Charity Hazard in Crop Insurance

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Abstract

The state potentially plays an important role as the "insurer of last resort" during non-idiosyncratic shocks, ranging from widespread natural disasters to national banking crises. By providing free assistance to those impacted by such shocks, however, the state potentially crowds out private insurance purchases or other preventative behaviors. This phenomenon – dubbed "charity hazard" to reflect the moral hazard induced by the expectation of charity – can increase the cost and impact of disasters. Charity hazard is thought to be an important explanation for the relatively low rates of insurance take-up in some markets. Although numerous models of charity hazard exist, there are very few empirical studies and no consensus on whether charity hazard occurs in practice. Effective policy design, however, requires an understanding of the size and extent of safety net-induced charity hazard.

In this paper, we estimate charity hazard in agricultural production. The presence of private crop insurance, along with the prevalence of federal disaster assistance, creates the ideal conditions for investigating charity hazard. Preliminary estimates show a strong negative correlation between current crop insurance takeup and historical disaster assistance. Confounding factors, such as actuarially unfair rates (Sherrick et al., 2004) and unobservables, however, likely bias these estimates. We address this bias by instrumenting for disaster aid to identify the causal relationship between disaster assistance and insurance coverage and demonstrate the extent to which expectations of a bailout are important for the insurance decision. Our first set of instruments is variants of political factors that previous literature has identified as being related to disaster payments (Garrett, Marsh, and Marshall, 2006). Our second set of instruments is the spatial extent of El Niño's effects around the farmer's county. We show that, controlling for the expected effect in the farmer's own county, the spatial extent of El Niño's effects is also a strong predictor of aid. Our preliminary results show that higher disaster payments driven by politics decrease the amount of insurance in the county, but disaster payments driven by the spatial extent of El Niño have no effect on insurance coverage.

1 Introduction

The state potentially plays an important role as the "insurer of last resort" during non-idiosyncratic shocks, ranging from widespread natural disasters to national banking crises. By providing free assistance to those impacted by such shocks, however, the state potentially crowds out private insurance purchases or other preventative behaviors. This phenomenon – dubbed "charity hazard" to reflect the moral hazard induced by the expectation of charity – can increase the cost and impact of disasters. Charity hazard is thought to be an important explanation for the relatively low rates of insurance take-up in some markets. Although numerous models of charity hazard exist, there are very few empirical studies and no consensus on whether charity hazard occurs in practice. Effective policy design, however, requires an understanding of the size and extent of safety net-induced charity hazard.

Although numerous models of charity hazard exist, there are few empirical studies. In this paper, we estimate charity hazard in US agricultural production. Crop insurance is a market where charity hazard has long been posited to exist. The Federal Crop Insurance Act of 1980 introduced (subsidized) crop insurance in the US. However, participation rates remained low into the late 1990's, despite increasing premium subsidies. Alongside an expanding insurance program, numerous ad-hoc disaster payment bills have been passed, possibly leading farmers to take out less insurance in hopes of being bailed out in case of a loss.

We use both previously identified and novel political factors as instruments for disaster payments to subsequently estimate the degree to which farmers underinsure due to hopes of government aid in the event of a disaster. Another novel instrument we develop is the spatial extent of the effect on yields of El Niño/Southern Oscillation (ENSO), a cycle of ocean temperature fluctuations that significantly affects agriculture in some parts of the US. We show that, controlling for the effect of ENSO on the reference county, the extent to which ENSO affects its neighbors within 50 miles affects the amount of disaster payments that county receives.

Studying charity hazard in the area of agricultural insurance is also important in and of itself. Agricultural loss is one of the biggest risks faced by rural areas worldwide. Most countries subsidize their agricultural sector on the grounds of compensating farmers for revenue variability as well as food security for their citizens. According to the IPCC, climate change will increase the frequency and intensity of extreme weather events and change their spatial distribution (Meehl et al., 2007; Schneider et al., 2007). This will likely increase the variability in the agricultural sector and the variance of food prices.

Our preliminary results depend on the instrument used, suggesting that the group of compliers for each instrument may be different. We find no evidence that disaster payments driven by the spatial extent of ENSO affect a county's crop insurance liability. We show that this is not due to farmers not anticipating El Niño: liability in counties that are strongly affected by ENSO changes significantly with the ENSO cycle. Disaster payments driven by the degree of political polarization in the county do not affect the total liability in a county but do decrease the liability per insured acre by about 0.2% for a 1% increase in disaster payments per insured acre, a crowd out rate of about 20%. Finally, a 1% increase in disaster payments driven by the fraction of voters voting for the majority party in the House and the Senate reduces total liability by $32 - 46\%$. One possible explanation for the heterogeneity in estimates is that, in addition to expected disaster payments, the certainty with which they will be received matters as well.

The rest of the paper is organized as follows. In Section 2, we provide background on crop insurance and disaster payments in the US as well as the ENSO phenomenon. In Section 3, we outline the conceptual framework. In Section 4, we describe and summarize the data. In Sections 5 and 6, we discuss the regression specifications and the results, respectively. Section 7 concludes.

2 Crop Insurance and Disaster Payments in the US

Federal crop insurance existed for 40 years before it began to play a role in the social safety net for farmers. In 1938, spurred on by the decade-long drought that produced the Dust Bowl, policy makers introduced the Federal Crop Insurance Program as part of New Deal legislation.[1]

[1] The Agricultural Adjustment Act of 1938 established a national crop insurance product for wheat that insured against losses due to, "drought, flood, hail, wind, winter-kill, lightning, tornado, insect infestation, plant disease, and

Crop insurance premiums exceeded indemnity payments for the first time in 1947. In that same year, however, Congress severely reduced the program size, essentially making it an experimental program. From 1947 until 1981 the Federal Crop Insurance Program remained a relatively small experimental program; by 1980 only about half of the counties in the U.S. and just 26 crops were eligible for insurance coverage.

While crop insurance was in an experimental phase, Congress pursued another method to address the crop insurance market failure. The Agriculture and Consumer Protection Act of 1973 and the Rice Production Act of 1975 established a disaster payments program, which, for some crops, overlapped with the protection provided by federal crop insurance. Essentially, disaster payments amounted to free universal coverage for a select group of crops. Low-yield payments were made to farmers who participated in income- and price-support programs when yields fell below two-thirds of normal. This program was popular with farmers because it provided catastrophic coverage with no premium. However, detractors claimed that the program resulted in heavily distorted behavior. In particular, they argued that the moral hazard behavior of farmers planting on high-risk, environmentally sensitive land imposed a great cost to society (CITE). As a result, the program ended in 1981, having paid out $3.4 billion in total.

2.1 Modern Crop Insurance

The modern era of federal crop insurance began with passage of the Federal Crop Insurance Act of 1980. The Act authorized crop insurance expansion to every county in the United States with significant agriculture and to every crop with sufficient actuarial data to establish premiums. In 1981, 252 additional counties received crop insurance, resulting in 1,340 additional county programs (a county program is a particular crop-county combination). Crop insurance extended to 1,050 additional counties in 1982, adding 8,278 county programs.

Crop insurance plans in the US differ in the metric that determines payments and the level of the deductible, i.e., the "coverage level".[2] Payments can be determined by (a) individual yield, (b) individual revenue, (c) mean county yield or (d) mean county revenue. Farmers cannot take out multiple insurance plans for the same plot. Within these plan types, farmers can choose from

... other unavoidable causes..." (52 Stat. 74).

[2] For a more comprehensive overview of the US crop insurance market, see Babcock (2011).

several coverage levels ranging from 50% to 90%.[3] The coverage level implicitly defines the amount by which yield or revenue has to fall (relative to a baseline) before any payment is made. If a farmer chooses a 75% coverage level, for example, he does not receive payments until his yield, revenue, the county yield or the county revenue (depending on the type of plan) falls to more than 25% below the established baseline. The plan type and coverage level largely describe the insurance plans available to farmers.[4]

Crop insurance policies were consistently structured from 1980-1994. Producers selected from three guaranteed yield levels (50-, 65-, or 75-percent of their insurable yield) and from three guaranteed price levels. Price-election levels were determined from FCIC forecasts of expected prices. The top price election level was set at 90-100 percent of the expected market price. If the producer's yield fell below the elected coverage level, the producer received an indemnity payment equal to the product of the elected price coverage and the yield shortfall. This yield shortfall was determined by the amount that actual yields fell short of the farm's insured yield. Determination of the farm's insured yield initially was based on area average yields. This method increased the adverse selection problem as the risk pool became increasingly filled with farms that had loss-risks above the area average (Skees and Reed, 1986). Consequently, after 1985 a farm's insured yield was based on the preceding ten years of the farm's actual production data.

2.2 Dual Programs

The 1980 Act sought to create an insurance program that would replace disaster relief measures. However, Congress quickly established a precedent of providing ad hoc, ex post disaster relief, thereby sustaining the pattern established in the 1970s of having two parallel mechanisms for dealing with crop-loss risk: crop insurance and disaster payments.

In spite of premium subsidies, enrollment in the Federal Crop Insurance Program was low and grew little through the 1980s. Table 1 contains measures of program size from 1981–2009. From 1981–1988 participation remained around 20-percent, increasing to 40-percent in 1989 only as a consequence of mandatory insurance for those receiving disaster payments in 1988.

The implicit guarantee of ex post disaster payments is a key reason for the historically low par-

[3] Not all coverage levels are available for all plan types and in all counties.

[4] Farmers also have some choices within a plan-coverage-level combination, such as how to combine different plots and how much to get paid in the case of a shortfall. These are briefly discussed below.

ticipation rates. The U.S. General Accounting Office (1989) reported that, "other federal disaster assistance programs provide farmers with direct cash payments at no cost to the farmers, resulting in the perception [among farmers] that crop insurance is unnecessary." As many others have pointed out, e.g., Just, Calvin, and Quiggin (1999) and J. Glauber (2004), those who did participate were adversely selected and more likely to collect indemnity payments. Table 1 contains the annual loss ratio (indemnities paid out divided by premiums collected), which averaged 1.47 in 1981 – 1994 and dropped below 1 only in 1994. The consistent payout of more indemnities that premiums collected from 1981 – 1994 supports the idea that those who chose to purchase crop insurance expected a positive return, while those who did not chose to rely on the costless disaster payments.

Although the current participation rate is high, it comes at a high subsidy cost: the federal government pays nearly 60% of the annual premiums. Because of the large costs of the current insurance program, there have been proposals to eliminate the crop insurance program and return to a standing disaster assistance program (J. W. Glauber, 2007).

Despite the existence of an increasingly subsidized insurance program, the government continued to pass numerous ad-hoc disaster bills, granting assistance to farmers whose crops have been affected by disasters even if those farmers did not have insurance (CITE public laws). Payments between 1980 and 2008 were typically authorized through special appropriations passed by Congress. The disasters have typically been ones in which large areas were affected. Because the passage of a bill requires the majority's support, it's likely that only large agricultural disasters will prompt a disaster bill, either because there will be enough politicians who will support it for the direct benefit of their constituents or because the disasters are highly visible events, garnering the public's sympathy and putting pressure on congressmen whose districts were not affected.

Farmers in declared disaster areas who have taken out insurance were not allowed to concurrently receive disaster assistance (preventing "double indemnity"), although in one bill, they were refunded their premiums (CITE). Disaster bills also typically contain clauses requiring farmers who receive disaster assistance to purchase insurance for the next two years.

To reduce the amount of moral hazard and adverse selection, farmers are required to initiate the purchase of insurance by a certain date, called the "sales closing date". This date varies by county, crop, and year and precedes the earliest allowed planting date. In some circumstances, a farmer may purchase insurance after the sales closing date, but these circumstances are limited.[5] In all cases, the insurance decision is made months before yields for that year are realized.

3 Conceptual Framework and Identification Strategy

3.1 Identification

Charity hazard is evident when producers who expect to receive a disaster payment in a bad state of the world purchase less crop insurance than they otherwise would. Note that charity hazard cannot be observed by comparing the crop insurance purchases of farmers who expect disaster payments to farmers who do not. An infinite number of unobservable factors influence farmers' crop insurance purchases and invariably bias the results of such a comparison. For instance, one would expect areas prone to disaster (hence disaster payments) to be more likely to insure than those that are not—resulting in spurious positive correlation. Rather, charity hazard is observed by comparing farmers who expect disaster payments to identical farmers in an alternate state of the world where disaster payments are not available. Our problem, obviously, is that we cannot observe "alternate states of the world." It is possible, however, to approximate such omniscience (on average) by randomizing disaster-payment expectations. Since random expecations are unrelated to the near-infinite unobservable confounders, we can measure charity hazard by simply regressing crop insurance liability per cropland acre on (random) disaster payment expecations, as follows:

$$\ln\left(Liability_{ct}\right) = a_c + a_t + \beta \ln\left(Disaster_{ct}\right) + \varepsilon_{ct}, \tag{1}$$

where $\beta < 0$ indicates charity-hazard behavior.

3.2 An Instrumental Variables Strategy

In light of our inability to randomize policy, the challenge of identifying charity hazard lies in finding a measure that (a) affects farmers' beliefs about future disaster assistance, (b) is time varying so that persistent differences in propensity to insure and to receive disaster payments can be controlled for, and (c) does not affect the net benefit from holding insurance through channels

[5] One example is where the farmer's first planted crop failed.

other than disaster aid.

For example, suppose that a farmer believes that, with high probability, his county will be affected by El Niño next year. If the county is affected, the government is almost certain to provide some help. A measure of El Niño risk would not allow us to identify the effect of probable aid, however, because it also affects the farmer's expectation about risk to his crops. Without knowing the probability with which the government would step in or the expected fraction of the loss the government would cover, we cannot credibly claim that the farmer's insurance choice following a change in the probability of El Niño is solely due to expectations about disaster payments.

Suppose, however, that counties in which more *neighbors* are affected by El Niño are more likely to get bailed out by the government, all else equal—we call this the disaster's *visibility.* A measure of the expected spatial extent of El Niño's effects around the county, controlling for the change in El Niño risk, then serves as a credible measure of disaster aid expectations. This is indeed one of the measures we employ in our estimation. Specifically, for every county, we construct an index of how much its neighbors are affected by El Niño. Then, controlling flexibly for El Niño's effect on the county itself, we can use this index as a valid instrument for disaster payments.

Politics also affects a farmer's disaster-payment expectations. Garrett, Marsh, and Marshall (2006) find that the presence of a state's congressmen on committees that have the power to approve agricultural disaster aid is correlated with higher payments. Thus, if there is charity hazard, we should also expect farmers in these areas to be less likely to insure. Other political variables may also have an effect on the propensity of an area to receive disaster payments. Because the political power of an area should not directly affect an individual farmer's decision to insure, the exogeneity requirement is likely to hold.

4 Data

4.1 Insurance and Disaster Payments

Insurance and disaster payment data used in the estimation come from the Risk Management Agency (RMA) and Farm Services Agency (FSA), respectively, which are both part of the United States Department of Agriculture (USDA). The RMA data contains information on acres insured, indemnity, premiums paid, liability and subsidies. The data are annual and broken down by county, crop, insurance plan, and coverage level. The time range for these data is 1989-2009. The FSA data set is also annual and contains information on various payments to producers, including disaster payments. The data are broken down by individual producer and payment type, providing detailed information about disaster payments. However, the crop variable is not provided in the FSA data set, prompting us to combine all crops in our analysis.

In addition, we use data on acres harvested from the National Agricultural Statistics Service (NASS). Because disaster payments legislation does not require that the farmer receiving the payments have insurance, the relevant quantity to consider is either total liability in the county or liability per insurable acre. Because data on insurable acres is unavailable for many crops, we use planted acres wherever possible and harvested acres otherwise. We later discuss how this can bias our results.

4.2 Political data

Several papers have considered the effect of politics on agricultural and non-agricultural disaster payments at the state-level (Garrett, Marsh, and Marshall, 2006). Here, we use county-level political variation to instrument for the amount of disaster payments. Specifically, we use data on county-level voting in presidential elections. The 2004 and 2008 data come from Dave Leip's Atlas of U.S. Presidential Elections, while earlier data were generously shared by James Snyder. In addition, we use 2010 Statistical Abstract data from the US Census to determine the majority party in each chamber of Congress.[6] We consider three political measures that may be important in determining a county's disaster payments, as measured by the most recent presidential election: the extent to which a county is a "swing county," i.e., how evenly are voters split between the two parties, the percent voting for the majority party in the Senate and the percent voting for the majority party in the House of Representatives.

4.3 ENSO

El Niño/Southern Oscillation (or "ENSO") is a cycle of oceanic temperature fluctuations that affects climate worldwide. It has three distinct phases. The "El Niño" phase is characterized by unusually warm water, while the "La Niña" phase is characterized by unusually cool water. There

[6] Available from `www.census.gov/compendia/statab/2010/tables/10s0393.xls`

is also a neutral phase. We follow the El Niño classifications of Golden Gate Weather Service, based on the Ocean Niño Index compiled by the National Oceanic and Atmospheric Administration (NOAA).[7] The Ocean Niño Index tracks the three-month moving average of sea surface temperature anomalies—temperature deviation from the 1971-2000 mean. An El Niño episode is defined as five or more consecutive overlapping anomalies of 0.5 or more degrees C, while a La Niña event is defined as five or more anomalies of -0.5 degrees C or lower. As we show later, agriculture in certain areas of the US is significantly affected by ENSO events.

The forecastability of El Niño is key for correct inference. Even if the spatial extent of ENSO near one's county affects the expectation of disaster payments, farmers need to have additional information about ENSO in the upcoming growing season for us to be able to identify their response to it. We test whether farmers anticipate ENSO events by looking at changes in liability in the county in which the farmer is located prior to the beginning of a particular phase. If we see no change in liability in response to either the expected effect of ENSO on one's own county or the expected effect of ENSO on neighboring counties, this may be indicative of farmers not anticipating ENSO rather than the absence of charity hazard.

5 Regression Specifications

In this section, we outline the regression specifications used to test for the presence of charity hazard, using the spatial extent of ENSO and political variation as the predictors of federal disaster aid. The key identifying assumption is that changes in these variables affect the propensity to take out insurance only through expectations about disaster aid. For ENSO, this means that the relevant variation will be how neighboring counties are affected by ENSO, controlling for the expected effect on the county itself.

There are several benefits from using multiple measures of disaster aid expectations. First, the set of counties that experience ENSO-related changes in disaster aid may be different from the set of counties that experience politics-related changes. ENSO largely affects Southern and Southeastern states, while political fluctuations may be present anywhere. Second, there may be different risks involved in foregoing insurance in expectation of ENSO-driven disaster payments

[7] Available from `http://ggweather.com/enso/oni.htm` and `http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml`, respectively.

rather than politically-driven ones. Thus, using multiple measures is informative as to the possible range of changes in insurance we can expect to see in response to other determinants of disaster payments.

We measure the amount of insurance take up by the reported liability in the county. Specifically, we use the log of total liability and the log of liability per planted acre as the preferred measure of insurance coverage. This measure reflects the amount of insurance farmers have taken out and is not dependent on the type of plan. An alternative measure is the total premiums paid, net of subsidies. Measuring coverage through net premiums paid has the advantage that it is from the farmer's point of view, rather than the insurer's. One drawback of both these measures is that they do not account for risk aversion: an individual plan with a given liability level may be much more attractive than an area-yield plan with the same liability.

One might also consider looking at the average coverage level in the county. However, although the ranking of coverage levels within plan types is straightforward, it is unclear how one would rank coverage levels *across* plan types. For example, an area-yield plan with a 70% coverage level may not be providing more protection than an individual plan with a 60% coverage level.

5.1 Political

First, we consider the impact of changes in political behavior (as measured by voting behavior) on (a) changes in disaster payments and (b) changes in liability per acre. The key identification assumption is that voting behavior changes are unrelated to unobservables that also affect insurance preferences.

We test whether political variables predict disaster payments using the following regression specification:

$$\ln\left(Disaster_{ct}\right) = a_c + a_t + \beta Swing_{c,t-1} + \gamma MajHouse_{c,t-1} + \delta MajSenate_{c,t-1} + \phi X_{c,t} + \varepsilon_{ct} \quad (2)$$

where c indexes the county and t the year. $Swing_{c,t-1}$ measures how close the county is to being split 50-50, based on the most recent (but not the current) presidential election.[8] We compute the degree to which a county is a "swing" county using $\{1-(2\times|50-\% \quad \text{Republican}|)\}$. $MajHouse_{c,t-1}$ and

[8] We lag the voting data one year because crop-insurance decisions happen earlier in the year (the spring) than presidential elections, which occur in November.

$MajSenate_{c,t-1}$ represent the percent of voters voting for the House majority or Senate majority party in the most recent presidential election, respectively. X_{ct} represents the time-varying control variables that affect the crop-insurance decision. $\ln(Disaster_{ct})$ is the log of the per-planted-acre amount of disaster payments made to county c in year t.

In the second stage of a two-stage least squares framework, we test whether disaster payments per acre affect liability per acre, using the political variables above as instruments:

$$\ln(Liability_{ct}) = a_c + a_t + \beta \ln(\widehat{Disaster}_{ct}) + \phi X_{c,t} + \varepsilon_{ct}. \tag{3}$$

$\ln(Liability_{ct})$ is the log of the liability per planted acre in the county c in year t and $\ln(\widehat{Disaster}_{ct})$ represents the instrumented log of per-acre disaster payments. As above, X_{ct} represents the time-varying control variables that affect the crop-insurance decision. In this specification, $\beta < 0$ indicates charity hazard, so the t-tests are one-sided.

5.2 ENSO

Second, we consider the effect of the spatial extent of ENSO on (a) disaster payments and (b) the propensity to take out insurance. The key identification assumption is that counties whose neighbors are more similarly affected by ENSO don't have unobservably worse outcomes. Examples where this would be violated is if a widespread heat wave with no rain dries up groundwater supplies more than a localized heat wave.

In this section we instrument for disaster payments with the anticipated effects of El Niño. We measure El Niño's expected effect with a regression-based estimate of the regional ENSO effect on average crop production (detailed below). We use this estimate as a *synthetic* instrument for disaster payments.[9]

5.2.1 The Expected ENSO Effect

To construct the synthetic instrument, we first estimate El Niño's impact on yields, using 3-by-3 degree subregions of the US. For each crop-region combination, we estimate β_{rp}, where r is the

[9] We adjust the estimate with the standard errors to account for the fact that it has a distribution, i.e., it is not a realized event.

region, c is the county, and p is the crop:

$$\ln\left(Yield_{cpt}\right) = a_c + a_t + \sum_r \beta_{rp} ENSO_t * \mathbb{I}\left[Loc_c = r\right] + \varepsilon_{cpt}. \tag{4}$$

$ENSO_t$ is the observed intensity of ENSO at time t. This variable is equal to 1 during a strong La Niña, 2 during a moderate La Niña, 3 during a weak La Niña, 4 during a neural phase, 5 during a weak El Niño, 6 during a moderate El Niño and 7 during a strong El Niño. $\mathbb{I}\left[Loc_c = r\right]$ is an indicator variable for the 3-degree bin that county c falls into. The unit of observation is a county-crop-year. We run this regression separately for each crop.

Using the results of this regression, we then construct the following measure of expected damages in a county's neighborhood:

$$E\left[D_{N(c)}\right] = \sum_p \sum_{l \subseteq N(c)} w_{lp} \beta_{lp} A_{lp} \tag{5}$$

where A_{lp} refers to the harvested area of crop p in county l and $N\left(c\right)$ refers to the neighborhood of county c, which we assume to be a radius of 50, 100, 150 or 200 miles around the county's center.

We account for the synthetic nature of this instrument by weighting the estimates with the standard errors. w_{lp} is the weight of each coefficient, constructed from the t-statistics of the regressions. Specifically, the weight for crop p in county l is defined as:

$$w_{lp} = \frac{t_{lp}}{\sum_r \sum_{m \subseteq N(l)} t_{mr}} \tag{6}$$

We also construct the expected effect of El Niño on yields in one's own county:

$$E\left[D_c\right] = \sum_p w_{cp} \beta_{cp} A_{cp} \tag{7}$$

where the weight w_{cp} is now equal to:

$$w_{cp} = \frac{t_{cp}}{\sum_r t_{cr}} \tag{8}$$

5.2.2 The IV Specification

The variable $E\left[D_{N(c)}\right]$, when interacted with the ENSO magnitude in year t, is the instrument in the following regression:

$$\ln(Disaster_{ct}) = a_c + a_t + \theta E\left[D_{N(c)}\right] ElNino_t + \gamma_1 E\left[D_c\right] ElNino_t + \gamma_2 E\left[D_c\right]^2 ElNino_t + \varepsilon_{ct} \quad (9)$$

In the second stage, we estimate charity hazard by regressing the log liability per acre, $\ln(Liability_{ct})$, on the instrumented log per-acre disaster payment, $\ln(\widehat{Disaster}_{ct})$, while controlling for El Niño's expected own-county effect, $E\left[D_c\right]$ interacted with El Niño in year t:

$$\ln(Liability_{ct}) = a_c + a_t + \theta \ln(\widehat{Disaster}_{ct}) + \gamma_1 E\left[D_c\right] ElNino_t + \gamma_2 E\left[D_c\right]^2 ElNino_t + \varepsilon_{ct}. \quad (10)$$

6 Results

Table 2 shows the means and standard deviations of the key regression variables. The average county receives \$323 thousand in disaster payments each year. This corresponds to \$152 per insured acre or \$11 per harvested acre. The total liability in a county is much larger, about \$10.6 million per county, which corresponds to \$1,756 per insured acre or \$336 per harvested acre. Nevertheless, the average disaster payment represents a non-trivial fraction of the total liability.

The second part of Table 2 shows the summary statistics for the voting measures. The average percent voting Republican is 52 with a standard deviation of 14 percentage points. The summary statistics for the percent voting for the majorities in the House and the Senate are similar.

6.1 First stage

Table 3 shows the results of regressing various measures of disaster payments on the fraction voting Republican in the most recent presidential election as well as the deviation from an even split between Republican and Democrat votes. The swing measure ranges from 0 if 100 percent of the county's voters voted for one party to 1 if the county is split 50-50. 1 is added to the amount of disaster payments before taking the log; this is due to the presence of many zeros. Table 4 shows the same regressions with the standard errors clustered by county. We present both results at this stage because clustering by county may be inadequate, while clustering by state may be too conservative.

The results in Tables 3 and 4 clearly show that more polarized counties receive more disaster aid, but that this doesn't favor any particular party. This is consistent with politicians rewarding loyal voters rather than trying to buy them. The results indicate that if a county were to go from being split 50-50 to being completely dominated by one party, aggregate disaster payments would increase by 141 percent, while disaster payments per harvested and per insured acre would increase by 139 and 113 percent, respectively.

Table 5 adds two more political measures to the regression specifications - the fraction voting for the majority party in the House and the fraction voting for the majority party in the Senate. Standard errors are clustered by county in this case; clustering by state results in weak F-statistics. Having more votes for the majority party in the House significantly increases disaster payments while having more votes for the Senate majority decreases them. This may seem counterintuitive, as the two chambers of Congress have comparable power in allocating disaster payments. However, the results may be in part due to the fact that the two chambers are often controlled by different parties. Thus, the F-statistics of the specifications, which are all very high, are more informative.

Tables 6-8 show the first stage regressions using measures of ENSO intensity, clustered by state. Table 6 shows the effect on log disaster payments. The variable of interest is "effect on neighbors". This is the estimated effect on yields in counties within the given radius of the reference county's center (excluding the reference county itself), interacted with the continuous measure of ENSO intensity in a given year. A negative coefficient means that, with stronger El Nino, counties whose neighbors are less adversely affected by El Nino on average (have a lower negative or higher positive effect) receive fewer disaster payments. This is the expected effect. Indeed, all the estimated coefficients on "effect on neighbors" are negative, although only the 50 mile radius measure produces significant results. The estimated coefficient on "own effect" is also negative and convex. As discussed before, this effect is important to control for in order to avoid confounding the effect of El Nino on expected disaster payments with the effect of El Nino on other reasons to take out insurance.

Tables 7 and 8 show the estimated effect of ENSO intensity on log disaster payments per harvested and per insured acre, respectively. The results are generally similar to Table 6. In all cases, only the effect of neighbors within 50 miles of the reference county is a significant predictor of disaster payments; thus, this is the instrument we use to generate the second stage results. F-statistics for the preferred instrument are around 8-9, slightly lower than the rule-of-thumb threshold of 10.

6.2 Second stage

Tables 9 and 10 show the estimated effect of disaster payment expectations on a county's liability, using the fraction voting Republican and the corresponding swing measure as instruments. The standard errors in Table 9 are clustered by state, while those in Table 10 are clustered by county. Total liability in a county is estimated to be unaffected by disaster payment expectations. Moreover, the point estimate is positive, which means that we can rule out fairly small negative effects. The point estimates on the effect of log disaster payments per harvested and per insured acres are both negative. Log liability per insured acre decreases significantly in both tables, while log liability per harvested acre is only significant when standard errors are clustered by county. Following a 1% increase in disaster payments per harvested acre, liability per harvested acre is estimated to decline by 0.12%. The corresponding response of liability per insured acre to disaster payments per insured acre is -0.20%.

Table 11 shows the estimated effect of disaster payment expectations instrumented for using (a) fraction voting for the majority party in the House (as measured by the most recent presidential election) and (b) fraction voting for the majority party in the House, fraction voting for the majority party in the Senate, and fraction voting Republican. Standard errors are clustered by county. For this set of instruments, log of total liability and log of liability per harvested acre are both estimated to decline significantly in response to higher expectations of disaster payments. The estimated response is also much larger: a 1% increase in disaster payments per harvested acre decreases liability per harvested acre by $0.31 - 0.38\%$, while the same increase in aggregate disaster payments decreases aggregate liability by $0.32 - 0.46\%$. The estimated effect of disaster payments per insured acre on the corresponding liability measure is no longer significant.

Table 12 shows the estimated effect of disaster payment expectations using the spatial extent of ENSO within a 50-mile radius as the instrument. The estimated effects are insignificant and the estimated coefficients for total liability and liability per harvested acre are positive, ruling out moderate and large reductions in liability as a result of ENSO-driven disaster payment expectations.

One question raised by these results in Table 12 is whether farmers can anticipate El Nino. As discussed before, even if farmers know that disaster payments in their county will be larger during El Nino years, they cannot adjust their liability accordingly if they do not know when El Nino occurs. To test whether farmers react to El Nino, we regress disaster payments and liability using only the measures of the expected effect of El Nino in one's own county and the expected effect squared. The results for disaster payments and liability are shown in Tables 13 and 14, respectively. Table 13 shows that disaster payments during more extreme El Nino years are significantly higher in counties that are more adversely impacted by it and that this relationship is convex. Of course, this is an ex-post relationship. Table 14 shows the relationship between liability and El Nino. Because insurance decisions are made before any outcomes for the year are known, this is a good test of whether farmers anticipate El Nino. Liability is estimated to vary significantly with ENSO, suggesting that farmers do anticipate ENSO to some extent. The results show that farmers in counties that are more negatively affected by El Nino reduce the amount of insurance liability they hold during El Nino years. This is not an unbiased estimate of charity hazard, however; the expectations of higher disaster aid payments, which lower the return to insurance, are accompanied by expectations of more damages to crops, which increase it.

7 Conclusion

Aggregate risk may sometimes make it beneficial for the government to step in and act as an insurer of last resort. However, the possibility of a government bailout may also encourage risk-taking and crowd out private insurance takeup, leading to what is known as "charity hazard". This phenomenon may exist in many areas of the economy, from banks taking on excessive risk to homeowners foregoing flood insurance. Thus, understanding it is extremely important. However, the extent to which charity hazard is a problem is debated and few empirical papers exist that confirm or deny its existence.

In this paper, we test for the existence of charity hazard in US agriculture, an area in which it has long been posited to be a problem. From the establishment of federally-sponsored crop insurance in 1980, Congress has passed ad-hoc bills granting disaster aid to farmers who did not have insurance or whose insurance didn't cover all their crop losses. We instrument for disaster payments using several instruments. First, we use political variables, which have previously been shown to affect disaster payments at the state level. We show that county-level political polarization as well as the fraction of a county's voters voting for the majority parties in the House and the Senate also affect disaster payments. Second, we use the spatial extent of ENSO's effects around each county, which is also a significant predictor of disaster payments. We then test how the expected disaster payments affect total crop insurance liability in the county.

The preliminary results depend on the instrument used, suggesting that the group of compliers for each instrument may be different. We find no evidence that disaster payments driven by the spatial extent of ENSO affect a county's crop insurance liability. We show that this is not due to farmers not anticipating El Nino - liability in counties that are strongly affected by ENSO changes significantly with the ENSO cycle. Disaster payments driven by the degree of political polarization in the county do not affect the total liability in a county but do decrease the liability per insured acre by about 0.2% for a 1% increase in disaster payments per insured acre, a crowdout rate of about 20%. Finally, a 1% increase in disaster payments driven by the fraction of voters voting for the majority party in the House and the Senate reduces total liability by $32 - 46\%$. One possible explanation for the heterogeneity in estimates is that, in addition to expected disaster payments, the certainty with which they will be received matters as well.

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8 Tables and Figures

Table 1: Crop Insurance and Disaster Payment Details

Year	Policies (thousands)	Acres (mil)	Participation Rate	Total Premium ($ mil)	Indemnity ($ mil)	Total Loss Ratio	Crop Disaster Payments ($ mil)
1981	416.8	45.0	16	376.8	407.3	1.08	306
1982	386.0	42.7	15	396.1	529.1	1.34	115
1983	310.0	27.9	12	285.8	583.7	2.04	1
1984	389.8	42.7	16	433.9	638.4	1.47	0
1985	414.6	48.6	18	439.8	683.1	1.55	0
1986	406.9	48.7	20	379.7	615.7	1.62	556
1987	433.9	49.1	22	365.1	369.8	1.01	10
1988	461.0	55.6	25	436.4	1,067.6	2.45	3,386
1989	949.7	101.7	40	205.0	1,215.3	1.48	846
1990	893.7	101.3	40	836.5	1,033.6	1.24	453
1991	706.2	82.3	33	737.0	958.5	1.30	619
1992	663.1	83.1	31	758.8	922.5	1.22	688
1993	678.8	83.7	32	755.7	1,653.4	2.19	2,530
1994	800.4	99.6	38	949.4	600.9	0.63	605
1995	2,039.2	220.6	41/85	1,543.3	1,566.5	1.02	29
1996	1,623.3	205.0	44/76	1,838.6	1,491.0	0.81	80
1997	1,320.1	181.9	43/67	1,775.4	990.1	0.56	21
1998	1,242.4	181.7	46/69	1,875.9	1,659.3	0.89	1,960
1999	1,287.9	196.3	53/73	2,310.1	2,416.1	1.05	53
2000	1,323.2	206.5	59/76	2,540.2	2,591.0	1.02	2,140
2001	1,297.9	211.8	63/78	2,961.8	2,959.4	1.00	177
2002	1,259.4	215.5	66/80	2,915.9	4,054.0	1.39	225
2003	1,241.5	217.4	67	3,431.4	3,260.8	0.95	2,500
2004	1,228.8	221.0	69	4,186.1	3,209.7	0.77	484
2005	1,190.6	245.9	77	3,949.2	2,367.3	0.60	2,790
2006	1,147.8	242.1	77	4,579.4	3,504.3	0.77	202
2007	1,137.7	271.6	85	6,561.7	3,546.5	0.54	375

Notes: Source: U.S. Department of Agriculture - Risk Management Agency. Participation rate calculated as acres insured as percent of eligible acres. For 1995 - 2002, the first number is the participation in "buy-up" and the second number is total participation.

Table 2: Summary Statistics

Disaster payments	322616
	(1116576)
Disaster payments per insured acre	152
	(3200)
Disaster pyaments per harvested acre	11
	(116)
Total liability	10595157
	(23825790)
Liability per insured acre	1756
	(65183)
Liability per harvested acre	336
	(3040)
Percent voting Republican	52
	(14)
Percent voting for House majority	47
	(14)
Percent voting for Senate majority	46
	(14)
Swing measure	78
	(16)
Observations	64,887

Standard deviations in parentheses. Unit of observation is a county-year. All voting measures are based on the most recent presidential election in the county

Table 3: Effect of politics on disaster payments

	Total payments (log)	Payment per harvested acre (log)	Payment per insured acre (log)
Fraction voting Republican	-0.566	0.018	1.312
	(1.027)	(1.273)	(1.217)
Swing measure	-1.411***	-1.394***	-1.128***
	(0.295)	(0.304)	(0.259)
Observations	61,149	52,987	54,344
R-squared	0.616	0.619	0.641
F-value	11.505	10.691	10.882

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 4: Effect of politics on disaster payments

	Total payments (log)	Payment per harvested acre (log)	Payment per insured acre (log)
Fraction voting Republican	-0.566	0.018	1.312***
	(0.409)	(0.465)	(0.437)
Swing measure	-1.411***	-1.394***	-1.128***
	(0.142)	(0.153)	(0.147)
Observations	61,149	52,987	54,344
R-squared	0.616	0.619	0.641
F-value	49.141	43.601	43.060

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 5: Effect of politics on disaster payments

	Total payments (log)	Total payments (log)	Payment per harvested acre (log)	Payment per harvested acre (log)	Payment per insured acre (log)	Payment per insured acre (log)
Fraction voting Republican		-0.228		-0.084		1.188***
		(0.401)		(0.460)		(0.422)
Fraction voting for Senate majority		-1.748***		-1.759***		-1.892***
		(0.208)		(0.226)		(0.223)
Fraction voting for House majority	1.102***	2.544***	1.604***	3.043***	1.869***	3.326***
	(0.167)	(0.262)	(0.196)	(0.295)	(0.185)	(0.287)
Observations	61,149	61,149	52,987	52,987	54,344	54,344
R-squared	0.616	0.616	0.619	0.620	0.641	0.642
F-value	43.703	31.923	67.185	35.850	101.780	50.660

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 6: Effect of ENSO on total disaster payments

	50 miles	100 miles	150 miles	200 miles
Effect on neighbors	-8.369***	-2.070	-0.711	-0.178
	(2.979)	(1.260)	(0.918)	(0.744)
Own effect	-15.650	-21.382**	-29.745**	-34.017***
	(9.931)	(10.131)	(11.206)	(12.207)
Own effect squared	-467.296*	-584.963**	-699.248**	-755.777**
	(235.482)	(239.230)	(269.848)	(294.746)
F-value	7.892	2.698	0.599	0.057
Observations	58,519	58,519	58,519	58,519
R-squared	0.621	0.621	0.621	0.621

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 7: Effect of ENSO on disaster payments per harvested acre

	50 miles	100 miles	150 miles	200 miles
Effect on neighbors	-8.842***	-2.218*	-0.739	-0.102
	(3.059)	(1.306)	(0.945)	(0.749)
Own effect	-12.758	-18.608*	-27.749**	-32.855**
	(11.239)	(10.958)	(11.455)	(12.388)
Own effect squared	-498.359*	-619.590**	-744.368**	-812.324**
	(265.854)	(261.442)	(282.939)	(304.110)
F-value	8.356	2.883	0.612	0.019
Observations	52,195	52,195	52,195	52,195
R-squared	0.623	0.623	0.623	0.623

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Includes county and year fixed effects.

Table 8: Effect of ENSO on disaster payments per insured acre

	50 miles	100 miles	150 miles	200 miles
Effect on neighbors	-8.400***	-2.063	-0.706	-0.188
	(2.806)	(1.357)	(0.911)	(0.693)
Own effect	-15.593*	-21.452**	-29.800***	-33.957***
	(9.136)	(9.550)	(10.537)	(12.151)
Own effect squared	-485.095**	-604.278***	-718.175***	-773.277***
	(205.464)	(200.192)	(244.922)	(283.955)
F-value	8.965	2.310	0.601	0.073
Observations	51,820	51,820	51,820	51,820
R-squared	0.657	0.657	0.657	0.657

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Includes county and year fixed effects.

Table 9: Effect of politics on liability

	Total liability (log)	Liability per harvested acre (log)	Liability per insured acre (log)
Disaster payments (log)	0.102		
	(0.143)		
Disaster payments per planted acre (log)		-0.116	
		(0.121)	
Disaster payments per insured acre (log)			-0.196**
			(0.087)
First stage F-value	12.114	11.310	11.501
Observations	61,149	52,963	54,318
R-squared	0.160	0.215	-0.980

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 10: Effect of politics on liability

	Total liability (log)	Liability per harvested acre (log)	Liability per insured acre (log)
Disaster payments (log)	0.102		
	(0.078)		
Disaster payments per planted acre (log)		-0.116*	
		(0.067)	
Disaster payments per insured acre (log)			-0.196***
			(0.038)
First stage F-value	51.742	46.124	45.511
Observations	61,149	52,963	54,318
R-squared	0.160	0.215	-0.980

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 11: Effect of politics on liability

	Total liability (log)	Total liability (log)	Liability per harvested acre (log)	Liability per harvested acre (log)	Liability per insured acre (log)	Liability per insured acre (log)
Disaster payments (log)	-0.460***	-0.320***				
	(0.147)	(0.082)				
Disaster payments per planted acre (log)			-0.375***	-0.313***		
			(0.107)	(0.075)		
Disaster payments per insured acre (log)					0.036	-0.018
					(0.025)	(0.021)
First stage F-value	46.017	33.613	71.072	37.924	107.574	53.544
Observations	61,149	61,149	52,963	52,963	54,318	54,318
R-squared	-0.427	-0.118	-0.243	-0.093	0.204	0.205

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 12: Effect of ENSO on liability

	Total liability (log)	Liability per harvested acre (log)	Liability per insured acre (log)
Effect on neighbors	0.055	0.100	-0.015
	(0.155)	(0.126)	(0.035)
Own effect	4.379	7.563	1.479
	(3.935)	(4.842)	(1.158)
Own effect squared	226.133**	163.226	19.824
	(89.182)	(109.947)	(27.430)
First stage F-value	8.354	8.848	9.502
Observations	58,416	52,174	51,791
R-squared	0.274	0.317	0.586

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 13: El Nino and disaster payments in own county

	Disaster payments per insured acre (log)	Disaster payments per harvested acre (log)	Total disaster payments (log)
Own effect	-35.467**	-33.676**	-35.450***
	(13.741)	(14.102)	(13.063)
Own effect squared	-793.837**	-823.496**	-775.058**
	(311.304)	(317.688)	(308.370)
Observations	51,820	52,195	58,519
R-squared	0.657	0.623	0.621

Standard errors (clustered by state) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

Table 14: El Nino and liability in own county

	Total liability (log)	Liability per insured acre (log)	Liability per harvested acre (log)
Own effect	2.320	1.983***	4.038*
	(1.561)	(0.646)	(2.366)
Own effect squared	181.915***	31.159**	78.817
	(37.230)	(15.296)	(76.520)
Observations	58,574	51,975	52,348
R-squared	0.864	0.826	0.814

Standard errors (clustered by county) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Includes county and year fixed effects.

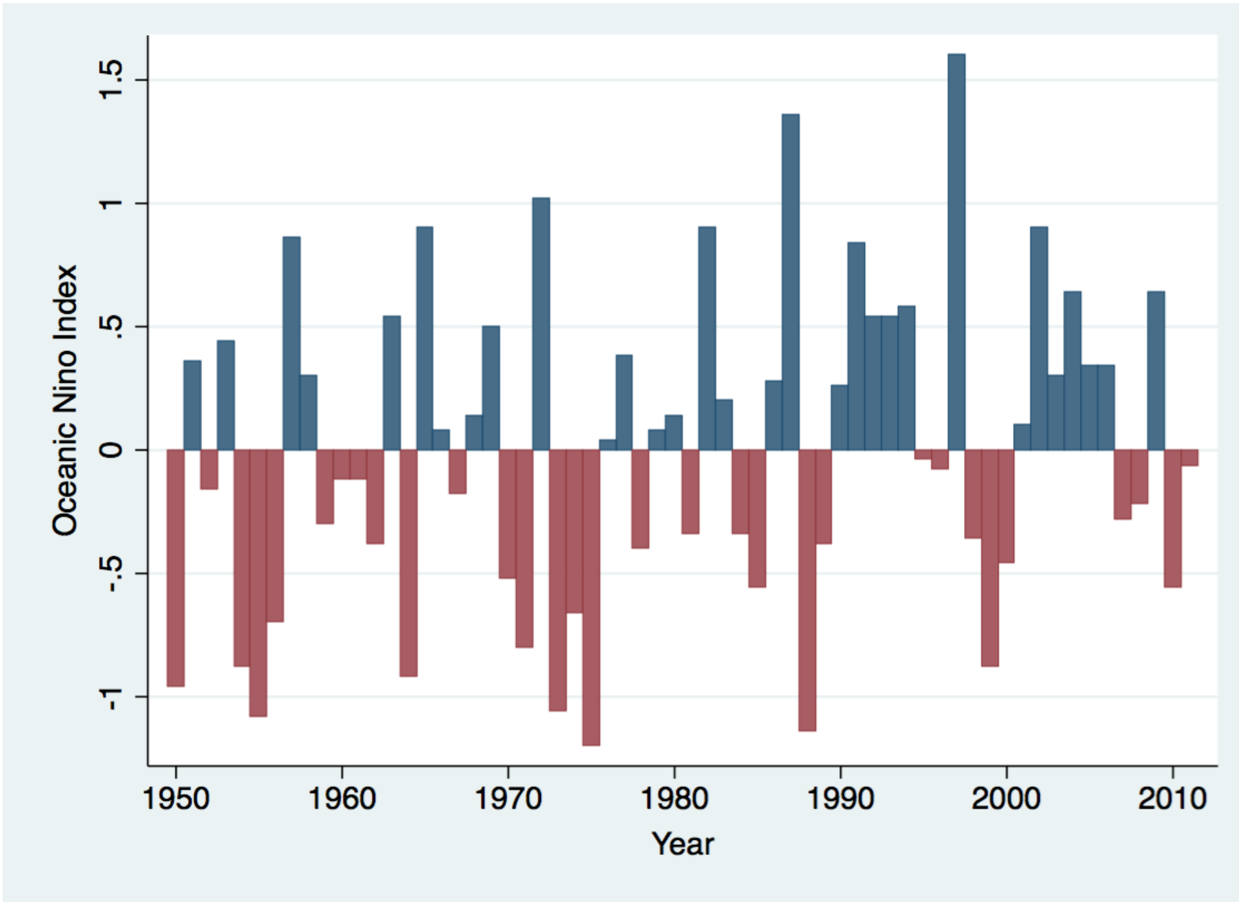

Figure 1: Oceanic Nino Index

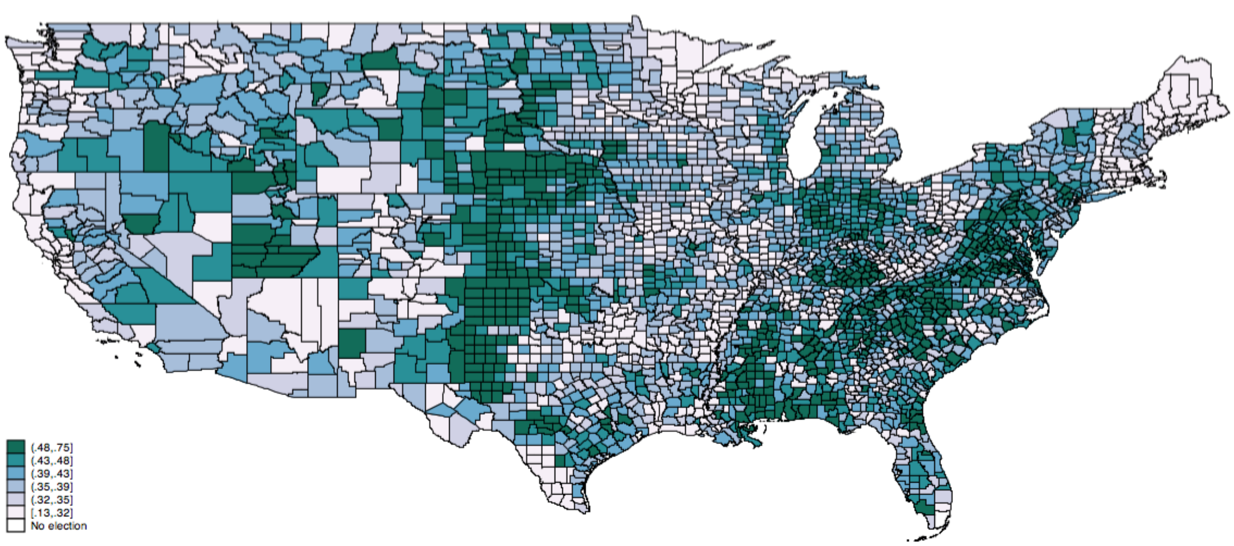

Figure 2: Percent Voting for the Majority Party in the House in 1996

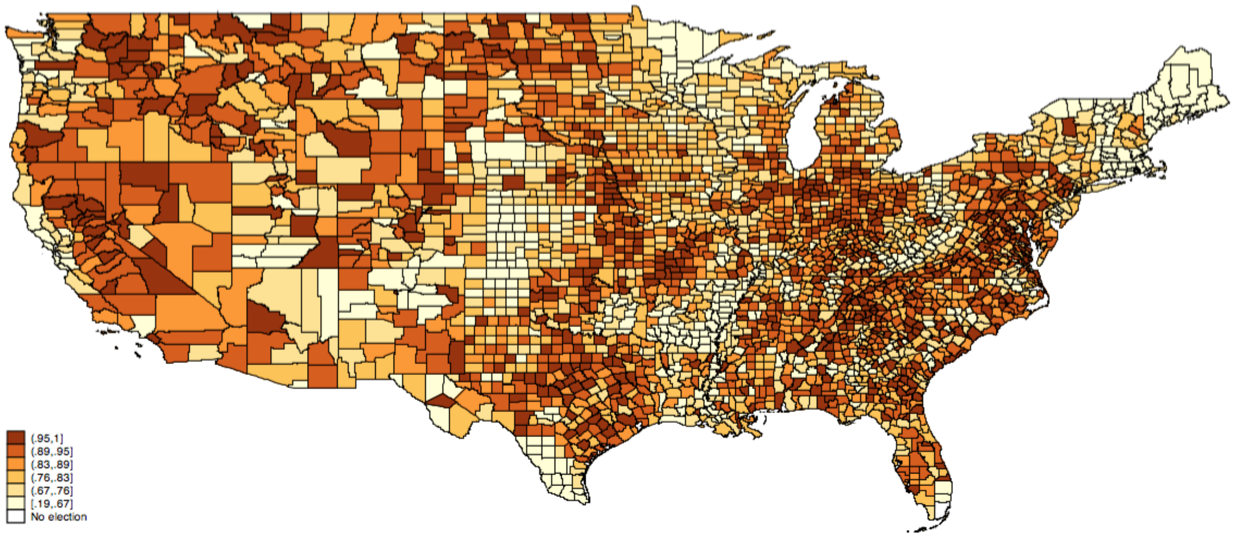

Figure 3: "Swing" Status Based on the 1996 Presidential Election

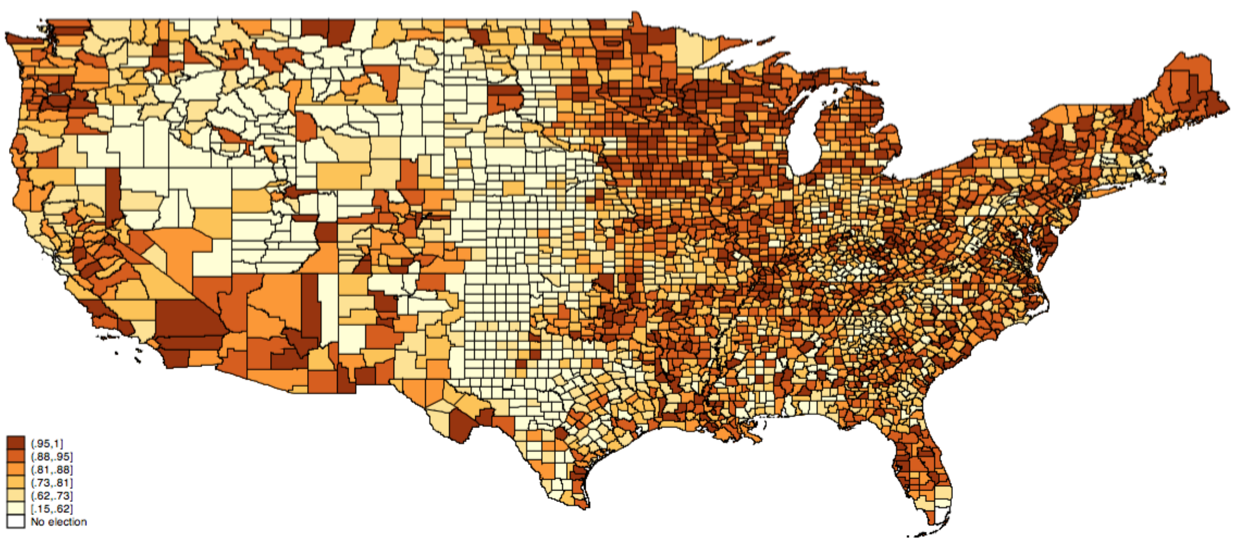

Figure 4: "Swing" Status Based on 2000 Presidential Election

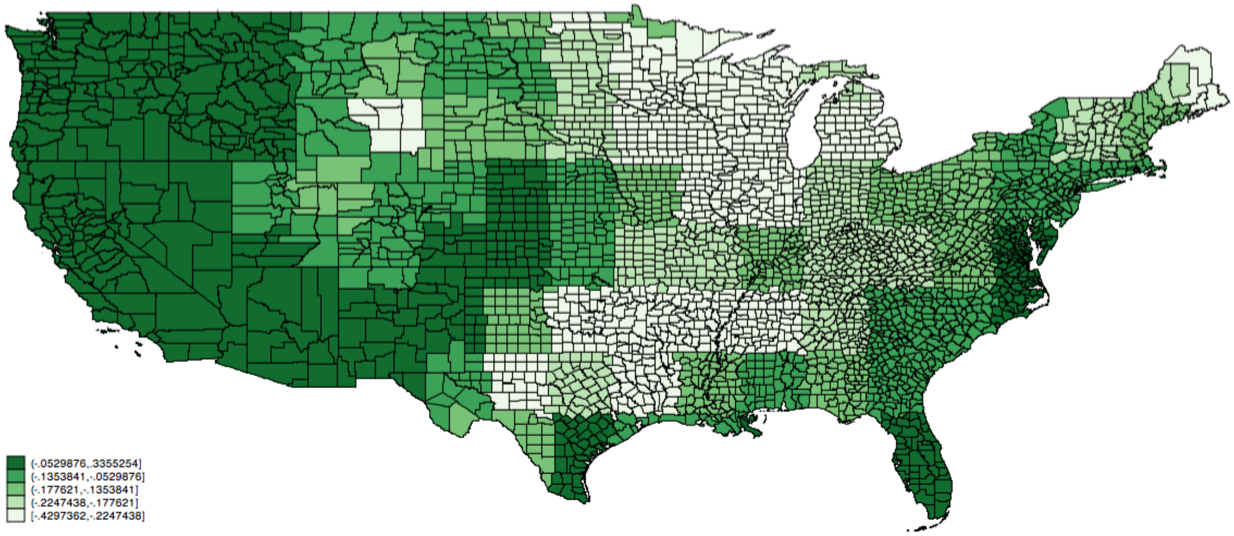

Figure 5: Predicted Effect of El Nino on Average Temperature

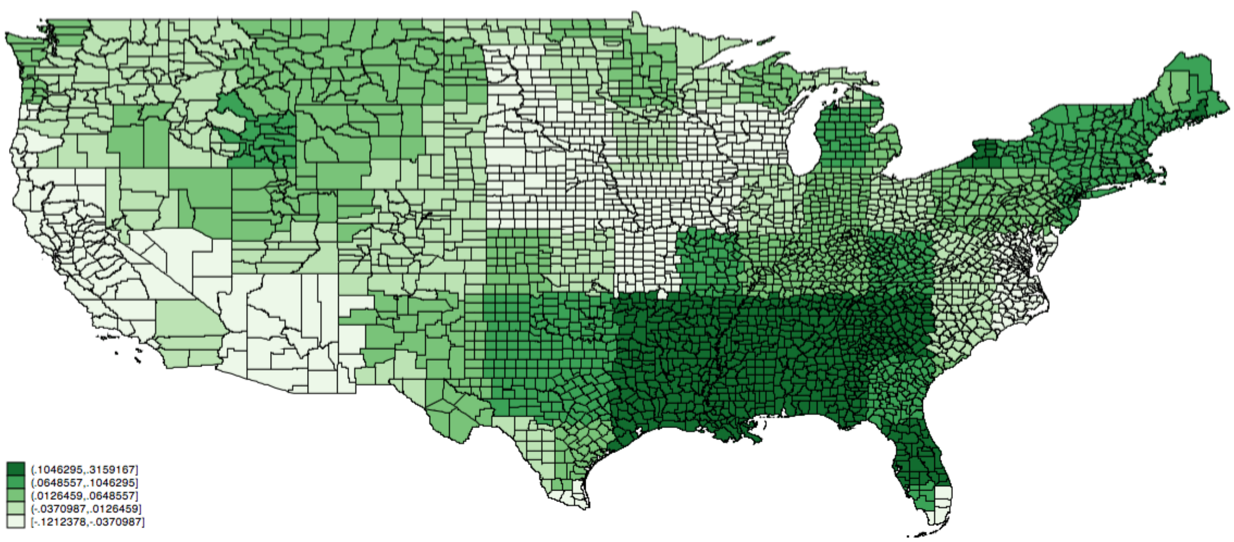

Figure 6: Predicted Effect of El Nino on Total Rainfall