Dance for the rain or pay for insurance? An empirical analysis of the Italian crop insurance market*

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Abstract

Despite the increased frequency of extreme weather events, the utilization of climate-related crop insurance contracts in Italy and other European countries remains low and highly heterogenous across areas. In this paper we investigate the economic factors characterizing low coverage rates by aligning administrative data on insurance purchases and subsequent damage claims at the crop-municipality level with 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 drive a wedge between the value for insurance and actual demand. In order to identify adverse selection, we leverage variation from a 2014 reform that lowered the cap for premium subsidies in all EU countries. As for frictions we investigate whether firms are more likely to buy insurance when faced with "salient" extreme events. Our main findings indicate that both adverse selection and choice frictions are present in this market. We conclude by discussing how current price subsidies may be less effective than mandates in this context.

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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. Recently, during the 26^{th} Conference of the Parties (COP) in Glasgow, the Secretary-General of the World Meteorological Organization has declared that climate extremes[1] such as heatwaves, flooding, hailstorms and drought are becoming the "new norm".[2] As a stable weather is a key input for plant growth, the increased frequency of very adverse weather conditions is expected to severely affect the agricultural sector, depleting firms' physical capital and reducing land productivity (Wang et al., 2017; Dell et al., 2014).

Despite this, farmers' propensity to rely on insurance schemes that transfer part or all of such risks to a third party, is highly heterogeneous across areas and remains low in many European countries (Santeramo and Ford Ramsey, 2017). This is puzzling because, conditional on subscribing insurance, the benefits of a coverage against extreme weather events among agricultural firms have been largely documented (Cole and Xiong, 2017).

One common hypothesis for why insurance coverage could be low is that buyers and sellers of insurance have asymmetric information on risk and its consequences. When insurers cannot price-discriminate based on expected costs, 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 and inefficiently high equilibrium prices (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 has to offer 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). Both adverse selection and choice frictions are of practical importance in other insurance markets and create the scope for specific types of government interventions.

In this paper we test for the presence of both of these failures in the market for crop insurance, and discuss their policy implications drawing from the recent theoretical literature on selection markets. Our empirical analyses rely on administrative data on insurance coverage, premia and damage claims for all Italian municipalities, and on a high-resolution database

[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.

of extreme weather events. Together with Spain, Italy is the largest European crop insurance market, which makes it an interesting case study (Santeramo and Ford Ramsey, 2017).

In order to identify adverse selection in the data, we exploit a 2014 EU-wide reform (Article 37 of Regulation No. 1305/2013) that lowered the cap to government premium subsidies from 80% to 65% (of the premium), inducing sudden and exogenous price variation. Following a long tradition in the literature on insurance markets[3], we exploit the plausibly exogenous variation in price to estimate the slope of the average cost curves for insurers i.e. what are the expected damage claims as a function of the share of covered firms. We uncover a negatively-sloped average cost curve, which is indicative of adverse selection, as the farmers who have higher willingness to pay end up claiming more damages and costing more to the insurers (Einav et al., 2010a).

The direct identification of choice frictions is way more challenging. In order to identify choices that are inconsistent with true preferences, one would need to know what utility function the agent is maximizing. Absent this information, we cannot but rely on an indirect test. Concretely, we study the evolution of demand for insurance around salient extreme weather events, in a staggered difference-in-differences framework. Absent frictions, specific *realizations* of extreme events should not impact demand, which should only vary with the underlying climate risk distribution. Risk, and not realizations of this risk, should matter in practice. Yet, our results point in the opposite direction: the number of insured firms responds sharply to the occurrence of extreme events, in a way that cannot be rationalized by underlying changes in risk, as the climate changes slowly. We take this as evidence that farmers are imperfectly informed about the value they assign to insurance contracts, or at least that they do not act upon this information, creating a wedge between value and demand.

We make several contributions to the literature on crop insurance markets and more in general on the importance of choice frictions in insurance markets with asymmetric information. First, the paper relates to the extensive literature documenting selection in these markets. Previous contributions have mostly focused on health insurance (Einav et al., 2010a; Hackmann et al., 2012; Einav et al., 2013), although other contributions have also emerged in the market for automobiles (Chiappori and Salanié, 2000; Dionne et al., 2013) or annuities (Einav et al., 2010c). The closest – yet distinct – setting to ours is house insurance against natural disasters such as hurricanes (Wagner, 2021). To the best of our knowledge, we are the first to test for the presence of adverse selection in the crop insurance market using plausibly exogenous and quasi-experimental price variation. Earlier studies on this type of markets relied on regression adjustments to estimate the relation between price, demand and cost

[3] See Einav et al. (2010b) for a survey.

(see e.g. Just et al. (1999); Makki and Somwaru (2001)).

Second, we contribute to a recent literature highlighting the role of choice frictions in insurance markets. Recent empirical work has highlighted the role specific behavioral frictions such as inattention (Chang et al., 2018a), inertia (Handel, 2013), underestimation of risk (Barseghyan et al., 2013), but also of 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 famers, especially in developing countries (Cole et al., 2017). Although we do not shed light on the particular friction present in this market, we document their presence, which has direct welfare implications.

The Italian crop insurance market has already been studied by Santeramo et al. (2016), who find that geographical location, firm size and profitability are important predictors of insurance demand and, more recently, by Porrini et al. (2019) who use region-level data to show that insurance reimbursements have a positive impact on profitability. Yet, we are the first to systematically study this insurance market by explicitly considering the sources of market imperfections.

In the last part of the paper, we provide some qualitative policy recommendations. The subsidization of insurance premia in EU countries is widespread. Crop insurance policy has indeed been part of the Common Agricultural Policy (CAP) since 2010 and many European countries offer large subsidies – co-financed by the EU – to incentivize its use (ISMEA, 2018). Based on our empirical results, choice frictions seem to be severe in climate insurance markets. This generates potentially large welfare losses even in the presence of moderate adverse selection.

In the presence of choice frictions, the demand side of the market is less responsive to price signals. Therefore price subsidies – the most used policy at the moment – are less effective as a tool to incentivize demand and attenuate adverse selection. For this reason, it might be reasonable to evaluate *mandates* as an alternative policy tool. Costs and benefits of mandates should be evaluated carefully. When all firms in a market are forced to buy insurance, there is no adverse selection, but the allocation is still inefficient compared to the first best: transactions occur also for firms for whom the marginal cost of insuring is above the private value of insurance. In absence of micro-level data on firms, which would allow us to estimate the slope of the observed demand curve and a more precise measure of choice frictions, we leave a quantitative comparison of subsidies and mandates to further research.[4]

[4]The Italian Budget Bill for 2022 has introduced a National mutual fund for the coverage (of agricultural firms) against adverse weather events. In the future this could be used to introduce a mandate in this market.

The rest of the paper is structured as follows. In Section 2 we describe a conceptual framework that guides our empirical analysis and our policy suggestions. In Section 3 we describe the institutional setting. In Section 4 we describe the data and how we build our main variables of interest. In Section 5 we present our methodology and results on adverse selection. In Section 6 we do the same for choice frictions. In Section 7 we discuss our findings and policy suggestions, while in Section 8 we conclude.

2 Conceptual framework

In this section, we outline a conceptual framework that guides our empirical analysis and our policy discussion. We draw our considerations from the canonical model of insurance markets with selection (Einav et al., 2010a), as extended by Spinnewijn (2017) and Handel et al. (2019), who allow for choice frictions on the demand side.

The model allows for a separation between the *revealed* value of insurance and the *true* value of insurance. The revealed value measures the price that a firm is willing to pay for insurance: any contract whose price is below this value will be purchased. Ordering firms on the basis of their revealed value determines the "observed" demand curve, which is employed in the canonical insurance framework to evaluate the welfare costs associated with adverse selection. In the extended model, however, the revealed value of insurance can differ from the *true* value of insurance, which is the welfare-relevant measure of the willingness to pay for insurance contracts.[5] Importantly, a true value curve must stem from a correct risk assessment. The revealed and true value can differ in two meaningful ways, as illustrated in Figure 1. First, although on average firms have correct evaluations of their true willingness to pay, some might overestimate it, while others might underestimate it. This results in a tilted and steeper revealed demand function relative to the true demand curve (Panel A). Second, firms might underestimate on average their true willingness to pay, which results in a left shift of the revealed demand function relative to the true one (Panel B). Several reasons might explain the wedge between the two curves. We refer to them as "choice frictions", encompassing information frictions, and wrong risk assessments among others. Crucially, a partial – although rational – knowledge of weather risk is considered a friction in our framework since it reduces/increases the willingness to pay for insurance contracts relative to the one that would prevail with a correct risk assessment.

[5]The true value of insurance incorporates all frictions that might influence the willingness to pay, but that are taken as given in the welfare evaluation of the insurance market. One example is liquidity constraints that are often a feature of the economy, but whose solution is beyond the purpose of the analysis of insurance markets and therefore are not considered a friction in this context.

The supply side of the market features perfectly competitive insurers that cannot perfectly observe farmers' characteristics and risk. The notion of asymmetric information in this context might be less easy to understand relative to the one prevailing in other markets e.g. health insurance. Since climate events and their distribution are observed by both the insurance company and agricultural firms, one might wonder why asymmetric information is a problem at all. However, risk in this model is plausibly linked to heterogeneous abilities of firms to deal with extreme weather events. For example some firms may be able to choose more resilient varieties for their crops or build infrastructures such as nets that protect their produce from weather adversities. Alternatively, insurance companies might not be able to condition their pricing strategies on enough observable characteristics that would allow to target specific geographical subregions. If this was the case, there would be heterogeneity in climate risk within the population of farmers that are offered the same contract. As a consequence of asymmetric information, insurers cannot price-discriminate based on the risk type of each firm and must charge a unique price for the contract. In order to break-even on average, insurers set the competitive price equal to the average expected costs among those buying insurance. Pricing at average cost rather than marginal cost (*i.e.* the cost of the marginal firm buying insurance) is the defining characteristic of selection markets. Whenever riskier firms are those willing to pay more for insurance, the average cost of those insuring at any given price is larger than the average cost for the uninsured and the market suffers from adverse selection. This selection generates a downward-sloping average and marginal cost curves as those illustrated in Figure 1 Panel C and D.

The welfare cost from adverse selection is measured by the total aggregate surplus that is lost because some socially desirable transactions do not occur due to the presence of asymmetric information. In particular, these are the transactions in which the willingness to pay of the firm is above the marginal cost of insurance for the insurer. Canonical sufficient statistics models quantify this welfare cost using an estimate of the area between the revealed demand curve and the marginal cost curve between the realized equilibrium demand ($s(p')$ in Figure 1) and the socially optimal demand ($s(p^\star)$). Figure 1 Panel C and D shows, however, that in the presence of choice frictions generating wedges between true and revealed values such as those described above, the cost of adverse selection is amplified. The reason is that the equilibrium share of firms that buy insurance is further below the socially optimal level relative to the frictionless world. It follows that there are more transactions that do not occur because of asymmetric information, but for which the value for the firm would be larger than the marginal cost of providing insurance. It is therefore important to establish the presence of choice frictions in order to evaluate the welfare costs of asymmetric information in a market.

In this paper, we run two sets of exercises. First, we exploit quasi-experimental variation in prices to establish the presence of adverse selection. Relying on our conceptual framework, we know that any price decrease should cause a decrease in average costs in the presence of adverse selection. Hence, we study the response of insurance costs to a reform that changed price subsidies in the market for insurance against adverse weather events. Second, we exploit area-specific extreme weather events to establish the presence of choice frictions. The test relies on the idea that if true and revealed values coincide, a firm should not respond to a single realization of the risky event. Indeed, the true value of insurance already embeds the correct risk perception. Hence, a non-null demand response to an extreme events is indirect evidence of the presence of some choice frictions.

3 Institutional setting

3.a Historical background

Traditionally, Italian agricultural policy distinguishes risk-management tools in *ex post* and *ex ante*. The first forms of government interventions aimed at supporting agricultural firms in face of adverse weather shocks, dating back to the 1970s, mostly followed an *ex post* approach. For this purpose, the government created a National Solidarity Fund (FSN). Such *ex post* interventions were activated with special Ministerial and Regional decrees that acknowledged the exceptionality of the event, after claims were filed by regions.[6] *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.[7] These tools acquired even more importance in the 2014-2020 CAP. The new agreement on CAP reform reached in 2013 consisted of a complete revision of the policy to obtain a more integrated approach across the different pillars. The change in the orientation aimed to address the complex challenges of environmental sustainability and rural development.

Sustainable agriculture represented a key objective of the new 2014-2020 CAP and the approach of the policy moved from a "producer support" to a "land-oriented" approach. An

[6] Art.2 L. 14 febbraio 1992, n. 185
[7] Art. 68 Regulation No. 73/2009

important novelty was that the risk management was no longer financed through direct payments (Art. 68 reg. 73/2009) as it was in the old CAP 2010-2014, but it was now part of the II Pillar. In terms of economic efforts, the new CAP provides a total amount of 380 billion euros, with nearly 75% of this amount foreseen for direct payments and market-related expenditure (Pillar I), and 25% for rural development (Pillar II).[8]

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

Currently, the agricultural insurance market in Italy is economically relevant, consisting in about 7 billion euro with a public expenditure of about 400 million euro/year. Nearly 80% of the subsidized contracts are financed by the European Commission. This implies an average expenditure of 25 euro/hectare and 215 euro/farmer (ISMEA, 2018). Since its introduction, the insurance market has been characterized by a high degree of concentration as – in terms of insured crops – grape, apples, corn, rice and tomatoes absorb nearly 70% of the total national insured value. At 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. Overall, the policy take-up is relatively weak as subsidized farmers represent only 19% of the total gross production and 9% of the total agricultural lands.

3.b Subsidized insurance

Depending on the type of impact on production and frequency, subsidized insurance covers three distinct categories of adverse events: catastrophes or infrequent perils (drought, ice formation and flood), frequent perils (hail, excess snow, excess rain, extreme wind) and additional adversities, also known as *garanzie accessorie* (hot wind and temperature fluctuations)[9]

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

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

[9]Source: Mipaaf, PAAN (2015)

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)[10]. 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.[11]

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".

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

In our setting, a key feature of the agricultural insurance policy is represented by the amount of premium that is publicly subsidized for damages caused by adverse weather events. This was initially set at 80% of the premium price, but in 2014 the EU Regulation no. 1305/2013 introduced a lower cap of 65% of the insurance premium due.[12] It is the discontinuity in the subsidized price occurred in 2014 that allows us to run an explicit empirical test for the presence of adverse selection in the Italian insurance market (see Section 5).

[10]Miniterial Decree 2/2015, Agricoltura 2.0

[11]Source: http://www.psrn-network.it/wp-content/uploads/2018/06/opuscolo$_A5_web_final.pdf$

[12]The cap was further modified to 70% in 2018

4 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 providing services to the agricultural sector. The data spans the 1998-2018 time window and has information on insured values, number of insured firms (since 2004), premia and costs at the crop $\times$ municipality level.[13] Ideally, we would like to restrict our analyses to the set of municipalities where the crops are cultivated. Unfortunately, we do not know of any database at the crop $\times$ municipality $\times$ 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 a positive insured value at least during one year. Our restricted sample considers 5,135 municipalities out of 7,954.[14] In order to obtain a crude 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 2011 Agricultural Census. Figure 5 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 much higher in the Po Valley, with peaks of 100% in some areas. This is not surprising as the Po Valley is densely populated of farms adopting intensive agriculture and accounts for more than one third of national agricultural production. We present summary statistics for all the relevant variables from this dataset in Table 1. (Angelini et al., 2010).

The use of this dataset in the literature is scant. A few papers use *SicurAgro* to provide aggregate statistics for the Italian crop insurance market, but it has rarely been used for conducting economic research. The only contribution we are aware of is Fusco et al. (2018), who use province-level data for the period 2004-2011 to correlate weather variables and insurance coverage and premia.

Environmental data — We align the Sicuragro database with data on extreme weather events. Extreme weather information come from the European Severe Weather Database (ESWD, henceforth), which are provided by the European Severe Storms Laboratory, and consist of a collection of several types of climate extremes: tornado, severe wind, large hail, heavy rain, funnel cloud, gustnado, lesser whirlwind, heavy snowfall/snowstorm, ice accumulation, avalanche and damaging lightning. For each event we have information on the

[13]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 collapse everything at the municipality level and ignore this dimension.

[14]The list of municipalities is uniform and defined as on 30th of June 2018.

exact geographical location and time, along with an indicator of report status as a measure of event reliability, which assumes four values: GC0 (as received), QC0+ (plausibility check passed), QC1 (report confirmed by reliable source) and QC2 (scientific case study). We restrict the data to severe wind, large hail and heavy rain, and to events classified as QC2 and QC1. Moreover, since reporting rates can change over time and early reporting period are more likely to be underrated due to limited reporting network, we consider events reported since 2010.[15] The advantage of using the ESWD data is that they allow to exactly identify the specific weather shocks that hit the municipality, disentangling the effect of simple rainfall precipitation and a heavy hailstorm. This is a key feature in our setting since some crops can be strongly affected by hail and not affected by rainfall. Our baseline shock measures consist in a set of dummy variables calculated for each event-date-municipality combination. Extreme weather events have been growing during the last ten years. Figure 4 shows the number of extreme events considered in the analysis by year. The increasing trend is particularly pronounced for large hail and extreme wind, while excess rain seems to follow a more erratic pattern. Yet, considering that – on average – nearly 1,000 extreme events occur each year, Italy appears as a particularly exposed country in relation to climate change.

Figure 6, 7 and 8 show the geographical distribution of extreme hail, wind and rain events respectively that occurred in the Italian municipalities included in our sample. All of the three categories of extreme events display the same spatial pattern, with a high concentration of events in the Northern municipalities, especially in the regions of Piemonte, Lombardia and Veneto, which are in between the Alps and the Po Valley.

5 Testing for adverse selection

As described in Section 2, an insurance market is adversely selected when the marginal and average cost curves are downward sloping. Intuitively, adverse selection arises when firms that have higher willingness to pay are also costlier to insure and such differences in costs cannot be priced by insurers. As discussed in Section 2, adverse selection might appear not to be an issue in the context of climate risk since climate events are observed by both insurers and farmers. For this reason, in our application the concept of risk is linked to the ability of firms to cope with extreme events.[16] If the farms that are better in dealing with

[15] The European Severe Storm Laboratory (ESSL) acknowledges that: “ESWD data is not exhaustive. The rate at which events are recorded in the ESWD generally varies for non-meteorological reasons from country to country and between hazard types. Reporting rates can also change over time.”

[16] Alternatively, it might be related to the inability of insurers to tailor contracts to specific subgroups of the firms population, which generates dispersion in climate risk in the population of farms that are offered a given

extreme events are less likely to buy insurance as a consequence of their investments and this difference in risk is not incorporated in premia, adverse selection may arise.

The ideal experiment to test for the slope of the average cost curve is to randomly assign offer insurance prices to different firms and check whether firms facing higher offer prices end up claiming more damages (Einav et al., 2010a).[17] Although we cannot generate this type of ideal variation in the data, we try to mimic it by exploiting a large nation-wide price change occurring in 2014 after a reform decreased the maximum subsidy that the government provided to insured firms from 80% to 65% of the premium (Article 37 of EU Regulation 1305/2013). The price variation induced by reform had a large effect on demand, which is clearly visible also in the aggregate data. In Figure 2 we show that in 2014 – the first post-reform year – the total number of insured firms decreased from a peak of ≈ 160,000 firms to ≈ 100,000 firms i.e. a 37.5% decline.[18] Firms that remain insured even after an increase in the effective price must have higher willingness to pay for insurance by construction. In the presence of adverse selection, this set of firms should be costlier to insure and so average costs should rise in the years following the reform. In Figure 3 we see that average costs slightly increase around the year of the reform compared to their pre-trend, which could be indicative of adverse selection.

We test these ideas more formally by using the sharp price variation induced by the reform in two different empirical strategies. First, we present clear non-parametric estimates of the average change in demand and insurers' costs in Italian municipalities around the year of the reform. Since both demand and costs were trending in the years before the reform, we first residualize outcomes against a linear trend using pre-reform data, and then show "event-study"-like graphs based on residualized outcomes (similarly to Gruber et al. (2021)). We show graphically that this approach performs well in absorbing underlying trends. We interpret any difference in outcomes between the post-reform years and the last pre-reform year as the causal effect of the reform. The credibility of our design relies on the absence of other confounders that are not absorbed by the pre-reform linear trend and occur around 2014. In other words, our identification assumption is that absent the reform, outcomes would have followed the underlying trend that we observe before 2014. The flat outcomes in the pre-reform years and the sharp changes in demand that we observe exactly around the year of the reform lend credibility to our research design.

More in detail, we proceed in two steps: first, we first regress outcomes Y_{it} on a constant and

contract.

[17]Crucially, this price variation must be orthogonal to unobserved drivers of demand.

[18]This corresponded to a 25% decline in insured values.

a linear time trend $\theta_1 \cdot t$ using data on the 2010-2013 (pre-reform) period. Then we regress residualized outcomes $\widetilde{Y_{it}}$ against year dummies as follows:

$$\widetilde{Y_{it}} = \alpha_i + \sum_{k \neq 2013} \beta_k \cdot \mathbf{1}(t = k) + \epsilon_{it} \tag{1}$$

where α_i are municipality fixed effects and $\mathbf{1}(t = k)$ are calendar year dummies ranging from 2010 to 2017. The 2013 dummy is omitted for multicollinearity reasons and constitutes the reference category. The coefficients of interest β_k can be interpreted in deviation from the 2013 average, net of the pre-reform linear trend. The regression is run on a balanced yearly panel of municipalities ranging from 2010 to 2017. When using average costs as a dependent variable, the regression is run on the subsample of observations where insured values are strictly positive. We cluster standard errors at the municipality level to avoid well-known serial correlation issues (Bertrand et al., 2004).

Our graphical results are displayed in Figure 10 and 10. The figures show the estimated effects from equation 2 on the share of insured firms and the average costs, where the effect in year 2013 has been normalized to zero. The share of insured firms is defined as the number of insured firms in a given year t divided by the number of agricultural firms operating in the same municipality, according to the 2011 Agricultural Census. Average costs are defined as claimed damages per Euro of insured value. We see that the outcomes are flat in the pre-reform years, as the linear trend captures all of the underlying variability. After 2014, demand drops sharply although with some inertia, in a continuous way up to 2017.[19] Our estimates indicate that in 2017 the average share of insured firms is 12.2 p.p. lower than it would have been absent the reform. Given that the average share of insured firms was 28% in the pre-reform years (2010-2013), this corresponds to a 44% decline over a five-year horizon. Corresponding changes in costs are not as visible from the reduced-form estimates. In order to benchmark the change in cost that emerges after the demand drop induced by the reform, we run an IV regression where we rescale the changes in average costs by the change in the share of firms causing it. Specifically, we run the following regression:

$$\widetilde{C_{it}} = \delta_i + \gamma_1 \cdot \widetilde{S_{it}} + u_{it} \tag{2}$$

where δ_i are municipality fixed effects; $\widetilde{C_{it}}$ are (residualized) average costs and $\widetilde{S_{it}}$ is the (residualized) share of insured firms. The latter is instrumented by year dummies $\mathbf{1}(t = k)$

[19] In 2018 a reform changed again the cap to subsidies in the opposite direction, stimulating demand.

with $k = 2010, ..., 2017$ (2013 is omitted). The identifying assumption behind this rescaling exercise is that calendar year dummies have an effect on *residualized* average costs only through changes in *residualized* demand. Given that pre-trends are relatively flat before the reform, we think this is a reasonable assumption to make and it leads us to an estimate of the slope of the average cost curve γ_1. A negative coefficient is indicative of the presence of adverse selection. We report results in Table 2. In Panel (a) we report OLS and 2SLS estimates of the effect of the share of insured firms on average costs. The corresponding first-stage estimates are reported in Panel (b), together with Kleibergen and Paap (K-P) F-statistics. The first stage estimates replicates the event-study pattern in Figure 10, with economically sizable effects after 2013. The K-P F-statistic is indicative of a strong first stage and rule out weak instrument issues. The OLS estimate in column (1), which we report as a benchmark, indicates that a 10 p.p. increase in the share of insured firms is associated with a decline in average costs of 0.3 €-cents. The 2SLS estimates, reported in column (2) show a slightly larger effect of half a €-cent. Since the average damage claim per € insured was equal to ≈ 4 cents during this period, the 2SLS estimate indicates that the impact of a 10 p.p. change in the share of insured firms would translate into a 12.5 percent decline in costs. We interpret this result as evidence of adverse selection.

In order to provide some further evidence on adverse selection and to probe the robustness of our results we also carry out another empirical strategy. Our second empirical strategy exploits the fact that not all municipalities were equally affected by the reform, even if the same change in the subsidy cap applied equally to all firms: areas where the share of insured firms was already low before the reform-induced price change mechanically faced a smaller change in demand around the reform years. To the contrary, areas with higher initial shares of insured firms have witnessed larger decreases in demand. In the presence of adverse selection, we expect changes in average costs to be greater in areas with larger demand swings occurring because of the reform. Contrary, if willingness to pay was unrelated to costs, we would expect areas to experience no change in average costs regardless of the size of the demand shock.

In order to test for this hypothesis, we use the 2013 share of insured firms in a given municipality as an instrument for the subsequent demand change between the pre-reform (2011-2012) and the post-reform (2016-2017) years.[20] The identification assumption is that municipalities that had higher take-up in the pre-reform years witnessed larger *exogenous* demand decreases that were uncorrelated with the future potential evolution of average costs. In order to rule

[20]This approach closely follows Deryugina and Konar (2017), who study the impact of insurance demand on water use. The same idea is applied in a slightly different way also in Hackmann et al. (2012).

out that our instrument captures underlying trends in the take up of insurance or costs at the municipality level, we also flexibly control for pre-trends by adding growth rates of the share of insured firms in previous years as controls. If our coefficient estimates are sensitive to the inclusion of these controls, then it is more likely that our results are biased by unobserved trends (Deryugina and Konar, 2017). Our first-stage equation takes the form:

$$\Delta S_i = \gamma + \delta_1 S_{i,2013} + \sum_t \theta_t \cdot \text{Growth}_{it} + \nu_i, \tag{3}$$

where ΔS_i is the change in the average share of insured firms between the pre-reform (2011-2012) and the post-reform (2016-2017) years. $S_{i,2013}$ is the share of insured firms in 2013, one year before the reform is implemented; Growth_{it} are the growth rates of the share of insured firms between years t and $t-1$ in the same municipality. We include growth rates going back to 2008. The second stage is:

$$\Delta C_i = \alpha + \beta \Delta S_i + \sum_t \lambda_t \cdot \text{Growth}_{it} + \epsilon_i, \tag{4}$$

where C_i indicates average costs. We run our specification as a single long difference, on a balanced panel of all municipalities that appear for at least one year in the *SicurAgro* data.[21]

We report results in Table 3. In Panel (a) we report OLS and 2SLS estimates of the effect of a change in the share of insured firms on average costs for insurers. The corresponding first-stage estimates are reported in Panel (b), together with Kleibergen and Paap (K-P) F-statistics. The first stage estimates have the expected sign and K-P F-statistics are always above conventional threshold levels. Municipalities with higher shares of insured firms witnessed larger decreases in demand in the following years. Across all specifications we find a negative and statistically significant effect on demand on costs, indicating the presence of adverse selection. Results are very robust to the inclusion of the growth controls (columns (2) and (4)), mitigating concerns that our results are driven by pre-existing trends. The coefficient associated with the ΔS_i variable in column (4), our preferred specification, indicates that a 10 p.p. increase in the share of insured firms is associated with a decrease in average costs of 0.3 Euro cents per insured €. Coefficients are in the same ballpark of those displayed Table 2, which probes the robustness of our findings.

[21] First-differencing absorbs time-invariant differences in the level of insurance coverage across municipalities. We take averages to take into account the possibility of mean reversion.

6 Testing for choice frictions

Testing for the presence of choice frictions is harder conceptually than testing for adverse selection: in order to argue that an agent is not maximizing an objective function, one must be able to observe such function (Allcott and Greenstone, 2012). Since we are unable to observe all the different benefits and costs related to insurance purchases and how these are weighted by different firms, we cannot but rely on *indirect* tests that aim at isolating frictions.

In a frictionless world, demand reflects the value that agricultural firms assign to insurance, which uniquely depends on the probability distribution of weather events, risk preferences and idiosyncratic risk. Absent changes in these primitives, demand should not respond to specific climate *realizations*. Demand responses after certain weather events would indicate that firms know their insurance value only imperfectly and thus that there exist a wedge between demand and value. Notice that choice frictions do not imply irrational behavior *per se*. Even if demand responses are the result of rational Bayesian updating about the climate, it is still true that demand does not reflect the welfare-relevant value for insurance.

In this section we provide a test for frictions by studying how demand measures change in response to extreme weather events. This test is similar in spirit to Chang et al. (2018b), who study the take up of health insurance in days with high air pollution. To do so we compare the evolution of these outcomes in municipalities that experience an adverse weather event and in those that do not. Our design exploits two sources of variation: (1) the cross-sectional variation in the probability of receiving an adverse event (2) the timing variation in the exact year the adverse shock hits within a short period of time. To reassure about the validity of our design we always present event-study graphs where we show that control and treated municipalities are on parallel trends in the years before the event hits. Also, in order to rule out recent concerns of "invalid comparisons" raised in the dynamic-diff-in-diff literature, we adopt a so-called *stacked-by-event* design as in Cengiz et al. (2019); Deshpande and Li (2019); Fadlon and Nielsen (2019). We construct seven different datasets, one for each possible cohort of treated units (2012-2018). Each dataset contains units that are treated in that year and all units that are not treated in a [-6,+6] years window around the treatment year of that cohort. We then append all the datasets and run the following specification:

Our main estimating equation is:

$$y_{ict} = \alpha_i + \gamma_t + \delta_0 \text{Treated}_{ic} + \sum_{k \neq -1}^{3} \eta_k \cdot \mathbf{1}(\text{distance}_{ct} = k) \cdot \text{Treated}_{ic} + \epsilon_{ict} \quad (5)$$

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; Treated_{ic} is an indicator function taking value 1 if municipality i was a treated unit when considered in the cohort c dataset. We then include a set of distance-to-time-of-event indicators $\mathbf{1}(\text{distance}_{ct} = k)$ interacted with a dummy for whether the municipality is treated in that cohort.[22] The corresponding coefficients η_k indicate the difference in the outcomes between treated and control units, relative to the same difference in $k = -1$ (which we omit for multicollinearity reasons). We run this regression on a balanced panel in distance time around events occurring in years 2012-2018. We always 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).

Similarly to other parts of the paper, we analyze the response of demand but also that of average costs. In this context, looking at average costs serves two purposes: first it allows us to check that the event induces some damage, a useful "first stage"; second, we check whether the change in demand induces changes in average costs in the following years firms who select after the event are adversely selected. If not, then this reinforces the idea that adverse selection plays a minor role and that demand changes after this is more likely related to "saliency" rather than rational "bayesian updating".[23]

We report results from this specification in Figure 11 for hail, 12 for rain, 13 and for wind. We are able to identify clear-cut responses only in the case of hail. The first interesting thing to be noticed is that average costs for insurers respond in the year of the event for the already insured firms. This is a useful sanity check because it tells us that the shock is indeed inducing some economic damage in the municipality that gets hit. Interestingly enough, average costs return to their previous average level in the following years, revealing that shocks do not induce *adverse selection* of costlier firms into insurance. Demand for insurance contracts increases gradually starting from the year of the event. The effect is precisely estimated in the first two years and then it becomes more imprecise. The overall level of demand in the post-event years is anyway higher throughout.[24] The patterns for wind and rain are not so clear and warrant further investigation. It is interesting to see that average

[22]Municipalities that never experience an adverse event in the years considered have no natural distance-to-time-of-event dummies. Their only purpose in the regression is to allow a better estimation of the calendar time effects. Results are more precise including this pure control group but point estimates are very similar with or without them.

[23]We also see little or no effect on premia, meaning that demand is not likely to be affected by changes in prices that occur after the adverse event. Results are available upon request.

[24]Here we report the change in demand as the log of (1+) the number of insured firms. Very similar results hold when looking at the share of insured firms and the log of (1+) insured values. Results are available upon request.

costs do not even respond in the year of the event, as if this was not a real shock.

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. Then 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 (something found in Santeramo et al. (2016)) may thus be more linked to the fact that these firms are less subject to behavioral frictions.[25]

7 Discussion

Our results provide some guidance in evaluating current subsidies to premia and in thinking about what are the desirable interventions in this insurance market. In this section we relate our findings to an analysis of welfare using the conceptual framework of Section 2.

In Section 5 we exploited variation in prices induced by a Europe-wide reform to show evidence of adverse selection. We showed that when demand decreases as a consequence of higher prices, the average cost for insurers increases.

In Section 6, we documented that in the average municipality a weather shock causes an increase in the demand for insurance and we interpret this finding as evidence that there exists some demand friction that prevents firms from subscribing insurance contracts. Two implicit assumptions are needed to reach this conclusion. First, we must require that every firm that was buying insurance before the event does not change its behavior *because of* the event.[26] Second, we assume that firms can learn about the true climate distribution from observing the sequence of shock realization over time and that this learning resembles Bayesian updating. In other words, the more firms observe the insurance-covered events, the closer they get to a correct probability assessment. These two conditions guarantee that the weather shock causes a right shift of the revealed demand curve.

When the revealed demand curve lies on the left of the value curve and there is adverse selection, the inefficiency cost associated with it is larger relative to a benchmark with no frictions. The extent to which this cost is magnified depends on how relevant frictions are and on the slope of the value curve. Quantifying frictions is a challenging task without micro data and survey information about the firm's perceptions. However, we can provide some bounds on their scope by observing that the documented change in demand in response to

[25]In future versions of this work we plan to work directly with credit availability measures at the municipality level

[26]In the instrumental variable jargon, this assumption asks that there are no defiers.

weather shocks occurs in a world with premium subsidies in place. Hence, we can conclude that the subsidy is not enough to close the gap between the revealed value curve and the true value curve, and therefore it represents a lower bound on the size of frictions in the market. The exact quantification of the welfare cost of insurance would, however, also require an estimate of the slope of the value curve. We cannot draw any conclusion about the latter within our empirical framework since the unit of analysis is the single insurance market for which we only observe the realized level of demand. We could overcome this limitation using firm-level data and a structural demand model.

Having established that frictions magnify the cost of adverse selection in our context, we now discuss which policies could be useful to reduce this inefficiency. Two interventions that do not affect the sorting of firms along the demand curve are typically considered in insurance markets: insurance mandates and premium subsidies. As discussed by Spinnewijn (2017) and Handel et al. (2019), in the presence of frictions the cost of a price subsidy increases in the wedge between the revealed and the true value curves. In our setting, we have already established that the price subsidy in place is not large enough to close the gap between the two demand curves. For this reason, we expect the cost of shifting to the right the revealed value curve to be high. On the other hand, a mandate would not leave the choice of insurance to firms and would have no direct material cost for the government. However, it must be taken into account that a mandate enforces some transactions that are not socially efficient. Indeed, the equilibrium share of insured with a mandate is above the socially efficient one and therefore some transactions where the marginal cost for the insurer is above the value of insurance occur. In order to quantify how large this welfare loss is, we would need to know the slope of the average cost curve and the slope of the value curve. Our natural experiments provides some quantification of the slope of the cost curve. Indeed, under the assumption that a local weather shock does not affect the cost curve but shifts the revealed value curve, we can identify the slope of the average cost curve by looking at the effect of the shock on insurers costs. However, as discussed above, we have no way to identify the slope of demand so we can reach no safe conclusion about the best policy to reduce the cost of adverse selection in this market.

8 Conclusions

In this paper we have documented the presence of market failures in the Italian market for crop insurance against extreme weather events. We found that both adverse selection and choice frictions play a role in determining inefficiently low coverage and inefficiently high prices. Studying them both together is important as choice frictions *magnify* the efficiency cost of even moderate adverse selection. Given the interplay between these frictions, policy-makers should be cautious in using price-based mechanisms like subsidies, and should consider mandates as an alternative. The relative desirability of the two instruments hinges on quantitative considerations that we cannot carry out due to lack of micro data. We leave these investigations to further research.

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Figures

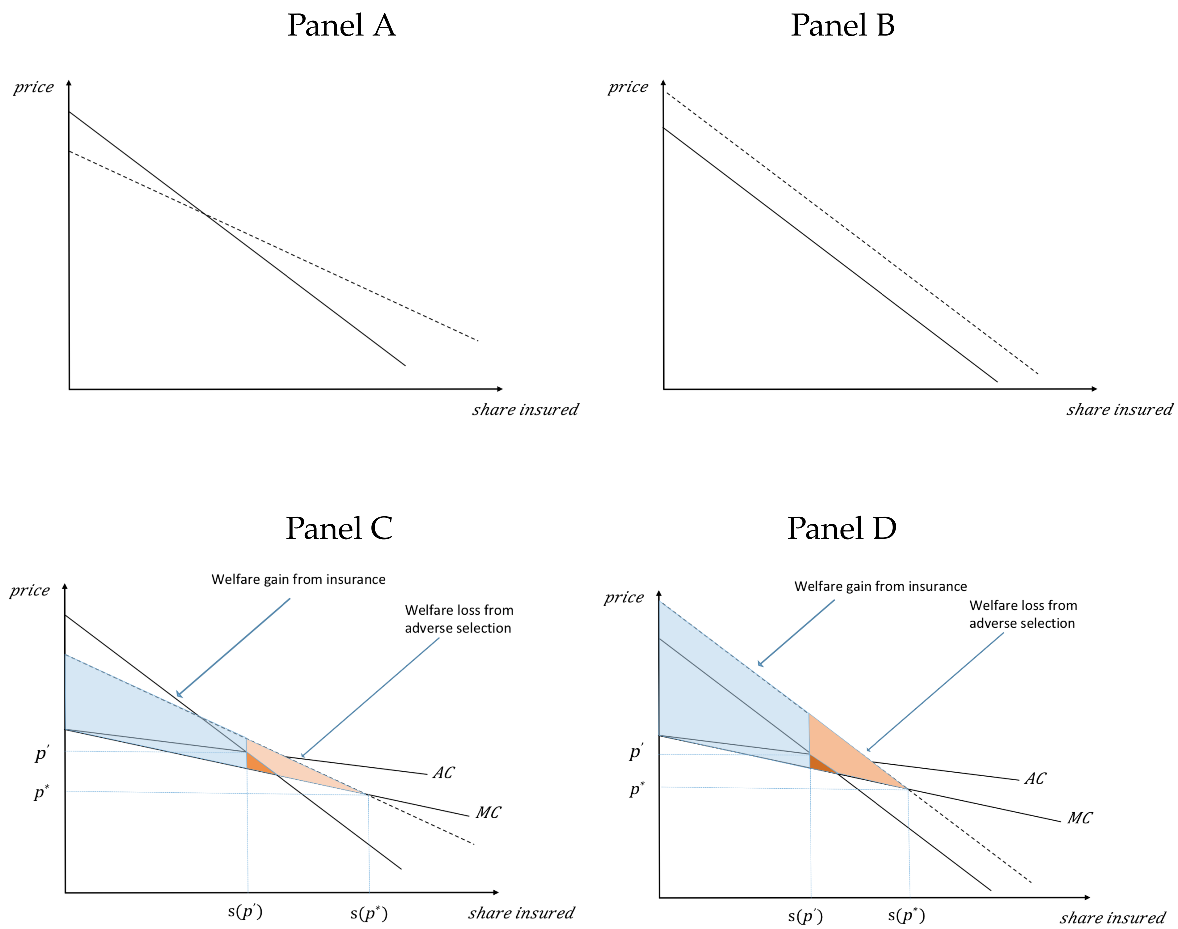


Figure 1: Equilibrium in a Market with choice frictions

Notes: The Figure shows a representation of the equilibrium in our conceptual framework. Panel A and B illustrate the two alternative ways in which revealed and true value curves differ. Panel C and D show the equilibrium for each of the two above mentioned cases. Shaded areas represent gains from insurance and losses due to adverse selection. Among the losses, the darker-shaded areas represent the loss that would be estimated using the revealed demand, and ignoring the existence of choice frictions. In both cases, this area is strictly smaller than the true loss obtained measuring the area between the true value curve and the marginal cost curve between the equilibrium share $s(p')$ and the socially efficient share of insured $s(p^{\star})$.

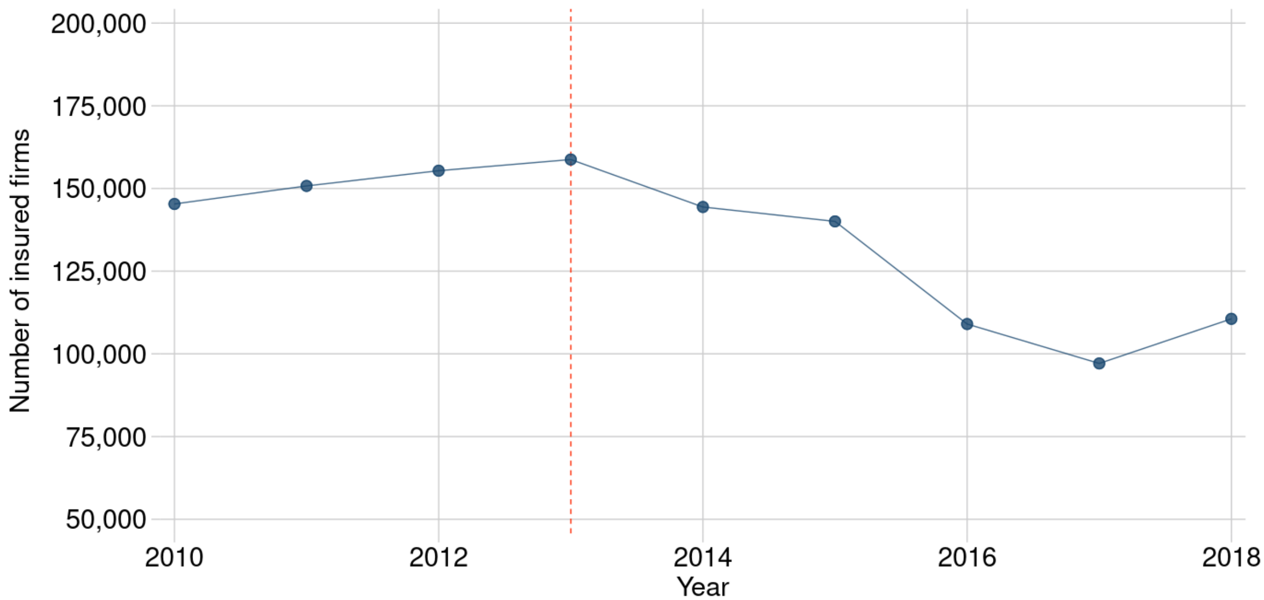


Figure 2: Number of insured firms by year (2010-2018)

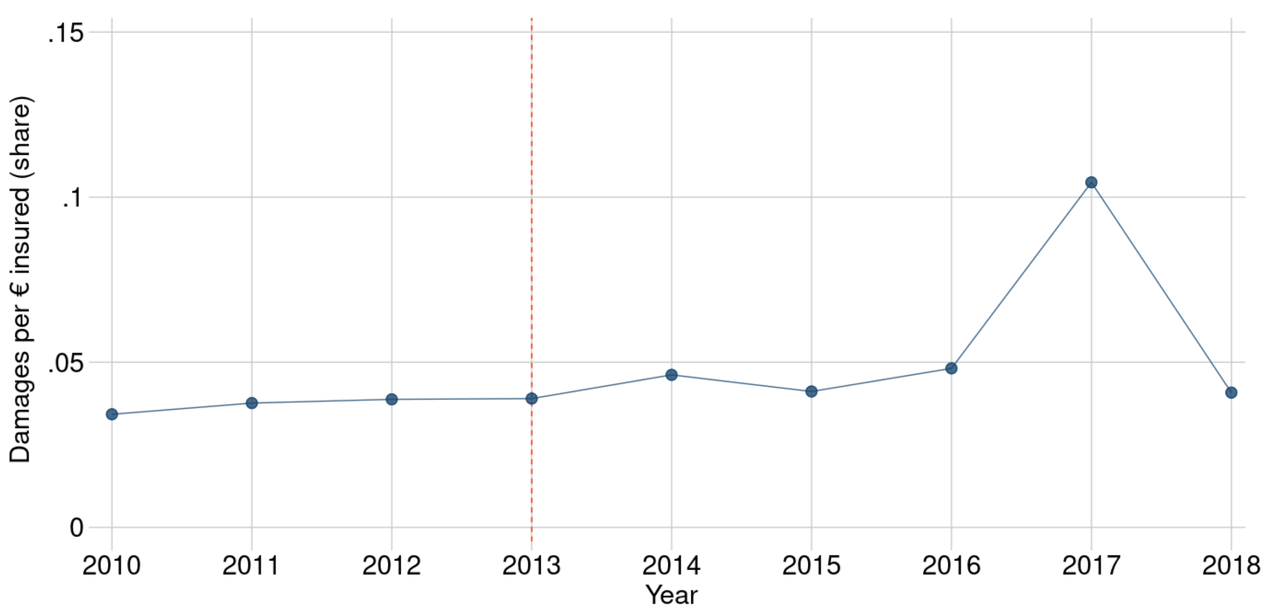


Figure 3: Average costs (damages per € insured) by year (2010-2018)

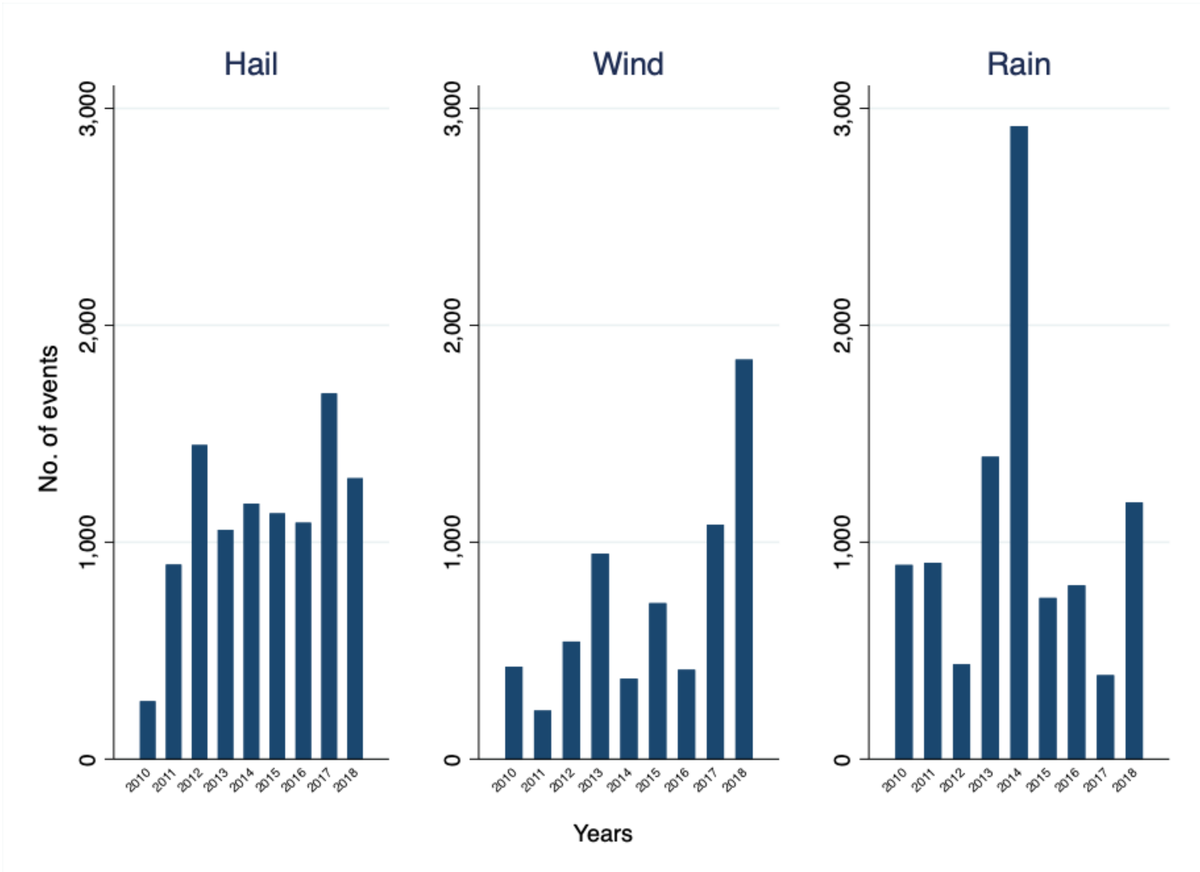
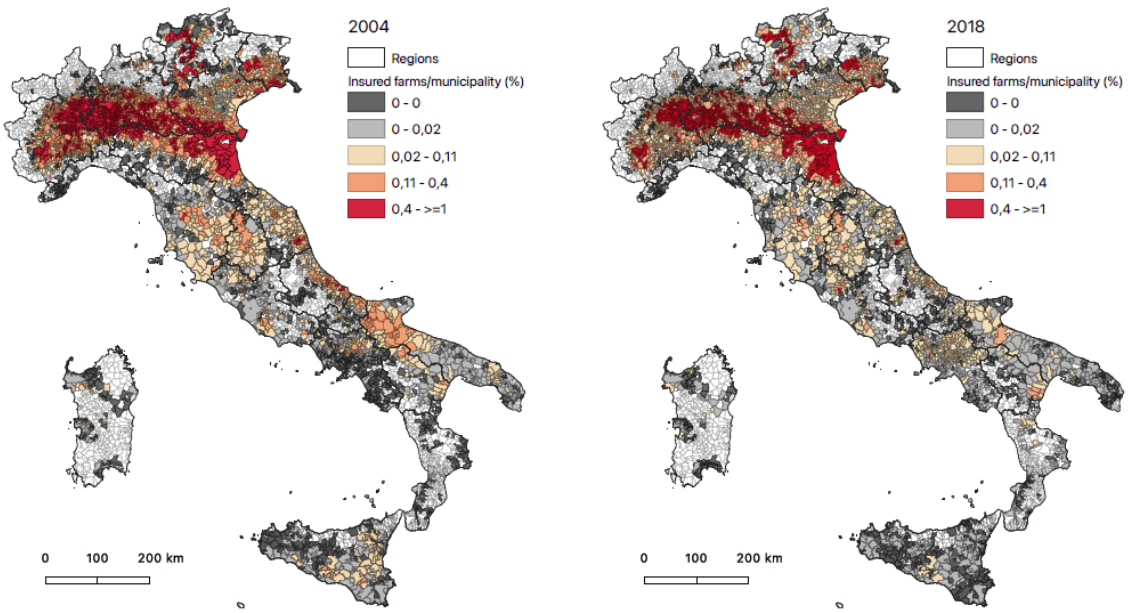


Figure 4: Number of yearly extreme weather events from 2010 to 2018. Source: own elaborations based on ESWD data.

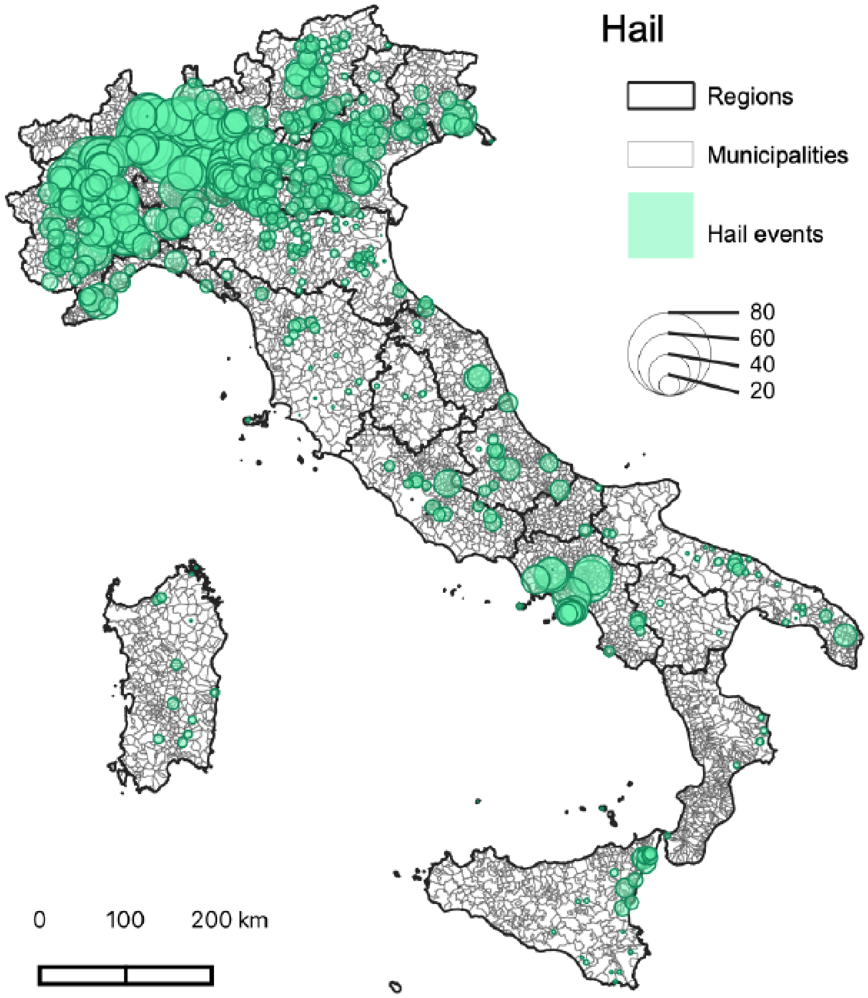
Figure 5: Map of insured farms in 2004 and 2018

(a) 2004 (b) 2018



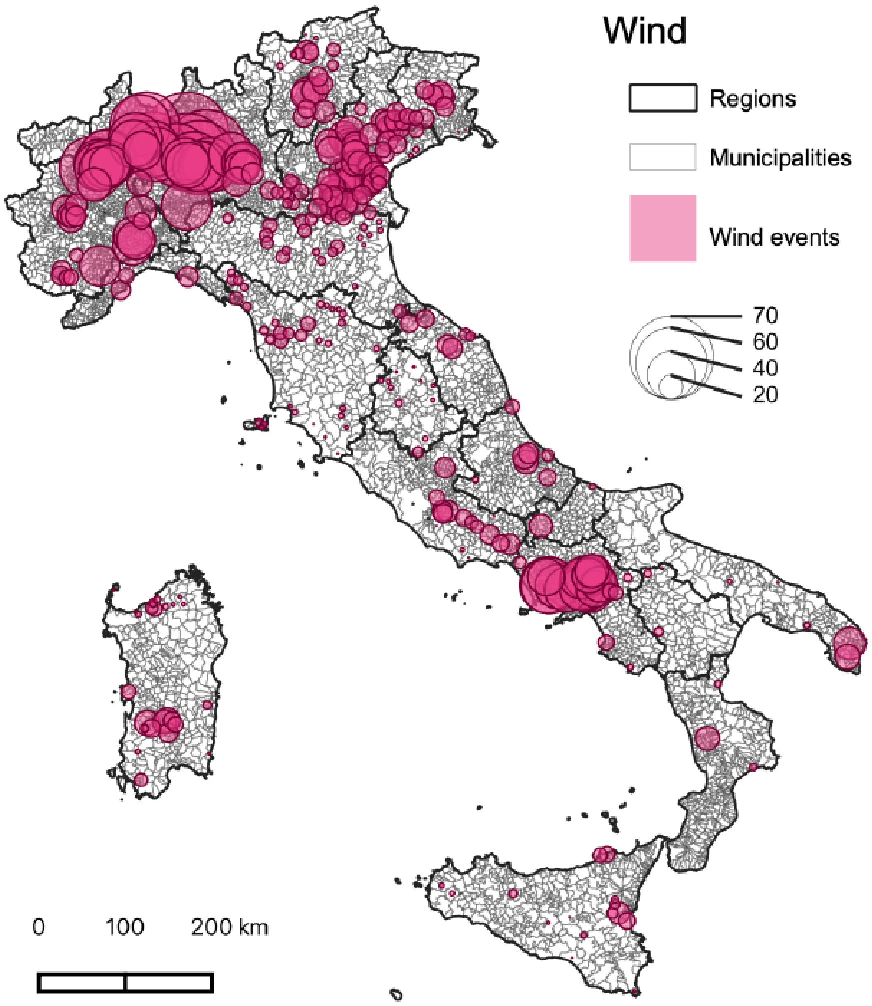
Notes: The figure displays the map of insured farms (in percentage) in each Italian municipality in 2004 and 2018. Source: authors' elaboration based on Sicuragro data and firm census 2011. Percentages above 100% exist because the number of total firms (denominator) derives from the firm census at 2011 and does not vary over time.

Figure 6: Map of extreme hail events in the estimation sample



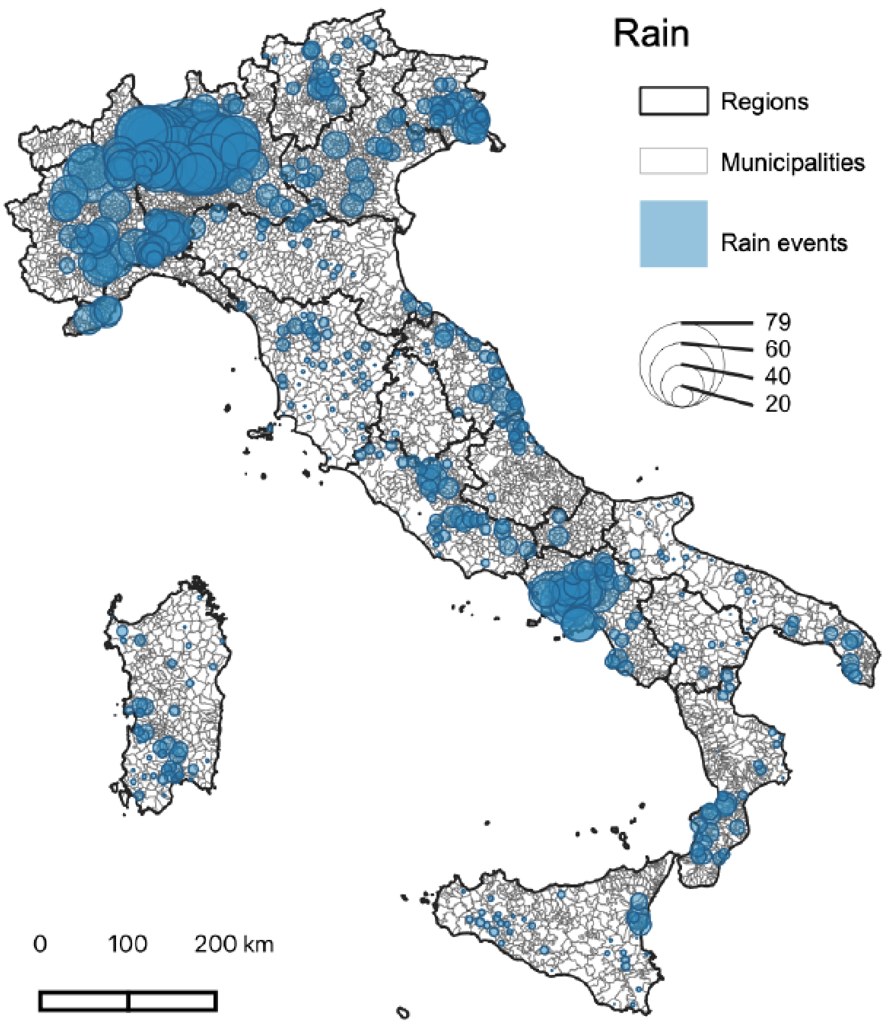
Notes: The figure displays the map of all extreme hail events occurred in Italian municipalities included in our main estimation sample. Source: authors' elaboration based on ESWD data.

Figure 7: Map of extreme wind events in the estimation sample



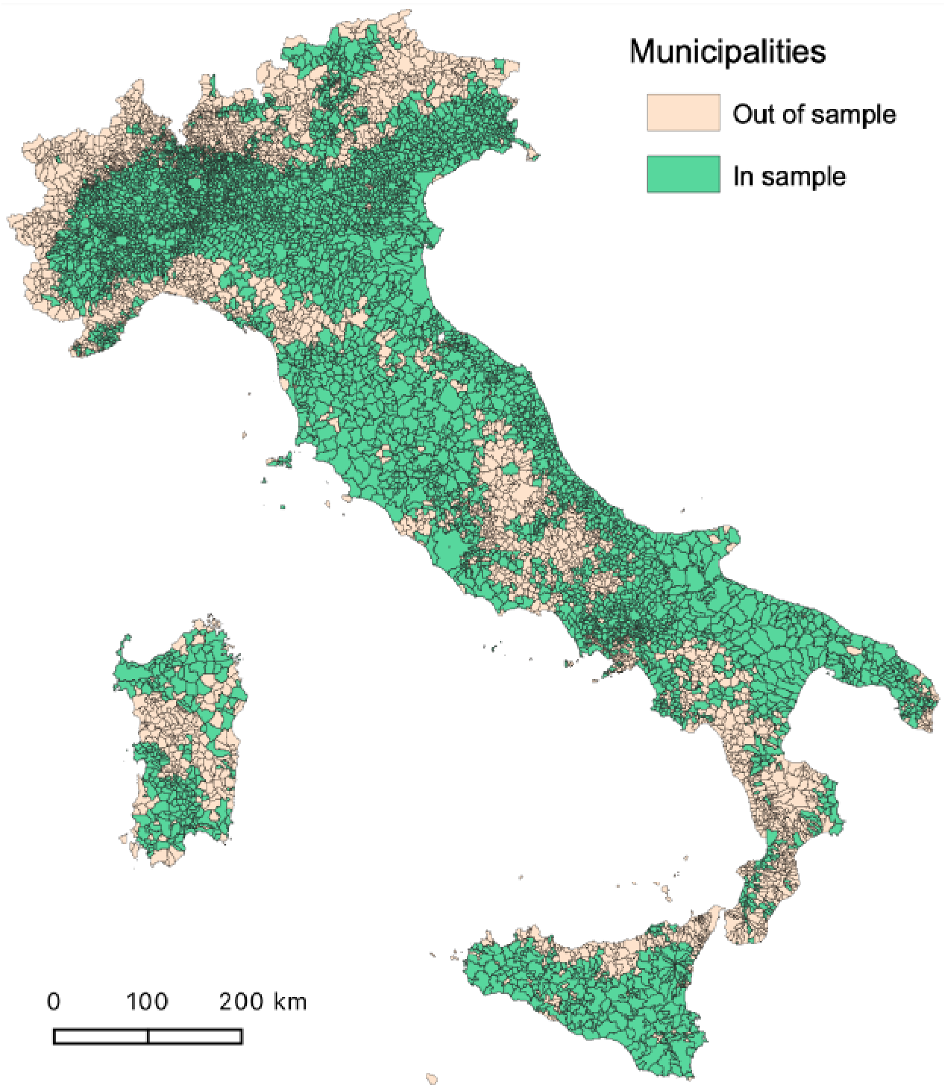
Notes: The figure displays the map of all extreme wind events occurred in Italian municipalities included in our main estimation sample. Source: authors' elaboration based on ESWD data.

Figure 8: Map of extreme rainfall events in the estimation sample



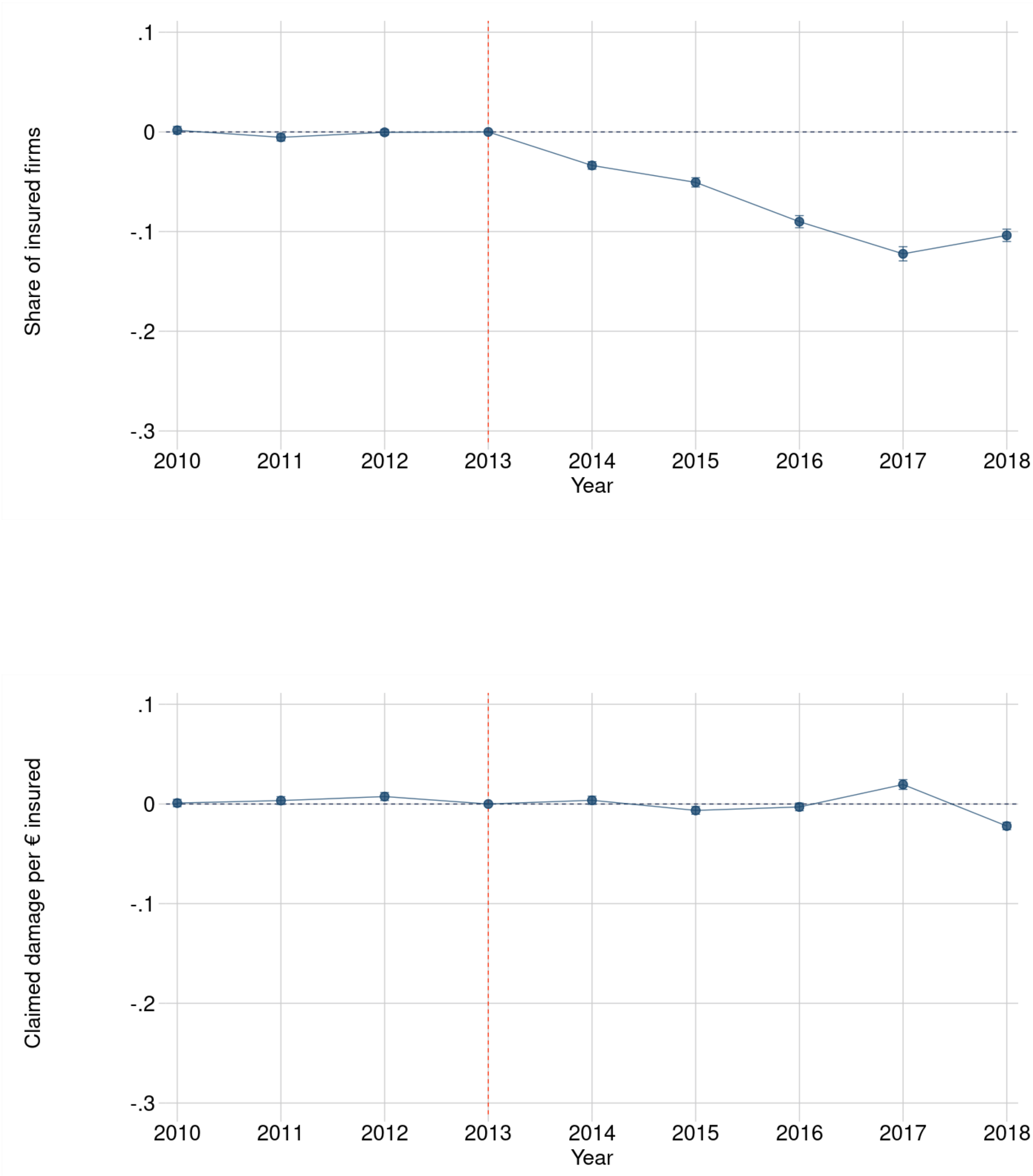
Notes: The figure displays the map of all extreme rainfall events occurred in Italian municipalities included in our main estimation sample. Source: authors' elaboration based on ESWD data.

Figure 9: Map of the Italian municipalities in the estimation sample



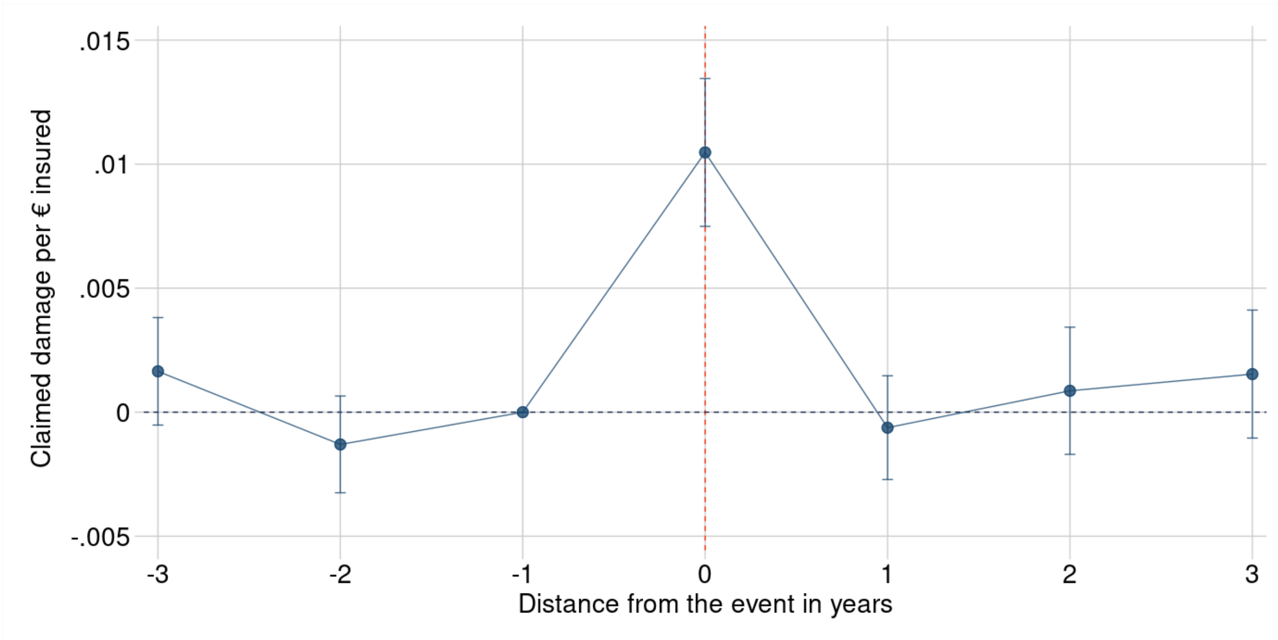
Notes: The figure displays the map of all Italian municipalities included in our main estimation sample (in green) and excluded because they never appear in the *Sicuragro* database (in orange).

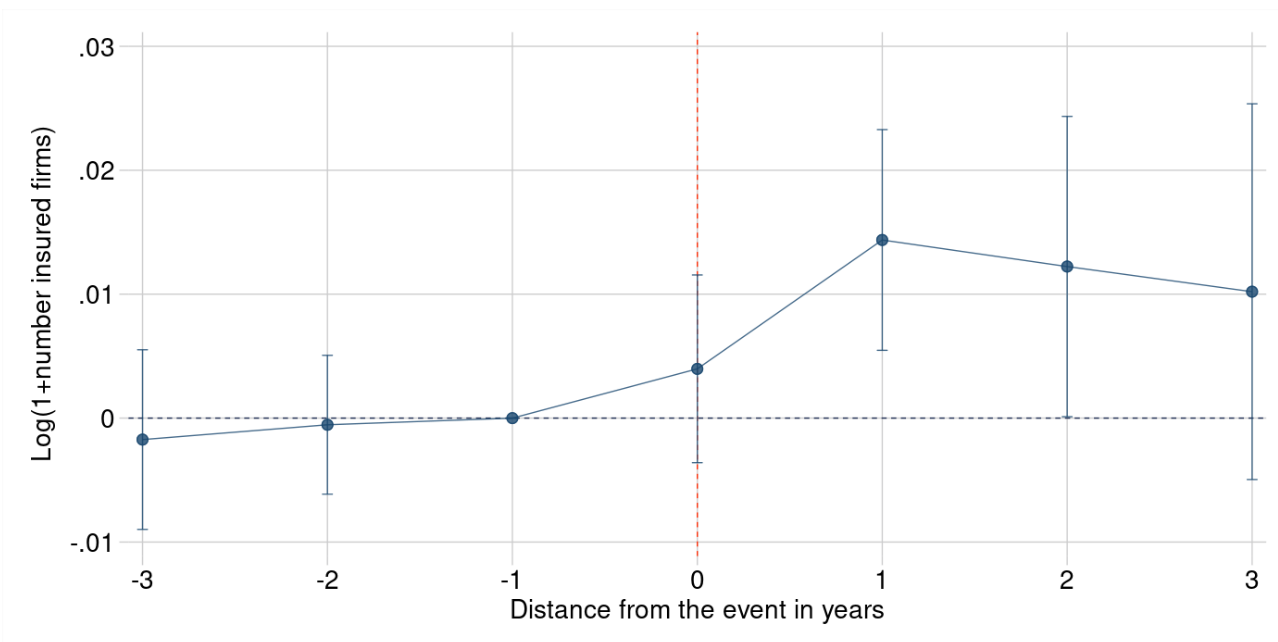
Figure 10: Reform effects on the share of insured firms and on average costs



Notes: This figure reports the regression coefficients and the associated 95% confidence intervals that identify the reduced-form impacts of the reform, i.e., $\hat{\beta}_k$ from equation 2. The coefficients β_{2013} are normalized to zero. The dependent variables are share of insured firms (Figure A) and average costs, as measured by damages per € insured (Figure B). Standard errors are clustered at the municipality level. The x-axis indexes time.

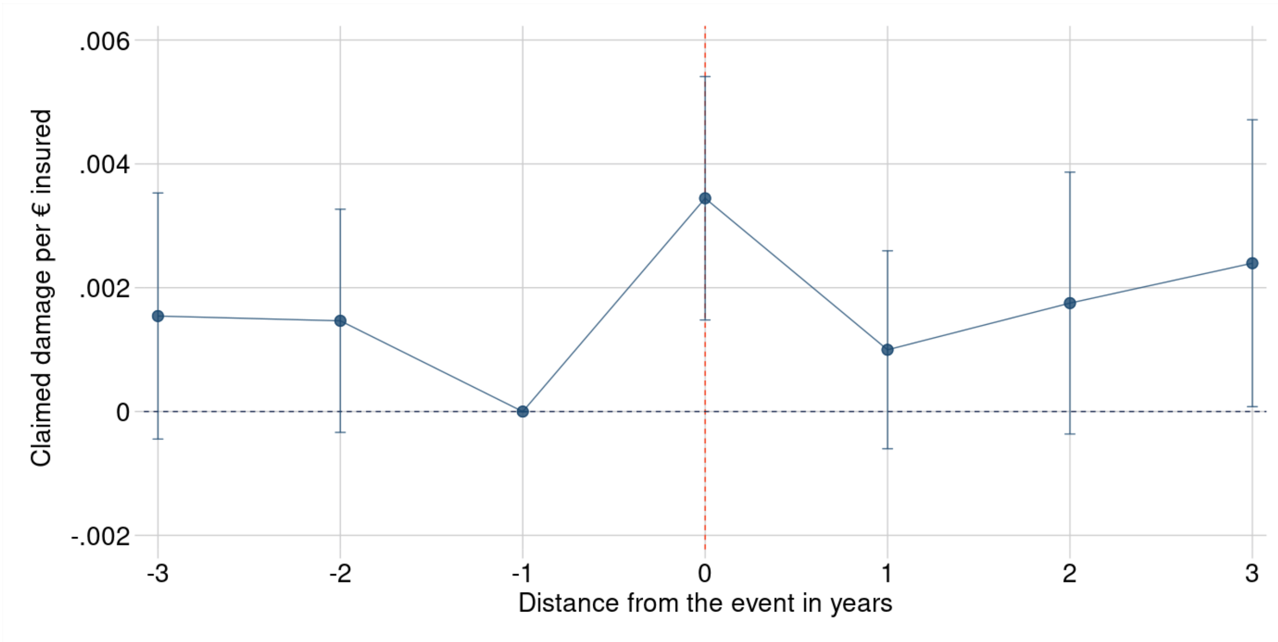
Figure 11: Effect of a hail shock on the number of insured firms and on average costs

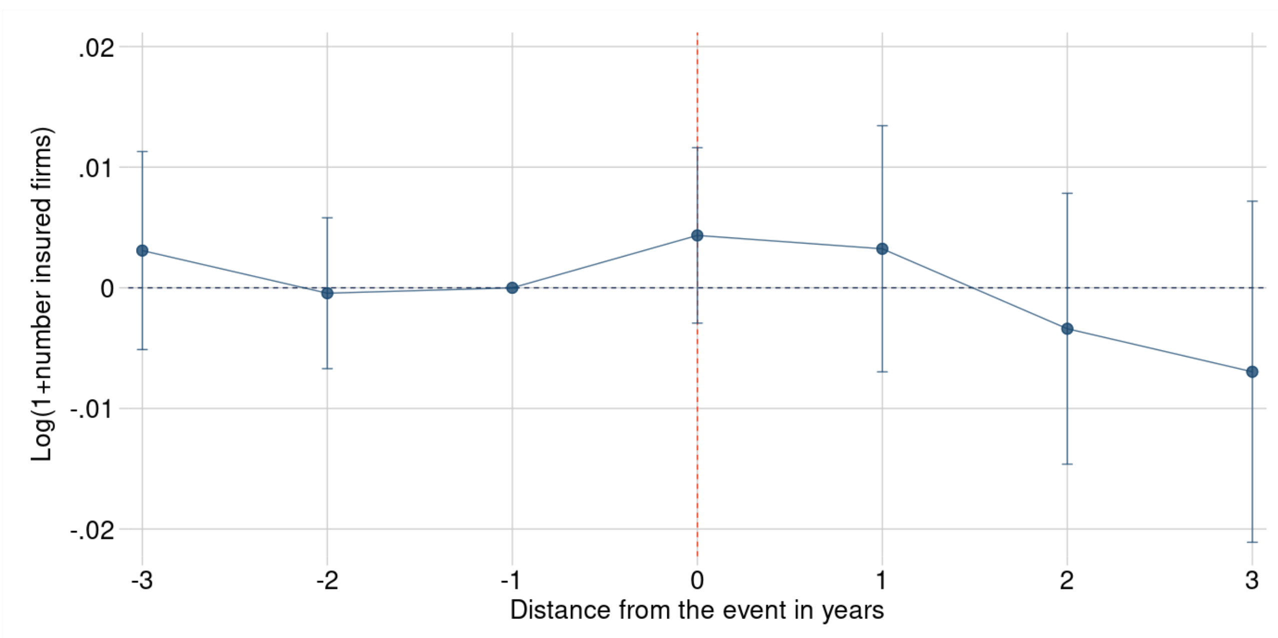




Notes: This figure reports the regression coefficients and the associated 95% confidence intervals that identify the effect of a hail shock, i.e., $\hat{\eta}_k$ from equation 2. The coefficients η_{-1} are normalized to zero. The dependent variables are log(1+number of insured firms) (Figure A) and average costs, as measured by damages per € insured (Figure B). Standard errors are clustered at the municipality level. The x-axis indexes time.

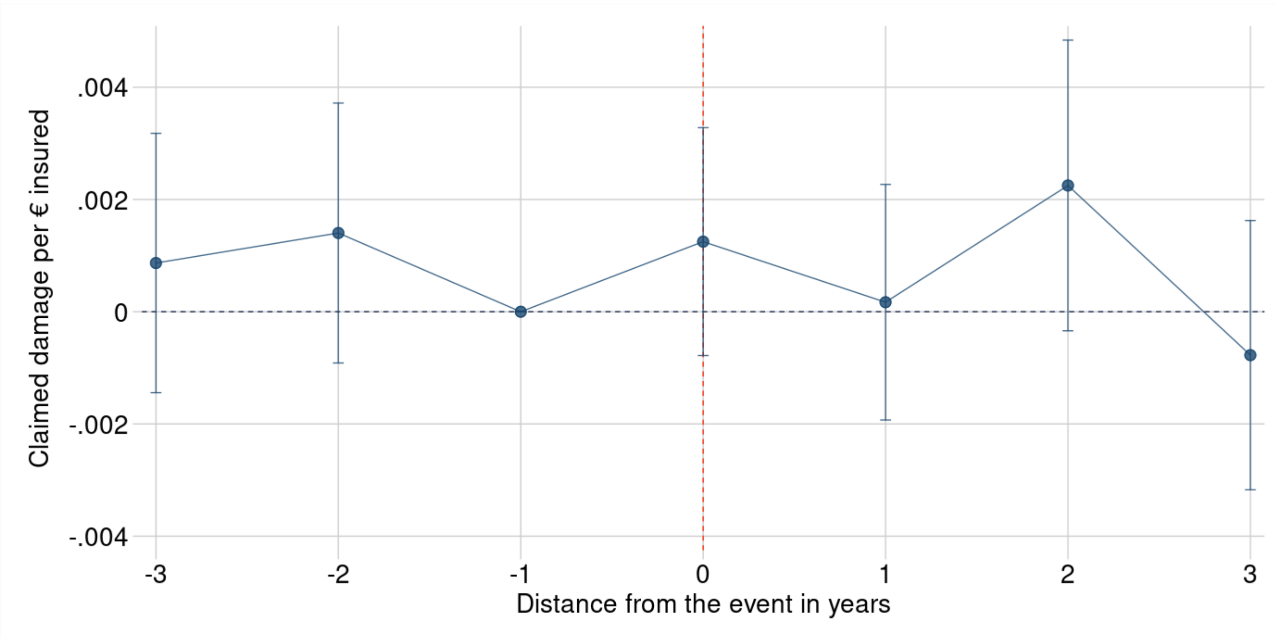
Figure 12: Effect of a rain shock on the number of insured firms and on average costs

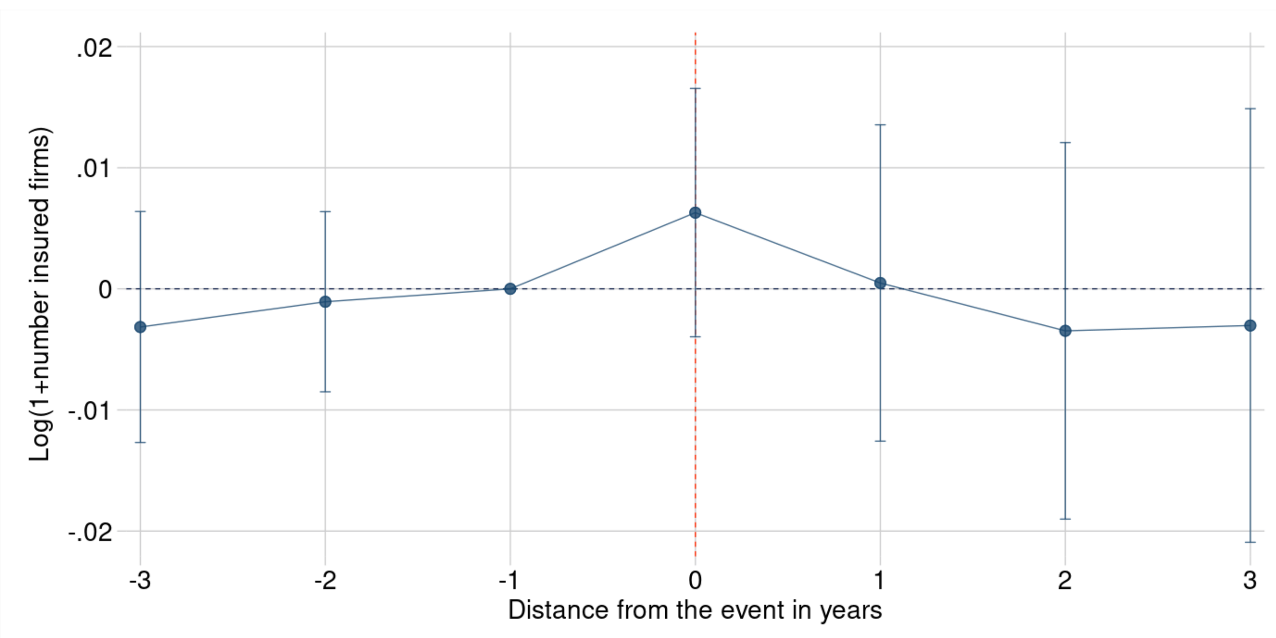




Notes: This figure reports the regression coefficients and the associated 95% confidence intervals that identify the effect of a rain shock, i.e., $\hat{\eta}_k$ from equation 2. The coefficients η_{-1} are normalized to zero. The dependent variables are log(1+number of insured firms) (Figure A) and average costs, as measured by damages per € insured (Figure B). Standard errors are clustered at the municipality level. The x-axis indexes time.

Figure 13: Effect of a wind shock on the number of insured firms and on average costs





Notes: This figure reports the regression coefficients and the associated 95% confidence intervals that identify the effect of a wind shock, i.e., $\hat{\eta}_k$ from equation 2. The coefficients η_{-1} are normalized to zero. The dependent variables are log(1+number of insured firms) (Figure A) and average costs, as measured by damages per € insured (Figure B). Standard errors are clustered at the municipality level. The x-axis indexes time.

Tables

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	P10	P90
Insured value (€)	77025	737673.2	2177242	0	1945390
Claimed damages (€)	77025	34114.68	202627	0	46148.37
Total premium (€)	77025	48926.22	188431.4	0	105398.9
Number of insured firms	77025	24.281	71.898	0	61
Purchased insurance	77025	.754	.43	0	1
Claimed damages	77025	.364	.481	0	1
Claimed damage per € insured	58110	.04	.097	0	.127
Average insured value	58110	26954.73	31500.93	4004.722	58148.27
Premium per insured €	58110	.054	.039	.021	.103

Note: Authors' elaboration on the *SicurAgro* database (2004-2018). 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 at the denominator are computed on the set of municipalities that have at least one euro of insured values.

Table 2: A first test for the presence of adverse selection - OLS and 2SLS estimates

	average costs for insurers (€-cents of damages per € insured)	
	OLS	2SLS
	(1)	(2)
Panel (a) : Main equation estimates		
100 × Δ share of insured firms	-0.0327***	-0.0541***
	(0.00455)	(0.0116)
Panel (b) : First stage estimates		
Year dummies		-0.216***
		(0.0205)
1(t = 2010)		0.167
		(0.194)
1(t = 2011)		-0.540***
		(0.187)
1(t = 2012)		-0.0389
		(0.142)
1(t = 2014)		-3.364***
		(0.193)
1(t = 2015)		-5.058***
		(0.237)
1(t = 2016)		-9.001***
		(0.311)
1(t = 2017)		-12.23***
		(0.364)
Observations	30764	30764
K-P F-stat.		176.0
Municipality FE	YES	YES

Notes: The table presents OLS and 2SLS regressions of damages per € insured against the change in the share of insured firms, that is the average cost curve. 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. 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 3: A second test for the presence of adverse selection - OLS and 2SLS estimates

	Δ average costs for insurers (€-cents of damages per € insured)			
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Panel (a) : Main equation estimates				
$100 \times \Delta$ share of insured firms	-0.0203***	-0.0198***	-0.0325***	-0.0325***
	(0.00606)	(0.00606)	(0.00807)	(0.00809)
Panel (b) : First stage estimates				
Share of insured firms in 2013			-0.216***	-0.215***
			(0.0205)	(0.0205)
Observations	5208	5208	5208	5208
K-P F-stat.			110.5	109.8
Growth controls	NO	YES	NO	YES

Notes: The table presents OLS and 2SLS regressions of the change in damages 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. A negative coefficient indicates the presence of adverse selection. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$