Does The Samaritan's Dilemma Matter? Evidence From U.S. Agriculture

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Abstract

The Samaritan's dilemma posits a downside to charity: recipients may rely on free aid instead of their own efforts. Anecdotally, the expectation of free assistance is thought to be important for decisions about insurance and risky behavior in numerous settings, but reliable empirical evidence is scarce. We estimate whether the Samaritan's dilemma exists in U.S. agriculture, where both private crop insurance and frequent federal disaster assistance are present. We find that bailout expectations are qualitatively and quantitatively important for the insurance decision. Furthermore, aid expectations reduce both expenditure on farm inputs and subsequent crop revenue.

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1 Introduction

The state periodically steps in as the "insurer of last resort" during systemic shocks, such as natural disasters (e.g., Hurricanes Katrina and Sandy) and economic crises (e.g., the financial crisis of 2007-2008). In doing so it faces the Samaritan's dilemma, first described by Buchanan (1975): victims who expect to be bailed out may take on additional risk in response. For example, potential bailout recipients may purchase less flood insurance or invest in riskier securities.[1] This type of moral hazard increases the economic cost of the shock and decreases overall welfare due to the variability in the marginal utility of income across states of nature (Kaplow, 1991; Coate, 1995; Kim and Schlesinger, 2005). In other words, bailout expectations lead to unequal marginal utilities of income across states of nature, which in turn creates a welfare loss even if real outcomes such as output are unaffected. If real outcomes are affected as well, the welfare loss is larger.

We provide some of the first evidence on the empirical importance of the Samaritan's dilemma with respect to *ad hoc* aid. Anecdotally, the expectation of free assistance is thought to be an important explanation for the relatively low rates of insurance take-up and self-protection measures in several important settings, including natural disaster insurance, foreign aid, and financial markets. However, empirically estimating the Samaritan's dilemma is incredibly challenging for at least two reasons. First, bailouts and risk exposure are simultaneously determined: the size of a bailout depends on economic agents' risk exposure, and agents' risk exposure depends on their expectation of a bailout. Moreover, changes in background risk that are unobservable to the econometrician may affect both the size of a bailout and the agents' choice of risk exposure (Gollier and Pratt, 1996; Harrison et al., 2007). Few empirical studies have attempted to tackle the simultaneity and confounding variables issues.[2] Second, shocks during which agents can reasonably expect to be bailed out, such as Hurricane Katrina or the financial crisis of 2007-2008, are rare in most settings, and rare shocks do not easily lend themselves to systematic statistical examination.

To credibly gauge the relevance of the Samaritan's dilemma for the provision of social insurance, we would need a setting with fairly frequent shocks, extensive insurance availability, and relatively frequent government bailouts that, to some extent, vary exogenously. U.S. agriculture provides such a setting. Agricultural producers can purchase heavily subsidized crop insurance, but the government appears unable to withhold *ex post* aid: Congress provided *ad hoc* disaster

[1]Terms that describe phenomena similar to the Samaritan's dilemma include "*ex ante* moral hazard" and, more generally, "crowd out". *ex ante* moral hazard typically refers to market insurance crowding out self-protection activities (Ehrlich and Becker, 1972). Papers that deal with crowd out more generally typically consider the relationship between a permanent public insurance program and private insurance (e.g., Cutler and Gruber, 1996; Brown and Finkelstein, 2008; Gruber and Simon, 2008). By contrast, the *ad hoc* nature of bailouts makes them more similar to charity than to public insurance.

[2]Exceptions are Raschky and Schwindt (2009) and Kousky et al. (2015). See Raschky and Weckhannemann (2007) for an overview of the literature.

payments every year between 1990 and 2010, the period of our analysis, at an average of $1.8 billion per year.[3] Politics has long been thought to play a role in agricultural disaster aid allocation, both in the U.S. and elsewhere (e.g., Garrett, Marsh, and Marshall, 2006; Goodwin and Vado, 2007; Cole, Healy, and Werker, 2012; Chang and Zilberman, 2014), creating plausibly exogenous variation in aid that is not directly related to farmers' insurance decisions.

Motivated by these facts, we rely on political variation to identify the causal relationship between aid expectations and insurance decisions. Our choice of instrument is guided by the theory of tactical redistribution in which politicians make pre-election promises in a bid to gain votes (Dixit and Londregan, 1996, 1998). Specifically, we employ the "swing voter" model, which is the most commonly used model in this literature (Lindbeck and Weibull, 1987; Dahlberg and Johansson, 2002). We use changes in the percent of a county's voters who voted for a third-party candidate in the most recent prior presidential election as an instrument for disaster aid. As we discuss later, third-party voters are easier to sway than someone voting for a Republican or Democrat, making them excellent targets for any politician who is trying to gain voters in county, congressional, state, or even national elections. Likewise, agricultural disaster aid is a cost-effective way to target voters, because the majority of Americans of both parties favor financially supporting farmers, especially in bad years (see, e.g., Kull et al., 2004). At the same time, farmers represent a small share of the population, reducing the likelihood of instrument endogeneity with respect to crop insurance.

We use county fixed effects to account for unobserved cross-sectional heterogeneity, such as the inherent riskiness of an area for crop production. We account for macro-level shocks, such as price variation or policy changes, with year fixed effects. Thus, our identification comes from within-county *changes* in voting patterns, disaster aid, and insurance coverage. We also control for a number of time-varying county characteristics, including farm and non-farm incomes, total employment, population, the share of population employed in agriculture, and the number of farm proprietors. Our identifying assumption is that, conditional on these controls, recent voting behavior in a county is related to the crop insurance decisions of a county's farmers only through the disaster aid channel. We argue that our instrument is likely to meet the exogeneity requirement, in part because farmers make up a small fraction of the electorate in the modern U.S. We also show that our estimates are robust to employing additional instrumental variables based on other political theories.

We find that the elasticity of farmers' out-of-pocket expenditure on insurance with respect to expected disaster payments is about -0.2. That is, a 10-percent increase in expected disaster payments reduces the premiums farmers pay by 2 percent. We confirm this result by using alternative measures of coverage, such as total liability, total number of policies, and premium subsidies.

[3] All dollars are inflation-adjusted to 2011.

Consistent with farmers reducing insurance coverage rather than foregoing it altogether, we find evidence that farmers are choosing less generous insurance plans. Finally, we find that bailout expectations result in reduced spending on farm labor and fertilizer, lower price-weighted yields, and lower revenue from crop sales.

Theoretical literature predicts that subsidizing risk-reduction activities such as insurance reduces agents' reliance on bailouts (Coate, 1995); the theory can be extended to show that increasing the uncertainty of a bailout also reduces the Samaritan's dilemma. Crop insurance is heavily subsidized—the government currently pays about two-thirds of the premiums—and bailouts are *ad hoc* and thus inherently uncertain, especially from the point of view of an individual farmer. Yet we find that the Samaritan's dilemma still exists and is non-trivial in magnitude, suggesting that it is a more pervasive phenomenon than expected.

Our findings have important implications for a number of other settings. Two that are particularly similar are domestic disaster aid more generally and foreign aid.[4] The U.S. spent about $100 billion on non-agricultural domestic disaster relief in the 2011-2013 fiscal years (Weiss and Weidman, 2013) and about $31 billion in foreign economic assistance in the 2012 fiscal year (United States Agency for International Development, 2014). In both cases, the aid is discretionary and thus uncertain. At the same time, it is awarded fairly regularly, making it more likely that potential recipients will expect it. The similarities between these settings and ours make the existence of the Samaritan's dilemma in the former very likely.

Our results also empirically validate the idea that the Samaritan's dilemma and, more generally, *ex ante* moral hazard—where recipients expose themselves to a higher risk of income loss because of the presence of some safety net—are present in social insurance settings such as unemployment insurance, TANF, or SNAP (Buchanan, 1975). In contrast to private insurance markets where premiums, deductibles, and co-payments can be adjusted to internalize *ex ante* moral hazard (Chiappori, 2000; Dave and Kaestner, 2009), the Samaritan's dilemma implies long-run, persistent welfare losses in social insurance programs that cannot easily be tailored to individual behavior.

In addition, our findings are relevant for gauging the effects of agricultural subsidies, which are prevalent in developed nations. In their theoretical work on the Samaritan's dilemma, Bruce and Waldman (1991) and Coate (1995) suggest that replacing *ex post* disaster aid with an *ex ante* in-kind transfer in the form of full insurance coverage eliminates the Samaritan's dilemma. Although some U.S. agricultural subsidies are independent of production or prices, many are effectively partial insurance programs where payments depend on market conditions. Indeed, direct (unconditional) payments to U.S. producers have been shrinking over time, while subsidies for crop insurance have grown substantially and now account for a large share of agricultural support. Our

[4]For theoretical considerations of the Samaritan's dilemma in foreign aid settings, see Pedersen (1996); Svensson (2000); Pedersen (2001); Svensson (2003) and Hagen (2006).

findings suggest that even these large subsidies appear to not eliminate the Samaritan's dilemma entirely.

Finally, our results also provide insight into how farmers alter their risk-management behavior in anticipation of future government payments. A substantial body of research examines the relationship between farmers' risk-management behavior and land-specific subsidies that are known to the farmer *ex ante*, e.g., Direct Payments (see Weber and Key, 2012, for an overview of this literature). Surprisingly little work, however, provides carefully identified empirical estimates of the risk-management response to *ex ante unknown* subsidies, such as Counter-Cyclical Payments or Loan Deficiency Payments.[5] Our research, therefore, provides an innovative way to examine the effect of expected government benefits on farmers' risk-management behavior.

To our knowledge, only two working papers have attempted to credibly estimate the importance of the Samaritan's dilemma in the areas of foreign aid and domestic disaster aid. Raschky and Schwindt (2009) estimate the impact of foreign aid on recipient countries' death tolls from natural disasters, a proxy for disaster preparedness. To get around the endogeneity problem, they use voting patterns in the U.N. General Assembly and the aid recipient's oil reserves and natural gas production as instruments for foreign aid. More foreign aid leads to *higher* death tolls from storms, which provides some evidence for the Samaritan's dilemma. However, they cannot measure disaster preparedness efforts directly and do not find any effect of foreign aid on death tolls from earthquakes or floods. With respect to domestic disaster assistance, Kousky, Michel-Kerjan, and Raschky (2015) use several measures of political variation as instrument for aid. They find that higher disaster aid in the previous year leads to lower flood insurance takeup on the intensive but not the extensive margin.

The rest of the paper is organized as follows. In Section 2, we outline the basic intuition for the inefficiency of *ex post* relief, which has been shown formally in previous theoretical literature. In Section 3, we provide background on crop insurance and disaster payments in the U.S. In Section 4, we describe our data and empirical strategy. Section 5 presents the results, and Section 6 concludes.

2 The Inefficiency of *Ex Post* Aid

Numerous theoretical papers have demonstrated the inefficiency behind the Samaritan's dilemma (Kaplow, 1991; Bruce and Waldman, 1991; Coate, 1995; Kim and Schlesinger, 2005; Dijkstra, 2007). To frame our empirical work, we highlight the salient intuition from this literature. Altruism is a fundamental tenet of the Samaritan's dilemma— it is the altruism of some economic agents (the "Samaritans") that leads to the recipients' inefficient behavior. In our setting, non-farmers are altruistic toward farmers, which is a well-documented phenomenon (Variyam et al., 1990;

[5]McDonald and Sumner (2003) review the shortcomings of this literature.

Kull et al., 2004; Ellison et al., 2010a; Lusk, 2012). As a consequence, farmers' consumption is a public good for non-farmers, and private charity will be inefficiently low due to the free-rider problem. In the theoretical literature, the government acts to address the free-rider problem with *ex post* transfers, which in our empirical setting corresponds to providing farmers with *ad hoc* aid following a negative shock.

Despite solving the free-rider problem, the socially optimal level of the public good is unlikely to be privately optimal for farmers. The Samaritan's dilemma has adverse efficiency effects stemming from the fact that the government acts *ex post* rather than *ex ante* and acts in the interest of the Samaritans rather than the farmers. Coate (1995) shows that *ex post* aid will be less than the net indemnity under full insurance in the loss state. This outcome is *ex ante* inefficient because farmers will have unequal consumption in the "loss" and "no-loss" states of nature. And by under-insuring in the first period, risk-averse farmers take on too much risk.

Finally, Kaplow (1991) and Bruce and Waldman (1991) show that *ex post* aid is not cost-effective because it affects agents' self-insurance. This fact is also potentially relevant in our setting, as farmers have multiple means of self-insurance. For instance, they can ameliorate the consequences of an adverse production shock through irrigation, pesticides, or increased labor; and savings and inventory can ease the burden of a price shock. When the amount of *ex post* aid depends on the size of the loss, farmers have incentive to reduce self-insurance, which exacerbates the cost of a bailout.

3 Crop Insurance and Disaster Payments

Federal crop insurance and agricultural disaster payments have provided overlapping risk protection to farmers for over 40 years. The Agricultural Adjustment Act of 1938 established the Federal Crop Insurance Corporation (FCIC) to administer what was essentially an experimental crop insurance program until 1980.[6] In 1973, while crop insurance was in this experimental phase, Congress established a standing Crop Disaster Payment (CDP) program that was akin to free insurance coverage for a select group of crops. When yields fell below two-thirds of normal, low-yield payments were made to farmers who participated in income- and price-support programs. The Government Accountability Office (GAO) suspected that there was a conflict between these programs—the Samaritan's dilemma—when it reported that, where crop insurance was offered, "[disaster] payments actually compete with crop insurance because they require no premiums" (U.S. Government Accountability Office, 1980). Aware of the disincentive effects disaster payments have on crop insurance demand, some crop insurance demand models have included proxies for disaster payments (e.g. Niewuwoudt and Bullock, 1985; Barnett and Skees, 1995). These models typically reveal a

[6]For a more detailed history of the early crop insurance program see Glauber and Collins (2002).

negative correlation, but they cannot identify the direct effect of disaster payments on crop insurance demand.

In 1980, Congress ended the standing CDP program and greatly expanded the Federal Crop Insurance (FCI) program. In spite of this expansion, Congress continued the pattern of having two parallel mechanisms for dealing with crop-loss risk by providing $6.9 billion in disaster payments on top of $4.3 billion in crop insurance indemnities in 1980–1988 (U.S. General Accounting Office, 1989). At the same time, FCI participation stagnated at 50 million acres, less than 25% of insurable land (Glauber and Collins, 2002). In 1989 the GAO reported that, "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." Despite GAO warnings, Congress continued to frequently authorize *ad hoc* disaster aid throughout the 1990's and 2000's, allocating a total of $40.2 billion (2011 dollars) to CDP programs in 1990–2011.[7]

3.1 Crop Insurance

Starting from the mid-1990's, farmers have had a lot of choice when it comes to crop insurance. Importantly, farmers can choose the generosity of the insurance plan they purchase. The options typically range from a 50% coverage plan, which only pays indemnities after the farmer's yield or revenue has fallen to 50% or less of its expected value, to a 90% coverage plan, which begins paying after only a 10% drop. Farmers can also choose how much money they are paid per unit of shortfall from a pre-specified range.[8]

In addition, if a farmer owns multiple plots growing the same crop in the same county, he can choose to insure them jointly and pay a lower insurance premium. If crop insurance were actuarially fair, economic theory predicts that a farmer would want to combine all his plots under a single insurance policy, as he should care about his aggregate income rather than income from any single plot. However, because crop insurance is heavily subsidized, farmers sometimes find it advantageous to insure plots under different policies in order to maximize the expected return per dollar of premium, even if doing so raises the overall variance of their income. Importantly, because of farmers' ability to insure plots separately, the number of policies can reflect both the extensive and intensive measure of insurance takeup.

Unlike many other insurance markets, providers of crop insurance cannot set their own prices or offer customized insurance plans. However, the federal government reinsures the providers and reimburses them for administrative expenses. The prices and plans are determined by the Risk Management Agency (RMA) of the USDA and are typically made public near the end of the preceding calendar year. The rating methodology used to set prices has been fairly consistent and

[7] See the appendix for a list of public laws passed between 1989 and 2009 that authorize crop disaster payments.
[8] For more details on how indemnity payments are determined, see the Online Appendix.

largely formulaic throughout our sample period.[9] This is another important feature of our setting, as it rules out the possibility that insurance *prices* might be changing for political reasons or in anticipation of greater disaster aid from the government.

Since Congress ended the CDP program in 1980, it has subsidized crop insurance premiums to encourage farmers to purchase more coverage and thereby reduce the need for *ad hoc* disaster payments. Figure 1 illustrates the evolution of premium subsidy rates from 1990–2011. Despite premium subsidies ranging from 17% (for 75% coverage) to 30% (for 50% and 65% coverage) during the 1980s and early 1990s, voluntary participation in the Federal Crop Insurance (FCI) program remained low. The Federal Crop Insurance Reform (FCIR) Act of 1994 greatly expanded the crop insurance program by requiring farmers who received other government support to adopt fully subsidized catastrophic-level (50%) coverage. The FCIR also increased premium subsidies for higher coverage levels. The insurance requirement was removed in the following year, but the higher subsidy rates remained. The Agricultural Risk Protection Act of 2000 (ARPA) further increased premium subsidies, especially for higher coverage levels. The subsidy rate increased by half for the 65% coverage level, more than doubled for the 75% coverage level, and nearly tripled for the 85% coverage level. It is important to note that the premium subsidy rates do not vary geographically. Thus, they cannot be manipulated by politicians to target specific areas in the same way that disaster payments can.

Predictably, the above-mentioned reforms raised insurance coverage. Figure 2 illustrates the share of total acres insured by FCI by coverage level from 1990–2011. Nearly all of the increase in participation in 1995 came from an increase in the mandated (and most heavily subsidized) 50% coverage. In 2001, participation levels increased further when premium subsidies were raised even more under ARPA. With these dramatically increased subsidy rates, participation returned to the 1994-mandated level in 2004 and has hovered around 80% of eligible acreage since then. However, insurance coverage among the insureds is far from full—most acres are insured under plans with at least a 25% deductible (coverage level of 75% or lower). About a third of insured acres are covered by plans with at least a 35% deductible (coverage level of 65% or lower).

3.2 Disaster Payments

Unlike crop insurance indemnities, which are known for a given loss level and plan choice, disaster payments are not perfectly predictable, especially from an individual farmer's point of view. The disaster designation process adds to the uncertainty. First, a state's governor requests a disaster designation for the affected counties in the state. The Secretary of Agriculture then determines whether a natural disaster has caused a 30-percent or more production loss of at least one crop in

[9] See the Online Appendix, Coble et al. (2010), and Coble et al. (2011) for more details on how prices are set.

the county. Once the Secretary of Agriculture issues a disaster designation, farmers in the primary *and contiguous* counties become eligible for emergency loans. Farmers in these counties may also receive disaster payments if Congress passes legislation funding an *ad hoc* disaster program. Disaster payments are usually calculated in a way that is very similar to a not-very-generous crop insurance plan.[10]

Figure 3 shows the pattern of indemnity payments, made by insurance companies, and crop disaster payments, made by the government, over the same time period. To control for the growth of insurance coverage, we show these quantities as a percent of total liability. On average, disaster and indemnity payments are similar in magnitude. In several years, disaster payments exceed indemnity payments. In recent years, disaster payments have been relatively low, potentially due to increasing coverage. Disaster payments were made in every year, although in some years the amount is very small. Consistent with their *ad hoc* nature, disaster payments are much more volatile than indemnity payments.

Disaster aid programs are administered in such a way that disaster payments are a *de facto* supplement to indemnity payments. In an effort to be equitable and not discourage crop insurance purchase, Congress typically mandates that "there should not be discrimination, in making payments, against persons who had acquired federal crop insurance" (2000 Crop Disaster Program, 2001). In other words, both insured and uninsured farmers can qualify for disaster payments. Only the U.S. Troop Readiness, Veterans' Care, Katrina Recovery, and Iraq Accountability Appropriations Act of 2007 (2007) and the Food, Conservation, and Energy Act of 2008 (2008) have limited disaster payments to farmers who purchased insurance or who did not have the option to purchase insurance.[11] For insured farmers, disaster payments "top up" indemnity payments. However, insurance payments are not ignored completely; once the sum of indemnity and disaster payments reaches 95% of the farmer's expected revenue, the farmer is not eligible for more disaster payments.[12] Allowing disaster payments to be given *in addition* to crop insurance creates a strong incentive for farmers to respond on the intensive margin by purchasing less insurance than they otherwise would, rather than foregoing crop insurance entirely.

Although Congress has regularly responded to agricultural disasters with CDP programs, it has not been without reluctance. Over the period of our analysis Congress attempted to move away from CDP programs by strengthening the Federal Crop Insurance (FCI) program and weakening its own ability to pass disaster-assistance legislation by tightening budgetary constraints. In 1990–

[10]We provide more details on how crop insurance and disaster aid payments are typically calculated in the Online Appendix.

[11]The latter group has access to a separate disaster assistance program called Noninsured Crop Disaster Assistance Program (NAP), which we do not consider here.

[12]Typically, a CDP program stipulates "the sum of the value of the crop not lost, if any; the disaster payment received under this part; and any crop insurance payment . . . for losses to the same crop, cannot exceed 95 percent of what the crop's value would have been if there had been no loss" (2005–2007 Crop Disaster Program, 2008).

1994, disaster payments came from emergency supplemental appropriations that were exempted from discretionary spending caps. The 1994 FCIR eliminated the use of emergency legislation for agricultural crop disaster assistance, thereby making future disaster payments subject to discretionary spending caps. Together with mandatory catastrophic coverage, these requirements were meant to send a signal that future disaster payments were unlikely (see Jose and Valluru, 1997).[13] Congress, however, rescinded the catastrophic-coverage mandate after just one year. In 1998, it also reverted disaster spending to "emergency" status and implemented a multi-year CDP program—something it said it would not do four years earlier.[14]

In an attempt to reduce disaster payment uncertainty, the 2008 farm bill established a standing disaster program called the Supplemental Revenue Assistance Program (SURE) (Food, Conservation, and Energy Act of 2008, 2008). The program, however, failed to reduce uncertainty; according to USDA officials it was "the most complex program USDA's Farm Service Agency has undertaken" (Shields, 2010). Moreover, despite the standing disaster program, Congress passed *ad hoc* disaster payment legislation in 2009, and in a rare move the president sidestepped Congress and implemented a CDP program in 2010. SURE expired in 2011 and was not renewed in the 2014 farm bill. Thus, the current pattern of a heavily subsidized insurance market combined with relatively frequent *ad hoc* disaster aid can be expected to continue.

It is important to note that crop insurance and disaster payments are part of a larger safety net that includes price supports, production subsidies, and input-specific subsidies. Subsidy programs are unlikely to confound our analysis, however. They are determined by the federal farm bill, which only changes every six years and applies uniformly to all farms in the U.S. Because of this uniformity, it is unlikely that politicians use general agricultural subsidies to target counties based on changes in their third-party voting patterns, although they can use such subsidies to target agricultural counties more generally. In contrast, crop insurance-coverage decisions and disaster-payment legislation occur annually and apply differentially depending on a county's disaster designation. Thus, politicians can deliver on their election-year promises more quickly and in a more targeted fashion with disaster payments than with changes to the farm safety net.

3.3 The Likely Importance of the Samaritan's Dilemma in U.S. Agriculture

Despite circumstances that seem to favor the Samaritan's dilemma in our setting, it is not a foregone conclusion. Four potentially offsetting factors make it difficult to determine, *ex ante*, the extent to which government bailouts affect insurance decisions. First, free disaster payments may seem

[13] Speaking just before passage of FCIR, Rep. Larry Combest declared, "This means an end to emergency spending for agricultural disasters." (Rep. Combest (Texas), 1994)

[14] Agriculture, Rural Development, Food and Drug Administration, and Related Agencies Appropriations Act, 1999 (1998)

preferable to costly insurance, but due to heavy premium subsidies, crop insurance is cheap, which should reduce the amount of crowd out. Second, although disaster payments have been made fairly regularly, they are still more uncertain than insurance payments, especially from the point of view of an individual farmer. Third, because disaster payments can supplement indemnity payments, we expect lower crowd out than if insured producers could not receive disaster payments. Finally, if the conditions that trigger crop insurance and disaster payments are very similar, then the latter might be a good substitute for the former. However, as we show in later sections, disaster payments are heavily influenced by politics, and thus might be a poor replacement for market insurance.

To gain some insight into the likely importance of the Samaritan's dilemma in U.S. agriculture, we simulate farmers' insurance choices, taking into account insurance subsidies, the uncertainty of disaster payments, and the fact that the correlation between disaster payments and losses may be low. Specifically, we model the farmers' choice of coverage level in a plan that insures individual revenue and calculate the corresponding out-of-pocket payments for a range of realistic loss and disaster payment parameters. The details of the simulation are presented in the Online Appendix. As expected, increasing the uncertainty of disaster payments or decreasing their correlation with losses reduces the amount of crowd out. Overall, we find a substantial amount of crowd out across a variety of scenarios, suggesting that the Samaritan's dilemma is likely to be important in this setting.

4 Empirical Strategy

4.1 Data

We identify the effect of expected disaster payments on crop insurance coverage with county-level administrative data. Despite the absence of individual-level data connecting disaster payments to crop insurance decisions, the designs of these two programs allow us to estimate the magnitude of the Samaritan's dilemma at the county level. Notably, all farms in a county face similar incentives because both the disaster designation process and the crop-insurance base premium calculation occur at the county level.

Crop insurance takeup information is publicly available from the RMA.[15] For each year between 1990 and 2011, the dataset reports the number of insurance policies purchased, the amount of premiums and premium subsidies paid, total liability, the number of acres insured, and the total indemnity payments.[16] We measure county-level crop-related disaster payments with USDA

[15]Available at `http://www.rma.usda.gov/data/sob.html`

[16]We exclude rangeland, which became insurable in the middle of our sample period, from the crop insurance sample. Because of its low value, it is not likely to be receiving a substantial amount of disaster payments. However, it makes up a significant fraction of insured acres (but not of premiums or liabilities), and its inclusion may obscure

Farm Services Agency (FSA) data, obtained through a Freedom of Information Act request. After 1994, uninsurable crops received disaster payments through the "Non-insurable Crop Disaster Assistance Program" (NAP). We eliminate NAP payments from our data and focus on the disaster payments that may directly affect farmers' insurance decisions. The county-level characteristics we control for in our estimation come from the Regional Economic Information Systems (REIS) and the County Business Patterns (CBP) databases. Expenditure on farm labor and fertilizer, as well as crop revenue are also reported by REIS. Finally, data on production and average farm price received are from the National Agricultural Statistical Service. Total production and acres harvested are observed at the crop-county-year level, while prices received are summarized at the crop-year level.

Table 1 shows key summary statistics for our main regression sample. As we discuss below, it is important for our identification strategy that only a small fraction of a county's population is composed of farmers and their employees. Indeed, we see that less than 4% of the average county's population consists of farm proprietors. About 1% of total employment is in the forestry/agriculture sectors, and farm income represents only about 3.5% of total personal income on average.[17] Of course, while agriculture is a small share of economic activity on average, in some counties it makes up a much larger share. We later show that excluding these counties from our sample does not affect our results.

The next few variables in Table 1 summarize the insurance coverage in our sample. On average, there are about 420 crop insurance policies issued per county in each year, covering about 66,000 acres. Farmers in the average county spend about $677,000 on insurance, with the government contributing an additional $889,000 in premium subsidies. Because of the heavy premium subsidies, we distinguish between premiums that are paid by the farmers themselves and total spending on insurance coverage. Specifically, we refer to the former as "out-of-pocket" insurance expenditure and premiums that include subsidies *and* out-of-pocket payments as "gross premiums."

The mean total liability in a county is about $18 million. Over our sample period, insurers paid $1.24 million in indemnity payments in the average county each year, while the government disbursed an additional $464,000 in disaster payments to producers of insurable crops. Thus, disaster payments are over a third of the size of indemnity payments, while premium subsidies are two-thirds as large as indemnity payments. Taken together, premium subsidies and disaster payments exceed indemnity payments, reinforcing the idea that farmers enjoy substantial government support in this area.

farmer responses to disaster payments on that margin.

[17]Farm income is reported net of costs, and it is not unusual for county-level farm income to be negative. It is also possible for farm income to exceed 100% of personal income in some cases because of some methodological differences in calculating personal and farm incomes. For further details, see `http://www.bea.gov/regional/pdf/lapi2010.pdf`.

Finally, as we discuss in detail below, we use the percent of voters casting ballots for a third-party candidate in the most recent previous presidential election as our instrument. The 2004 and 2008 county-level data come from Dave Leip's Atlas of U.S. Presidential Elections (Leip, 2014), while earlier data were generously shared by James Snyder. For non-election years, we use votes from the most recent past presidential election. In the average county, about 33,000 votes were cast, with about 7% of those votes going to a third-party candidate. The standard deviation of 8.2 suggests that there is substantial variation in third-party voting in our sample.

Figure 4 shows the spatial distribution of third-party voting for the counties in our preferred regression sample. To illustrate the variation used in subsequent analysis, we subtract the county-level mean and account for year fixed effects. We then take the absolute values of these deviations from geographic and temporal trends and average them by county. The resulting map thus demonstrates the locations of the largest sources of variation in third party voters (darker areas). Although we see some geographic concentration in parts of the South and Midwest, there is substantial idiosyncratic variation outside these areas, suggesting that our results will not be driven by a particular part of the country.

4.2 Regression Specification

The central empirical question examined in this paper is "Is the Samaritan's dilemma relevant in US agriculture?" We answer this question by testing whether farmers in county c and year t purchase less crop insurance—$Insurance_{c,t}$, as measured by one of the metrics discussed below—when they expect more *ad hoc* disaster payments conditional on *a*) county fixed effects (a_c) that account for the underlying soil type, climate, and other characteristics that determine the inherent riskiness of producing in each area and *b*) year fixed effects (a_t) that account for macroeconomic shocks such as annual crop price variation and broad changes in the crop insurance program over time (e.g., the premium subsidy rates).

If the Samaritan's dilemma holds, we would expect estimates of γ in the following equation to be negative:

$$Insurance_{c,t} = \gamma E[Disaster_{c,t}] + \mathbf{X}'_{\mathbf{c,t-1}}\phi + a_c + a_t + \varepsilon_{c,t}. \tag{1}$$

The key variable in equation (1) is farmers' expectation of disaster payments in county c and year t, $E[Disaster_{c,t}]$. The county-level control variables, $\mathbf{X}_{\mathbf{c,t-1}}$, include population, the number of farm proprietors, total farm income, and per capita income from REIS, as well as the fraction of total employment in forestry and agriculture sectors from CBP. The characteristics are lagged throughout because the insurance decision must be made by March of each year in most cases.

Several metrics of the multifaceted insurance decision are available to us. Given the institutional background, much of the response to disaster aid expectations may be on the intensive margin, with farmers reducing their insurance coverage rather than foregoing it altogether. A variable that captures both the intensive and extensive margins, farmers' out-of-pocket expenditure on insurance, is arguably the most relevant measure of the Samaritan's dilemma in our setting. Total liability and subsidy payments made by the government provide alternative measures of both the intensive and extensive margins.

The total number of policies seemingly provides a clear measure of the extensive margin of the insurance decision. However, because farmers may consolidate multiple plots under one policy or insure them separately, a drop in the number of policies is not straightforward to interpret. Instead, the number of acres insured provides a cleaner measure of the extensive margin.

Three challenges in estimating and interpreting equation (1) are apparent. First, insurance decisions are based on expected disaster payments, $E[Disaster_{c,t}]$, which are unobservable to us. Instead, we observe *actual* disaster payments, $Disaster_{c,t}$. To the extent that the latter is a noisy estimate of farmer expectations, the potential for measurement error and attenuation bias arises. Thus, our estimates of the extent to which the Samaritan's dilemma matters in agriculture should be viewed as lower bounds. Second, realized disaster payments are likely themselves affected by farmers' insurance decisions, as outlined in the theoretical models of the Samaritan's dilemma: areas that buy less insurance coverage may receive more aid. In this case, the simultaneity of the insurance and bailout decisions will cause estimates of γ to be meaningless from a causal point of view. Third, unobservable (to us) changes in risk may affect both insurance coverage and disaster payments, again introducing bias to estimates of γ (e.g., Gollier and Pratt, 1996). Over the period of our analysis several innovations, e.g., climate change and genetically modified seed, have changed the pattern and practice of crop production in ways that may have affected both the crop insurance decision and disaster payments but remain unobserved and unaccounted for in the analysis. We discuss how we try to overcome these challenges in Section 4.3.

Table 2 shows the results of estimating equation (1) with ordinary least squares where our measure of $Insurance_{c,t}$ is $\ln(Premiums_{c,t})$, the log of farmers' out-of-pocket expenditure on insurance (i.e., not counting subsidies) in county c in year t. We substitute the log of realized disaster payments, $\ln(Disaster_{c,t} + 1)$, for $E[Disaster_{c,t}]$.[18] All specifications include county and year fixed effects, while Columns 4–6 also control for lagged county-level characteristics. Standard errors are clustered by county.

We find a *positive* and highly significant relationship between contemporaneous disaster payments and insurance expenditure, possibly because both variables are responding to an unobserv-

[18]We add 1 to disaster payments prior to taking the natural log due to the presence of many zeros. Our results are robust to adding other positive numbers to all disaster payments and to replacing the zeros with small positive numbers. Adding 1 to the dependent variables prior to taking the log, which we do not do in our preferred specifications, increases the magnitude of most of our estimates, making our conclusions even stronger.

able shock. For example, low precipitation prior to the growing season may be indicative of adverse growing conditions, prompting farmers to take out more insurance to protect themselves and leading to higher disaster payments. Additionally, the adoption of a high-value crop might prompt more coverage and increase the size of disaster payments.

We also find a positive relationship between lagged disaster payments and insurance expenditure; when we include both lagged and contemporaneous disaster payments, each is significant. Specifically, a 1% increase in disaster payments is associated with a 0.007 to 0.009% increase in insurance expenditure in the current year and a 0.011 to 0.012% increase in the following year. The lagged positive relationship can arise for a number of reasons. First, farmers who receive disaster payments are typically required to purchase crop insurance in the next one or two years. Second, an adverse event can trigger disaster payments *and* change farmers' beliefs about risk to their crops, resulting in more insurance in future years. More generally, simultaneity confounds the OLS estimate of γ in equation (1). Thus, without a valid instrument for disaster payments, we cannot say much about the Samaritan's dilemma.

To address potential sources of bias in estimating γ, we need to isolate variation in disaster payments that is correlated with farmers' disaster aid expectations but uncorrelated with the risk environment or insurance decisions more broadly. Consonant with the idea that the government provides *ad hoc* disaster payments because of voters' altruistic preferences toward farmers, our instrument is derived from county-level voting patterns, which plausibly affect the benefits of crop insurance only through their effect on disaster payments. We discuss this assumption in more detail in the next section.

4.3 The Political Determinants of Disaster Aid

To identify the effect of aid expectations on the insurance decision, we exploit the political determinants of agricultural disaster aid over a twenty-year period, using the tactical redistribution theory as our guide (Dixit and Londregan, 1996, 1998). The most commonly used model of tactical redistribution is the "swing voter" model, which posits that elected officials cater to easily persuadable voters with pre-election promises (e.g., Lindbeck and Weibull, 1987; Dahlberg and Johansson, 2002).[19] This model is typically formulated as two competing political parties promising transfers in exchange for votes. The parties have limited resources and must thus direct transfers to places or voters where they get the most "bang for their buck." Rationally, the parties promise the marginal dollar in a way that maximizes the number of votes they subsequently receive. The easiest-to-persuade voters that are targeted by the marginal dollar of political funds are then referred to as "swing voters."

[19] A full review of the literature on models of tactical redistribution is beyond the scope of this paper. For an overview of special interest politics, see Grossman and Helpman (2002).

Although the theory behind the swing voter model is clear, the empirical literature in political science and political economy has surprisingly little to say about the characteristics of actual swing voters in the United States or even how to measure whether someone is easily persuadable.[20] In one of only two systematic studies, Mayer (2007) defines a swing voter as one who equally likes or dislikes the two major parties.[21] Using National Election Studies data from 1972–2004, he finds that approximately 9% of voters view the two major parties equally favorably or equally unfavorably and that these voters are almost equally likely to vote for Democrats and Republicans. Expanding this definition to include voters who very slightly favor one party over another, he finds that about 23% of the electorate can be classified as a swing voter in each presidential election during this time period, on average. Surprisingly, there are few systematic demographic differences (e.g., age, race, or gender) between swing and non-swing voters. However, swing voters are less partisan, are more likely to be moderates, and care less about who wins the election.

No county-level surveys tell us how many voters are indifferent or close to indifferent between the major parties. Our measure of easily persuadable voters in a county is the percentage of votes cast for a third-party candidate in the most recent previous presidential election. It is generally agreed that third-party voters are dissatisfied with the major parties and/or the government, feeling alienated from or perceiving little difference between the two major parties (e.g., Rosenstone, 1996; Donovan et al., 2000; Allen and Brox, 2005). Gold (1995) attributes the fact that 19% of voters cast their ballot for Perot in the 1992 election to a "large base of weak partisans." Contrary to popular belief, Herron and Lewis (2007) predict that at least 40% of Nader voters in Florida would have voted for Bush, not Gore, if Nader were not running.[22] Both these findings support the idea that third-party voters are promising targets for both major parties. Overall, the characteristics of third-party voters correspond nicely to those we would expect swing voters to have.

Of course, if third-party voters' expression of dissatisfaction were permanent, they would not be easy to persuade. However, the national share of votes going to a third party in a presidential election varies widely: between 1988 and 2012, it ranged from under 2% in 2008 to almost 19% in 1992. At the county level, the variation is even larger. Because we use county fixed effects, our identification comes from the *changes* in the share of votes going to a third party, which corresponds to voters who switch between (a) voting for a major party or not voting at all and (b) voting for a third-party candidate. Year fixed effects flexibly account for the overall trend in third-party voting over this time period. As discussed in Section 4.1, the geographic variation in the residual changes in third-party voting patterns is substantial.

[20] For example, considering only "undecided" voters as swing voters might miss a substantial fraction of the electorate with a very weak and easily changeable preference (Mayer, 2007).

[21] Also see Kelley (1983).

[22] To do this, they analyze actual ballots, using individual voting patterns in non-presidential races to estimate the counterfactual in the presidential race.

Politicians appear to be aware of the perils and opportunities that third parties represent. For example, the Nader candidacy appears to have affected how and where Al Gore campaigned in 2000 (Ceaser and Busch, 2001). More generally, Hirano and Snyder (2007) find that much of the 20th century decline in third-party voting in the United States was due to the Democratic Party adopting left-wing third parties' agendas. More recently, the emergence of the Tea Party movement seems to have caused the Republican party to shift to the right in order to attract disaffected voters (Jacobson, 2011; Abramowitz, 2011; Williamson et al., 2011).

We do not claim that the swing voter channel is the only one through which politicians direct agricultural funds to their advantage. Politicians may also allocate aid in response to their core constituents' preferences—the "core voter" theory (e.g., Cox and McCubbins, 1986; Levitt and Snyder, 1995)—or to increase voter support by a combination of increasing turnout of loyal voters and decreasing turnout of non-loyal voters (Chen, 2013). Because our main goal is to estimate the effect of disaster aid on the decision to insure, we require only one credible instrument for disaster aid, and fully explaining the political process behind the allocation of funds is outside the scope of our inquiry.

Counties are natural geo-political units at which to direct disaster payments, and politicians need not be trying to win elections at the county level to want to direct disaster payments to specific counties. Rather, politicians competing (or expecting to compete) in elections at the congressional district, state, or even national level may find targeting specific counties appealing because counties are the "units" of disaster declarations and because certain counties contain more easily persuadable voters. However, we do not use the *number* of third-party voters as our instrument to avoid capturing variation driven by unobservable county growth patterns that may be, for example, reducing the amount of farmland.

Despite being a small share of the voting population, targeting farmers can yield many votes at the margin, because voters who are concerned about farmers are likely to respond to disaster payments to farmers. Previous research has shown that the majority of Americans favor agricultural subsidies for small farms (e.g., Kull et al., 2004; Ellison et al., 2010b,a; Lusk, 2012). At the same time, most Americans believe that small farmers get an equal or greater share of agricultural subsidies than large farmers, while in reality the former receive only 20% (Kull et al., 2004). Moreover, the second most common reason for favoring subsidies is the unpredictability of farmers' incomes, due to weather and other factors (Ellison et al., 2010a).[23] Relatedly, the majority of subsidy proponents prefer to give farmers subsidies only in "bad years" (Kull et al., 2004). Finally, although an earlier study finds higher levels of support for farm subsidies among Democrats (Variyam et al., 1990), more recent studies find no relationship between a Republican versus Democratic party af-

[23] The most common reason is to maintain a secure food supply for U.S. citizens, which might also lead voters to support disaster aid.

filiation and the level of support for farm subsidies (Ellison et al., 2010a; Lusk, 2012). Thus, it is rational for Congressmen to allocate agricultural disaster spending strategically, including to areas where farmers are not a large fraction of the voting population.

While it is true that farmers make up a small share of the average county's population, there are a few counties where farm proprietors make up a quarter or more of the population and where farm employment is a very large component of total employment. In order for third-party voting to remain a valid source of exogenous variation in these counties, it must be true that (a) variations in third-party voting are largely driven by non-farmers and non-farm workers OR (b) the factors that drive farmers'/farm workers voting patterns (and are unobservable to us) do not also affect farmers' crop insurance decisions directly. While the first condition almost certainly does not hold in counties where farmers and their employees make up a large share of the population, the second condition is more plausible, especially once we control for time-varying characteristics such as farm income and the agricultural share of employment. However, because identifying assumptions are fundamentally untestable, we also replicate our analysis using only the sample of counties where agricultural employment never exceeds 5% of total employment, with little changes to our results.

Other commonly considered determinants of disaster payments, such as Representatives' membership on the Agriculture or Appropriations Committee (see, e.g., Garrett, Marsh, and Marshall, 2006; Goodwin and Vado, 2007), are less likely to be appropriate instruments because they relate to farmers' insurance purchases through more channels that just disaster payments, i.e., they violate the instrument exclusion restriction. Assignment to these committees is not random. Unobservable (to the econometrician) changes in the agricultural sector in their jurisdictions that might directly affect insurance purchase decisions also could cause a Congressperson to pursue these committee assignments. These unobservable changes are precisely the reason an instrumental variables strategy is necessary, so using these disaster payment determinants would not solve the problem. As a robustness check, however, we will explore the impact of using Congressional committee membership as instrumental variables.

In the next section, we show that recent third-party voting behavior is correlated with realized disaster aid. However, a reasonable concern is whether such behavior is correlated with farmers' *expectations* about disaster aid, which we cannot observe. As discussed in the previous section, to the extent that the first stage reflects a noisy measure of farmer expectations, our estimates will be lower bounds. It is unlikely that farmers use observed third-party voting results *directly* in forming expectations about future disaster payments. However, third-party voting behavior is likely correlated with other manifestations of discontent that predict future disaster payments and are easier for the farmer to observe (but that are impossible for us to observe). For example, what farmers may actually observe and use to form their expectations is discontent with elected leaders expressed through conversations, town hall meetings, bumper stickers, third-party promotional material, and so on. This discontent leads both to more third-party voting and more disaster payments. In this case, third-party voting is a relevant instrument because it is a good proxy for voter discontent. Alternatively, it could be that past voting patterns lead politicians to make promises about future disaster aid in the event of a disaster, in which case third-party voting is again an appropriate instrument. Election-year promises aimed at farmers appear to be fairly common (e.g., Ganzel, 2007; Seidl, 2010; Nosowitz, 2016), although systematic data on this phenomenon are not available.

To summarize, it seems plausible that politicians would target counties where a third-party candidate had recently won a surprisingly large number of votes by promising to allocate more agricultural disaster payments to farmers in that county. The identifying assumption is that county-level voting outcomes are only related to the insurance decision through the disaster aid channel. The summary statistics in Table 1 demonstrate that farmers represent a small fraction of the electorate in most counties, and are thus unlikely to be driving the political trends. Thus, the exclusion restriction is likely to hold because we do not expect county-wide voting changes to directly affect or be affected by an individual farmer's incentives to insure. Nonetheless, in subsequent analysis we control for time-varying county characteristics that could potentially affect both the crop insurance decision and political attitudes.

5 The Effect of Disaster Aid on Crop Insurance

5.1 Swing Voters and the Allocation of Disaster Aid

We proceed by estimating the swing voter model, which makes up the first stage of our two-stage approach:

$$\ln\left(Disaster_{c,t}\right) = \beta PctInd_{c,t-1} + \mathbf{X'_{c,t-1}}\theta + a_c + a_t + \nu_{c,t}, \tag{2}$$

where $\ln\left(Disaster_{c,t}\right)$ is the log of total payments made to county c for a disaster in year t, with 1 added to avoid dropping zeroes. The variable $PctInd_{c,t-1}$ measures the percentage of the electorate that voted for a third party candidate, based on the most recent *previous* presidential election. We use all the years for which we have crop insurance and disaster data for the estimation, including ones which did not follow a presidential election. For example, if $X\%$ of the county's electorate voted for a third-party candidate in 2004, we set $PctInd_{c,t-1} = X$ for $t = 2005, 2006, 2007,$ and 2008. Finally, as in equation (1), $\mathbf{X_{c,t-1}}$ represents the time-varying control variables that could potentially affect both the crop insurance decision and political attitudes and a_c and a_t represent county and year fixed effects. Standard errors are clustered by county.

Table 3 reports ordinary-least-squares regression estimates of equation (2). When no controls or only county fixed effects are included (Columns 1 and 2), there is no significant relationship between third-party voting and disaster payments, suggesting that there are important fixed determinants of third-party voting and/or disaster payments. For example, a charismatic third-party candidate may attract a lot of votes, but if politicians understand that this is a temporary "shock," they are less likely to respond to such changes in voting patterns with disaster payments. Similarly, widespread crop devastation in some years (e.g., the Great Flood of 1993) could lead to large disaster payments regardless of voting patterns, again leading to a weak correlation. For these reasons, relying on more idiosyncratic variation is more appropriate.

The results when county and year fixed effects are included (Columns 3 and 4) show a strong relationship between disaster payments and political changes in the county. Specifically, a one standard deviation increase in the percent of people who voted for a third party candidate in the last presidential election increases disaster payments in that county by $33 - 35\%$, suggesting that disaster payments are indeed being used to sway independent voters. The F-statistic in the specification that includes controls for county characteristics, as well as year and county fixed effects (Column 4), is well above the conventional threshold of 10.

All else equal, counties with higher populations, lower per-capita income and lower total employment receive more disaster payments. Perhaps surprisingly, changes in the number of farm proprietors and the share of agricultural employment are *not* significant predictors of disaster payments. However, this pattern is consistent with our earlier hypothesis that agricultural disaster payments are being used to sway the non-farming portion of the constituency. In this case, it would not be unreasonable for changes in the local agricultural sector to make little difference for disaster aid.

5.2 IV Regression Results

We next estimate the importance of the Samaritan's dilemma for out-of-pocket spending on insurance, $\ln(Premiums_{c,t})$, by instrumenting for log disaster payments, $\ln(Disaster_{c,t})$, with the percentage of the electorate that voted for a third party candidate, $PctInd_{c,t-1}$. Specifically, the second stage of our two-stage approach is:

$$\ln\left(Premiums_{c,t}\right) = a_c + a_t + \gamma \widehat{\ln\left(Disaster_{c,t}\right)} + \mathbf{X}'_{\mathbf{c,t-1}}\phi + \varepsilon_{c,t}. \tag{3}$$

The variable $\widehat{\ln\left(Disaster_{c,t}\right)}$ is the predicted value of the log of disaster payments from equation 2, the first stage. As above, $\mathbf{X_{c,t-1}}$ represents the time-varying control variables that could affect the crop insurance decision. In this specification, $\gamma < 0$ indicates the presence of the Samaritan's dilemma.

Table 4 shows the effect of disaster payments on out-of-pocket crop insurance expenditure in a county, as estimated by equation (3). Column 2 shows our preferred specification, which includes controls for lagged county characteristics. A one-percent increase in expected disaster payments causes spending on insurance to drop by 0.20 percent. This estimate is highly significant. Without controlling for county characteristics, we get a slightly lower but still highly significant estimate of -0.14 (Column 1). Furthermore, the results are even stronger if we include observations where no out-of-pocket premiums are paid by adding 1 to net premiums prior to taking the log (Columns 3-4). In dollar terms, our preferred estimate roughly corresponds to a decrease in out-of-pocket insurance spending of about $\$25,000$ per county for every percent increase in expected disaster aid.[24]

Other measures of the insurance coverage are available to us. In Table 5, we estimate how disaster payment expectations change total liability (Column 1). We again find evidence of the Samaritan's dilemma: a one percent increase in expected disaster payments lowers total liability by 0.19% or about $\$570,000$ per county. Column 2 in Table 5 shows the causal relationship between disaster payments and the total number of policies (in logs). As with out-of-pocket premiums and liability, the number of policies falls as expectations of disaster payments increase, with an elasticity of about -0.2. However, without additional analyses, we cannot tell whether farmers are completely dropping insurance coverage for some plots or simply consolidating multiple plots into a single policy.

Total out-of-pocket premiums, liability, and (to some extent) the number of policies capture both the extensive margin of the insurance decision (choosing whether or not to have crop insurance) and the intensive margin (choosing how much crop insurance to purchase). We cannot estimate the intensive margin separately by looking at premiums per insured acre, for example, because there could be differential selection out of insurance. We can, however, look at the extensive margin. In Column 3, we look at the number of insured acres as the outcome. Here, we find no evidence that the number of acres insured declines, suggesting that farmers respond to disaster payment expectations by reducing their coverage level rather than foregoing insurance altogether. This response is sensible for several reasons. First, completely dropping coverage is risky because disaster payments may end up not being given. Second, the 50% coverage level plans are almost fully subsidized. Finally, disaster payments top up insurance indemnity payments until the sum of the two reaches 95% of the farmer's expected income, which means that farmers with the least generous insurance plans will not lose out on most disaster payments.

Finally, we consider the extent to which the government crowds out its own premium subsidy payments (Column 4). We find that insurance subsidy payments decrease by 0.34% for every

[24]We arrive at this approximation by calculating $e^{\mu+\widehat{\gamma}} - e^{\mu}$, where μ is the mean of the log of out-of-pocket premiums and $\widehat{\gamma}$ is the estimated impact of additional disaster payments.

percent increase in expected disaster payments. In dollar terms, this corresponds to about $\$43,000$ per county. Thus, for every dollar the government crowds out in farmer out-of-pocket spending, it crowds out about $\$1.72$ in subsidy spending.

One potential worry is that premium subsidies are changing with politics and/or disaster aid expectations. However, as discussed earlier, premium subsidy rates do not vary geographically. Unlike agricultural disaster payments, they are not *ad hoc*, do not change frequently, and, because of their national nature, cannot be used to target specific geographic areas. Thus, politicians cannot use the premium subsidy channel to deliver funds to particular areas, and any relationship between premium subsidies and national politics will be accounted for by year fixed effects.

The facts that (a) the government pays for the majority of the costs of the crop insurance program and (b) government spending on disaster aid crowds out government spending on insurance subsidies may make it seem like the crowding out of insurance by disaster aid is mostly semantics and should not create an efficiency loss. However, the crowding out of subsidies only implies that the total cost of public funds used for disaster aid is smaller than it would be if crop insurance were not subsidized. The real source of inefficiency is that farmers are exposing themselves to more risk in response to disaster aid expectations, as explained in Section 2. This inefficiency will arise as long as *ad hoc* disaster aid reduces insurance coverage, regardless of whether crop insurance is publicly or privately funded.

Next, we investigate whether the expectation of disaster payments causes some farmers to switch to a less generous insurance plan. Recall that a farmer's combined payments from crop insurance and disaster programs cannot exceed 95% of his baseline income. The probability that this happens is increasing in the plan's coverage level. Thus, instead of dropping insurance coverage altogether, which could be devastating if disaster aid is not given, a farmer may choose a plan with a lower coverage level.

To see if farmers are selecting out of more generous insurance plans, we look at changes in the number of policies in different coverage levels. As in the case of liability and premiums paid, these estimates will include both changes in who purchases insurance and changes in insurance decisions among those who continue to insure. For simplicity, we combine coverage levels into four groups: 50%, 55-65%, 70-75%, and 80-90% coverage levels. To avoid missing values, we add 1 to each variable prior to taking the log.[25] The results are shown in Table 6. We find that for a 1% increase in expected disaster payments, the number of farmers choosing the most generous set of plans falls by about 1.2%, while the number of plans with a 70 or 75% coverage level falls by 0.4%. Correspondingly, there is a *rise* in the number of the less generous plans, by about 0.2% in both the 50% and 55-65% coverage levels. The latter results confirm that some farmers are

[25] Our results are similar if we do not add 1 to the number of policies prior to taking the log, although the number of observations becomes unbalanced and the first stage F-statistics fall.

responding to higher expected disaster payments by switching to less generous insurance plans.[26]

Finally, it is important to recognize that farmers may also respond to disaster payments by switching to a higher-risk crop, adopting a riskier farming strategy without switching crops (e.g., lowering pest control expenditure), or exerting less effort in maintaining crop yields if they anticipate that a disaster payment is likely. For example, extant literature suggests that in some cases increased fertilizer applications reduce risk (Sheriff, 2005) or are perceived by farmers to reduce risk (Stuart et al., 2014; Osmond et al., 2015). Alternatively, crop-switching can have an indirect effect on farm inputs if the newly adopted crop requires a different amount of them.

How changes in farming strategies affect average yields is unclear. It is possible that average yields are unchanged if the riskier strategy simply raises the yield variance. However, the riskier strategy may also result in a higher expected yield *and* higher yield variance. Finally, because disaster payments are higher when yields are lower, farmers have an incentive to reduce yield-enhancing efforts in times when disaster payments are likely. However, because historic yields also affect payments, both under crop insurance and disaster aid, consistently targeting lower yields is costly. It is thus theoretically unclear whether yields should increase, decrease, or remain unchanged with higher expectations of disaster payments. To construct a single measure of yields, we use data on prices and production of eight major crops (barley, corn, cotton, oats, rice, sorghum, soybeans, and wheat), and calculate the price-weighted yield in a county by summing price times production across these crops, dividing by the total number of acres harvested, and taking the log.

In Table 7, we look at how disaster payments affect expenditure on farm labor and fertilizer, price-weighted yields, and crop revenue. The results point to further welfare losses from farmers altering their farming strategies in response to disaster payment expectations. We find that farm labor costs fall by a small but significant amount (0.06% for a one-percent increase in disaster payments), and fertilizer expenditure falls by about 0.12%. Price-weighted yields also fall by a small but significant 0.03%, suggesting that farmers are switching to lower-value crops and/or realizing lower crop yields. Relatedly, we find no evidence that farmers are switching to higher-value crops, as receipts from crop sales fall by 0.35% for every one-percent increase in expected disaster payments.

5.3 Robustness

If our first stage yields a noisy measure of farmer expectations, then our second stage estimates will be attenuated. While we cannot directly evaluate the seriousness of this problem because we do not observe farmers' expectations, we can check the robustness of our results by estimating a

[26] If we look at the number of acres insured at each coverage level, our results are similar with the exception that the number of acres covered at 70-75% coverage levels increases. This further points to farmers consolidating multiple plots under the same insurance plan in response to disaster payment expectations.

model where farmer expectations are based on past disaster payments and instrument for these with a deeper voting lag. Past disaster payments may affect farmer expectations about future disaster payments more than local political activity.

An issue with using lagged disaster payments to study the Samaritan's dilemma is that farmers are often required to purchase crop insurance for 1-2 years after they receive disaster payments, resulting in a mechanical positive relationship between past disaster payments and current insurance holdings. Unlike measurement error, which only attenuates estimates toward zero, such a requirement could in principle cause us to find a *positive* relationship between past disaster payments and current insurance holdings, even if farmers do reduce insurance coverage in expectations of disaster payments when they are not constrained by such requirements. Nonetheless, the results we obtain from this model (shown in Appendix Table A3) are broadly similar to our preferred specification. One exception is that we find a significant decrease in acres insured when using the lagged model. This similarity suggests that post-aid insurance requirements are not important for the dynamics we study here, possibly because the responses we measure appear to be happening on the intensive rather than extensive margin.

In the mid-1990's, the Federal Crop Insurance Reform and Department of Agriculture Reorganization Act of 1994 substantially reformed crop insurance. It is worth asking whether the Samaritan's dilemma phenomenon was affected by this regime change. While we do not have enough data to consider the pre-1996 period, we can easily restrict our sample to years 1996 and later. The results, shown in Table A4, are generally stronger than what we obtain by using the entire sample period. Importantly, we now find a significant extensive margin effect, with insured acres falling in response to disaster payment expectations. These results demonstrate that the Samaritan's dilemma is a highly relevant phenomenon under the current crop insurance regime.

Our estimates could also be affected by dynamics where past third-party voting affects disaster payments (and crop insurance choices) and disaster payments subsequently affect third-party voting. In another robustness check, we control for third-party voting two elections ago, which should reduce the influence of these dynamics, and use third-party voting in the most recent election as the instrument. The results, shown in Table A5, are not substantially affected by the inclusion of this additional control variable.

As discussed earlier, while farming is a small fraction of the average county's economy, there are counties that rely heavily on agriculture. In these areas, overall agricultural outcomes may drive voting patterns, implying that the instrument exclusion restriction no longer holds. To see whether this affects our results, we exclude counties that report more than 5% agricultural employment at *any* point in the sample. This restriction does not have a meaningful impact on the results, except that the drop in labor costs is no longer significant (Appendix Table A6). In another robustness check, we exclude counties that are not in our data for the full sample period (Appendix Table A7).

Our results are almost unchanged.

We also explored the impact of alternative measures of political influence as instrumental variables. Garrett et al. (2006) and Goodwin and Vado (2007) report that states receive more disaster payments when they have a Representative or Senator on the Agriculture or Appropriations committee. A concern is that congresspeople choose membership on these committees when their state experiences unobservable changes in the agricultural sector that might directly affect insurance-purchase decisions. Nevertheless, we examine the effect of including indicator variables of whether a county's congressperson is on the House Agriculture or Appropriations committee, committee membership interacted with majority party membership, and whether the congressperson is chair of the committee in the set of instrumental variables (Appendix Table A8).[27] The results remain essentially the same.

Our results are generally robust to a number of other assumptions. Adding 1 to the outcome variables prior to taking the log generally *increases* the magnitude of our estimates and strengthens our conclusions (Appendix Table A9). In addition, we find a marginally significant drop in the number of acres insured in this case. Similarly, our results are invariant to adding larger or smaller numbers (from 0.0001 to 100) to disaster aid payments prior to taking the log.[28] Normalizing insurance coverage and disaster aid measures by population, by the number of farm proprietors, or by total cropland (as reported in the Census of Agriculture, with linear interpolation between Census years) prior to taking the log also yields similar conclusions.

Finally, we have also probed the robustness of our instrument and second-stage results to including other controls that could affect both the insurance decisions of farmers and the population's decision of whether to vote for a third-party candidate. For example, the occurrence of extreme events could plausibly lead farmers to increase their insurance coverage and cause voters to prefer or stay away from a third-party candidate. Using data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), we added flexible controls for up to four years of past extreme events to our preferred specification. Our point estimates become slightly (but not significantly) *larger* in absolute terms, but our overall conclusions are again left unchanged.

6 Conclusion

The Samaritan's dilemma was described by James Buchanan forty years ago. This type of moral hazard may exist in many areas of the economy, from banks taking on excessive risk to homeowners foregoing flood insurance because they expect to be bailed out. Its existence and magnitude both have important implications for efficiency. However, few empirical papers confirm or dis-

[27] Population-weighted shares are used when a county contains multiple congressional districts.

[28] These and other results not in the Online Appendix are available upon request.

prove its existence.

We test for the existence of the Samaritan's dilemma in U.S. agriculture, an area in which it has long been posited to be a problem: since the establishment of modern crop insurance in 1980, Congress has passed *ad hoc* bills granting disaster aid to farmers who suffered crop losses, even if they had insurance. We instrument for disaster payments using political variation at the county level. We then estimate how expected disaster payments affect farmers' crop insurance decisions.

We find that the Samaritan's dilemma exists and is of a non-trivial magnitude. Out-of-pocket insurance expenditure is moderately sensitive to disaster payments, decreasing by 0.2% for every percent increase in expected disaster payments. This is largely driven by farmers switching to less generous insurance plans and consolidating multiple plots under the same policy. Furthermore, bailout expectations also affect real outcomes, as farmers reduce expenditure on farm labor and fertilizer and subsequently realize lower yields and lower revenues from crop sales.

Comparing our results to the previously estimated distortions from crop insurance, we find that the distortions from *ad hoc* assistance appear to be greater. In contrast to disaster payments, crop insurance deters moral hazard through deductibles, experience rating and nonlinear pricing as coverage increases. Consequently, the moral hazard associated with crop insurance appears to be small. Goodwin et al. (2004) find a small relationship between crop insurance and corn acreage, and Weber et al. (2016) find no effect of expanded crop insurance coverage on farm revenue or fertilizer expenditure. This contrast underscores the unique nature of the *ex ante* moral hazard associated with the Samaritan's dilemma. While insurance can be priced to minimize moral hazard, *ad hoc* disaster relief addresses losses without distinguishing loss due to moral hazard.

Overall, our estimates imply that eliminating disaster payments would significantly raise crop insurance coverage and reduce inefficiencies in farm investment decisions. Of course, eliminating disaster payments would require the government to be able to commit to not grant them *ex post*, something that it has not been able to do thus far.

If the government is unable to commit to not bail out farmers, why does it not give farmers completely free insurance, as Coate (1995) suggests? One possibility is that it is politically advantageous to target *ex post* disaster payments to particular constituencies. Congress members may get more "credit" from their constituencies for voting for disaster payments each year than for a one-time passage of a free crop insurance bill. Alternatively, disaster payments might be useful as a bargaining chip for Congressmen from non-disaster counties, who may use them to garner support for their own policies. Finally, it is possible that an insurance system where farmers make no out-of-pocket payments is politically infeasible or would result in even greater moral hazard on other dimensions than those affected by *ex ante* uncertain *ex post* aid. Although the definitive answer is outside the scope of this paper, it is a fruitful area for future research.

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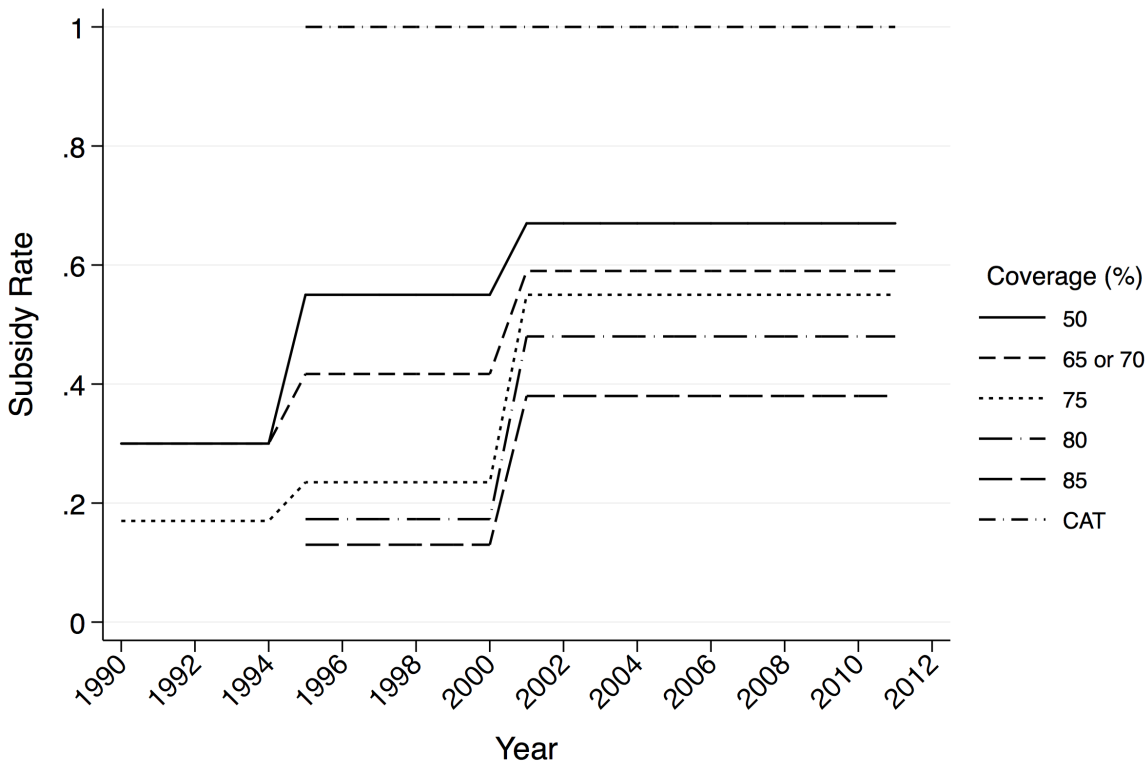
Figures

Figure 1: Crop Insurance Premium Subsidy Rates from 1990-2011



Notes: Each line illustrates the national subsidy rate for individual yield and individual revenue insurance plans at each coverage level under the assumption that the farmer does not combine multiple crops under one insurance policy. *Data Source*: USDA Risk Management Agency Summary of Business files.

Figure 2: Share of Insurable Acres Covered by Crop Insurance from 1990-2011

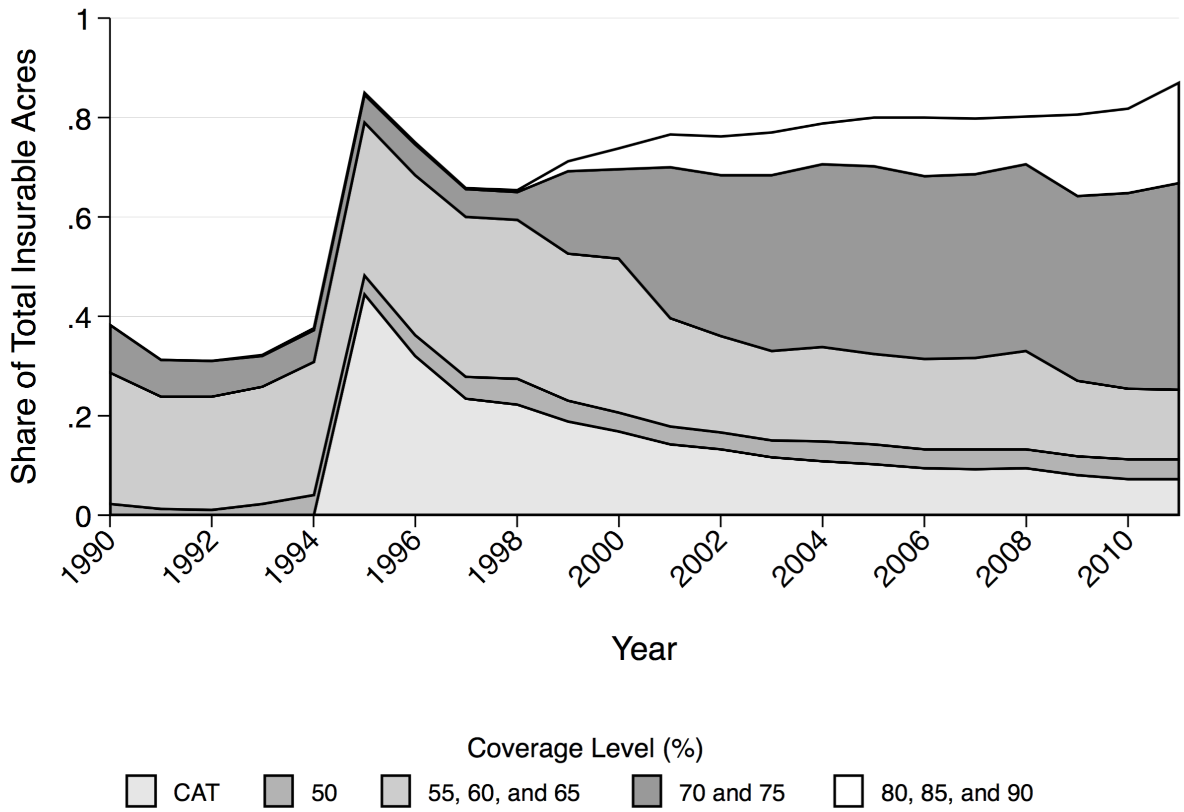
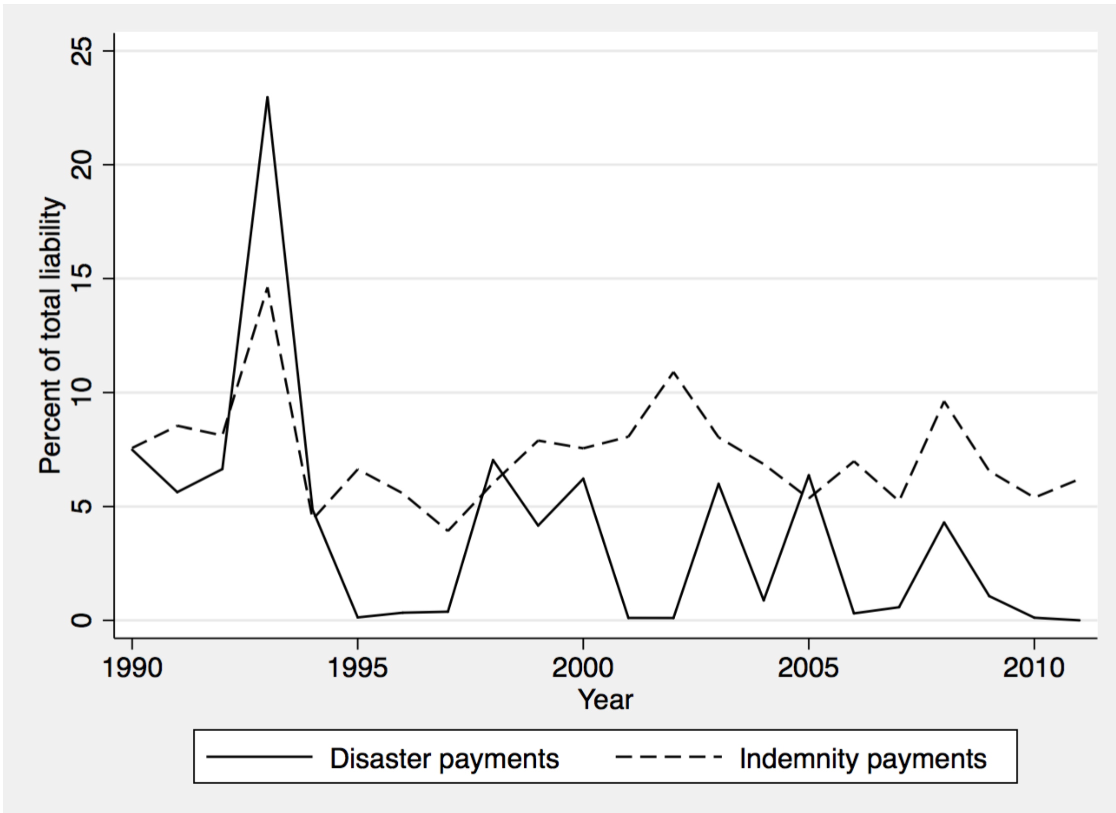
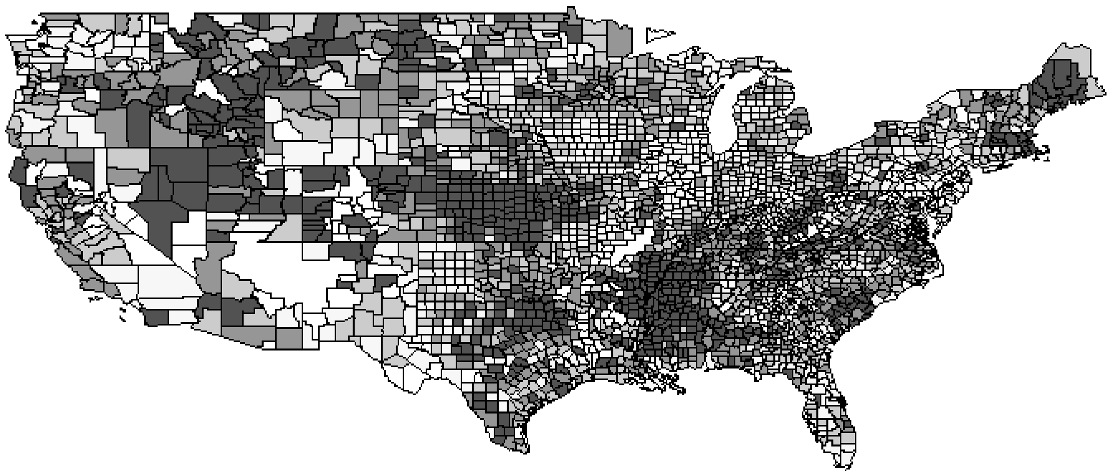


Figure 3: Indemnity and disaster payments over time



Notes: Disaster payment series represents payments to producers of crops for which insurance is available.

Figure 4: Absolute mean changes in percent voting for third party candidate



Notes: Illustrates mean absolute changes between 1988 and 2008, accounting for national trends and county fixed effects. Darker areas indicate larger changes. Shown only for counties included in the regression sample.

Tables

Table 1: Summary statistics

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max	(5) Obs
Percent of population who are farm proprietors	3.71	3.96	0	37	60,592
Percent employed in forestry or agriculture	1.03	2.35	0	100	60,590
Farm income as percent of total income	3.50	8.22	-314	125	60,592
Number of policies	420	602	0	7,304	60,592
Acres insured (thousands)	66	98	0	1,036	60,592
Premiums net of subsidies (thousands)	673	1,233	0	22,455	60,592
Subsidies (thousands)	883	1,775	0	32,163	60,592
Liability (millions)	18	34	0	890	60,592
Indemnity (thousands)	1,236	3,385	0	152,862	60,592
Disaster payments (thousands)	460	1,539	-95	109,931	60,592

Sources: Regional Economic Information Systems, County Business Patterns, and David Leip's Atlas of U.S. Presidential Elections. Unit of observation is a county-year. All monetary amounts are in 2011 dollars. Excludes counties with fewer than 18 observations over the sample period and observations that are missing control variables. Total number of counties in the sample is 2916.

Table 2: The relationship between insurance expenditure and disaster payments, OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Disaster aid this year (log)	0.009***		0.007***	0.009***		0.007***
	(0.001)		(0.001)	(0.001)		(0.001)
Disaster aid last year (log)		0.012***	0.012***		0.012***	0.011***
		(0.001)	(0.001)		(0.001)	(0.001)
Farm proprietors (log)				-0.283***	-0.217**	-0.216**
				(0.093)	(0.096)	(0.096)
Pct. employed in ag.				-0.004	-0.004	-0.004
				(0.004)	(0.004)	(0.004)
Population (log)				-0.177	-0.260**	-0.266**
				(0.124)	(0.129)	(0.129)
Per capita pers. inc. (log)				-0.676***	-0.649***	-0.646***
				(0.115)	(0.112)	(0.112)
Total employment (log)				-0.035	-0.014	-0.011
				(0.056)	(0.057)	(0.057)
Dep. var. mean	11.837	11.861	11.861	11.837	11.862	11.861
Observations	57,879	55,105	55,105	57,879	55,210	55,105
R-squared	0.916	0.920	0.920	0.917	0.920	0.920

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Outcome variable is log of farmers' out-of-pocket expenditure on crop insurance in the county. All regressions include county and year fixed effects. Specifications with controls also include farm income decile indicators, which are omitted for readability. All control variables are lagged by one year.

Table 3: The effect of politics on disaster payments

	(1)	(2)	(3)	(4)
Pct. voting for third party (std. dev.)	0.029	-0.014	0.319***	0.291***
	(0.019)	(0.018)	(0.049)	(0.049)
Number of farm proprietors (log)				-0.044
				(0.173)
Pct. employed in forestry/agriculture				-0.012
				(0.009)
Population (log)				0.557**
				(0.249)
Per capita personal income (log)				-0.590**
				(0.272)
Total employment (log)				-0.395***
				(0.134)
Fixed effects	None	County	County, Year	County, Year
F-statistic	2.347	0.654	41.846	35.262
Dep. var. mean	7.681	7.681	7.681	7.681
Observations	60,475	60,475	60,475	60,475
R-squared	0.000	0.103	0.663	0.664

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. The outcome variable is log of (total disaster payments in the county + 1). Specifications with controls also include farm income decile indicators, which are omitted for readability. All characteristics controls are lags.

Table 4: The effect of disaster payments on out-of-pocket insurance expenditure, IV

	(1)	(2)	(3)	(4)
	Net premium (log)		Net premium + 1 (log)	
Disaster payments (log)	-0.137**	-0.197***	-0.285**	-0.371***
	(0.058)	(0.066)	(0.119)	(0.136)
Number of farm proprietors (log)		-0.293***		-0.372**
		(0.101)		(0.171)
Pct. employed in forestry/agriculture		-0.005		-0.010
		(0.005)		(0.007)
Population (log)		-0.023		-0.146
		(0.145)		(0.251)
Per capita personal income (log)		-0.817***		-1.054***
		(0.137)		(0.224)
Total employment (log)		-0.124*		-0.161
		(0.069)		(0.115)
F-statistic	52.195	44.827	43.967	37.050
Dep. var. mean	11.837	11.837	11.328	11.328
Observations	57,845	57,845	60,455	60,455

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. The net premium is the farmers' out-of-pocket expenditure on crop insurance in the county. All regressions include county and year fixed effects. Specifications with county characteristics controls also include farm income decile indicators, which are omitted for readability. All control variables are lagged by one year.

Table 5: The effect of disaster payments on other measures of insurance coverage, IV

	(1) Liability (log)	(2) Policies (log)	(3) Acres insured (log)	(4) Subsidy (log)
Disaster payments (log)	-0.185***	-0.186***	0.019	-0.336***
	(0.067)	(0.052)	(0.041)	(0.077)
Number of farm proprietors (log)	0.114	0.088	-0.284***	-0.206**
	(0.100)	(0.079)	(0.071)	(0.099)
Pct. employed in forestry/agriculture	-0.006	-0.004	0.000	-0.007
	(0.005)	(0.003)	(0.003)	(0.005)
Population (log)	0.704***	0.341***	0.572***	0.287*
	(0.151)	(0.119)	(0.104)	(0.150)
Per capita personal income (log)	-0.406***	-0.530***	-0.292***	-0.538***
	(0.133)	(0.104)	(0.087)	(0.148)
Total employment (log)	-0.194***	-0.142***	-0.214***	-0.214***
	(0.071)	(0.051)	(0.047)	(0.078)
F-statistic	37.816	37.816	38.327	37.816
Dep. var. mean	15.026	4.698	9.470	11.925
Observations	60,004	60,004	59,396	60,004

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. All regressions include year and county fixed effects as well as farm income decile indicators, which are omitted for readability. All control variables are lagged by one year.

Table 6: The effect of disaster payments on coverage level choice, IV

	(1) 50% (log)	(2) 55-65% (log)	(3) 70-75% (log)	(4) 80-90% (log)
Disaster payments (log)	0.203***	0.178***	-0.374***	-1.150***
	(0.064)	(0.057)	(0.100)	(0.199)
Number of farm proprietors (log)	0.115	0.630***	-0.437***	-2.501***
	(0.083)	(0.080)	(0.126)	(0.230)
Pct. employed in forestry/agriculture	0.004	0.007**	-0.037***	-0.037***
	(0.003)	(0.003)	(0.008)	(0.012)
Population (log)	0.552***	0.602***	-1.094***	-1.768***
	(0.134)	(0.122)	(0.203)	(0.350)
Per capita personal income (log)	0.286**	-0.099	-0.388**	-2.445***
	(0.122)	(0.109)	(0.198)	(0.366)
Total employment (log)	0.023	-0.047	-0.034	0.043
	(0.064)	(0.054)	(0.097)	(0.185)
F-statistic	37.050	37.050	37.050	37.050
Dep. var. mean	3.237	3.579	2.912	0.997
Observations	60,455	60,455	60,455	60,455

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are the logged number of policies in the coverage levels indicated at the top of each column. 1 has been added to all outcome variables prior to taking the log. All regressions include year and county fixed effects, as well as controls for county characteristics. Farm income decile indicators are included in the regression but are omitted from the table for readability. All control variables are lagged by one year.

Table 7: The effect of disaster payments on input spending and real outcomes, IV

	(1) Labor cost (log)	(2) Fertilizer spending (log)	(3) Price-weighted mean yield (log)	(4) Cash receipts (log)
Disaster payments (log)	-0.060**	-0.121***	-0.034**	-0.347***
	(0.024)	(0.029)	(0.015)	(0.063)
Number of farm proprietors (log)	0.140***	-0.041	-0.057***	0.248***
	(0.033)	(0.035)	(0.019)	(0.069)
Pct. employed in forestry/agriculture	-0.001	-0.006**	-0.001	-0.004
	(0.002)	(0.002)	(0.002)	(0.004)
Population (log)	0.211***	-0.398***	-0.156***	-0.135
	(0.052)	(0.061)	(0.029)	(0.109)
Per capita personal income (log)	0.191***	-0.063	-0.033	-0.108
	(0.050)	(0.057)	(0.030)	(0.113)
Total employment (log)	0.018	0.011	0.004	-0.079
	(0.025)	(0.028)	(0.015)	(0.057)
F-statistic	34.966	36.758	28.656	35.172
Dep. var. mean	8.434	8.375	1.496	9.876
Observations	60,881	60,704	51,544	60,942

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. All regressions include year and county fixed effects, as well as controls for county characteristics. Farm income decile indicators are included in the regression but are omitted from the table for readability. All control variables are lagged by one year.

Appendix (For Online Publication Only)

Crop Insurance and Disaster Aid Payment Calculations

Individual farmers' disaster payments are calculated in much the same way as a crop insurance indemnity payment.[29] Equation (4) illustrates the basic structure of an insurance indemnity or a disaster payment.

$$Payment = \underbrace{\bar{P} \times \bar{Y}}_{\text{Protection}} \times \underbrace{\frac{\max[0, \bar{Y} - Y]}{\bar{Y}}}_{\text{Trigger}}, \tag{4}$$

where $\bar{P}$ is the price guarantee, $\bar{Y}$ is the yield guarantee, and Y is the actual yield. The yield guarantee equals the farmer's average actual yield over the past 4–10 years.[30]

As the left half of equation (4) shows, the protection level for both crop insurance and disaster assistance equals the price guarantee multiplied by the yield guarantee. The right half of Equation (4) illustrates the triggering mechanism: farmers begin to receive payments once the actual yield falls below the yield guarantee.

Farmers choose the price and yield guarantees ($\bar{P} \times \bar{Y}$) that determine their crop insurance indemnity payment. They typically choose 100% of the USDA-calculated expected market price as the price guarantee. The indemnity payment trigger 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. However, farmers who have multiple land parcels within the same county can choose to combine them under a single policy, as long as the same crop is grown on each one. This lowers the farmers' premium as well as the probability that the farmer receives an indemnity payment.

Within these plan types, farmers choose the covered yield—$\bar{Y}$ in equation (4)—as a percentage of their historical yield ranging from 50% to 90% in 5% increments.[31] For example, if a farmer chooses a 65% coverage level in an individual yield plan, he does not receive payments until his actual yield (Y) falls to more than 35% below his historical baseline.

The trigger for free-to-the-farmer disaster payments is legislated by Congress. However, as with crop insurance, its basis is determined by the yield shortfall. Historically, Congress has set the yield guarantee ($\bar{Y}$) to 65% of a farm's historical-average yield. The price guarantee ($\bar{P}$) is often set at 60% of the market price, but it has been set as low as 45% in some years. To encourage

[29] Only the Supplemental Revenue Assistance Program (SURE) differs substantively from the following description. Despite program differences, SURE provides similar incentives for farmers to under insure. See Shields (2010) for details on SURE.

[30] In cases where insurance is based on the county's rather than the individual's yield, the yield guarantee is the expected county yield, as calculated from historic data.

[31] Not all coverage levels are available for all plan types and in all years. For a more comprehensive overview of the U.S. crop insurance market, see Babcock (2012).

future uptake of crop insurance, the legislation provides a higher price guarantee for disaster aid to farms with crop insurance vis-à-vis farms who could have purchased crop insurance but did not.

Because disaster payments "top up" indemnities, crop insurance coverage does not crowd out disaster payments until crop revenue, indemnity payments, and disaster payments add up to 95% of expected revenue. The following table shows the production loss at which indemnity payments begin to crowd out disaster payments one-for-one due to the 95% rule.

Table 8: Crop loss at which the 95% rule binds for a given coverage level

(1) Coverage Level	(2) Crop Loss (%)
85	50–100
80	58–100
75	66–100
70	73.5–100
65	81–100
60	89–100
55	96.5–100

Calculated based on a 60% replacement rate starting at 35% crop loss.

Crop Insurance Pricing

As discussed earlier, approved crop insurance providers are restricted to offering a uniform set of products at uniform prices. The prices are, in turn, set by the Risk Management Agency (RMA) of the USDA. In this section, we discuss the key features of RMA's price-setting methodology in more detail. Although a full overview of the methodology is far beyond the scope of this paper, the omitted nuances do not affect our overall assertion that price-setting in crop insurance is overwhelmingly formulaic and thus extremely unlikely to be affected by disaster aid expectations or politics, especially at a sub-national level.[32]

RMA's main goal in setting crop insurance prices is to achieve an expected loss ratio (indemnities divided by gross premiums) of 1.[33] This is feasible because crop insurance providers are reimbursed for administrative and overhead costs separately, removing the need to load premiums.[34] In this section, we discuss how rates are set for plans that insure individual yield ("Actual Production History" or APH plans), which were the most popular plans during the time period of

[32]For more details, interested readers should consult Coble et al. (2010) or RMA's actuarial publications, available through `http://www.rma.usda.gov/pubs/`, including the "Rate Methodology Handbook Actual Production History" (`http://www.rma.usda.gov/pubs/2008/ratemethodology.pdf`).

[33]Prior to the 2008 Farm Bill, the RMA had to achieve an expected loss ratio of 1.075 (Coble et al., 2010).

[34]Administrative and overhead costs are likewise formulaic and are a function of the insurer's portfolio of plans.

our study. APH prices also form the basis for plans that insure individual revenue ("Crop Revenue Coverage" or CRC plans and "Revenue Assurance" or RA plans). CRC and RA plans are on average the second most popular crop insurance products in our sample and in recent years have surpassed APH plans in their popularity. Together, these individual yield and revenue protection plans accounted for 83% of insurance liability and 91% of insured acres during the 1990–2011 time period, on average. Other insurance plans rely on different rate-making methodologies, all of which are nevertheless as formulaic as those for APH plans.

To price the plans, the RMA first determines a "base rate" for each county-crop combination in each year, using the 65% coverage level as the baseline. The base rates form the backbone of the crop insurance pricing formula and are calculated from that county's insured individuals' loss experiences going back as far as 1975. Observations at or above the 80th percentile of losses are considered "catastrophic" and are excluded from the calculation of the county base rate.[35] To arrive at the final base rate, RMA uses a spatial smoothing algorithm, combining a weighted average of the county's own calculated rate with those of its neighbors.

Another key component of the pricing formula is the "reference yield", which is roughly the expected yield across all producers of a given crop in a given area. The reference yield is based on the county's historic yield experience, accounting for the fact that average yields have been increasing over time. The fluctuations around the trend are then used to construct the expected distribution of losses, which also plays a key role in crop insurance pricing. Unlike the county base rate, the reference yield is constructed using National Agricultural Statistics Service (NASS) data, which include yields of both insured and uninsured farmers.

Next, the RMA sets the formula for how base rates should be translated into the price paid for insuring a particular plot, using observable characteristics such as the growing practice, the plot's own yield history relative to the county's, whether the crop is irrigated or not, whether the land is considered high-risk, etc. In addition, adjustment factors for additional insurance coverage, such as prevented or delayed planting protection, are calculated. Finally, the RMA calculates "coverage differential" factors to translate the 65% coverage level price into prices for higher or lower coverage levels. The pricing formula does not vary geographically, while the adjustment factors and coverage differentials do. Unlike the base rate and reference yield, the pricing formula and other above-mentioned factors rarely change from year to year.

Importantly, this formulaic approach is applied uniformly to all counties and crops that are part of the insurance program, leaving little room for discretion. Unsurprisingly, this sometimes results in significant outliers. Several rules are in place to handle such cases. With few exceptions, for example, the rate that any producer would pay for the same coverage cannot change by more than 20% between years. In extreme cases, usually involving poor data quality, a more direct

[35]Catastrophic loads are incorporated into prices during a later step.

intervention is warranted, and rates are reviewed by underwriting experts. Although we do not have exact information on how often this happens, such expert reviews appear to be rare. Most importantly, there is no evidence, anecdotal or otherwise, that politics or disaster aid expectations have ever played a role in these reviews.

Simulating the Samaritan's Dilemma in Crop Insurance

In this section, we describe the methodology and results of our simulation of farmer insurance choice when there is a possibility for disaster payments. For simplicity, we assume that the farmer is choosing only between plans that insure individual revenue, which we model as the farmer's total annual income. We assume that the farmer's income is normally distributed with a mean of $50,000 and standard deviation of $25,000. The farmer can take out subsidized insurance against this risk. Specifically, he can choose coverage levels ranging from 50% to 90%, in increments of 5%, as in the federal crop insurance program. The coverage levels are relative to expected income. Each coverage level can be thought of as the amount of guaranteed income relative to expected income. This means, for example, that if the farmer chooses a coverage level of 75%, he will begin receiving insurance indemnities once his income falls to $0.75 * \$50,000 = \$37,500$. The payouts will restore his wealth to $\$37,500$.

We assume that crop insurance prices are actuarially fair from the insurer's point of view and are subsidized from the farmer's point of view. We use the subsidy rates from the 2001 and later insurance years. Specifically, the subsidy rate for a 50% coverage level plan in our simulation is 0.67 or 67%; for 55 and 60%, it is 0.64; for 65 and 70%, it is 0.59; for 75%, it is 0.55; for 80%, it is 0.48; for 85%, it is 0.38. Plans with 90% coverage are not subsidized. The farmers can also choose a fully subsidized "catastrophic" insurance plan that only covers *half* the losses after the farmer's income falls to below 50% of the mean.[36] However, because the 50% coverage plans cover all losses beyond a 50% loss and are generously subsidized, the catastrophic insurance plans are never chosen in our simulation.

Disaster payments are given on top of insurance payments, up to 95% of the farmer's expected income. Like income, they are variable, following a normal distribution with some expected value μ and standard deviation σ. Disaster payments are negatively correlated with income with a correlation coefficient of ρ. We proceed by simulating a range of these three features of *ad hoc* disaster payments: (1) how generous they are, as measured by the expected disaster payment, $\mu \in [\$5,000, \$30,000]$, in increments of $\$2,500$, (2) how variable they are, as measured by their standard deviation, $\sigma \in [\$5,000, \mu]$, in increments of $\$2,500$, and (3) how correlated they are with income, as measured by the correlation coefficient, $\rho \in [-0.9, -0.1]$, in increments of 0.1. In

[36] Technically, farmers have to pay a small flat administrative fee for these plans. However, we ignore this in the simulation.

theory, all three of these variations should play an important role in the effect of disaster payments on crop insurance choice.

We assume that the farmer has constant relative risk aversion (CRRA) utility, given by $\frac{w^{1-\alpha}}{1-\alpha}$, where w is total income (net of premium payments, indemnities, etc) and α is the degree of risk aversion. To generate the results shown below, we use a relative risk aversion coefficient of 1.5 (Chetty, 2006), although larger and smaller values of α do not change our results in a meaningful way.

To implement the simulation, we draw 10,000 joint realizations of income and disaster payments under each scenario described above. We truncate any negative incomes and negative disaster payments at zero. We also restrict disaster payments to be less than or equal to the difference between expected income and realized income, and assume that the farmer receives no disaster payments if realized income exceeds expected income. We use the resulting data to numerically calculate actuarially fair insurance prices, subsidized insurance prices, and the farmer's expected utility under different coverage levels. Finally, we calculate which coverage level maximizes the farmer's expected utility in that scenario.

In our simulation, the crowdout of insurance by disaster payments is substantial. To summarize the results in a way that is consistent with the analysis in the paper, we regress the calculated log of out-of-pocket spending on the expected amount of disaster payments (in logs), the correlation between disaster payments and income, and the standard deviation of disaster payments (also in logs). The results of these regressions are shown in Table A10. Across all 594 scenarios, a one-percent increase in expected disaster payments lowers the amount of out-of-pocket expenditure on insurance by 0.78 percent (Column 1). That number remains virtually unchanged when we control for the correlation between disaster payments and income (Column 2) and rises to 0.84 when we also control for the variability of disaster payments (Column 3). A higher correlation between disaster payments and income, which implies a *lower* correlation between disaster payments and losses significantly raises the out-of-pocket expenditure on insurance, as does a higher standard deviation of disaster payments. Overall, the amount of crowd out we find in the simulation is on average even higher than what we find empirically.

Appendix Tables

Table A1: Laws providing disaster assistance for farmers, 1989-2009

Disaster Assistance Act of 1988 (P.L. 100-387, August 11, 1988)	Disaster Assistance Act of 1989 (P.L. 101-82, August 14, 1989)
Dire Emergency Supplemental Appropriations for Natural Disasters and Operation Desert Shield/Desert Storm (P.L. 102-229, December 12, 1991)	Dire Emergency Supplemental Appropriations Act, 1992; Hurricane Andrew, Typhoon Omar, Hurricane Iniki, etc. (P.L. 102-368, September 23, 1992)
1997 Emergency Supplemental Appropriations Act for Recovery from Natural Disasters, and for Overseas Peacekeeping Efforts, Including Those in Bosnia (P.L. 105-18, June 12, 1997)	Emergency Supplemental Appropriations for Relief from the Major, Widespread Flooding in the Midwest Act of 1993 (P.L. 103-75, August 12, 1993)
Emergency Supplemental Appropriations Act of 1994 (P.L. 103-211, February 12, 1994)	Agricultural, Rural Development, FDA, and Related Agencies Appropriations Act, 1995 (P.L. 103-330, September 30, 1994)
Omnibus Consolidated Rescissions and Appropriations Act of 1996 (P.L. 104-134, April 26, 1996)	Agricultural, Rural Development, FDA, and Related Agencies Appropriations Act, 1997 (P.L. 104-180, August 6, 1996)
Omnibus Consolidated Appropriations Act, 1997 (P.L. 104-208, September 30, 1996)	Supplemental Appropriations Act of 1993 (P.L. 103-50, July 2, 1993)
1998 Supplemental Appropriations and Rescissions Act (P.L. 105-174, May 1, 1998)	Omnibus Appropriations Act of 1999 (P.L. 105-277, October 21, 1998)
Agricultural, Rural Development, Food and Drug Administration, and Related Agencies Appropriations Act, FY2001 (P.L. 106-387, October 28, 2000)	Agricultural, Rural Development, Food and Drug Administration, and Related Agencies Appropriations Act, FY2000 (P.L. 106-78, October 22, 1999)
Consolidated Appropriations Act for FY2000 (P.L. 106-113, November 29, 1999)	Agriculture Risk Protection Act of 2000 (P.L. 106-224, June 20, 2000)
Emergency Supplemental Act for FY2000 (Title II of the Military Construction Appropriations Act, 2001) (P.L. 106-246, July 13, 2000)	1999 Emergency Supplemental Appropriations Act (P.L. 106-31, May 21, 1999)
Supplemental Appropriations Act, 2001 (P.L. 107-20, July 24, 2001)	FY2001 Supplemental Authorization for Agriculture (P.L. 107-25, August 13, 2001)
Consolidated Appropriations Resolution, FY2003 (P.L. 108-7, February 20, 2003)	Military Construction Appropriations and Emergency Hurricane Supplemental Appropriations Act, 2005 (P.L. 108-324, October 13, 2004)
Department of Defense, Emergency Supplemental Appropriations to Address Hurricanes in the Gulf of Mexico, and Pandemic Influenza Act, 2006 (P.L. 109-148, December 30, 2005)	U.S. Troop Readiness, Veterans' Care, Katrina Recovery, and Iraq Accountability Appropriations Act, 2007 (P.L. 110-28, May 25, 2007)
Consolidated Appropriations Act, 2008 (P.L. 110-161, December 26, 2007)	American Recovery and Reinvestment Act (ARRA), 2009 (P.L. 111-5, Feb. 17, 2009)

Table A2: Examples of crop disaster assistance programs

Crop Disaster Assistance	1999 Citrus Losses In California
Apple & Potato Quality Loss	Crop Hurricane Damage Program
Disaster - Cane Sugar	Disaster - Hurricane Hugo
Disaster Assistance - Big Horn River	Disaster Reserve Flood Compensation Program
Disaster Supplemental Appropriation	Disaster – Non-Program Crops
Disaster – Program Crops	Emergency Assistance Program
Emergency Conservation Program	Florida Hurricane Citrus Disaster
Florida Sugarcane Disaster Assistance Program	Hawaii Sugar Disaster
Hurricane Indemnity Program	Karnal Bunt Fungus Payment
Louisiana Sugarcane Disaster - Hurricane	Multi-Year Crop Loss Disaster Assistance
North Carolina Crop Hurricane Damage Program	Pasture Flood Compensation
Quality Losses Program	Single-Year Crop Loss Disaster Assistance
Specialty Crop Hurricane Disaster	Supplemental Revenue Assistance Program
Sugar Beet Disaster Program	Tree Assistance Programs
Tobacco Disaster Assistance	

Table A3: The effect of past disaster payments on insurance coverage, IV

	(1) Net premium (log)	(2) Liability (log)	(3) Policies (log)	(4) Acres insured (log)	(5) Subsidy (log)
Disaster payments last year (log)	-0.138**	-0.268***	-0.350***	-0.189***	-0.507***
	(0.066)	(0.069)	(0.070)	(0.054)	(0.096)
Number of farm proprietors (log)	-0.305***	0.102	0.067	-0.314***	-0.229*
	(0.096)	(0.106)	(0.097)	(0.081)	(0.121)
Pct. employed in forestry/agriculture	-0.003	-0.004	-0.002	0.001	-0.002
	(0.004)	(0.005)	(0.004)	(0.003)	(0.006)
Population (log)	-0.209	0.494***	0.099	0.522***	-0.106
	(0.129)	(0.153)	(0.137)	(0.115)	(0.172)
Per capita personal income (log)	-0.676***	-0.252*	-0.362***	-0.292***	-0.256
	(0.120)	(0.136)	(0.130)	(0.100)	(0.174)
Total employment (log)	-0.072	-0.176**	-0.142**	-0.265***	-0.186**
	(0.061)	(0.071)	(0.061)	(0.053)	(0.087)
F-statistic	34.626	38.367	38.367	36.776	38.367
Dep. var. mean	11.837	15.026	4.698	9.470	11.925
Observations	57,843	60,002	60,002	59,394	60,002

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. All regressions include year and county fixed effects as well as farm income decile indicators, which are omitted for readability. All control variables are lagged by one year.

Table A4: The effect of disaster payments after 1995, IV

	(1) Net premiums (log)	(2) Liability (log)	(3) Policies (log)	(4) Acres insured (log)	(5) Subsidy (log)
Disaster payments (log)	-0.392***	-0.400***	-0.343***	-0.241***	-0.588***
	(0.099)	(0.102)	(0.083)	(0.067)	(0.132)
Number of farm proprietors (log)	0.019	0.120	0.138	-0.245**	-0.224
	(0.149)	(0.141)	(0.114)	(0.097)	(0.177)
Pct. employed in forestry/agriculture	-0.001	-0.006	-0.001	0.001	-0.008
	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)
Population (log)	-0.018	0.188	0.088	0.184	-0.402
	(0.238)	(0.236)	(0.185)	(0.148)	(0.292)
Per capita personal income (log)	-1.324***	-0.908***	-0.761***	-0.675***	-1.249***
	(0.245)	(0.226)	(0.186)	(0.153)	(0.302)
Total employment (log)	-0.405***	-0.320**	-0.281***	-0.275***	-0.400**
	(0.127)	(0.131)	(0.102)	(0.086)	(0.169)
F-statistic	27.359	23.882	23.882	24.665	23.882
Dep. var. mean	12.036	15.306	4.800	9.697	12.432
Observations	42,317	44,214	44,214	43,625	44,214

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. All regressions include county and year fixed effects and controls for county characteristics. Coefficients on farm income decile indicators are omitted for readability. All control variables are lagged by one year.

Table A5: Estimated effects when controlling for third-party voting two elections ago, IV

	(1) Net premiums (log)	(2) Liability (log)	(3) Policies (log)	(4) Acres insured (log)	(5) Subsidy (log)
Panel A: Controlling for third-party voting two elections ago					
Disaster payments (log)	-0.298***	-0.197**	-0.140**	0.061	-0.290***
	(0.088)	(0.086)	(0.058)	(0.053)	(0.085)
F-statistic	37.495	30.751	30.751	30.754	30.751
Dep. var. mean	11.927	15.163	4.775	9.603	12.185
Observations	50,024	52,176	52,176	51,581	52,176
Panel B: Estimates for panel A sample without controlling for third-party voting two elections ago					
Disaster payments (log)	-0.334***	-0.261***	-0.188***	0.027	-0.388***
	(0.095)	(0.095)	(0.066)	(0.055)	(0.101)
F-statistic	36.085	29.269	29.269	29.787	29.269
Dep. var. mean	11.927	15.163	4.775	9.603	12.185
Observations	50,024	52,176	52,176	51,581	52,176

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. All regressions include county and year fixed effects and controls for county characteristics (omitted for readability). All control variables are lagged by one year.

Table A6: The effect of disaster payments on insurance decisions, no farm counties, IV

	(1) Net premium (log)	(2) Policies (log)	(3) Acres insured (log)	(4) Subsidy (log)
Disaster payments (log)	-0.145**	-0.176***	0.031	-0.290***
	(0.062)	(0.051)	(0.042)	(0.071)
F-statistic	44.215	38.083	38.328	38.083
Dep. var. mean	11.837	4.736	9.476	11.928
Observations	50,417	52,303	51,794	52,303
	Labor cost (log)	Fertilizer spending (log)	Price-weighted mean yield (log)	Cash receipts (log)
Disaster payments (log)	-0.021	-0.094***	-0.036***	-0.332***
	(0.021)	(0.025)	(0.013)	(0.060)
F-statistic	36.244	38.057	31.581	35.847
Dep. var. mean	8.473	8.416	1.524	9.932
Observations	53,033	52,877	45,173	53,064

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. Sample excludes counties where more than 5% of the population was employed in farming at any point in time during our sample period. All regressions include county and year fixed effects and controls for county characteristics, which are not shown for readability. All control variables are lagged by one year.

Table A7: The effect of disaster payments on insurance decisions, counties with 22 observations, IV

	(1) Net premium (log)	(2) Policies (log)	(3) Acres insured (log)	(4) Subsidy (log)
Disaster payments (log)	-0.236***	-0.176***	0.030	-0.403***
	(0.077)	(0.054)	(0.040)	(0.089)
F-statistic	34.157	32.475	32.424	32.475
Dep. var. mean	12.177	5.090	9.882	12.325
Observations	52,670	53,004	52,932	53,004
	Labor cost (log)	Fertilizer spending (log)	Price-weighted mean yield (log)	Cash receipts (log)
Disaster payments (log)	-0.064**	-0.147***	-0.029**	-0.341***
	(0.026)	(0.034)	(0.015)	(0.064)
F-statistic	32.324	32.237	25.323	32.154
Dep. var. mean	8.513	8.584	1.502	10.086
Observations	53,048	53,028	48,489	53,052

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. Sample restricted to counties that were present in each of the 22 years of the sample. All regressions include county and year fixed effects and controls for county characteristics, which are not shown for readability. All control variables are lagged by one year.

Table A8: The effect of disaster payments on insurance decisions, Including House Committees in the IV

	(1) Net premium (log)	(2) Policies (log)	(3) Acres insured (log)	(4) Subsidy (log)
Disaster payments (log)	-0.144**	-0.133***	-0.068*	-0.239***
	(0.066)	(0.029)	(0.038)	(0.052)
F-statistic	12.240	12.240	12.240	12.240
Dep. var. mean	11.328	4.724	9.308	11.837
Observations	60,455	60,455	60,455	60,455

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election, dummy variables indicating whether the county's Representative is on the House Agriculture committee or the House Appropriations commitee, whether the committee member is a member of the majority party, and whether the Representative is the chair of the committee. All regressions include county and year fixed effects and controls for county characteristics, which are not shown for readability. All control variables are lagged by one year.

Table A9: The effect of disaster payments with 1 added prior to taking logs, IV

	(1) Liability (log)	(2) Policies (log)	(3) Acres insured (log)	(4) Subsidy (log)
Disaster payments (log)	-0.373***	-0.212***	-0.112*	-0.487***
	(0.109)	(0.054)	(0.063)	(0.111)
Number of farm proprietors (log)	-0.175	0.042	-0.533***	-0.417***
	(0.152)	(0.078)	(0.101)	(0.141)
Pct. employed in forestry/agriculture	-0.012*	-0.005	-0.005	-0.011*
	(0.006)	(0.003)	(0.004)	(0.006)
Population (log)	0.628***	0.287**	0.399***	0.240
	(0.218)	(0.118)	(0.155)	(0.209)
Per capita personal income (log)	-0.719***	-0.565***	-0.496***	-0.802***
	(0.206)	(0.107)	(0.124)	(0.211)
Total employment (log)	-0.302***	-0.147***	-0.293***	-0.307***
	(0.106)	(0.052)	(0.063)	(0.108)
F-statistic	37.050	37.050	37.050	37.050
Dep. var. mean	14.915	4.724	9.308	11.837
Observations	60,455	60,455	60,455	60,455

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Standard errors (in parentheses) clustered by county. Disaster payments are instrumented for with the share of voters voting for a third-party candidate in the most recent presidential election. Outcome variables are specified at the top of each column. 1 has been added to all dependent variables prior to taking the log. All regressions include county and year fixed effects and controls for county characteristics. Coefficients on farm income decile indicators are omitted for readability. All control variables are lagged by one year.

Table A10: The relationship between out-of-pocket insurance spending and disaster expectations

	(1)	(2)	(3)
Expected disaster payment (log)	-0.784***	-0.784***	-0.841***
	(0.023)	(0.017)	(0.021)
Corr. between dis. pay. and income		0.637***	0.637***
		(0.034)	(0.032)
Std. dev. of disaster payments (log)			0.085***
			(0.016)
Observations	594	594	594
Adjusted R-squared	0.599	0.772	0.782

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Robust standard errors in parentheses. Dependent variable is log of out-of-pocket spending on insurance.