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The crop insurance demand response to premium subsidies: Evidence from U.S. Agriculture

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ABSTRACT

Premium subsidies are a common policy tool to promote crop insurance participation in many countries. However, the relationship between subsidies and demand is not entirely obvious given the variation in the use of subsidies and crop insurance participation within the international crop insurance landscape. Focusing on the U.S. Federal Crop Insurance Program (FCIP) demand is modeled as a system of equations representing decisions at the intensive [coverage level] and extensive [net insured acres] margins. The model makes use of an identification strategy that leverages exogenous variation in government-set pricing policy to address potential sources of endogeneity. Applying the model to over one million insurance pool level FCIP observations spanning two decades (2001–2022) suggest an inelastic response at both extensive and intensive margins to changes in producer-paid premium rates with the response to premium rates becoming increasingly more elastic as subsidies decrease. These estimated elasticities are on the low end compared to previous literature, however, significant heterogeneity across commodity, production practices, policy type, and location are observed suggesting subsets of producers are likely to respond to changes in the cost of insurance in different ways.

1. Introduction

The use of insurance as a tool for agricultural risk management has rapidly expanded and become a critical component of the overall suite of support programs for farmers and ranchers in both developed and developing countries (Baldwin et al., 2023; Belasco, 2020; Mahul and Stutley, 2010; Smith and Glauber, 2012). As of 2007, about half of all countries had some sort of agricultural insurance generating a total of $15.10 billion in premiums (Mahul and Stutley, 2010). Relative to 2021, this figure is low, especially given that the US, which accounted for more than half of global premiums in 2007, has since more than doubled to $13.72 billion in 2021. This growth suggests that agricultural insurance is seen as a valuable resource for producers facing increased climatic and market uncertainty (Annan and Schlenker, 2015; Diffenbaugh and Burke, 2019; Falco et al., 2014; Finger and El Benni, 2021; Janzen and Carter, 2019; Lehmann et al., 2013; Ortiz-Bobea et al., 2019; Perry et al., 2020; Tack et al., 2018). However, global agricultural insurance coverage has historically remained relatively low compared to the value of global agricultural output, despite many governments attempting to use premium subsidies to increase participation (Mahul and Stutley, 2010).[1]

In the U.S., the Federal Crop Insurance Program (FCIP) saw rapid increases in enrolled acreage following a series of legislative changes that started in 1980 and increased premium subsidies (Fig. 1). Despite premium subsidies playing a seemingly significant role in establishing increased participation within the FCIP, the relationship between subsidies and demand is not entirely obvious. For one, looking at the international agricultural landscape suggests high subsidy levels are not a necessary condition for high levels of market penetration. For example, Switzerland, Sweden, and Australia have historically had participation rates of 50% or higher (measured as a percentage of cropped area insured) despite having no subsidies (Mahul and Stutley, 2010).[2]

This study seeks to identify the relationship between crop insurance premium subsidies and demand for crop insurance. Focusing on the U.S,

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[1] In the U.S., cash receipts for agricultural products (livestock and crops) totaled $437 billion (USDA Economic Research Service, 2023). Total FCIP insured liability (livestock and crops) for the 2021 crop year totaled $151 billion (Federal Crop Insurance Corporation, 2023) representing about 35% of total agricultural production (this same metric is approximately 57% when livestock are excluded from both cash receipts and FCIP liabilities).

[2] Cropped area insured is defined as the area of land with crops currently being cultivated. As of 2007, crop insurance penetration rates for privately offered hail and named peril crop insurance were 75% of cropped area insured in Switzerland, 52% in Sweden, and 50% in Australia (Mahul and Stutley, 2010).

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the empirical analysis leverages 1,174,932 FCIP insurance pool level observations spanning 22 years (2001–2022) to estimate the crop insurance demand response to changes in producers' out-of-pocket cost.[3] Demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres, respectively. An identification strategy is used that leverages the exogenous variation in USDA, Risk Management Agency (RMA) policy parameters to instrument for endogenously determined variables in the model. The empirical model includes insurance pool fixed effects to control for invariant confounders.

Estimation of the model yields results that suggest a relatively inelastic crop insurance demand response, to changes in producer-paid premium rates, at both the intensive (-0.022) and extensive (-0.052) margin. However, applying the results across a range of potential subsidy levels suggests that the crop insurance demand response to premium rates change depending on the underlying level of premium subsidies. Specifically, the demand response becomes increasingly elastic as the premium subsidy rate decreases. Further, decomposing results by observable insurance pool characteristics suggest that subsets of producers respond very differently based on the produced commodity, production practice (i.e., irrigated, certified organic), type of insurance policy, and location. This suggests that even though estimated demand elasticities are relatively small at the most aggregate level, changes in the subsidy rate are still capable of dramatically altering the observable characteristics of the crop insurance market.

This study contributes to the literature in several ways. First, the empirical approach in this study is one of the few to estimate demand elasticities in the context of the modern crop insurance policy landscape. Within the U.S. and the FCIP, a large literature has estimated the elasticity of demand for crop insurance with many existing studies characterizing demand as being inelastic (Barnett et al., 1990; Bulut and Hennessy, 2021; Calvin, 1990; Coble et al., 1996; Gardner and Kramer, 1986; Goodwin, 1993; Goodwin and Kastens, 1993; Hojjati and Bockstael, 1988; Maisashvili et al., 2020; Yi et al., 2020). This, in turn, has been used to fuel perennial arguments focused on premium reductions as a potential cost-saving measure for the FCIP (Barnaby and Russell, 2016; Bekkerman et al., 2019; Congressional Budget Office [CBO], 2020; Glauber, 2013; Goodwin and Smith, 2013; Lusk, 2017; Smith et al., 2017; United States Government Accountability Office [GAO], 2014). However, the results drawn from the bulk of existing literature may not necessarily generalize to the modern policy era since most

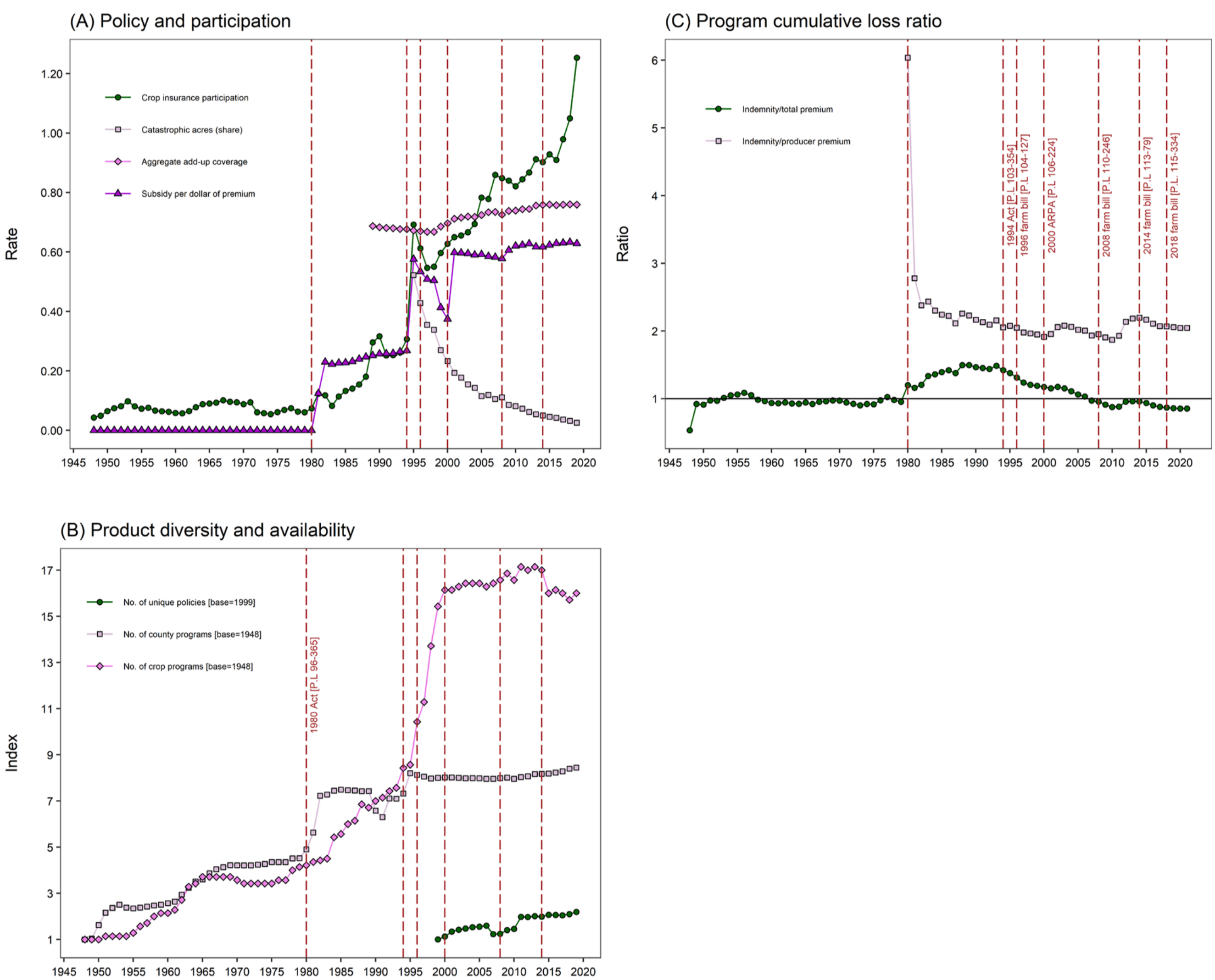

Fig. 1. Crop Insurance Policy, Participation and Product Diversity, and Availability Notes: Constructed by the authors using data from (1) Risk Management Agency's summary of business files, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

[3] An insurance pool is a group of producers with similar contract characteristics (commodity, production practices, location, and policy type) that are treated similarly from the point of view of the FCIP premium rating process.

existing studies are based upon historical iterations of the FCIP which offered notably different insurance products compared to what is available today (post-2000) [see Fig. 1]. Additionally, the 2001/2002 crop season saw the introduction of RMA's continuous rating formula which significantly altered the actuarial relationship between producer characteristics/choices and premium rates (Risk Management Agency RMA, 2000).[4] Consequently, it's not obvious that results drawn from analysis before the early 2000 s generalize to the modern crop insurance policy environment.

Second, the analysis in this study is one of the few to utilize instrumental variable techniques to address the endogenous relationship between "price" (i.e., the premium rate) and "quantity purchased" (total premiums paid, liability, acreage insured, coverage level, etc.). This source of endogeneity is partly attributable to the fact that "risk" serves as a key component in the pricing of insurance, but it is not directly observable, creating a case of omitted variable bias. Additionally, empirical researchers must contend with the fact that sound actuarial practice dictates that premium rates increase with coverage levels to reflect the increased probability of indemnification at higher levels of coverage (and corresponding lower deductibles). This creates a source of simultaneity bias in a regression framework (Woodard and Yi, 2020).[5] Further, subsidy rates within the FCIP vary by chosen coverage level, with higher coverage levels receiving lower subsidy rates which enhances the deterministic relationship between a chosen coverage level and premium rates.[6]

Some existing studies have utilized Heckman-type models of participation (Goodwin and Kastens, 1993; Richards, 2000; Shaik et al., 2008) to address endogeneity. However, these studies remain in the minority. To the best of knowledge, Woodard and Yi (2020) is the only study that utilizes an instrumental variables strategy to provide estimates of crop insurance demand elasticities for the modern FCIP policy environment. By using a parsimonious functional form, they estimate a pair of rating parameters to describe the observed relationship between premium rates and coverage levels which they then use as instruments in their analysis. However, as discussed later, using estimated instrumental variables potentially introduces an alternative source of estimation error. Alternatively, the approach in this study makes use of observed RMA-rating parameters – i.e., the exact rating parameters set by RMA.

Third, by using more granular level data (i.e., by disaggregating observational units into insurance pools within each county), the study minimizes the potential for aggregation bias by using observational units with similar crop insurance contract characteristics, and by extension similar production characteristics. This coupled with the attention to endogeneity and focus on the modern crop insurance policy environment means this study address three potential sources of bias. Although each of these sources of bias has been addressed separately in previous literature, to our knowledge, this study is the first to deal with each simultaneously. Additionally, by defining the observational unit as an insurance pool, it is possible to decompose results by observable characteristics which include the commodity produced, irrigation practice, organic certification, type of insurance policy, insurance unit structure, and location. This exercise is particularly noteworthy given the varied (and sometimes counteracting) elasticities observed across segments of the crop insurance market; this could be potentially important for designing policies that are effective at achieving their stated goal.

The rest of this paper is organized as follows. Section 2 describes the conceptual framework which is used to motivate the empirical analysis. Section 3 presents the data sources and discusses the construction of relevant variables for the analysis. Section 4 formally defines the empirical model while section 5 outlines the identification strategy. Section 6 presents the empirical results, while section 7 discusses the results and implications for policymaking. Section 8 concludes.

2. Conceptual framework

An extensive literature has developed several conceptual frameworks that are of interest to this study. While insights are drawn from a few of these (Calvin, 1990; Coble et al., 1996; Goodwin, 1993; Hojjati and Bockstael, 1988; Woodard and Yi, 2020; Yu et al., 2018), the theoretical structure used to link premium rate responsiveness to premium subsidies in this study is novel in the sense that it is based on the actual premium rating framework within the modern FCIP and explicitly accommodates crop insurance demand at both the extensive and intensive margins simultaneously.

In the FCIP, producers can choose among policies that protect against a shortfall in yields or revenue with indemnity payments being conditional on either individual production (or revenue) or group-level production. Since the conceptual framework is designed to motivate and provide background for the empirical analysis, the focus is given to individual-level yield protection policies. Ideally our conceptualizations should include production inputs (i.e., land, fertilizer, labor, chemicals, etc.) as endogenous variables to be determined in addition to the endogenous crop insurance choices. Our empirical analysis is at the insurance pool level sourced from RMA's loss experience database, which does not come with the level of input usage (i.e., planted acres). Thus, following Coble et al. (1996), we assume that the representative producer is making crop insurance choices after having made production decisions. This is a reasonable assumption given that marketing and production contracts are widely used in U.S. Agriculture (Burns and MacDonald, 2018; MacDonald et al., 2004) and forward contracting of inputs in production agriculture is becoming increasingly important as more farmers attempt to manage risk (Mishra, 1999).[7]

Consider a representative producer who allocates a fixed number of arable acres (A) to crop production at a fixed cost of $C(\mathrm{A})$ tied to acres. The revenue associated with producing A acres of the crop is $yp\mathrm{A}$, where y is the stochastic non-negative yield of the crop and p is its marketed price. Conditional on availability, the producer can choose to insure expected crop yield at a coverage level of θ via a crop insurance contract with a respective yield guarantee of $\theta\ddot{y}$.[8] Current FCIP policy stipulates that a producer must elect the level of coverage (θ) and the share (γ) of A to insure for a given policy. This study distinguishes between crop insurance demand at the intensive and extensive margins via the choice of

[4] Before the continuous rating formula, RMA published Base Premium Rates for APH-based crops using a fixed rate for a span of yields, which was typically nine rate spans (R-span) per crop. The continuous rating formula develops a rate for each yield rather than for ranges of yields as the R-span does. Recent work shows that the main component of the continuous rating formula that induces rating heterogeneity amongst farmers does a relatively good job of incorporating soil information into rates when a long yield history is used to approximate the farmer's yield (Tsiboe and Tack, 2022).

[5] In other words, plotting premium rates against chosen coverage levels forms an upward sloping relationship (see Woodard and Yi [2020], Fig. 1 for example) that, in the absence of an identification strategy capable of addressing endogeneity, would result in the conclusion that demand for insurance at the intensive margin rises as the price of insurance rises.

[6] A couple of government reports acknowledge this issue and note the need for alternative identification methods to eliminate simultaneity bias (Congressional Budget Office [CBO], 2017; O'Donoghue, 2014).

[7] The effect of crop insurance on production input is well documented in the moral hazard literature (see Tack and Yu (2021) for extensive discussions) which is not the focus of our study. We however acknowledge the limitations of this assumption and include county planted acreage as a control for regional trends in land use.

[8] In the FCIP, the quantity $\ddot{y}$, is known as the approved yield which essentially is a measure of the insured's future expected yield. Approved yield calculations are based on the mean of the insured's actual production history (APH) which are typically adjusted higher through various mechanisms such as trend adjustments, yield exclusion, and yield substitution.

θ and γ, respectively.

The end-of-season revenue from crop production is the sum of the realized value of y and per acre indemnity ($I(y) = max[0, \theta\ddot{y} - y]$) times γA. In the FCIP, RMA is mandated by law to price insurance policies actuarially fairly such that per acre premiums are equal to expected per acre indemnities.[9] This is represented by the following equation:

$$E[I(y)] = \int_0^{\theta\ddot{y}} (\theta\ddot{y} - y)f(y)dy \tag{1}$$

where $f(y)$ is the probability density function of y. Given the focus of the paper, premiums are standardized by insured liability which can be characterized by the following equation.

$$\tau(\theta) = \frac{1}{\theta\ddot{y}}\int_0^{\theta\ddot{y}} (\theta\ddot{y} - y)f(y)dy \tag{2}$$

Using Leibniz's integral rule, Woodard and Yi (2020) showed that premium rates as a function of coverage are continuous, twice differentiable, and increasingly convex, i.e., $\tau(\theta) < 1$, $\tau(\theta) > 0$, $\tau(\theta) > 0$, $\forall\theta > 0$.

RMA assumes that $f(y)$ is conditional on an adjustment mechanism that relies on the underlying risk profile of the producer seeking insurance. This risk profile is not observable and is approximated by the productivity of the producer seeking insurance relative to their peers. Specifically, liabilities are known at the time the crop insurance contract is written, whereas indemnities are determined via a naturally occurring stochastic process, and thus cannot be known with certainty. The FCIP overcomes this by using the so-called "continuous rating formula" which adjusts some baseline rate given the insured's production experience and contract specification. The default form of the continuous rating formula is specified according to the following equation

$$\tau(\theta, u, \overline{y} : \alpha, \beta, \delta, \overline{y}_c) = \left[\alpha(\overline{y}/\overline{y}_c)^{\beta} + \delta\right]\vartheta(\theta)\rho(u) \tag{3}$$

where α and δ represent a county base rate and a catastrophic fixed loading factor, respectively, for some baseline coverage. In determining producer rates, the base rate is first adjusted with the assumption that risk co-varies with yield. This is achieved via the rate multiplier curve expressed by $(\overline{y}/\overline{y}_c)^{\beta}$ which leverages the ratio of the producer's historic mean yield ($\overline{y}$) over some county reference yield $\overline{y}_c$ to make that adjustment. The value of β, also known as the continuous rating exponent, is assigned a negative value based on early research suggesting that relatively more productive farms are at a lower risk of indemnification (Coble et al., 2010). Consequently, the county base rate is adjusted downward for farms with yields that are higher than the yield represented by the county reference yield (i.e., $\overline{y}/\overline{y}_c > 1$). The resulting initial rate $\alpha(\overline{y}/\overline{y}_c)^{\beta} + \delta$ is then adjusted via the scaling functions $\vartheta(\theta)$ and $\rho(u)$ which are tied to the producer's coverage level, θ, and insurance unit elections,u, respectively.[10]

The parameters α, β, δ, and $\overline{y}_c$ are the policy variables estimated by RMA for a given insurance pool using historical loss data from the FCIP. Even though information on carryover insureds (i.e., producers that participated in the FCIP in the past) is used in the determination of the policy variables, due to several practices employed by RMA, a single producer does not have appreciable influence over the policy variables governing their current or future premium rate. First, a single insured producer's decisions are negligible in influencing the total insurance pool's characteristics given that many individual producers make up a single insurance pool. Second, RMA applies a smoothing algorithm to bring new information into the rating process when the county being rated contains limited information (too few insured units) or has historically had highly variable loss experiences (Coble et al., 2010). This process also limits large discontinuities in premium rates between adjoining counties. Consequently, even small insurance pools are still rated based on the characteristics of a much larger group of nearby producers.

Since previous levels of yields are fixed and not under the control of producers, FCIP premium rates can be thought of as sequentially exogenous.[11] The exogenous portion of FCIP premium rates ($\tau(\theta, u, \overline{y}; \boldsymbol{\omega})$) are driven by the policy parameter space $\boldsymbol{\omega} \in \{\alpha, \beta, \delta, \overline{y}_c\}$ and the endogenous portion by the insured's choice of insurance unit $\rho(u)$, coverage level $\vartheta(\theta)$, and their historic production experience $\overline{y}$. Finally, in the FCIP, insurance premiums are subsidized at a rate $S(\theta, u)$ that is tied to coverage level and insurance unit and not to location or the crop. Figure S3 shows $S()$ is decreasing in θ and varies by insurance unit. The effective premium rate paid by the producer is given by $r() = (1 - S(\theta, u))\tau(\theta, u, \overline{y}; \boldsymbol{\omega})$. Putting all the preceding together, the accounting profit relationship of the representative producer's crop insurance decision after having decided on acres of crop production is defined as follows:

$$\pi() = \mathrm{A}py(1-\gamma) + \mathrm{A}p\gamma\left(\ddot{y} + \int_0^{\theta\ddot{y}} (\theta\ddot{y} - y)f(y)dy - r()\theta\ddot{y}\right) - C() \tag{4}$$

Combining $\ddot{y} + \int_0^{\theta\ddot{y}} (\theta\ddot{y} - y)f(y)dy - r()\theta\ddot{y}$ with equations (2) and (3) produces the following simplified expression,

$$[1 + \Gamma(\theta, \ddot{y}, u; \boldsymbol{\omega})\theta]\ddot{y} \tag{5}$$

where $\Gamma(\bullet)$ is the premium subsidy, the producer receives per dollar of liability expressed as $S(\bullet)\tau(\bullet)$. Thus, the accounting profit reduces to:

$$\pi() = \mathrm{A}py(1 - \gamma + \gamma\ddot{y}[1 + \Gamma()\theta]) - C() \tag{6}$$

Following previous literature(Calvin, 1990; Goodwin, 1993; Hojjati and Bockstael, 1988; Yu et al., 2018), the study assumes that the representative producer maximizes a mean–variance utility function (Levy and Markowitz, 1979; Meyer, 1987) of the form:

$$\underset{\{\theta,\gamma\}}{\mathrm{Max}}\, U = \mu - \kappa\sigma \tag{7}$$

Where μ and σ represent expected profit and the standard deviation of profits, while κ is a parameter that characterizes the representative farmer's risk preferences. The respective expressions for the mean and variance of farm profits with simplifications adapted from Yu et al. (2018) are given by:

$$\mu = \mathrm{A}py(1 - \gamma + \gamma\ddot{y}[1 + \Gamma()\theta]) - C() \tag{8}$$

$$\sigma^2 = \mathrm{var}(\max[y, \theta\ddot{y}]\gamma) \tag{9}$$

The first-order conditions that maximize the producer's utility are then:

[9] The ratio of total indemnity to total premium (i.e., loss ratio) have been consistently above one for much of the FCIPs history, but this phenomenon was mostly observed prior to 1996. Significant underwriting/rating changes were made to the FCIP in 1995 and RMA was established in 1996. These legislative changes, along with increases in premium subsidies and introduction of the continuous rating formula in 2000/01 helped increase crop insurance participation (and in turn, create a more diversified risk pool). Since 1997, annual loss ratios have averaged 0.84. This is in line with RMA's target loss ratio of 0.88 which is designed to cover anticipated losses plus a "reasonable reserve".

[10] The value generated by the function, $\vartheta(\theta)$, also known as the coverage level differential factor, increases with coverage level (Figure S1), and that generated by $\rho(u)$, also known as a unit residual factor, increases with insurance unit disaggregation (Figure S2).

[11] Premium rates are sequentially exogenous in the sense that yields are not influenced by past premium rates, but future yields can influence future premium rates. In other words, current production decisions have no bearing on the cost of insurance for the current season.

$$\frac{\partial U}{\partial \theta}=\left[\Gamma()+\frac{\partial \Gamma()}{\partial \theta}\theta\right]\mathrm{A}py\ddot{y}\gamma-\kappa\frac{\partial \sigma}{\partial \theta}=0 \tag{10}$$

$$\frac{\partial U}{\partial \gamma}=\mathrm{A}py(\ddot{y}[1+\Gamma()\theta]-1)-\kappa\frac{\partial \sigma}{\partial \gamma}=0 \tag{11}$$

The first-order conditions show that the marginal utility from an additional unit of crop insurance at both the intensive (Equation (10)) and extensive (Equation (11)) margins depends on the planted acreage, coverage level, insured share, subsidy per liability, and the variance of profit.[12] The subsidy per liability and the variance of profit, in turn, are also dependent on coverage level, insurance unit, and $r()$.[13]

The channel through which the effective premium rate paid by the producer $r()$, affects the marginal utility from an additional level of insurance coverage at the intensive and extensive margin is dependent on the premium rate and the subsidy the producer will receive per dollar of liability insured. In this study's empirical setting, demand for crop insurance is modeled as a function of insurance contract specification, the effective premium rate paid by the producer, and other controls with several levels of model flexibilities to estimate the responsiveness of demand for crop insurance to changes in premium rates conditional on the level of premium rate subsidy level.

3. Data

Primary FCIP information for the analysis in this study was retrieved from RMA's summary of business files and contains insurance metrics aggregated by county, crop, crop type (e.g., corn can be grain or silage), production practice (e.g., irrigation, organic, etc..), insurance plan (e.g., Actual Production History [APH], Yield Protection [YP], Crop Revenue Coverage [CRC], Revenue Protection [RP], etc..), coverage level, and insurance unit (Optional unit [OU], Enterprise unit [EU], etc..); RMA refers to this data source as "Summary of Business" by "Type, Practice, Unit Structure" or "SOBTPU" for short.[14] The SOBTPU serves as the foundational data source for the study. The study defines the unit of analysis as an insurance pool, *i,* whose designation is defined at the SOBTPU aggregation level without the coverage level disaggregation, in crop year *t*. All pools with insurance plans designated as a group/area/index policy or an endorsement to an underlying policy (i.e., Supplemental Coverage Option [SCO], Enhanced Coverage Option [ECO], and Stacked Income Protection Program [STAX]) are dropped from the analyses as are pools with catastrophic, whole-farm-revenue coverage, or micro farm insurance.[15] Data from the SOBTPU was supplemented with; (1) actuarial information (i.e., design parameters for the FCIP that govern the premiums farmers face when making crop insurance decisions) from RMA's Actuarial Data Master (ADM)[16]; (2) established, projected, and harvest price information for 2001–2022 from RMA's ADM and price addendums; (3) acreage data from Farm Service Agency (FSA) with missing data filled in with planted, harvested, and baring acres from USDA National Agricultural Statistics Service (NASS) Quick Stats, in that order[17]; and (4) per-acre cost of crop production was approximated with state-level rental rates retrieved from NASS Quick Stats.

Measures of demand at the intensive margin were calculated using an aggregate coverage level defined as $\theta_{it} = \frac{1}{\sum A_{ijt}}\sum[\theta_{ijt}a_{ijt}]$, where, θ_{ijt} and a_{ijt} are the coverage level and net insured acres for the j^{th} entry associated with pool *i* in time *t*. For the case of the extensive margin, the ideal variable would be the insured share of planted acres, however, this is not observed in the public-facing version of the SOBTPU. As an alternative, we use the net insured acres (a_{it}) which we calculate as $\sum a_{ijt}$. The number of crop acres for the crop-county designation of pool *i*, A_{cct}, is calculated from the sources indicated above. Other information derived from the SOBTPU for each pool included premium per dollar of liability (τ_{it}) defined as the total premium divided by total liability, the subsidy per dollar of premium (s_{it}) defined as the total premium subsidy divided by the total premium, and the premium rate paid by the producer ($r_{it} = \tau_{it} \times s_{it}$).

The specific insurance pool's actuarial information (i.e., design parameters for the FCIP) retrieved from the ADM includes the county base rate (α_{it}) and catastrophic fixed loading factor (δ_{it}). For a given pool and crop year, the RMA-set continuous rating parameters were taken as their exact values retrieved from RMA's ADM. Given each pool's insurance unit, the FCIC-set subsidy rate for coverage level θ (i.e., a measure of aggregate subsidy rate set by policy $[\bar{s}_{\theta,t}]$) was derived as the total annual subsidy paid divided by the total premium paid for the respective coverage level and insurance unit of the pool. This aggregation was done over only individual yield and revenue protection information in the SOBTPU.

Using the data from the RMA sources above, the expected price was first taken as the projected price, if unavailable the established price was used before the harvest price is considered. The missing expected price that persists is replaced with the state-crop annual average of the price from the first step. Finally, the per-acre cost of crop production was approximated with state-level rental rates retrieved from NASS Quick Stats. Missing rental rates were approximated with the predictions from a regression of rental rates on land values also retrieved from NASS Quick Stats. All monetary values and prices were deflated by the producer price received index (rebased to 2022) constructed from the received-to-paid price index ratio multiplied by the index for the price paid retrieved from NASS Quick Stats.

Given that the continuous rating formula currently used by RMA came into effect in 2001/2002 this study is restricted to the period 2001–2022. Furthermore, the analysis is focused on 37 commodities covered under the FCIP that have; (1) premiums set using continuous rating, (2) 30 or more pool level observations per crop and crop year combination; and (3) ten or more crop year appearances. These commodities along with their sample size are shown on Table S1 in the online appendix.[18] The final data consists of 1,174,932 observations with 178,914 unique insurance pools. Figure S4 shows that the annual

[12] Alternative utility functions, besides the mean–variance form used here, can generate this same result in the sense that the marginal utility of additional units of insurance would still be conditional on a variety of factors that make the problem of identifying the relationship between subsidy rates and demand for insurance largely an empirical question. See for example, Woodard and Yi (2020) who show a similar result using a general utility function.

[13] If planted acres was treated as an endogenous variable in our conceptualization, Equation (7) will be represented as $\underset{\{\theta,\gamma,A\}}{\mathrm{Max}}\ \mathrm{U}=\mu-\kappa\sigma$ in which case a third first order condition characterizing the marginal utility with respect to acreage would be necessary $\left(\frac{\partial U}{\partial A}=py[1-\gamma]+p\gamma\ddot{y}[1-\Gamma\theta]-1-\frac{\partial C}{\partial A}-\kappa\frac{\partial \sigma}{\partial A}\right)$. This can be generalized for any other endogenous factor of production.

[14] SOBTPU files for each crop year are available at RMA (2023a).

[15] For coverage level, the focus is given to only buy-up coverage policies as catastrophic (CAT) policies are essentially free (aside from a fixed signup fee charged for enrolling) from the point of view of the producer, and their pricing is not tied to the continuous rating formula. Insurance plans designated as a group/area/index policy or as endorsements to an underlying policy (i.e., SCO, ECO, and STAX) follow a somewhat different rating formula that is not supported by the conceptual framework and identification strategy used in this study.

[16] ADM files for each insurance year are available at RMA (2023b). The aggregation of ADM information is based on initial work by Tsiboe and Tack (2021) using Beocat, a High-Performance Computing (HPC) cluster at Kansas State University.

[17] FSA Crop Acreage Data are available at FSA (2023).

[18] The crops included almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat.

appearance of an insurance pool in the sample ranged from 1 to 23 times with about 80% appearing in more than one crop year and about 40% appearing in ten or more crop years. The final data set represents 63% of total insured acreage within the FCIP from 2001 to 2022. Similarly, 73% of liabilities, 79% of premiums, 79% of subsidies, and 79% of indemnities were represented in the final data set.

Table 1 shows the descriptive statistics of all variables in the dataset across all the insurance pools. On average a pool in the data set had an insured liability of $847,000 with an insured area of 3,497 acres and a coverage level of 69% purchased at a premium cost of $86,591 of which $52,950 was paid for by government subsidies. Figure S5 (A) shows that from 2001 to 2022 insured acres [coverage level] decreased [increased] marginally, particularly after the passage of the 2008 farm bill. Respectively, the overall mean for premium per dollar of liability and subsidy per dollar of premium is $0.137 and $0.608, and figures S5 (C) and (D) show that whilst the former has reduced from 2001 to 2022, the latter has increased over the same period. In terms of the continuous rating parameters, Figures S5 (F) and (G) show that the mean base rate and catastrophic fixed loading factor have both declined, reflecting the reduction in the overall mean for premium per dollar of liability.

It is worth noting that the assignment of the insurance pools by this study is based on policy offerings and RMA's reporting guidelines and not necessarily on producer risk profiles. The kind of producer-level data needed to accomplish this is currently restricted. Ideally one might want to ascertain how producer characteristics change from year to year after the pool assignment. RMA uses the insured's average on-farm yields relative to their peers (relative yield) and presumes that their risk co-varies with that average. Thus, given the pool-level data, the rating formula in Equation (3) is instead used to uncover a representative relative yield for each pool-year combination in the sample. The mean of the representative relative yield across all pools for a given crop is then used to assess the temporal evolution of risk. This essentially gives a sense of how the risk profile as used by RMA is changing from year to year. Figure S6 shows that across the entire sample it can be observed that the relative productivity measure used by RMA has evolved differently for each crop.

Table 1
Means and Standard Deviations of US Federal Crop Insurance Pools (2001/22).

Variables	Mean (Standard deviation)
Coverage level ($\widehat{\theta}_{it}$)	0.688 (0.078)
Net insured area (acres)($\widehat{a}_{it}$)	3496.807 (10747.413)
County-crop area (1,000 acres)(A_{cct})	59.623 (99.361)
Total liability ($ 1,000) ($\sum l_{ijt}$) [A]	846.768 (3225.961)
Total premium paid ($ 1,000) [B]	86.591 (304.982)
Total premium subsidy paid ($ 1,000) [C]	52.950 (197.443)
Premium per dollar of liability ($\tau_{it} = B/A$)	0.137 (0.098)
Subsidy per dollar of liability premium ($s_{it} = C/B$)	0.608 (0.088)
Producer paid premium rate ($r_{it} = \tau_{it} \times s_{it}$)	0.083 (0.062)
Base rate ($\overline{\alpha}_{it}$)	0.098 (0.084)
Catastrophic fixed loading factor ($\overline{\delta}_{it}$)	0.029 (0.015)
Rate for 65% coverage ($\tau_{it,65} = \overline{\alpha}_{it} + \overline{\delta}_{it}$)	0.126 (0.093)
65% coverage subsidy rate ($\overline{s}_{65,t}$)	0.632 (0.084)
75% coverage subsidy rate ($\overline{s}_{75,t}$)	0.597 (0.087)
65 and 75% coverage subsidy rate ($\overline{s}_t = [\overline{s}_{65,t} + \overline{s}_{75,t}]/2$)	0.615 (0.085)
Preferred instrument ($\overline{r}_{it} = \tau_{it,65} \times \overline{s}_t$)	0.077 (0.058)
Mean normalized projected price	0.665 (0.417)
Rent ($/acre)	73.475 (42.390)
Number of insurance pools	178,914
Number of observations	1,174,932

Note: An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

4. Empirical model

Previous studies have used extensive or intensive margin measures of insurance as competing representations of the true level of insurance in single equation estimations (Barnett et al., 1990; Goodwin, 1993). Others have also presented these measures as recursive in the producer's insurance decisions (Richards, 2000). Neither of these approaches allows contemporaneous correlation between the producer's insurance decisions at the intensive and extensive margin. This study takes an alternative approach and works from the premise that crop insurance decisions at the extensive margin (i.e., net insured acres) and the intensive margin (i.e., coverage level) are made together and are likely to be influenced by the same set of unobservables. Thus, our empirical model can be defined by the following system of equations,[19]

$$\ln A_{it} = \beta_{a,0} + \beta_{a,r}\ln r_{it} + \boldsymbol{\beta}_{a,w}\boldsymbol{w}_{it} + v_{A,it} + \varepsilon_{A,it}$$

$$\ln\theta_{it} = \beta_{\theta,0} + \beta_{\theta,r}\ln r_{it} + \boldsymbol{\beta}_{\theta,w}\boldsymbol{w}_{it} + v_{\theta,it} + \varepsilon_{\theta,it}$$

$$\begin{bmatrix} \sigma_{aa} & \sigma_{\theta a} \\ \sigma_{a\theta} & \sigma_{\theta\theta} \end{bmatrix} = \Sigma \text{ where } \sigma_{kl} = \mathrm{cov}\left(\varepsilon_{k,it}, \varepsilon_{l,it}\right) \tag{12}$$

where the net insured acreage, a_{it}, and the average coverage level, θ_{it}, are modeled as a function of the same set of covariates which include the producer-paid premium rate, r_{it} and a vector of control variables, $\boldsymbol{w}_{it}$, which contains the log expected price for the i^{th} pool's crop, log planted acres for the respective crop for the i^{th} pool's county, the rental rate for land for the i^{th} pool's state, crop-specific time trends, and year-fixed effects. The term $v_{k,it}$ captures crop-insurance pool fixed effects. The error term for each equation, $\varepsilon_{k,it}$, is assumed to have an expected value of zero but can be heteroskedastic and autocorrelated since the data is an unbalanced panel. Thus, standard errors are clustered using two-way clustering by year and insurance pool to allow for $\varepsilon_{k,it}$ to be spatially correlated within each year and temporally correlated within each pool (Cameron et al., 2011; Petersen, 2009; Thompson, 2011). Since all the variables are in natural logarithms, the estimated coefficient for $\ln r_{it}$, $\{\widehat{\beta}_{\theta,r}, \widehat{\beta}_{a,r}\}$ can be interpreted as demand elasticities at the {intensive, extensive} margin to changes in the producer-paid premium rate. It also follows that the total demand elasticity for total protection (combined protection at both margins) is given by $\widehat{\beta}_{a,r} + \widehat{\beta}_{\theta,r} + \widehat{\beta}_{\theta,r}\widehat{\beta}_{a,r}$.

Estimating the empirical model for the entire sample provides average elasticity estimates for all producers in the FCIP. However, aggregating across all crops and regions could be misleading since policy offerings differ across commodities and counties.[20] If the demand response to changes in producer-paid premium rate was subject to significant spatial or commodity-specific heterogeneity, high-level

[19] Estimation of the extensive and intensive margin simultaneously is necessary to make our model theoretically consistent with the fact that both extensive and intensive margin decisions are required to completely define a policy. Estimating demand for insurance as two separate processes would generate bias. This is most obvious in the case where a budget constraint is binding in which case increasing insurance demand at the extensive margin would necessarily results in a proportional decrease in demand and the intensive margin (and vice versa).

[20] For example, while some commodities have both revenue and yield protection available, some of the crops represented in our dataset have only yield protection insurance available.

aggregated estimates would mask this variation. Given the large sample size available, additional estimation is conducted to assess how the demand elasticities change along the defining characteristics of each insurance pool (i.e., commodity, policy type, production practice, etc.) to assess potential heterogeneity in the elasticities. This is accomplished by allowing $\ln r_{it}$ to shift with the levels within each insurance pool characteristic (achieved by the inclusion of interaction terms between $\ln r_{it}$ and each value of the characteristics being considered [$\boldsymbol{D}_{it}$]). For these estimations, our empirical model was modified as,

$$\ln A_{it} = \beta_{a,0} + \boldsymbol{\beta}_{a,d,r}(\boldsymbol{D}_{it} \times \ln r_{it}) + \boldsymbol{\beta}_{a,w}\boldsymbol{w}_{it} + v_{A,it} + \varepsilon_{A,it}$$

$$\ln \theta_{it} = \beta_{\theta,0} + \boldsymbol{\beta}_{\theta,d,r}(\boldsymbol{D}_{it} \times \ln r_{it}) + \boldsymbol{\beta}_{\theta,w}\boldsymbol{w}_{it} + v_{\theta,it} + \varepsilon_{\theta,it}$$

$$\begin{bmatrix} \sigma_{aa} & \sigma_{\theta a} \\ \sigma_{a\theta} & \sigma_{\theta\theta} \end{bmatrix} = \Sigma \textit{ where } \sigma_{kl} = \mathrm{cov}\left(\varepsilon_{k,it}, \varepsilon_{l,it}\right) \tag{13}$$

Although producers presumably focus on the out-of-pocket cost (i.e., the producer paid premium rate, r_{it}), when making insurance decisions, it is possible that the base premium rate (before subsidization) is the relevant metric if their menu of insurance contracts is presented to them at pre-subsidized rates. As such, an alternative specification is estimated that uses the premium per dollar of liability ($\ln\tau_{it}$) as the primary independent variable while excluding the subsidy rate from the estimation. Another possibility (although rather unlikely) is that producers pay attention to the subsidy rate, but not the premium rate when making insurance decisions. For completeness, a specification is included that represents this situation (i.e., the inclusion of subsidy rate as an independent variable and exclusion of the premium per dollar of liability).

Finally, to analyze heterogeneity in the demand response to changes in out-of-pocket costs of crop insurance (which could be achieved via changes in subsidy rate) conditional on the initial (i.e., the current) subsidy rate, a series of categorical variables are used that capture the current range of the subsidy per dollar of premium (s_{it}) faced by the producers. The levels of the categorical variables are defined in 3% bins (i.e., I $[0.55 < s_{it} \leq 0.58] = 1$ defines a pool that currently faces a 55%-58% subsidy rate). Pools with s_{it} above 80% were rare, thus, the categorical variable for s_{it} at and above 80% were combined into a single indicator. Similarly, s_{it} at 40% and below were also combined. The demand elasticity for each bin is estimated by allowing the $\ln r_{it}$ to shift with the levels within the categorical variable (achieved by interacting each indicator with $\ln r_{it}$ in the empirical model).

5. Identification strategy

As was previously mentioned, several sources of endogeneity exist in the empirical framework utilized by this study. The first stems from the fact that variation observed in the key independent variable, producer paid premium rate (r_{it}),[21] is partly driven by the distribution of risk for a given insurance pool and producer's production choices which makes it potentially endogenous to the net insured acres and coverage level – i.e. an insurance pool with a greater risk of prompting an indemnity payment has a higher premium rate for a given crop insurance choice. At the same time, producers tend to self-select out of riskier pools by allocating fewer acres to crops associated with such pools, or fewer acres to any crop in a county characterized by a greater risk profile, *ceteris paribus* (Hojjati and Bockstael, 1988). In other words, crop insurance risk pools suffer from a classic adverse selection problem in which riskier pools tend to consist of producers who opt to insure more acreage, at higher coverage levels presumably because of their privately known production risk profile that is not easily observable by rate-setters.

The assumed specification of the empirical model is incorrect because it omits "risk" an independent variable that influences decisions on how much acreage to enroll and at what coverage level to insure. Consequently, risk is correlated with the subsidy rate and premium rate yet is unobserved meaning the producer-paid premium rate is correlated with the error term.[22] In addition to "risk" being omitted from the estimating equation, the study must also contend with the simultaneous determination between insurance decisions and the out-of-pocket cost of insurance. As noted by Woodard and Yi (2020), the relationship between coverage and paid premiums forms an upward-sloping demand curve as a matter of actuarial construction if premiums are used as the "price" variable since higher levels of coverage necessitate higher premiums to maintain actuarial soundness. All this is to say that choosing to estimate the empirical model via ordinary least squares (OLS) or as a seemingly unrelated regression will produce biased estimates. Another potential source of omitted variable bias is the dependence of s_{it} and τ_{it} on the choice of insurance unit. However, pools include insurance units as one of the pooling factors meaning this issue is addressed by the inclusion of pool fixed effects which control for time-invariant risk that differs by the pool. Endogeneity concerns are addressed by using the policy rating parameters set by RMA to instrument for producer-paid premiums.

As discussed in section 2, the RMA rating parameters are updated each year to maintain the actuarial soundness of the FCIP. Although these rating parameters are updated in part based on past actuarial performance, they remain exogenous to any one producer's decisions by virtue of several RMA rating practices. First, RMA employs what they refer to as "credibility weighting" which is their term for a spatial smoothing algorithm that seeks to attenuate large discontinuities in crop insurance pricing along county borders (Coble et al., 2010; Risk Management Agency [RMA], 2009). Credibility weighting also serves to down-weight the loss experience of counties that are highly variable (in which case the loss experience of neighboring counties is used more heavily in the rate making process). In effect, this means that a single producer's county base rate is based on all producers of the same commodity within their county and all the producers of the same commodity in all adjoining counties. Consequently, the influence that a single producer has on the future base rate that they face is negligible.[23] In addition to credibility weighting which spatially smooths county base rates, RMA also updates rating parameters on a three-year cycle using historic loss experience data from the previous 20 years starting from two crop years before the current [update] crop year. This also imposes additional temporal separation between the decisions of a producer and the county base rate they face. Due to the common practice of multi-crop rotations, rotational grazing, or letting fields lay fallow, the group of producers that purchase crop insurance for a certain commodity each year will face a base rate influenced by the outcomes of a different group (although unlikely to be entirely disjoint) of producers. Lastly, RMA retains the right to use their professional judgement to subjectively rate crop insurance policies (Coble et al., 2010) which provides an additional buffer between a producer's behavior and their county base rate.

This approach is like Woodard and Yi (2020), who, to the best of our knowledge, is the only prior study to address the simultaneity between premium rates and coverage decisions. While they also use rating

[21] i.e., the product of the subsidy per dollar of premium (s_{it}) and the premium per dollar of liability ($.\tau_{it}$)

[22] As a reminder, the subsidy rate is correlated with the premium rate under the subsidy rate being a function of chosen coverage level with subsidy rates decreasing as the coverage level increases (Figure S7).

[23] The average number of crop insurance policies associated with a county-crop-year group (ex: policies associated with corn producers in Monroe County, Iowa in 2018 would constitute one group) between 2000 and 2021 is 147. This means there are 147 crop insurance policies that contribute to the average county's loss experience that influences the county base rate. When credibility weighting is considered, the average county has an additional 769 policies in adjoining counties that can influence the county base rate. In other words, the owners of approximately 900 policies (or at least a large portion of those) would need to collude to intentionally influence their county base rate.

parameters as instruments, their approach to arriving at these instruments is different from what is used in this study. The major difference is that they use observed aggregate level data to estimate from a latent rate curve, an instrument that mimics the relationship between RMA's rate differential factors and coverage level to capture curvature in the premium schedule. One limitation of doing so is that any error in the estimation of the rating parameters could be translated into an error in their final elasticity estimates. Additionally, by estimating rating parameters using observed aggregate level data, a causal link is established between producer coverage decisions and the instruments used to generate, presumably, exogenous variation in premium rates. Thus, a potential source of simultaneity remains in the empirical framework.[24] Alternatively, the approach used in this study makes use of observed RMA-rating parameters that captures the initial level of premiums (i.e., the intercept of the premium schedule) to generate instruments that eliminate any direct influence between producer insurance decisions and the instrumental variables.[25]

Several studies have shown that instrumental variable estimators (IV) based on a large set of instruments may have undesirable properties (Bekker, 1994; Belloni et al., 2012; Chao et al., 2012; Chao and Swanson, 2005; Hansen et al., 2008) with a recent paper showing that in many micro-econometric applications, just identified IV is an appropriate identification strategy with bias that is minimal compared to high dimensional approaches (Angrist and Kolesár, 2021). Furthermore, empirically, using all potential instruments is computationally intractable. Consequently, instead of using all the rating parameters as separate instruments, we opt for the case of just identified IV by assimilating them into a single source of exogenous influence for the premium rate faced by each producer. Specifically, we use the base premium rate for a 65% coverage level for the average farm in a county (i.e., $\overline{y}/\overline{y}_c = 1$) which we calculate as $\tau_{it,65} = \overline{\alpha}_{it}\left(\overline{\overline{y}}_{cit}/\overline{\overline{y}}_{cit}\right)^{\overline{\beta}_{it}} + \overline{\delta}_{it} = \overline{\alpha}_{it} + \overline{\delta}_{it}$. This represents the initial premium rate (i.e., the intercept of the premium schedule) for a producer which is the sum of the county base rate with an additive catastrophic loading factor applied.[26] In other words, $\tau_{it,65}$, represents the cost of insurance before any adjustment is made based on the insured producer's past production history, insurance coverage level, or unit structure election.

To instrument for the subsidy per dollar of premium (s_{it}), the study adopts a strategy previously used by Yu et al. (2018) whose identification strategy is premised on the fact that changes in legislation create a structural break that shifts the suite of subsidy rates exogenously in a way that is not driven by endogenous factors related to crop production. Thus, to instrument for s_{it} the study follows Yu et al. (2018) and uses the aggregate subsidy rate for yield protection and revenue protection for 65% ($\overline{s}_{65,t}$) and 75% ($\overline{s}_{75,t}$) coverage levels associated with each pool's insurance unit.[27] In this application, a single instrument is defined as the mean of Yu et al. (2018)'s instruments $\left(\overline{s}_t = \left[\overline{s}_{65,t} + \overline{s}_{75,t}\right]/2\right)$. Finally, to instrument for the producer paid premium rate, which is the endogenous variable in the preferred empirical specification, the two previous described instruments are interacted ($\overline{r}_{it} = \tau_{it,65} \times \overline{s}_t$) to capture exogenous variation in the producer paid premium generated from both RMA set policy parameters and structural shifts in congressionally approved subsidy rate changes.

6. Results

Table 2 shows estimated results for the system defined in equation (12). Columns (1) and (2) report the estimation results with instruments via three-stage least squares (3SLS) with and without Fixed-Effect (FE), respectively while column (3) reports the results without instrumenting. The F-statistics separately computed for each endogenous variable are well above the thresholds suggested by Stock and Yogo (2005) indicating that weak instruments are not a statistically obvious concern.

Concerning the equation representing demand at the intensive margin, the preferred model [Model 1: FE-3SLS] has an estimated coefficient for the paid premium rate that is smaller in magnitude and of the opposite sign when compared to the non-instrumented model [Model 3: FE-OLS] which highlights the consequences of failing to correct for endogeneity in the empirical specification. Model 1 (FE-3SLS) also indicates that the effect of paid premium rate is roughly half as large relative to model 2 (3SLS without fixed effects). Results based on extensive margin demand do not indicate a significant relationship between paid premium rate and insurance demand when both instrumental variables and fixed effects are applied (Model 1). Instrumenting without fixed effects (Model 2) suggests a positive relationship between paid premium rate and insured acres while applying fixed effects in the absence of instrumental variables (Model 3) suggests the opposite effect. Models 4 and 5 estimate the effects of premiums and subsidies in isolation. Both specifications have signs consistent with theory (i.e., increasing premiums attenuate demand while increasing subsidies augment demand). However, as previously discussed, these specifications are not as credible given that producers are unlikely to act on premiums or subsidies alone, but rather their interaction which governs their out-of-pocket cost.

The results from the preferred model (3SLS with fixed effects) show that the covariance between crop insurance at the intensive and extensive margins is positive (0.003) suggesting factors that increased demand at the intensive margin also increases demand at the extensive margin, and vice versa. However, this cross-demand effect is not symmetric. A one percent increase in demand at the intensive margin increases extensive margin demand by about 0.005% while a percent increase in demand at the extensive margin increases intensive margin demand by about 0.772%. We also observe that the producer-paid premium rate drives crop insurance demand at the extensive margin more than at the intensive margin, albeit, with increased statistical uncertainty due to large standard errors. Particularly, for a percent increase in paid premium rates, the net insured acres, and chosen coverage level decrease by 0.052 and 0.022%, respectively. These elasticities cumulate into a decrease in total demand elasticity for total protection (combined protection at both margins) of −0.074 for a percent increase in paid premium rates.

Allowing the estimated demand elasticities to vary with the underlying initial subsidy rate suggests that the demand response to premium subsidies varies based on the initial subsidy rate (illustrated in Fig. 2).

[24] For example, if producers who choose low levels of coverage tend to have fundamentally different actual production histories (which are used by RMA to set premiums) compared to producers who choose high levels of coverage, then the producers' coverage level choices would be correlated with the curvature of the observed rate curve. In other words, in this example, the rate curve derived from observed data would not maintain the same curvature if the producers choosing high coverage levels alternatively choose low coverage levels and vice versa. Thus, any estimated instruments are dependent on the insurance decisions of the producers. Consequently, the producer insurance decisions indirectly influence the estimated effect of premium rates on producer insurance decisions by way of the estimated instruments.

[25] Woodard and Yi (2020) conduct a series of simulations to show that using observed rating parameters eliminates the simultaneity bias but switches to using estimated rating parameters in their estimation of elasticities.

[26] A fixed catastrophic loading factor is applied to account for the fact that extreme tail events are not often observed in historical data making it more difficult to confidently derive actuarial sound rates. The loading factor serves as a buffer in the case where rare events are more probable than their historical occurrences would suggest.

[27] The 65 and 75 percent coverage levels are the most popular coverage level choices and have been available for several decades making a natural choice to use as instruments (Yu et al. 2018).

Table 2
Crop Insurance Demand System for US Federal Crop Insurance Pools (2001/22).

Variables	(1) \dag\dag	(2)	(3)	(4)	(5)
Coverage level ($\ln\theta_{it}$)					
Paid premium rate ($\ln r_{it} = \ln[\tau_{it} \times s_{it}]$)	−0.022*** (0.003)	−0.040*** (0.003)	0.085*** (0.004)	–	–
Premium per dollar of liability ($\ln\tau_{it}$)	–	–	–	−0.028*** (0.003)	–
Subsidy per dollar of premium ($\ln s_{it}$)	–	–	–	–	0.161*** (0.011)
County planted acres	0.001*** (0.000)	0.006*** (0.000)	0.002*** (0.001)	0.001*** (0.000)	0.002*** (0.000)
State rental rate for land	0.001 (0.007)	0.031*** (0.001)	0.010 (0.006)	0.000 (0.007)	0.003 (0.007)
Expected crop price	−0.011** (0.005)	−0.005** (0.002)	−0.014*** (0.004)	−0.010** (0.005)	−0.012*** (0.004)
Insured acres ($\ln a_{it}$)					
Paid premium rate ($\ln r_{it} = \ln[\tau_{it} \times s_{it}]$)	−0.052 (0.075)	0.082*** (0.015)	−0.076* (0.042)	–	–
Premium per dollar of liability ($\ln\tau_{it}$)	–	–	–	−0.194*** (0.028)	–
Subsidy per dollar of premium ($\ln s_{it}$)	–	–	–	–	5.907*** (0.322)
County planted acres	0.460*** (0.019)	0.477*** (0.019)	0.459*** (0.019)	0.459*** (0.018)	0.464*** (0.018)
State rental rate for land	−0.028 (0.072)	−0.034*** (0.009)	−0.029 (0.074)	−0.038 (0.073)	0.004 (0.082)
Expected crop price	0.141*** (0.036)	−0.572*** (0.036)	0.142*** (0.037)	0.146*** (0.037)	0.127*** (0.045)
Total protection response					
Paid premium rate ($\ln r_{it} = \ln[\tau_{it} \times s_{it}]$)	−0.074 (0.074)	0.038** (0.017)	0.003 (0.046)	–	–
Premium per dollar of liability ($\ln\tau_{it}$)	–	–	–	−0.216*** (0.028)	–
Covariance matrix					
σ_{aa}	0.543	3.029	0.543	0.545	0.665
$\sigma_{\theta\theta}$	0.004	0.013	0.003	0.004	0.004
$\sigma_{\theta a}$	0.003	0.027	0.003	0.004	0.018
Estimator	FE-3SLS	3SLS	FE-OLS	FE-3SLS	FE-3SLS
Number of observations	1,174,932	1,174,932	1,174,932	1,174,932	1,174,932
Number of insurance pools	178,914	178,914	178,914	178,914	178,914
Weak-instrument: F-statistics					
Preferred instrument ($\ln\bar{r}_{it} = \ln[\tau_{it,65} \times \bar{s}_t]$)	280652.424***	1789606.241***	–	–	–
Rate for 65% coverage ($\ln\tau_{it,65}$)	–	–	–	210607.806***	–
65 and 75% coverage subsidy rate ($\ln\bar{s}_t$)	–	–	–	–	59974.623***

Notes: Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data used was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats. The preferred model is \dag\dag. Significance levels - *$p < 0.1$ ** $p < 0.05$, ***$p < 0.01$. Standard errors in parentheses are clustered by insurance pool and year.

Notably, demand at the intensive margin responds either positively or negatively to changes in the out-of-pocket cost of insurance with the difference being conditional on the current subsidy level. With a premium subsidy of less than or equal to 40%, a percent increase in the paid premium rate leads to a 0.054% reduction in the coverage level whereas demand increases by 0.074% when initial subsidy rates are over 80%. Intensive margin demand exhibits no change with respect to changes in out-of-pocket costs when subsidy levels are in the range of 59–60%. However, intensive margin outcomes are only a single component of total demand. With respect to the extensive margin, demand elasticities are negative through most of the range of subsidy levels and generally become less elastic as subsidy rates approach zero. Total demand (the combination of changes at the extensive and intensive margin) indicates that demand responds negatively for most initial subsidy levels and remains roughly constant (mean of −0.08%) for subsidy levels below 70%.[28]

Observed Heterogeneity.

Figs. 3-6 report elasticities based on changes in the paid premium rate and a premium per dollar of liability across various observable characteristics.[29] These include commodity produced, irrigation practices, organic certification, insurance policy type, insurance unit, coverage level, and resource region. Fig. 3 panel A reports separately estimated elasticities for each insured commodity. Estimates for demand at the intensive margin are all negative (or have 95% confidence intervals inclusive of 0). Extensive margin demand indicates varied demand responses however most are statistically insignificant – the exceptions being negative responses for olives (-1.900), apples (-0.682), grapes (-0.491), flax (-0.425), wheat (-0.394), sweet corn (-0.379), tobacco (-0.325), peanuts (-0.204) with a positive response observed for oranges (1.088) and grain sorghum (0.328). For the intensive margin, 17 commodities had negative and significant elasticities ranging from tobacco (-0.014) to canola (-0.067); and only one, tomatoes (0.050), had a positive significant elasticity. Total protection responses generally mirror extensive margin elasticities due to that of the extensive margin being larger in magnitude than those derived at the intensive margin.

Differences persist across irrigation status as well (Fig. 4A). Non-irrigated practice units have statistically significant and negative elasticities at the intensive margin (-0.034) but have a statistically insignificant response at the extensive margin (0.128). The opposite is true for irrigated units (insignificant response in coverage level [-0.001] and statistically significant reduction in insured acreage [-0.345]).

[28] The exceptions are elasticities derived from respondents with subsidy rates higher than 80% and a single bin for subsidy rates of 80–90%, both of which have rather small sample sizes.

[29] The methodology used to derive Fig. 3 is the same approach used in Fig. 2. Indicator variables that segment the sample across some series of observable characteristics (e.g., corn producers, wheat producers, etc.) are included in the empirical specification and interacted with the relevant measure of insurance cost.

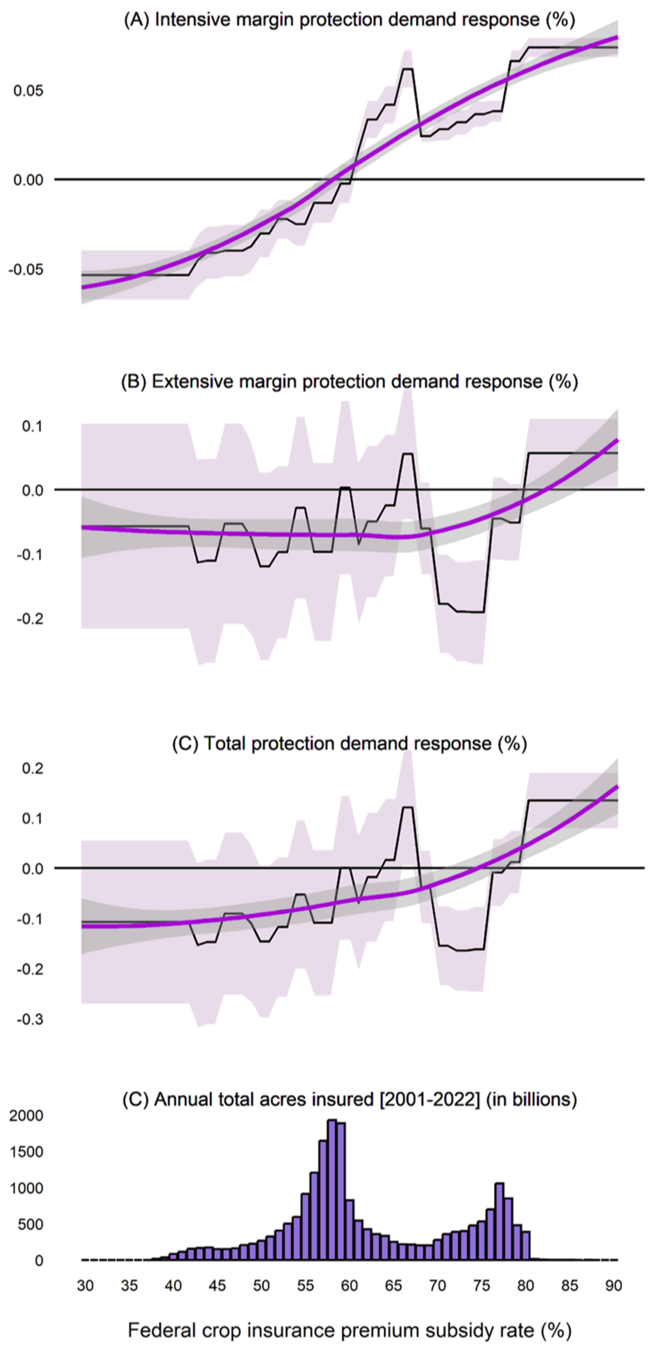

Fig. 2. US Federal Crop Insurance Pool's Demand Response Conditional on Premium Subsidy (2001/22) Notes: Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data used was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

Concerning organic classification (Fig. 4B), certified organic producers have responses (-0.037, −0.540, and −0.556 for intensive, extensive, and total, respectively) to changes in the cost of insurance that are negative, statistically significant, and larger in magnitude relative to the general pool of producers. This suggests organic producers may be particularly sensitive to increases in the cost of crop insurance relative to other production practices which may help explain the gap in demand for insurance between organic and conventional producers that have been observed in existing literature (Belasco and Fuller, 2022).

Decomposing results by crop insurance protection type (Fig. 5A) suggests that pools with an insurance policy protecting against a shortfall in revenue react with a significant decrease in total coverage (-0.556) with respect to changes in the cost of insurance. Insurance pools characterized by yield protection policies also produce negative elasticities at the intensive margin (-0.009) but lack statistical significance. Differences across policy types at the extensive margin are more pronounced with revenue protection policies producing negative and statistically significant elasticities (-0.540) whereas pools using yield protection policies exhibit statistically significant and positive elasticities (0.480). Notably, when heterogeneity in the extensive margin demand response across protection types is ignored, the aggregate response to changes in the paid premium rate is statistically indistinguishable from zero due to the competing effects across different protection types that cancel out.

Within the FCIP, insurance unit structures are groups of acreage that are insured under a common policy. Enterprise units encompass all a producer's insurable acreage producing the same crop in the same county whereas basic and optional units consist of smaller subdivisions of acreage each of which can have a different policy. Given that enterprise units eliminate the possibility of adverse selection and distribute risk across large geographic areas, electing to insure under an enterprise unit means the resulting policy is subject to a larger premium subsidy rate and a lower premium rate as shown by Figure S2. Decomposing results by insurance unit (Fig. 5B) suggests that enterprise units do not significantly alter coverage levels in response to increasing insurance costs whereas pools characterized by basic and optional units both have statistically significant and negative elasticities of comparable magnitudes; −0.027 and −0.032, respectively. Alternatively, at the extensive margin, pools based on enterprise units produce an elasticity (-0.432) that is statistically significant and below zero while basic units and optional units generate statistically insignificant elasticities.

Within the FCIP, the subsidy rate varies by coverage levels which can incentivize different responses to increased insurance costs that are conditional on a producer's current coverage level (this is discussed in more detail in the next section). Fig. 6A decomposes estimated elasticities by grouping insurance pools based on the coverage level within the pool that has the most insurance acreage (i.e., if the plurality of acreage in an insurance pool is insured at the 75% coverage level, that entire pool is assigned to the 75% group for purposes of the estimation that produces Fig. 6A). At the intensive margin, ordering insurance pools by estimated elasticity perfectly orders them by coverage level starting with the 85% coverage level producing the most negative elasticity (-0.054) and the 50% coverage level producing the largest positive elasticity (0.051). At the extensive margin, a similar ordering is observed, but differences in magnitude are not as pronounced and not generally statistically significant.

Fig. 6B breaks down estimated elasticities based on ERS farm resource regions (Heimlich, 2000). Estimated elasticities are generally negative with respect to demand at both the intensive and extensive margins. Given that commodities in the U.S. are typically grown in spatially clustered regions, much of the variation in estimates reported in Fig. 6B can likely be at least partially attributed to variation in the commodity being produced.

Robustness Checks.

To assess the reliability of our results presented in Table 2, we conduct several robustness checks. First, insurance pools, as defined by

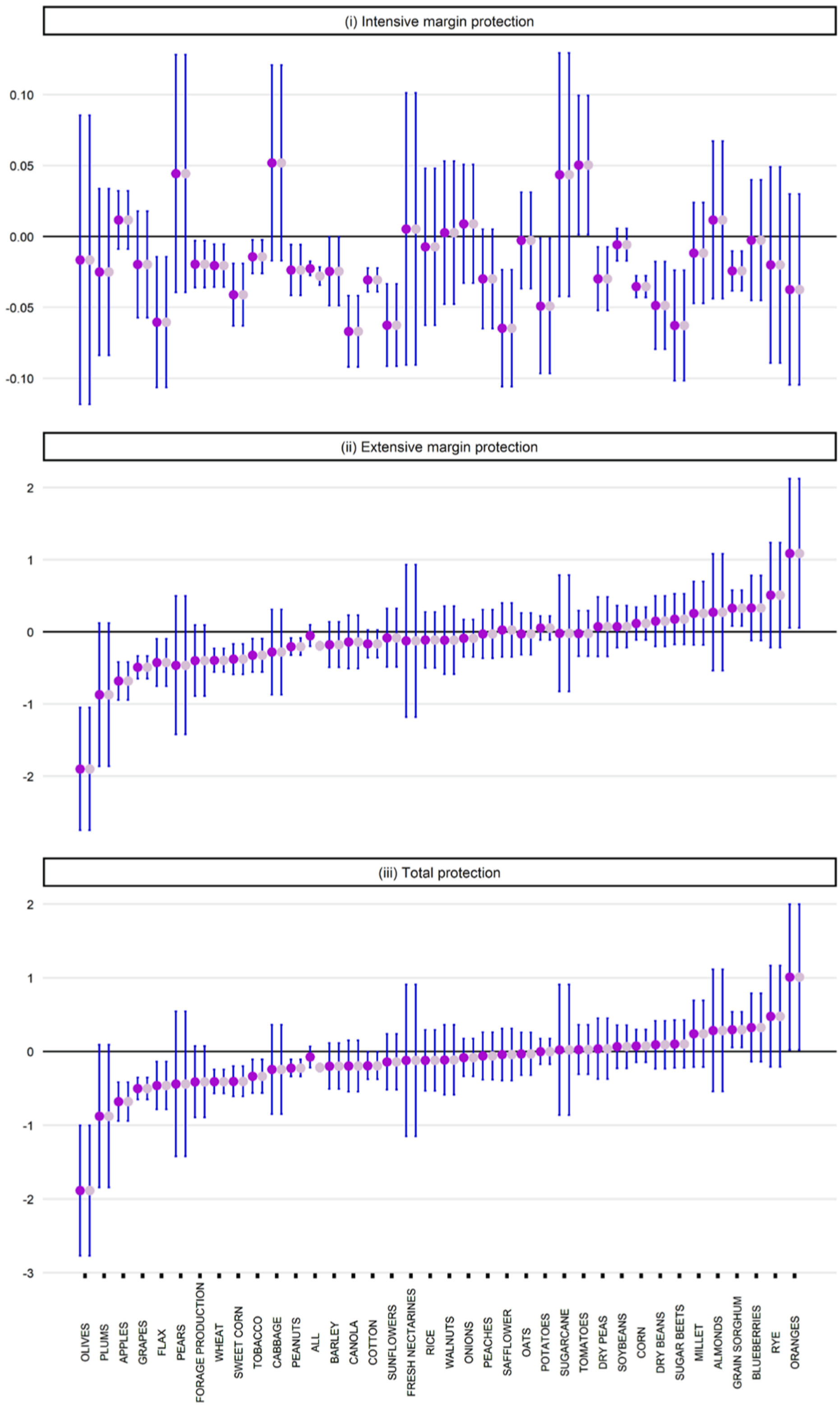

Fig. 3. US Federal Crop Insurance Pool's Demand Response Conditional on Insurance Pool Commodity (2001/22) Notes: Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data used was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

this study, involved the aggregation of policies of different coverage levels into one measure of intensive margin demand. In our forgoing model this aggregation was done by using an insured acreage weighted average of the constituent coverage levels of a given pool $\left(\theta_{it} = \frac{1}{\sum A_{ijt}} \sum [\theta_{ijt} a_{ijt}]\right)$. In Table S2 we present results based on alternative measures of intensive margin demand. Column 1 represents the acreage weighted average coverage level (used in the primary analysis). Column 2 measures intensive margin demand using the ratio of liability to total potential liability defined as $\left[\sum l_{ijt}\right] / \left[\sum \frac{l_{ijt}}{\theta_{ijt}}\right]$; where, θ_{ijt} and l_{ijt} are the coverage level and total liability for the jth entry associated with pool i in time t. The total potential liability $\left[\sum \frac{l_{ijt}}{\theta_{ijt}}\right]$ represents all liability that could conceivably be insured holding the year's enrolled acreage and current producers fixed. Column 3 measures intensive margin

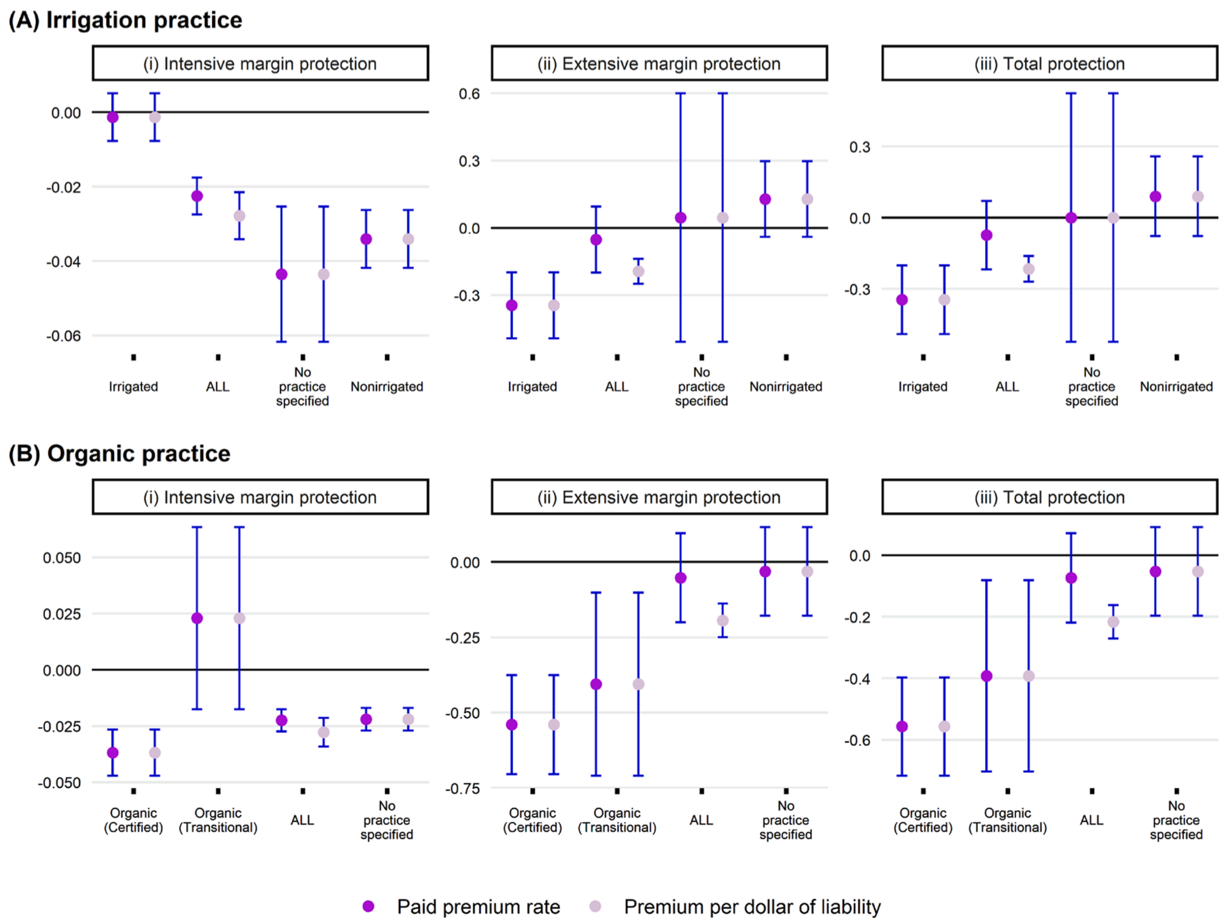

Fig. 4. US Federal Crop Insurance Pool's Demand Response Conditional on Insurance Pool Production Practices (2001/22) Notes: Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data used was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

demand by taking a simple average of the coverage level (i.e., equal weight as opposed to the acreage weighted measure in column 1). Finally, column 4 defines the coverage level by identifying which coverage level contains the highest number of acres and using that coverage level as the sole measure of intensive margin demand. The measure in column 4 can thus be thought of as a modal coverage level. In every alternative measure of intensive margin demand, results are quantitatively equivalent to those from our primary analysis.

Our next robustness check is based on the notion that crop rotations could influence our estimates of demand at the extensive margin. For example, in the case of a two-year corn-soy rotation, we may expect insured acres in an insurance pool to routinely vary based on which crop is currently being planted. To address this, we include the 1-year lag of insured acres into the extensive margin equation, the rationale being that if crop rotations influence insured acres than the lag of insured acres should be negatively correlated with the insured acres in the current year. Results from this specification are presented in Table S3. The one-year lag had a positive and significant influence on insured acres indicating a failure to find evidence that crop rotations were influencing current year insured acres. The conclusions from this alternative specification are qualitatively equivalent to our main specification; intensive margin demand elasticities are relatively inelastic and negative while elasticities from the extensive margin equation are statistically insignificant. Additional specifications are estimated using lags of the county planted acres as a proxy measure of county-wide patterns in rotation. The positive and significant influence of the one-year lag of insured acres on current insured acres, was confirmed by up to two lags in county planted acres. The demand elasticities conclusions from these alternative specifications are also qualitatively equivalent to our main specification (Table S3).

To assess whether increasing availability of crop insurance could have influenced our results via incentivizing land use decisions, we conduct a robustness check using only county-crop pairs that had FCIP policies available for the entirety of our study periods. Results from this exercise can be found in Table S4 in the supplementary materials. Overall, we find qualitatively equivalent results relative to the full sample. Temporal robustness checks using Farm Bill periods and a structural break in 2012 (corresponding to a rise in popularity of revenue protection policies), to assess temporal heterogeneity and potential variation due to different farm policy environments yielded estimated elasticities for all time periods that were statistically indistinguishable from our main results (see Figure S8).

To assess the sensitivity of our results to different levels of aggregation of our observational units, we conducted robustness checks for potential aggregation bias. Our approach was two-pronged: initially, we re-assessed our model by progressively aggregating our data from the

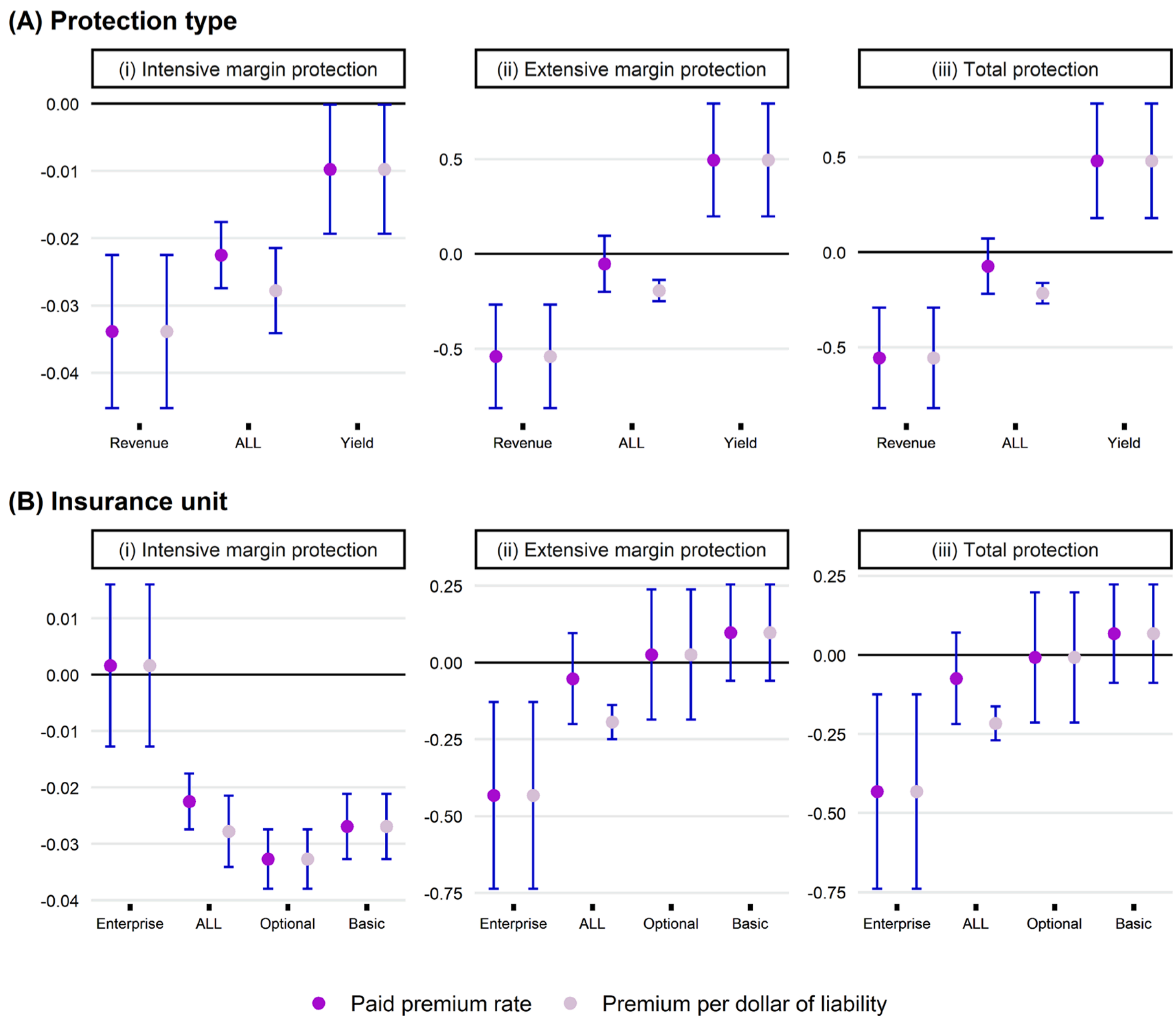

Fig. 5. US Federal Crop Insurance Pool's Demand Response Conditional on Insurance Pool Protection Type and Unit Structure (2001/22) Notes: Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data used was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

most detailed to the broadest level. Figure S9 depicts the total protection response for each level of aggregation considered. For most levels of aggregation, we see similar estimated demand responses. Most estimates have overlapping confidence intervals with point estimates between 0 and −0.5 indicating inelastic demand. It is not until aggregating up to the state level that we see estimates that are qualitatively different than our primary analysis. Using state level observations produces an estimated elasticity below −1 indicating elastic demand.

Additionally, we also perform a robustness check on a subset of the Risk Management Agency's 'Summary of Business' by 'Type, Practice, Unit Structure' that encompasses only observations that indicate a single insurance policy associated with the observation (i.e., pools = 22,256 with N = 81,045). This subset of the data represents insurance decisions that necessarily only have a single farm underlying them. We estimated our results on this subset of the data, before aggregating up to the level of observation used in our primary analysis (in effect aggregating across insurance coverage levels to form insurance pools) before re-estimating. The results from this exercise are depicted in figure S10. Estimating the total demand response at the insurance pool level produced an estimated total demand response −0.013 (statistically like the −0.074 we estimate on the full sample). Estimating the same result on the disaggregated policy level observations produces a point estimate that is larger in magnitude (-0.125), but still qualitatively equivalent in terms of both samples suggesting inelastic demand. Estimates from both samples are statistically indistinguishable from each other.

7. Policy implications

The elasticities representing the responsiveness of crop insurance demand to paid premium rates that are estimated in this study are at the lower bound of those from existing literature. Particularly, Barnett et al. (1990) used crop-county wheat observations in 1987 to show that acreage insured, and bushels insured decreased by 0.23% and 0.18% for a percentage increase in premium rate. Goodwin (1993) used crop-county corn observations in Iowa from 1985 to 1990 to show that insured acres and liability per planted acre decreased by 0.32% and

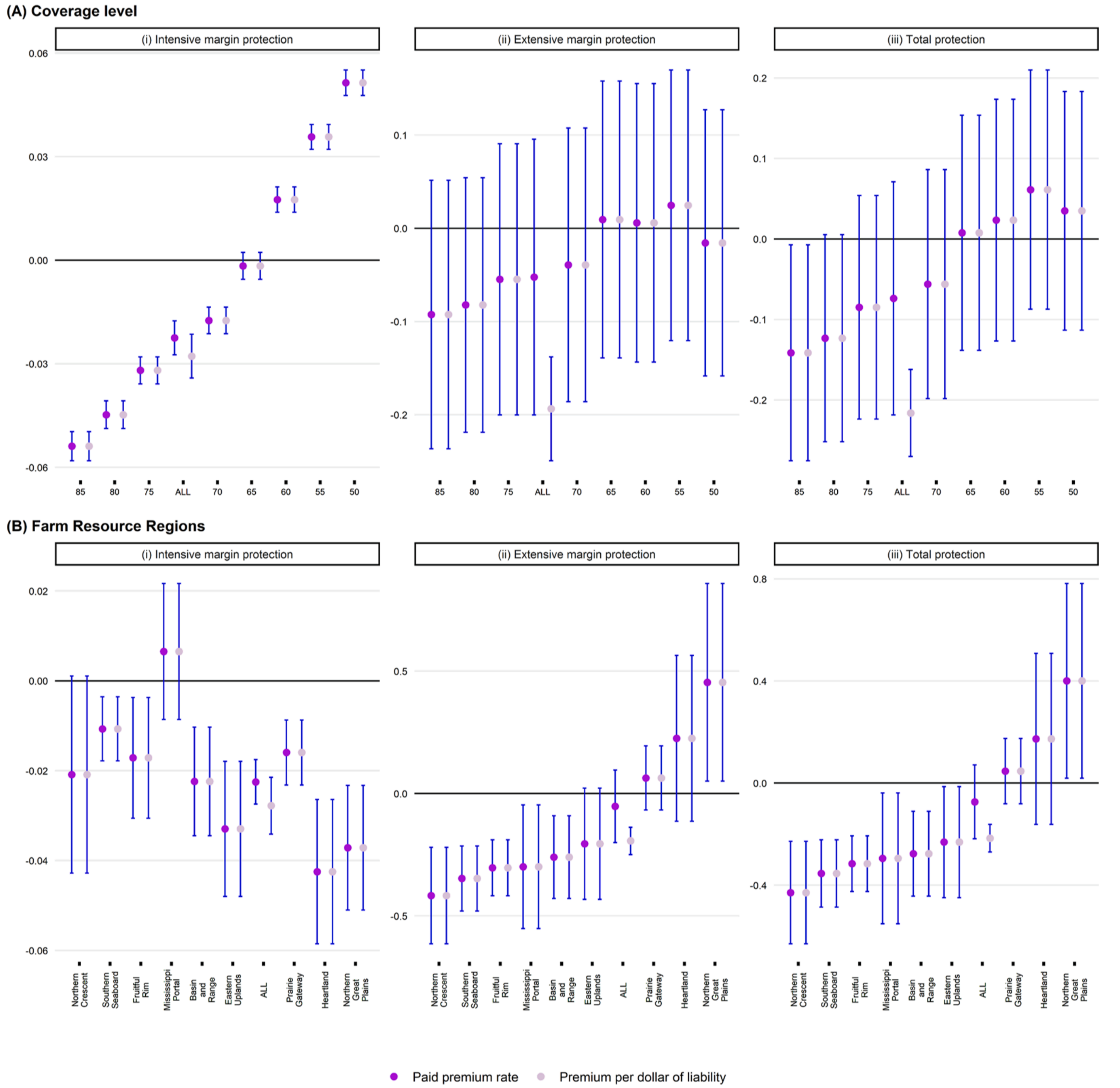

Fig. 6. US Federal Crop Insurance Pool's Demand Response Conditional on Insurance Pool Coverage Level and Location (2001/22) Notes: Crop insurance demand is modeled via a multi-equation structural model of crop insurance demand at the intensive and extensive margins measured by coverage level and insured acres. An insurance pool is defined as the unique combinations of crops (almonds, apples, barley, blueberries, cabbage, canola, corn, cotton, dry beans, dry peas, flax, forage production, fresh nectarines, grain sorghum, grapes, millet, oats, olives, onions, oranges, peaches, peanuts, pears, plums, potatoes, rice, rye, safflower, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tobacco, tomatoes, walnuts, and wheat), county, insurance unit (optional units [OU], basic units [BU], or enterprise units [EU]), insurance plan, irrigation practice (irrigated, non-irrigated, or unspecified), and organic practice (organic certified, organic transition, or unspecified). The data used was constructed by the authors using primary data from (1) Risk Management Agency's summary of business files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit, actuarial data master, and price addendums, (2) Farm Service Agency's crop acreage data, and (3) NASS Quick Stats.

0.73% for a percentage increase in producer premium paid per acre.[30] Using farm-level observations, Goodwin and Kastens (1993) and Coble et al. (1996) showed that crop insurance demand respectively decreased by 0.51% and 0.65% for a percent increase in premium rate. Yu et al. (2018) found that crop insurance subsidies increased planted acreage by 0.43%. By examining crop insurance choices of specialty crop growers, Yu et al. (2018), showed that lower expected returns from Buy-up products which are relatively expensive and have low subsidy rates lead to more CAT participation which is basically free.

In the same spirit as this paper, Woodard and Yi (2020) showed that crop insurance elasticities at the intensive margin with respect to changes in premium rate ranged from −0.64 to 1.890 and noted that

[30] Interestingly, when we assess the potential for aggregation bias, we find that our own empirical approach when performed at the county-crop level produces elasticities that are very similar in magnitude to previous county-crop level analyses (see Figure S9).

estimated elasticities were around 3–5 times greater in magnitude under an instrumental variable regression framework than under OLS. In this study, the 3SLS estimated demand response at the extensive [intensive] margin to paid premium rates is approximately 0.69 [0.26] times that of the OLS estimated elasticities. To the extent that the estimates from the intensive margin equation reflect that of Woodard and Yi (2020), the results in this study do not support their assertion that the mistreatment of endogeneity is likely partly responsible for pervasive findings of inelastic insurance demand in the FCIP. Several differences in research design could account for the disconnect between this study and Woodard and Yi (2020). Notable amongst these is that this study considers jointly both crop insurance demand at the intensive and extensive margins in one estimation that allows for both direct and indirect effects. This study uses policy set instruments that represents the initial level of premiums (i.e., the intercept of the premium schedule) producers face when buying a policy while the instruments used by Woodard and Yi (2020) were estimated from a latent rate curve the capture curvature in the premium schedule. Finally, this study uses annual insurance pool level data spanning (2001–2022) while that of Woodard and Yi (2020) is based on annual county-level aggregated data from 1999 to 2014. Policy set FCIP design parameters shown in Figure S5 indicate that starting in 2001 RMA has progressively been altering its rating parameters. Thus, the results in this study and that of Woodard and Yi (2020) could be capturing, at different spatial resolutions, different iterations of the FCIP from a policy standpoint, with ours reflecting a more modern version of the FCIP at the most granular level possible with publicly available data.

Calculating demand elasticities, conditional on a 2% subsidy range, suggests that the demand response at both the extensive and intensive margin to paid premium rates becomes increasingly inelastic as premium subsidies decline (see Fig. 2). This marked dependence of crop insurance demand response on premium subsidies explains the relatively low magnitude of the elasticity estimate in this study when compared to existing estimates. Past studies are primarily based on the FCIP as it was in the mid-1990 s which is very different from the contemporary FCIP (post-2000) that this study covers. Notably, the periods analyzed in this study correspond with a period of a considerable increase in government subsidies. Since the demand response becomes increasingly inelastic with increased premium subsidy levels it should not be surprising that this study suggests a more inelastic demand response compared to most existing studies. These findings echo the sentiments of Smith and Baquet (1996) who used individual farm data and assessed the impacts on price elasticities of demand as expected returns from crop insurance purchases approach zero, either from below or above, and found that elasticities of demand increase as expected payoffs from the contract approach zero. Since expected returns from crop insurance decrease with subsidy reduction, the insights from Smith and Baquet (1996) offer a plausible mechanism for observing the dependence of crop insurance demand response on premium subsidies.

The consistent finding that elasticities decrease in magnitude as subsidy rates approach zero is also consistent with economic theory related to decision-making under risk and uncertainty. As subsidies increase the expected payoff, and by extension the expected utility, of purchasing crop insurance is likely to be positive for a wider range of producer risk preferences.[31] Decreasing subsidy rates (and in turn increasing the out-of-pocket cost to the producer) lowers the expected utility of a given insurance contract. However, if subsidy rates are sufficiently high enough for it to be rational to purchase insurance under levels of risk aversion that are much lower than what is commonly observed, then the decreasing subsidy rate would not be expected to alter most producers' purchasing decisions.

In the context of policy proposals to reduce FCIP premium subsidies (Congressional Budget Office [CBO], 2020, 2017), our estimates of demand at the intensive margin suggest a 1 percent increase in paid premium rate would correspond to a 0.23% decrease in aggregate coverage levels. Excluding livestock policies, the 2021 crop year had total FCIP premiums of \$13.41 billion, \$8.41 billion in premium subsidies, and \$4.92 billion in producer paid premiums corresponding to a subsidy rate of 62.7% at the program level. At these levels, our results suggest that a 1 percent decrease in subsidies, equivalent to 1.7 percent decrease in producer paid premiums, would correspond to a decrease in insured liability of approximately \$502 million. However, observed heterogeneity in results suggest that these decreases in liability are unlikely to be evenly distributed across FCIP participants.

Decomposing estimated demand elasticities by insurance pool characteristics revealed that the response to changes in the out-of-pocket cost of crop insurance can vary dramatically depending on the characteristics of the insurance policy, and by extension producer characteristics. From a policy perspective, this is an important consideration depending on the goal of the policy. For example, our aggregate level estimates suggest a null result between a change in the out-of-pocket cost of insurance (which could be achieved by a change in the subsidy rate schedule) and the insured share of acreage. However, decomposing results by crop insurance policy type indicated that this null result was at least partially attributable to insurance pools characterized by revenue protection (RP) policies having an opposing effect (of similar magnitudes) to yield protection (YP) policies. This suggests that a decrease in the subsidy rate within the FCIP may prompt a shift away from RP policies to YP policies. This is intuitive as RP policies offer more comprehensive protection, but also have higher premiums compared to YP policies. For a producer that is subject to higher out-of-pocket costs due to a decrease in the subsidy rate schedule, switching from an RP policy to a YP policy could be a rational way to offset the increase in total insurance costs. From a policy perspective, this is noteworthy. Even though our aggregate level estimates suggest that the change in demand from subsidy rate decrease would be small, a potential shift away from RP policies would effectively reduce protection against price risk – something that is not captured in typical measures of crop insurance demand but may be important depending on the goals of a policy maker.

Several differences in the demand response to changes in crop insurance costs could be attributable to how subsidy rates are set within the FCIP. Notably, subsidy rates differ based on the insurance unit (enterprise, optional, and basic) as well as with the chosen coverage level. Enterprise units, which encompass more acreage in a single unit, have higher subsidy rates since they are less prone to adverse selection and can geographically distribute risk better than basic or optional units. Concerning coverage levels, policies with higher coverage levels receive lower subsidy rates while lower coverage levels receive higher subsidy rates. These differences are depicted in figure S7 where 1) enterprise units have higher subsidy rates than basic or optional units, and 2) subsidy rates for basic and optional units continue to increase all the way down to the 50% coverage level whereas all coverage levels for enterprise units at or below 70% receive the same 80% subsidy rate.

The variation in subsidy rates creates different incentives for producers faced with a rise in out-of-pocket insurance costs (either due to subsidy rate decreases or changes in the premium rating calculation) depending on initial insurance allocation at the time of the change. For example, producers with high coverage levels can lower coverage levels and increase their insured share of acreage to achieve a similar level of overall protection, but by lowering their coverage level they can take advantage of higher subsidy rates. This same strategy for limiting overall insurance costs is not available if producers are already at a low coverage level and are thus already receiving the most favorable subsidy rate available – in such a case reducing protection at the extensive margin may be the only way to reduce overall insurance costs. Decomposing results based on the predominant coverage level within each pool (Fig. 6A) indicated that higher coverage levels had more elastic demand at the intensive margin – a result that is consistent with the mechanism described above. Similarly, enterprise units were found

[31] This is true for all risk-averse individuals but does not hold for any potential producers that exhibit risk-loving behavior.

to have less elastic intensive margin demand compared to basic or enterprise units (Fig. 5B) likely reflecting the fact that the marginal benefit of reducing coverage (in terms of obtaining a higher subsidy rate) is zero for coverage levels below 75%. Thus, producers insured under enterprise units may have stronger incentives to reduce demand at the extensive margin to reduce overall crop insurance costs. We found evidence consistent with this claim in the form of pools defined by enterprise units having more elastic demand at the extensive margin.

Finally, several publications have identified issues of moral hazard in the context of agricultural insurance markets (Chemeris et al., 2022; Connor et al., 2021; Deryugina and Kirwan, 2018; Goodwin and Rejesus, 2008; Turner and Tsiboe, 2022). The results presented here offer deeper insights into how various segments of producers respond to changes in the cost of insurance. This could potentially help identify, a priori, how future changes in agricultural insurance subsidies may reorganize the relative ratio of insured to uninsured producers among various market segments and help identify where crop insurance may compete with (and crowd out demand for) other risk mitigation strategies or where other risk mitigation strategies may be more alluring than crop insurance (in the case of a subsidy rate decrease for example).

8. Conclusion

Despite the determinants of crop insurance demand receiving significant research interest over the last several decades, a consensus on the demand response likely to stem from changes in the out-of-pocket cost of crop insurance has not been reached. Much of the early work estimating crop insurance demand elasticities did so without addressing the endogeneity inherent in the FCIP data sources. Additionally, major changes in the FCIP in the early 2000 s raised questions as to whether it is prudent to generalize results drawn from earlier work to the modern crop insurance era, regardless of any endogeneity concerns.

Utilizing 1,174,872 insurance pool level observations from the FCIP, spanning the last 22 years, this study contributes to the literature that seeks to estimate a causal relationship between crop insurance premium subsidies and crop insurance demand in the context of the modern FCIP policy landscape. The study set up a two-equation structural model of insurance demand that captures responses at the intensive margin (as measured by crop insurance coverage level) and the extensive margin (as measured by net insured acres). The empirical model is estimated using three-stage least squares (3SLS), making use of instruments derived from RMA continuous rating parameters that are exogenous with respect to a given producer's crop insurance purchasing decisions. The results indicate that demand for crop insurance is inelastic at both the extensive and intensive margins with respect to changes in producer-paid premium rates. With respect to changes in premium subsidy rates, demand at both the extensive and intensive margins increase. Extending the analysis across a range of potential premium rates suggests that the demand response to premium rates is dependent on the level of premium subsidies with the response becoming increasingly elastic as premium subsidy levels approach zero. However, decomposing results by observable insurance pool characteristics suggest that various subsets of producers are likely to have very different reactions to the same change in the cost of crop insurance.

Although this study carefully addresses numerous potential biases, it's worth considering a few additional caveats: the exclusion of the price election share (an additional choice insured make), the need to account for endogenous production input use, and reliance on aggregated data representing multiple producers, which may introduce bias. The last point is of particular concern for research on crop insurance demand, as our robustness checks revealed nuanced evidence of bias linked with the level of data aggregation. Future studies could counter these issues by expanding the scope of analysis to include price election share, considering the interplay between insurance and production input use, and exploring a more stable risk assignment for insurance pools. However, it's worth noting the scarcity, if not total absence, of necessary producer-level panel data for more in-depth analysis. Despite these limitations, this study's demand response estimates, as they relate to insurance cost changes, offer useful insights for comprehending crop insurance demand and guiding policy discussions on crop insurance subsidy changes to promote uptake.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2023.102505.

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