over time (Bertrand et al., 2004).

To provide indirect evidence in favor of the parallel trend and no-anticipation assumptions that are implicit in our identification strategy, we estimate an auxiliary regression of the outcome on year fixed effects, municipality fixed effects and indicators for periods before treatment using only untreated observations, as suggested by Borusyak et al. (2021). This

[21] In order to isolate the effect of a single weather event we exclude municipalities that are treated multiple times in the observation window, but keep their untreated observations before the first event occurrence, which helps with the estimation of time fixed effects.

changes the interpretation of the event-study plots that we show below. Pre-treatment coefficients are relative to the first untreated period ($k = -4$), while post-treatment coefficients are relative to the average of the pre-treatment periods.

Furthermore, one may be concerned that an extreme weather event in a municipality can have a causal impact also on nearby municipalities. If the latter set of municipalities appear in the control group, the estimated effects could be biased downwards. To mitigate the issue of geographical spillovers across treated and control municipalities, we exclude from the control group all municipalities within a 20km radius from ever treated municipalities.

Figure 3 reports β_k coefficients from regression (4) and associated 95% confidence intervals. Panel (a) displays the evolution of damage claims (in €) over insured values, that is the average cost for the insurers. The event causes insurance claims in municipalities with some insurance coverage: an extreme event increases average costs per euro insured by about 4 Euro cents, compared to an average of 4.28 Euro cents in the pre-event period for treated municipalities.[22] This test serves as a useful "first stage," demonstrating the relevance of the events we study. Panel (b) displays the evolution of the share of insured firms. We observe that demand shows no anticipation and responds sharply and persistently to the shock. The estimates indicate that an extreme weather event increases demand by about 1 percentage point on average for treated municipalities (see Table 2), against an average insured share of 17.9% in the pre-event year. The estimates remain stable over the entire post-event period, although the coefficients are less precisely estimated towards the end of the window of analysis. In Table 2, we establish that the effect is mainly driven by the areas with a low initial insurance take-up. The municipalities with a below-median share of insured firms in 2010 experience an average 1.3 percentage points increase in insurance take-up after an extreme event, while the effect is only mildly positive for the above-median municipalities.[23] The average post-event coefficients for the two subgroups of municipalities are significantly different at the 5% level (p-value 0.0154). The effects of extreme events on insurance demand could be underestimated if insurance companies were to raise premia to reflect a higher risk in that area. Figure 3 Panel (c) shows that there is no impact on premia paid by firms and therefore indicates that demand responses occur uniquely because of a change in firms' risk appreciation and not because of contractual changes. The fact that premia do not change could be rationalized in two ways: i) either risk at the municipality level is not factored in

[22]As an alternative benchmark, the average cost per Euro insured in the pre-event period for treated municipalities, conditional on having a positive claim, is 7.8 Euro cents.

[23]Figure A3 shows the evolution of the outcomes of interest in the entire window of time around the event. The effect on insurance demand is persistent over the entire post-event period for the municipalities with below-median initial take-up.

price-setting decisions, ii) or a single weather realization – even if extreme – is not enough for insurance companies to change their risk assessment for the area.

From a welfare perspective, the exact microfoundation of demand frictions is not crucial. The impact of frictions on demand is a sufficient statistic for local policy recommendations (Spinnewijn, 2017). Absent further information, the documented demand response by firm could either be due to Bayesian learning or to an increase in saliency of the risk or of the damage, which is more in line with a behavioral friction. The evolution of average costs however is at least suggestive of the fact that the behavioral story is more important. Under Bayesian learning, marginal entrants should be riskier than the average in the population of previously uninsured. This should be reflected in a change in the average costs. The fact that we find a substantial change in average costs only in the year of the shock suggests that those who choose to insure after the event are not particularly selected on risk, which is more consistent with a saliency story.[24] Finally, we show in Table A2 that demand reacts more for events that generate greater damage on impact, providing evidence in favor of damage saliency being an important factor.

These results also speak – albeit indirectly – about the importance of credit constraints. Climate extremes represent a liquidity shock to uninsured firms. In spite of this, they still cause the number of insured firms to rise on average. Hence, it seems unlikely that liquidity plays a big role in the decision to insure or not. The fact that bigger or wealthier firms are more likely to insure, as found by Santeramo et al. (2016), may thus be more linked to the fact that these firms are more sophisticated and less subject to behavioral frictions.

Finally, in Appendix A2, we provide additional suggestive evidence of the presence of frictions. Motivated by the insurance framework with frictions in Spinnewijn (2017), we implement a variance decomposition of insurance demand to determine what fraction of take-up remains unexplained after accounting for numerous proxies for preferences and risk. We show that more than 70% of the variance is left unexplained after the estimation of a rich model of demand, consistently with the presence of frictions.

6 Discussion and conclusions

In this paper, we have documented the presence of market failures in the Italian market for crop insurance against extreme weather events. First, by examining a reform that altered the

[24] As a robustness, Figure A3 Panel (c) shows that average costs remain unchanged over the medium run also for the group of municipalities with below-median initial take-up for which demand increases persistently three years after the extreme event.

cap on insurance premium subsidies, we demonstrate that a decrease in insurance uptake leads to higher costs per euro insured, indicating adverse selection in the market. Second, we analyze how the occurrence of climate extremes influences insurance demand. We find that insurance demand increases following an extreme event, and particularly so in municipalities with initially low uptake, which suggests the presence of choice frictions in demand. Since average costs do not rise in the medium run after an extreme event, we claim that the salience of climate extremes, and of their consequences, might be a significant driver of these frictions.

Examining adverse selection and choice frictions together is crucial because choice frictions magnify the efficiency cost of even moderate adverse selection (Spinnewijn, 2017). Both factors suggest that insurance uptake is below the social optimum. In the case of adverse selection, when insurers price at the average cost, the equilibrium share of insured firms is lower than the share that would equate the marginal willingness to pay with the marginal cost of insurance (Einav et al., 2010a). Additionally, choice frictions in demand create a gap between the "revealed" willingness to pay and the true willingness to pay (Spinnewijn, 2017; Handel et al., 2019). Our empirical results indicate that firms might underestimate their true willingness to pay, resulting in an inefficiently low share of insured firms.

The welfare costs from adverse selection and choice frictions are measured by the total aggregate surplus lost because some socially desirable transactions do not occur due to these frictions. In this context, there is potential for government intervention to mitigate the welfare loss. Current policy interventions typically rely on price subsidies to stimulate insurance demand and bring it closer to the socially optimal level. However, in the presence of choice frictions, which we document for the first time in this context, demand might not respond adequately to price incentives. Despite a largely subsidized market, we provide evidence that firms' demand is likely inefficiently low. In such cases, alternative policy interventions, such as *insurance mandates*, could be more effective. These mandates, however, come with inherent welfare costs that must be weighed against their benefits. Mandating insurance for all firms can lead to transactions where the cost of insuring exceeds the willingness to pay. Quantifying these costs requires estimating the slope of the demand function and the extent of demand frictions, which is beyond the scope of this paper. We leave this to future research.

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7 Figures

Panel (a): Map of insured farms in 2018 Panel (b): Map of extreme events

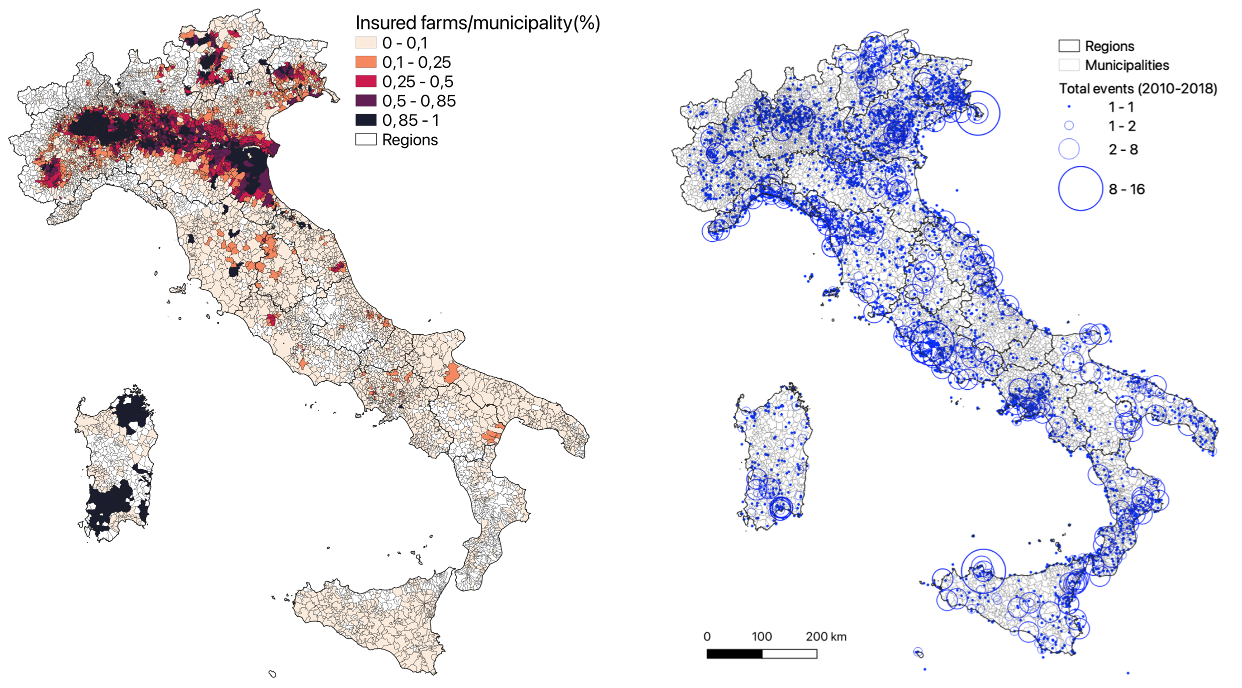


Figure 1: Geographical distribution of insurance take-up and extreme events

Notes: Panel (a) displays the geographical distribution in 2018 of the share of insured farms (in percentage of the number of farms active in 2010 and capped at 100%). Panel (b) shows the geographical distribution of the count of extreme events that we consider in the analysis. These include large hail, heavy precipitation and severe wind. Source: authors' elaboration based on *SicurAgro* data, Istat's 2010 Agricultural Census, and ESWD data.

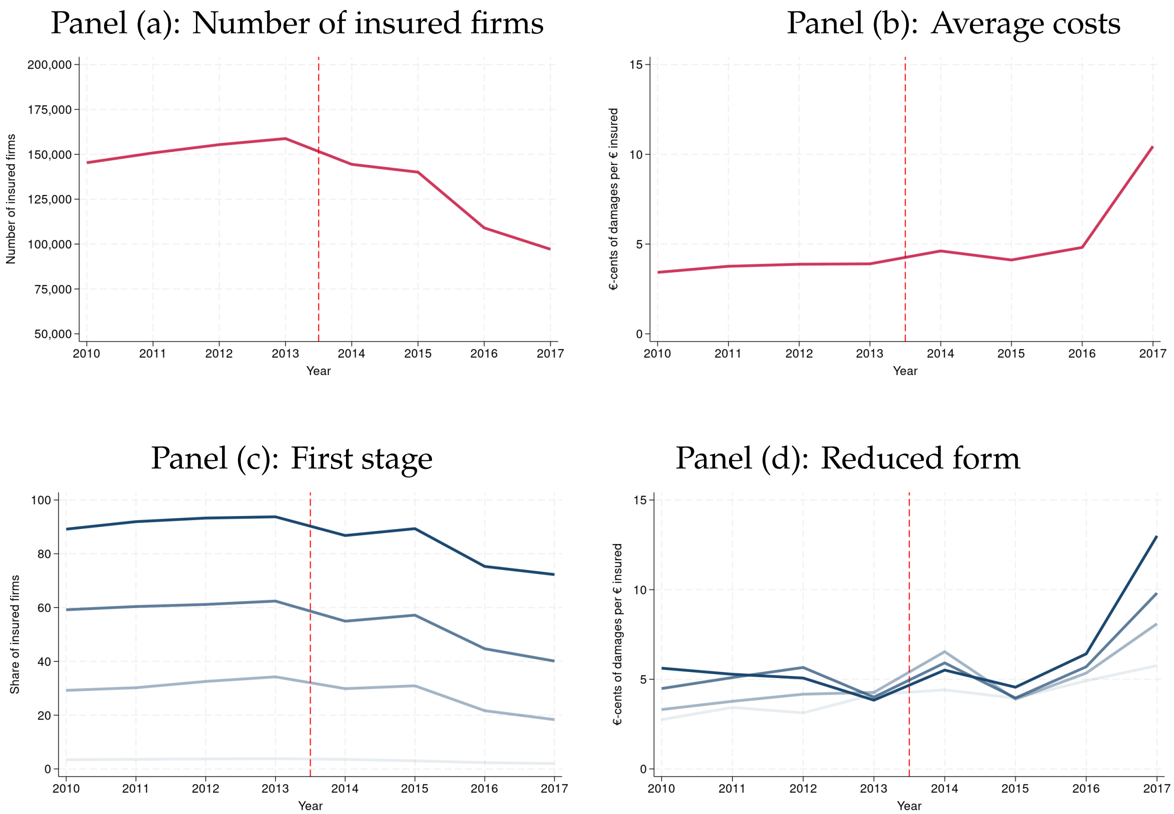


Figure 2: Graphical representation of the adverse selection test

Notes: The Figure reports the evolution over time in the number of insured firms (Panel (a)) and the ratio between total damages and total insured values (Panel (b)). Panel (c) and (d) report respectively the average share of insured firms and insurers' average costs for four groups of municipalities defined based on the 2013 share of insured firms. The groups (in terms of 2013 share) are: (i) [0,25%), (ii) [25%,50%), (iii) [50%,75%), and (iv) [75%,100%]. Darker colors represent a larger share. Averages across municipalities within each group are weighted by the number of agricultural firms in 2010, as from Istat's Agricultural Census.

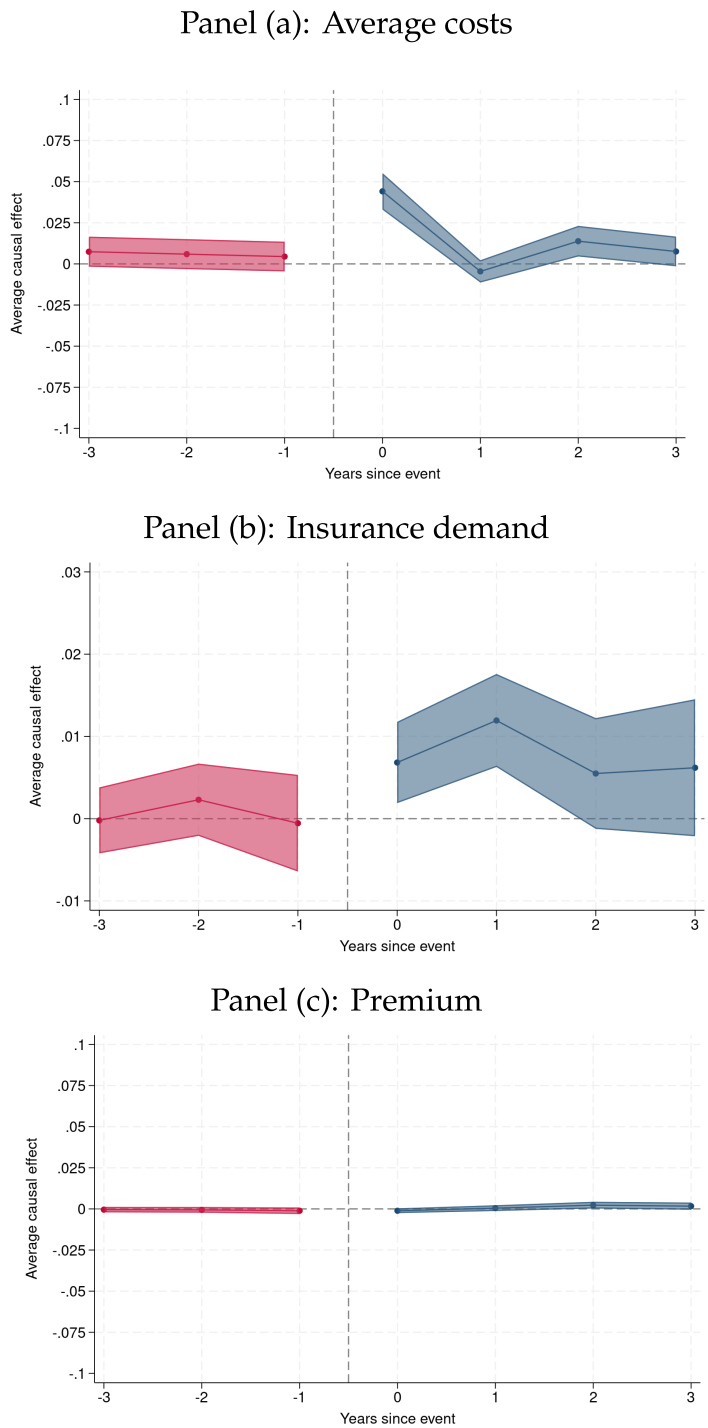


Figure 3: The effect of an extreme weather event on insurance claims, premia and demand

Notes: The figures show average causal effects of an extreme weather event on different outcomes. Panel (a), (b), and (c) report respectively the effects on average costs, insurance demand, and insurance premia. Average causal effects before and after the treatment are estimated in two separate regressions, using the "imputation" estimator by Borusyak et al. (2021), as described in Section 5.a. Confidence intervals are at the 95% level. The estimator is run on a smaller sample in panel (a) and (c) as these outcomes are only defined when the insured value in a municipality × year observation is different from zero.

8 Tables

Table 1: A test for the presence of adverse selection – 2SLS estimates

	Δ average costs for insurers (€-cents of damages per € insured)			
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Panel (a) : Main equation estimates. 100 × Δ share of insured firms				
2014	-0.105	-0.0920	0.111	0.112
	(0.0835)	(0.0846)	(0.0947)	(0.0950)
2015	-0.0558	-0.0490	-0.00304	-0.00271
	(0.0654)	(0.0654)	(0.0552)	(0.0553)
2016	-0.0389	-0.0324	-0.0413*	-0.0405*
	(0.0272)	(0.0279)	(0.0214)	(0.0214)
2017	-0.227***	-0.231***	-0.112***	-0.112***
	(0.0243)	(0.0243)	(0.0232)	(0.0232)
Panel (b) : First stage estimates. Share of insured firms in 2013				
2014	-0.0654***	-0.0654***	-0.0578***	-0.0575***
	(0.0107)	(0.0107)	(0.0108)	(0.0108)
2015	-0.0647***	-0.0649***	-0.0886***	-0.0886***
	(0.00651)	(0.00654)	(0.00717)	(0.00717)
2016	-0.223***	-0.222***	-0.244***	-0.243***
	(0.0123)	(0.0123)	(0.0128)	(0.0128)
2017	-0.291***	-0.290***	-0.315***	-0.315***
	(0.0118)	(0.0118)	(0.0127)	(0.0127)
Panel (c) : First stage K-P F statistics				
2014	37.19	37.26	28.51	28.27
2015	98.83	98.65	153.0	152.6
2016	327.4	325.9	359.9	359.8
2017	607.7	604.3	613.4	613.6
Observations	5,207	5,207	5,207	5,207
Growth controls	NO	YES	NO	YES
Region FE	NO	NO	YES	YES

Notes: The table presents OLS and 2SLS regressions of the change in claims per € insured against the change in the share of insured firms. The share of insured firms is defined as the number of insured firms in a given municipality-year divided by the number of agricultural firms in the same municipality in 2011, taken from the Agricultural census. Regressions are run in long difference between the post-reform (2016-2017) and pre-reform (2011-2012) years and weighted by the number of agricultural firms in 2011. A negative coefficient indicates the presence of adverse selection. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Average causal effects of the analysis on frictions

	Average costs (1)	Insurance demand (2)	Premium (3)
Panel (a) : Baseline estimates			
Average effect	0.0155***	0.00761***	0.000791
	(0.00286)	(0.00262)	(0.000728)
Panel (b) : Heterogeneous effects by baseline coverage			
Municipalities with below median coverage	0.0102**	0.0131***	0.00181
	(0.00417)	(0.00262)	(0.00116)
Municipalities with above median coverage	0.0195***	0.000830	0.00000457
	(0.00365)	(0.00456)	(0.000825)
Panel (c) : z-test on the equality of effects by baseline coverage.			
z-stat	-1.753	2.424	1.337
p-value	0.0796	0.0154	0.181
Observations	25,732	34,405	25,732

Notes: The table presents average causal effects of an extreme weather event on average costs (column 1), insurance demand (column 2), and insurance premia (column 3). Panel (a) reports the average treatment effect on the treated; panel (b) reports heterogeneous effects depending on whether insurance coverage in 2010 was above or below the median of the distribution; panel (c) reports a z-test for whether the difference in treatment effects for municipalities above and below the median is statistically significant. All of the effects are computed by using the "imputation" estimator by Borusyak et al. (2021), as described in Section 5.a. Standard errors are clustered at the municipality level, while confidence intervals are at the 95% level. The estimator is run on a smaller sample in panel (a) and (c) as these outcomes are only defined when the insured value in a municipality × year observation is different from zero. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A1 Additional details on the institutional setting

A1.a Historical background

Traditionally, Italian agricultural policy distinguishes risk-management tools in *ex post* and *ex ante*. The initial forms of government interventions aimed at supporting agricultural firms in the face of adverse weather shocks, dating back to the 1970s, mostly adopted an *ex post* approach. For this purpose, the government created a National Solidarity Fund (FSN). These interventions were triggered through special Ministerial and Regional decrees, recognizing the exceptional nature of the event, subsequent to the filing of claims by the regions.[25] However, *ex post* measures turned out to be very costly for public finances and also not consistent with European rules on State Aid. A shift of focus towards *ex ante* interventions thus occurred with Legislative Decree No. 102/2004, which introduced very generous subsidies (up to 80% of the premium) for the purchase of insurance contracts against adverse weather events. This marked the start of the *ex ante* approach.

After discussions started in 2005, risk management tools have entered the CAP in 2010.[26] These tools gained even greater significance in the 2014-2020 CAP. The 2013 agreement on CAP reform involved a comprehensive revision of the policy to achieve a more integrated approach across its various pillars. This change in orientation aimed to address the complex challenges of environmental sustainability and rural development.

Sustainable agriculture indeed represented a key objective of the new 2014-2020 Common Agricultural Policy (CAP), with the policy's approach shifting from a 'producer support' to a 'land-oriented' perspective. An important novelty was that the risk management was no longer financed through direct payments[27] as it was in the old CAP 2010-2014, but it was now part of the II Pillar. In terms of economic allocations, the new Common Agricultural Policy (CAP) allocates a total of 380 billion euros, with nearly 75% of this amount designated for direct payments and market-related expenditures (Pillar I), and the remaining 25% for rural development (Pillar II).[28]

A major change in the CAP framework is *greening*, which is directed to the provision of

[25] Art.2 L. 14 febbraio 1992, n. 185

[26] Art. 68 Regulation No. 73/2009

[27] Art. 68 reg. 73/2009)

[28] At 2011 constant prices. Source: https://www.europarl.europa.eu/factsheets/it/sheet/104/la-politica-agricola-comune-in-cifre

environmental public goods. Moreover, the new CAP also offers more responsive safety net measures and strengthens the EU's capacity for crisis management through new and powerful measures aimed at increasing market efficiency to deal with potential threats of market disturbances. In this respect, the second pillar offers a new risk-management toolkit including insurance schemes for crops.

A1.b Subsidized insurance

Subsidized insurance targets specifically (qualitative and quantitative) yield losses and envisages four combinations of insurable contracts: all perils (A), catastrophe and at least one frequent peril (B), at least three frequent perils, and a maximum of two among additional adversities (C), all types of infrequent perils (D). The insurance covers damages that result in a realized yield loss above 30% (deductible) of the historical yield, the latter being calculated as an average over three or five years, excluding the years with the minimum and maximum production.

The application process has been simplified since 2015 with the introduction of the new Risk Management System (Sistema di Gestione del Rischio, SGR hereafter)[29]. Farmers have to send their expression of interest before the plantation season which varies between late May and early July, depending on the crop insured. After the expression of interest, eligible farmers need to fill an Individual Insurance Plan (PAI) which defines the insurance contract and includes the historical yields on which the compensation is calculated. The Plan enters the National Agricultural Information System (SIAN). Eligibility rules are based on a series of basic requirements: farmers must be active in the agricultural sector and must own an updated cultivation plan, on which all the cultivated areas must be well identified.[30]

Insurance contracts can be subscribed individually or collectively through defense consortia (*consorzi di difesa*). Even though the insurance market is characterized by a relatively high degree of competitiveness signaled by the existence of many private and cooperative players, as highlighted by Santeramo (2019), "the existence of defense consortia is symptomatic of asymmetric information among insurers and farmers".

To calculate the value of production to insure, the Ministry of Agricultural Policies and Forestry (MIPAAF) provides a yearly list with indications on the maximum insurable prices for each crop so as farmers can easily calculate the maximum insurable value multiplying the price provided by the Ministry by their yields. The Ministry offers also a "reference yield"

[29]Miniterial Decree 2/2015, Agricoltura 2.0
[30]Source: http://www.psrn-network.it/wp-content/uploads/2018/06/opuscolo_A5_web_final.pdf

for each crop to benchmark yields for new crops adopted by farmers and for which farmers do not have historical information.

A2 A variance decomposition of insurance demand

To provide additional suggestive evidence on the presence of frictions, we perform a variance decomposition to assess whether a large part of the variation in insurance take-up is unexplained by observables, and could therefore be due to frictions. This exercise is motivated by the insurance framework with frictions in Spinnewijn (2017), where the variation in insurance takeup is determined by variation in preferences, risk, and choice frictions. In this decomposition we consider three sets of factors: (1) weather-related variables, meant to capture risk; (2) municipality-level time-invariant characteristics drawn from the 2011 Italian Census, meant to capture preferences for insurance; (3) calendar year effects, meant to capture general trends in insurance purchases and the nation-wide effects of policy reforms; (4) 110 province dummies, meant to capture residual variation that varies over space but is fixed over time. This could capture either frictions or other preferences or risk measures that are left unspecified in our model. While we cannot be sure that our model is neither well-specified nor that it contains the whole set of relevant proxy variables for the latent concepts we want to capture, we try to err in the direction of *not* finding frictions by including a very large set of covariates that could be both indicative of preferences *and* frictions. In case the overall R^2 is still low, this is suggestive that frictions are present in this market. Concretely, we run OLS regression models of the kind:

$$\ln(1 + n_{it}) = x'_{it}\beta + z'_i\gamma + d'_p\delta + d'_t\theta + \epsilon_{it} \tag{5}$$

where $\ln(1 + n_{it})$ is the log of (1+) the number of insured firms in municipality i in calendar year t. x_{it} is a set of weather-related covariates that vary with with i and t.[31] z_i is a set of other municipal level time-constant characteristics drawn from the 2011 Census.[32] $d'_p\delta$ are province fixed effects and $d'_t\theta$ are time fixed effects.

Following Gibbons et al. (2014), we compute the "uncorrelated variance share" (UVS) of each group of covariates. It can be calculated as the increase in R^2 that occurs when that group of covariates is added, controlling for all the other ones.[33] Results are reported in Table A3. Perhaps surprisingly, we find that risk – as measured by the weather-related variables – can

[31]These include (from the Agri4Cast database of the European Commission): the minimum and maximum temperature in every month of the year, maximum wind speed in every month of the year and maximum precipitation in every month of the year.

[32]These are: population, population density, fraction of population older than 75, fraction of foreign-born population, foreign-born employment rate, mean family size, participation rate, NEET incidence among 15- to 29-year-old individuals, unemployment rate, fraction of employed in agriculture, fraction of employed in medium and high-skill occupations and level of schooling for individuals aged 15-19.

[33]Formally, the UVS of a variable d, controlling for other covariates x is:

only explain 2.4% of the overall variance in demand. Not much more can be explained by local covariates present in the 2011 Census and that are meant to capture preferences (and possibly a portion of frictions). Their explanatory power stands at 5.6%. Time effects can explain a very small portion of the overall variation (0.5%). The lion's share of the variance is instead captured by the province fixed effects (18.3%), but especially by the variance of the residual. By construction, this corresponds approximately to 73%. We take this as evidence that risk and preferences are not nearly enough in explaining insurance demand in Italy and that much of the variation is left unexplained. This could be indicative of frictions in the market.[34]

$$UVS(d,x) = R^2(\ln(n), x, d) - R^2(\ln(n), x) = \frac{RSS(\ln(n), x, d) - RSS(\ln(n), x)}{TSS(\ln(n))}, \tag{6}$$

where RSS is the residual sum of squares of the regression and TSS is the total sum of squares of the dependent variable.

[34]Results are similar when employing alternative variance decomposition techniques also discussed in Gibbons et al. (2014), such as the balanced variance share, the raw variance share and the correlated variance share.

A3 Appendix Tables and Figures

Table A1: Summary statistics

Variable	Obs	Mean	Std. Dev.	p10	p90
Insured value (€)	77,025	737,673.2	2,177,242	0	1,945,390
Claimed damages (€)	77,025	34,114.68	202,627	0	46,148.37
Total premium (€)	77,025	48,926.22	188,431.4	0	105,398.9
Number of insured firms	77,025	24.281	71.898	0	61
Purchased insurance	77,025	0.754	0.43	0	1
Claimed damages	77,025	0.364	0.481	0	1
Claimed damage per € insured	58,110	0.04	0.097	0	0.127
Average insured value	58,110	26,954.73	31,500.93	4,004.722	58,148.27
Premium per insured €	58,110	0.054	0.039	0.021	0.103

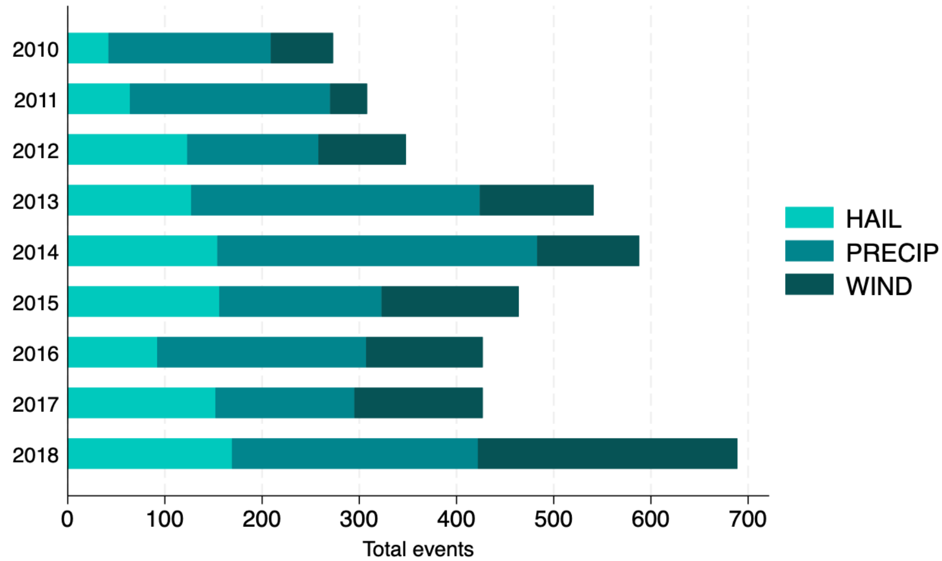
Note: The Table presents summary statistics for the analysis sample. The sample comprises only the municipalities that appear at least once in the database. The outcomes that have insured values or the number of insured firms in the denominator are computed on the set of municipalities that have at least one euro of insured values. Authors' elaboration on the *SicurAgro* database (2004-2018).

Table A2: The effects of different types of extreme events

	(1) Average costs	(2) Demand	(3) Premium
Large hail	0.0317***	0.0123**	0.000230
	(0.00499)	(0.00541)	(0.00124)
Heavy precipitations	0.00468	0.00410	0.00104
	(0.00372)	(0.00285)	(0.000920)
Severe wind	0.0111*	0.00876	0.00123
	(0.00595)	(0.00573)	(0.00160)
Observations	25,732	34,405	25,732

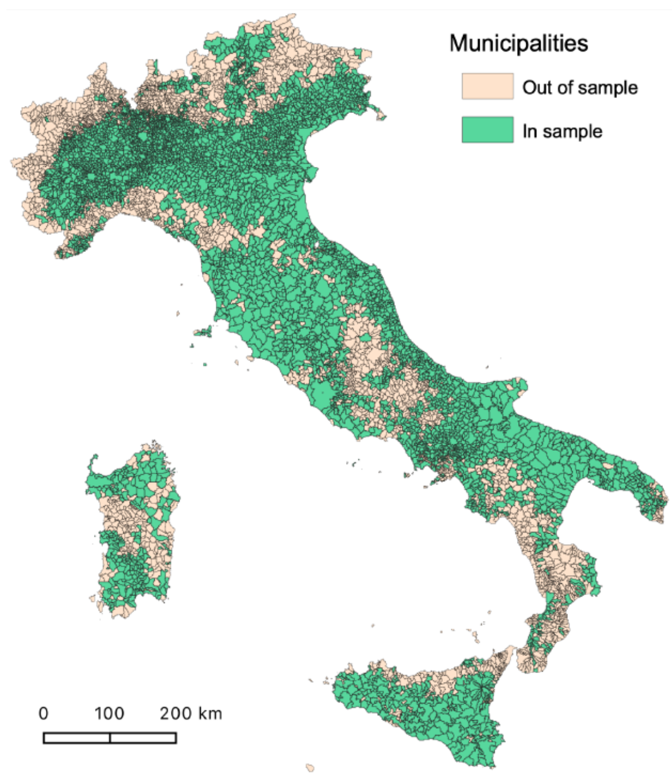
Notes: The table presents heterogeneous average causal effects of an extreme weather event on average costs (column 1), insurance demand (column 2), and insurance premia (column 3), by type of extreme event. All of the effects are computed by using the "imputation" estimator by Borusyak et al. (2021), as described in Section 5.a. Standard errors are clustered at the municipality level, while confidence intervals are at the 95% level. The estimator is run on a smaller sample in panel (a) and (c) as these outcomes are only defined when the insured value in a municipality × year observation is different from zero. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Number of yearly extreme weather events from 2010 to 2018



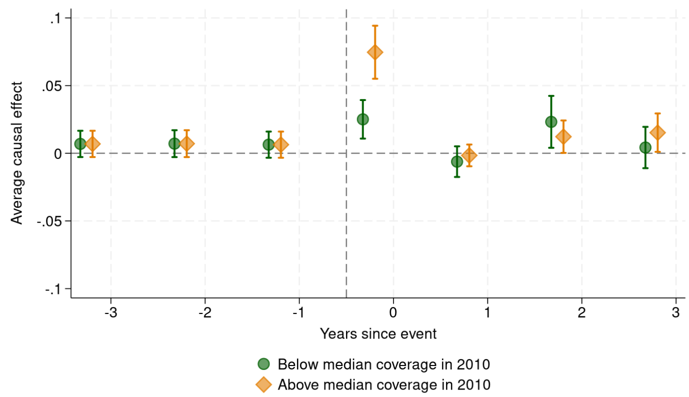
Notes: The figure displays the yearly count of weather extremes for different types of events. Source: own elaborations based on ESWD data.

Figure A2: Map of the Italian municipalities in the estimation sample

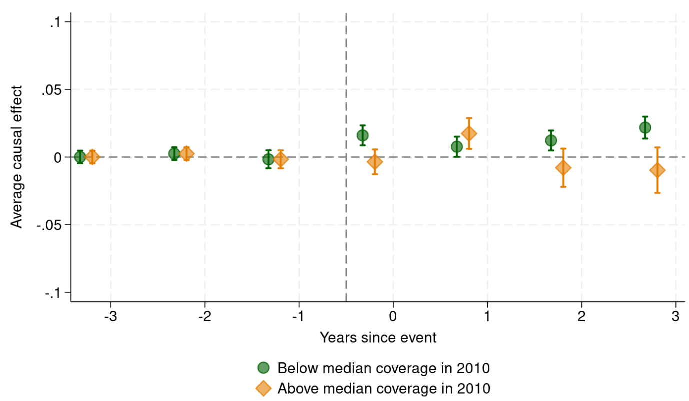


Notes: The figure displays the map of all Italian municipalities included in our main estimation sample (in green) and excluded because they never appear in the *Sicuragro* database (in orange).

Panel (a): Average costs



Panel (b): Insurance demand



Panel (c): Premium

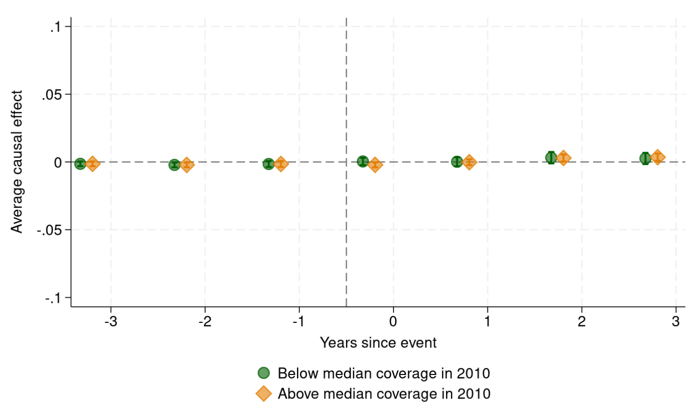


Figure A3: The effect of an extreme weather events: heterogeneity by initial take-up

Notes: The figures show average causal effects of an extreme weather event on different outcomes. Panel (a), (b), and (c) report respectively the effects on average costs, insurance demand, and insurance premia. Average causal effects before and after the treatment are estimated in two separate regressions, using the "imputation" estimator by Borusyak et al. (2021), as described in Section 5.a. Heterogeneous effects are obtained by averaging municipality-level treatment effects across the municipalities in each of the heterogeneity subgroups. Confidence intervals are at the 95% level. The estimator is run on a smaller sample in panel (a) and (c) as these outcomes are only defined when the insured value in a municipality $\times$ year observation is different from zero.

Table A3: Variance decomposition of log number of insured firms

	share
	(1)
Panel (a) : Variance share of the province effects	
UVS($\hat{\delta}$)	18.3%
Panel (b) : Variance share of the municipality characteristics	
UVS($\hat{\gamma}$)	5.6%
Panel (c) : Variance share of the weather variables	
UVS($\hat{\beta}$)	2.4%
Panel (d) : Variance share of the time effects	
UVS($\hat{\theta}$)	0.5%

Notes: The table presents uncorrelated variance shares (UVS) of different sets of covariates in a panel regression at the municipality-year level of the log number of insured firms on such sets of covariates. The UVS of a set of variables x is defined as the reduction in the residual sum of squares induced by the set, divided by the total sum of squares of the dependent variable. Municipality characteristics include: population, population density, fraction of population older than 75, fraction of foreign-born population, foreign-born employment rate, mean family size, participation rate, NEET incidence among 15-29 years old individuals, unemployment rate, fraction of employed in agriculture, fraction of employed in medium and high-skill occupations and level of schooling for individuals aged 15-19. Weather variables include: the minimum and maximum temperature in every month of the year, maximum wind speed in every month of the year and maximum precipitation in every month of the year.