THE RELATIONSHIP BETWEEN US CROP INSURANCE SUBSIDIES AND PLANTING DECISIONS: A STUDY OF THE 2000 AGRICULTURE RISK PROTECTION ACT

by

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The 2014 farm bill increased the cost of crop insurance programs to $9 billion per year. As the government diverts a larger share of farm bill financing to insurance programs, there is an accompanying need to explore the relationship between crop insurance and planting patterns. Popular authors like Michael Pollan claim that asymmetric subsidies have contributed to a shift in which crops are planted in the US. This study employs an empirical approach to test that claim; it looks at whether or not subsidizing insurance for a select group of commodity crops has a detrimental impact on the planting rates for crops excluded from the program. Specifically, it evaluates the impact that the Agriculture Risk Protection Act (ARPA) of 2000 had on the acreage for crops that did not benefit from the introduction and subsidization of revenue-based insurance subsidies. Until now, the literature on the relationship between crop insurance and planting decisions has focused exclusively on a potential increase in acreage for crops that are eligible for the program, rather than estimate the potential negative impacts on non-program crops. This study does not find substantial support for the claim that the introduction of ARPA corresponded with a significant change in acreage for non-program crops.

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Introduction

The unintended impacts of different types of farm subsidies have been a source of ongoing debate in the academic community. Existing research addresses how they influence land values (Weersink, Clark, Turvey, & Sarker, 1999), trade agreements (Sumner, 2003), and input use (Smith & Goodwin, 1996). A narrower body of research has explored whether or not crop insurance subsidies specifically have led to an increase in acreage for certain crops (e.g. Glauber, 2004; Goodwin, Vandeveer, & Deal, 2004; Skees, Harwood, Somwaru, & Perry, 1998; Young, Vandeerver, & Schnepf, 2001). Such research is warranted, given the disproportionate subsidization of the "big four" crops: corn, soy, wheat, and cotton. These four commodities received 80% of crop insurance subsidies between 1995 and 2010, though they represented just 30% of national commodity sales and 50% of US cropland. Meanwhile, organic, small scale, and fruit and vegetable producers have smaller subsidies, fewer insurance options, and lower participation rates (Sewell, 2012). Popular authors suggest that these subsidies have encouraged the production of some crops at the expense of others (e.g. Nestle 2002; Pollan 2003). If this is the case, there are significant implications for human and environmental health.

Existing studies detail the potential ramifications of planting certain crops over others (e.g. Lubowski, Bucholtz, and Claassen 2006; Wu and Adams 2001). Corn, soy, wheat and cotton are the most heavily fertilized crops in the US (Organic Trade Association, 2011). Corn uses a higher level of nitrogen fertilizers and pesticides than any other crop (Wu & Adams, 2001). Depending on the crops they are replacing, an increase in acreage for "big four" crops could lead to higher usage of chemical inputs.[1] These have adverse effects on human health as well as non-target species in the surrounding ecosystems (Matson, 1997).

It is also important to consider the potential opportunity cost of dedicating an increasing percentage of our farmland to a small number of crops. If the majority of agricultural acreage is dominated by a few crops, there is less diversity in the landscape. This could lead to an increased vulnerability to pest outbreaks or extreme variability in climate (Thrupp, 2000). If a particular strain of corn cannot tolerate the drought one year, and it makes up a large portion of US farmland, our harvest will be impacted substantially. Whether or not insurance programs are contributing to this shift, it poses a considerable challenge for the US government. It seems especially important that insurance programs—which aim to reduce risks for farmers—not unintentionally undermine the security of our food supply.

Existing studies disagree on the magnitude of the impact of crop insurance policies on crop acreage. According to Glauber (1999), a flawed pricing formula led to a revenue guarantee higher than the expected market value for durum wheat in North Dakota in 1999. As a result, it is estimated that durum wheat planting increased as much as one million acres over what would have been expected, absent the faulty policy. Skees (1986) finds that crop insurance participation and subsidies lead to an increase in crop acreage by more than 10%. However, he acknowledges significant limitations to the study, because of confounding variables. On the other hand, studies by Young et al. (2001) and Goodwin et al. (2004) find much more modest conclusions, with increases

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[1] For example, using the Central Nebraska Basin as a case study, Wu and Adams (2001) projected an increase in chemical inputs as a result of corn and soy replacing hay and pasture.

in subsidies leading to up to a 1.1% increase in planted acres, depending on the crop. The latter studies use modeling techniques that account for a much wider array of factors that influence planting decisions.

Not all studies, however, differentiate between the additional acres that result from utilizing marginal land versus substitution of other crops. Of the studies that look directly at how crop insurance programs impact crop mix, the majority focus on the trade-off between two crops using mathematical simulations that optimize profits at the farm level. Kaylen, Loehman, and Preckel (1989), for example, find that deploying different types of insurance reduces the acreage of the less risky of two hypothetical crops to zero given three out of four insurance options. A more recent study by Seo, Mitchell, and Leatham (2005) illustrates how crop insurance and loan programs lead to an increase in cotton acreage for cotton-sorghum farmers in Texas.

While it is broadly acknowledged that asymmetric subsidies might lead to shifts in which crops get planted,[2] there are no empirical studies that link insurance subsidies to a negative impact on acreage for less subsidized crops. This study contributes to filling that gap by evaluating the impact that the Agriculture Risk Protection Act (ARPA) of 2000 had on the number of planted acres for crops that did not benefit from the introduction and subsidization of revenue-based insurance subsidies. While revenue-based insurance was introduced on a pilot basis starting in 1996, ARPA made the program available on a geographically uniform basis and raised the subsidy rate

[2] For example, a USDA ERS report states that in light of unbalanced subsidies, farmers "would likely increase acres planted and also shift the mix of crops toward those with relatively high benefits" without citing any empirical research (Westcott and Young, 2000). Another study cites popular authors like Michael Pollan for claims that subsidies favor certain crops at the expense of others (Balagtas et al., 2013).

substantially.[3] More specifically, it allowed producers of a limited number of crops to access revenue-based insurance with the same subsidy levels provided for the more ubiquitously offered yield-based insurance.[4] This created two categories: farmers whose crops had no access to revenue-based insurance and farmers whose crops were provided access, with premiums subsidized at around 55% (Glauber, 2004). The latter group responded enthusiastically to the program. By 2011, 83% of the cost of premium subsidies was going to revenue guarantees rather than protecting against yield loss (Sewell, 2012). ARPA resulted in an almost 20% increase in enrollment for eligible acres, from 182 million acres in 1998 to over 217 million in 2003 (Glauber, 2004). Because this policy so clearly differentiates between the benefits that accrue to some farmers but not others, it provides a convenient framework for analysis.

This thesis exploits a distinct policy change to test whether government programs that increase access to revenue insurance for certain crops lead to changes in planting rates for the crops that are not included in the insurance scheme. I hypothesize that this change led to a decrease in acreage for non-program crops due to replacement from revenue insured crops. Accordingly, I utilize data from 1991 through 2008, which covers a significant amount of time before and after the implementation of ARPA. Because of limited data for certain crops, this time frame allows me to maximize the number of crops included in the study without sacrificing the integrity of the experimental design. Additionally, it excludes potential impacts from further policy

[3] For example, a corn farmer in Freeborn County, Minnesota, could receive a 17% subsidy on a Revenue Protection plan in 1998, but these programs and rates varied geographically and by year until ARPA (J. Burcham, personal communication, February 8, 2014).
[4] The USDA Risk Management Agency determines which crops are insurable in which locations. Yield-based insurance is available to dozens of crops in varying locations (National Crop Insurance Services, 2014).

changes enacted in 2011, when revenue-based insurance was made available for a larger number of crops.

This thesis differs from the existing literature in several ways. Most studies on the impacts of federal crop insurance programs employ structural econometric modeling. Structural modeling focuses on the factors that influence individual decisions when constructing an explanatory model.[5] Using a structural model can be difficult when considering land use decisions because it is hard to generalize beyond the parameters assumed in the model (Seo et al., 2005). Analysts must model how producers will react to different prices and policies for a range of crops, as well as the potential for alternate uses and what their risk preferences are. Alternately, this analysis utilizes a reduced form difference-in-difference approach. Reduced form econometric modeling focuses on the relationships between given variables. Specifically, difference-in-difference uses a control group as a counterfactual in order to measure the effect of a treatment, often a policy change. Though a difference-in-difference approach is used in related work (e.g. Balagtas et al. 2013; Roberts 2006), it has yet to be employed in relation to the question of how insurance subsidies impact crop mix.

Additionally, national level studies dealing with crop insurance have focused exclusively on a potential increase in high value commodity crops, rather than trying to expose a direct link between subsidy programs and a reduction in, for example, the amount of fruit and vegetable crops that are planted. Even the studies that highlight substitution focus on the trade-offs between various highly subsidized crops. This is the case in Barnett et al.'s (2002) study, which analyzes trade-offs between planting cotton

[5] For a more thorough explanation of structural econometric modeling, see Reiss & Wolak, 2007.

and soy when insurance programs are available. Wu and Adams (2001) examine how insurance programs alter the ratio of soy and corn, with little mention of how other non-subsidized crops would be impacted.

The main findings of this study did not indicate that formalizing and increasing subsidies for revenue-based insurance had a significant effect on planting rates for crops other than the “big four”. While the share of acreage dedicated to non-program crops has been declining, this trend began decades before ARPA (Sheaffer & Moncada, 2012). Additionally, farmland on the whole has been decreasing, which could account for some of the loss in non-program crop acreage (EPA, 2013). I found a significant decrease of non-program crop acreage in mixed counties in one form of the analysis. However, this result is not robust to the array of classifications set forth by the model. Thus, there is little evidence to support the claim that the increased subsidization of revenue-based insurance options aggravated the trend of substitution in the long run.

This thesis proceeds by first providing additional background information on the mechanics and introduction of the Federal Crop Insurance Program. Section 2 also addresses the changes brought by ARPA in greater detail. Next, I explore the mechanism by which access to subsidized revenue-based insurance could lead to substitution in section 3. In section 4, I describe the data, provide definitions, and explore summary statistics and figures. Section 5 explains the empirical model and its limitations. I relay the results of variations on this model in section 6. Finally, section 7 details my conclusions and offers further implications.

Further Context on the Federal Crop Insurance Program and ARPA

The United States Department of Agriculture Risk Management Agency (USDA RMA) partners with 19 private insurance companies to write and provide insurance policies to farmers. The most widely available policies are characterized as Multiple Peril Crop Insurance (MPCI)—coverage in the event of crop yield loss due to drought, excessive moisture, freezing, disease, and other natural causes. Other coverage options combine yield protection with revenue protection, which provide a price guarantee when yields are low or market prices drop significantly. The RMA sets the unsubsidized policy rates and dictates which crops can be insured and where. The private providers must sell insurance to any eligible farmer, though the risk is shared between the companies and the government.[6] The federal government provides subsidies for both the farmer-paid premiums to reduce costs for farmers and the private companies to compensate for administrative and operating costs (National Crop Insurance Services, 2014).

The Federal Crop Insurance Program (FCIP) was established in 1938, when Congress passed the Federal Crop Insurance Act in response to the Dust Bowl (Imhoff, Pollan, & Kirschenmann, 2012). However, due to high program costs and low participation, there were not enough reserves to pay claims. During the last several decades, various pieces of new legislation have tried to address this shortfall. The Federal Crop Insurance Act of 1980 established the use of public-private partnerships to make crop insurance more affordable (National Crop Insurance Services, 2014). Still,

[6] The government acts as a reinsurer—insurance for the insurance companies—through the Standard Reinsurance Agreement. Depending on the claims processed in a given year, the government either shares in underwriting gains or bears a portion of the underwriting losses (National Crop Insurance Services, 2014).

participation rates were lower than expected; Congress envisioned the enrollment of 50% of eligible acres by 1990, but in 1988, only 25% were enrolled. The Federal Crop Insurance Reform Act of 1994 created the RMA to administer the program, raised the premium subsidy rate and introduced revenue based insurance as a pilot program. This increased participation rates substantially; enrolled acres increased from around 84 million in 1993 up to more than 180 million in 1998 (Glauber, 2004).

In 2000, the Agriculture Risk Protection Act made it easier to access different kinds of insurance and increased the premium subsidies even more (National Crop Insurance Services, 2014). Again, the number of enrolled acres increased, up to over 200 million (Glauber, 2004). Before ARPA, subsidies were calculated as a fixed-dollar-per-acre premium subsidy. This meant it would fall on the farmer to pay the extra cost of buying a higher coverage level. A higher coverage level raises the guarantee for which a farmer is insured if production does not lead to the results they were expecting. ARPA changed the subsidy calculation to a percentage of the premium. This made it much cheaper to get higher levels of coverage than before. At a 50% coverage level, the premium subsidy increased from 57% to 67%, while at the 75% level, it more than doubled from 24% to 55% (Babcock, 2011). The subsidized price led more farmers to get higher levels of coverage. In 1995 almost all insured acres were at coverage levels of 65% or lower. By 2011, 75% of farms were insured at a 75% coverage level or higher (Sumner & Zulauf, 2011).

ARPA also brought revenue-based insurance subsidies up to the percentage level of MPCI coverage, which made it cheaper to get revenue-based insurance (Babcock, 2011). While the legislation had a large impact on the subsidy level, it did not change which crops were eligible for what type of insurance. Farmers across the board had cheaper access to high coverage levels of MPCI. However, the farmers who were eligible for revenue-based insurance received an additional benefit. This existing difference in insurance access, when intensified by the increase in subsidy rates as a result of ARPA, provides the subject of this research.

Analytical Framework

While my analysis takes place at the county level, this analytical framework explains why government programs may affect crop preferences at the farm level. Access to insurance adds a degree of security for producers by reducing the risk of planting a crop. The purpose of the insurance is to spread the cost of risk across producers, time, and insurance providers. However, insurance markets create the possibility of moral hazard—someone who is insured is more willing to take risks than someone who is not. In the literature on the US agricultural system, moral hazard is often employed when thinking about how government programs lead to an increase in planting on marginal and often less productive land (e.g. Coble and Knight 1997; Roberts 2006; Vercammen and Kooten 1994). This concept can also help explain the idea of crop substitution due to insurance. If a farmer has access to insurance for one crop but not another, they may opt for the insurable crop, even if it would normally be riskier to grow. For example, corn and soy farmers often use more chemical inputs than other crops (Organic Trade Association, 2011). Reliance on fertilizers and pesticides adds another element of risk to farming. However, access to guaranteed income may mitigate that risk and lead a farmer to choose corn or soy regardless.

On top of reduced risk, the subsidy element of insurance programs leads to greater net economic benefits for farmers. These gains can be explained using loss ratios. An actuarially fair premium is defined as having a loss ratio of one, which would indicate that the payouts in claims equal the total premiums paid. Premiums must also take administrative costs into account, so they are rarely actuarially fair. However, government subsidies distort any given loss ratio so that while the stated premium may lead to reasonably sound loss ratios, farmers are opting to participate based on a lower cost. This means that their expected payout relative to what they paid in is higher than if the subsidy was not in place. As producers evaluate the relative profit associated with different crops, the added gains could lead them to prefer crops with better coverage.

While some studies try to model the impact of differing degrees of subsidies (e.g. Wu and Adams 2001), I consider the combined effect of access to revenue-based insurance and the associated subsidies. This is a necessary consequence of the structure of the study, though I acknowledge that they could have independent impacts. In combination, I expect that the introduction and subsidization of revenue-based insurance subsidies created conditions that were favorable for substitution: the subsidies made it more lucrative to plant specific crops. Accordingly, this analysis seeks to evaluate whether or not these policies cause a decrease in the planting of the crops without access to the program.

Definitions and Data Description

This study employs National Agricultural Statistics Service (NASS) data at the county level from 1991-2008. The data contain information on the acreage of different crops planted in each county. I also include NASS data on the price received by state for the crops with well-reported information. The price data are adjusted for inflation, using 1991 as the index. Additionally, I employ climate data from the National Climatic Data Center. The dataset includes average annual temperature and precipitation rates by state.

I categorize corn, soy, wheat and cotton as “revenue insured” crops, or crops that received the benefits of highly subsidized revenue-based insurance from ARPA. Based on available data, I include oats, potatoes, beans, flaxseed, peanuts, sugar beets, rye, and sweet potatoes as “non-program” crops, or crops that did not have a revenue-based insurance option in the study years. A few crops are purposefully omitted because pilot revenue-based insurance programs were offered to them on a scattered basis in the late 90s.[7] As such, they cannot easily be classified in the “revenue insured” or “non-program” categories.

I compare counties using the sum of the planted acres for non-program crops. The assumption is that counties where both categories of crops were present are agriculturally suited to both types of crops and are thus susceptible to substitution. Accordingly, I define “mixed counties” as counties where one or more revenue insured crop and one or more non-program crops were both present at any point during the

[7] Crops that were intentionally excluded from the study: barley, canola, sorghum, rice, and sunflowers. They received revenue insurance options in some counties on a pilot basis starting in the 90s. Peas were also omitted because they had a negligible amount of acres planted in control counties.

study period. “Control counties” cultivated only non-program crops. Limiting the dataset to the mixed and control counties brings the total number of counties in the study down from 2,790 to 1,883. The states with more than 100 million planted acres represented in the study[8] fall into the Northern and Southern Plains, the Corn Belt, and the Lake States, areas known for their agricultural production. The distribution of non-program crop acres can be seen in Figure 3. In total, the dataset contains 31,811 observations across 1,883 counties in 37 states over an 18 year period.[9]

Summary statistics of the variables considered in the study are presented in Table 1. The mean planted acres by county are higher for the revenue insured crops, ranging from 5,578 acres to 38,211 acres. For the non-program crops, the mean acres range from 22 to 2,620. The mean of the summed acres—the dependent variable in the model—is 6,103. Corn, wheat, and soy clearly dominate the study in acres planted, with cotton close behind. This is reflective of national patterns, where a small number of commodity crops account for a majority of harvested acres (EPA, 2013). Table 1 also provides summary statistics on the control variables. The mean annual temperature across counties was 52.7 degrees Fahrenheit. The mean precipitation was 34.4 inches. The mean price received for corn, soy, wheat, oats and potatoes was $2.66 per bushel, $6.15 per bushel, $3.50 per bushel, $1.83 per bushel and $7.49 per centum weight respectively.

[8] Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Montana, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Texas and Wisconsin.

[9] A complete dataset with 18 years of observations in 1,883 counties would contain 33,894 observations. The discrepancy (my study uses 31,811 observations) is due to gaps in the NASS data. In some counties, data were not reported for given years, either because it was not collected or there was no planted acreage for the specified crops in that year.

Figure 1 provides further information to position the study in the context of US agriculture over the past few decades. It shows the aggregate means of acres planted for revenue insured versus non-program crops nationwide. Over the study period, revenue insured crops grew from a mean of about 80,000 acres per county to over 100,000. Alternately, mean acres for non-program crops dropped from about 5,000 acres to 3,000 per county. This graph helps demonstrate the degree to which corn, soy, wheat and cotton have been grown in increasing amounts, while other crops are on the decline. This trend appears to be true before 2000. In fact, corn and soy have been displacing other crops at significant rates since the 1920s (Sheaffer & Moncada, 2012). This could be due to a number of factors, from rising prices to the advent of GMOs, to government policies. The purpose of this study, then, is to determine whether the recent addition of revenue-based insurance subsidies also contributed to this trend.

Preliminary evidence of the effect of ARPA on the production of less subsidized crops can be seen in Figure 2. It displays the mean acres of non-program crops in mixed counties and control counties over the study period. The mean acres remain relatively stable in control counties, at around 1,000 acres. On the other hand, mean acres for non-program crops in mixed counties decline from around 8,000 in 1991 to half of that by 2008. The decrease in acres is roughly equal in both the pre- and post-ARPA periods. This steady decline suggests that ARPA did not lead to an additional decline in acreage for non-program crops. In the following sections, I reinforce this conclusion by empirically testing the role that ARPA played in the decline of non-program crops.

Empirical Estimation Model

In order to formalize the findings in this study, I employ a difference-in-difference technique. I utilize the following fixed-effects model in estimating the difference in planted acres for mixed and control counties:

$$Acres_{it} = \alpha_i + \gamma_t + \Sigma_k \lambda_k X_{kit} + \theta MixedCounty_i \times Year_t$$
$$+ \beta MixedCounty_i \times Years\ After\ ARPA_t + \varepsilon_{it} \tag{1}$$

In equation 1, *i* indexes counties and *t* indexes years. $Acres_{it}$ indicates the non-program crop acres in county *i* at time *t*, α_i represents a county-specific intercept that controls for time-invariant differences across counties (i.e. elevation), γ_t represents year effects, which control for yearly changes experienced uniformly across all counties (i.e. federal policy changes), X_{kit} represents a set of control variables for price and weather, $MixedCounty_i$ x $Year_t$ allows for separate time trends in planting rates in mixed counties (i.e. it allows for planting ratings in mixed and control counties to be converging or diverging linearly over the course of the sample), $MixedCounty_i$ x Years After $ARPA_t$ is an indicator variable equaling one for observations that represent a mixed county in a period following the introduction of ARPA, and ε is the error term, which captures unobserved influences on $Acres_{it}$. The coefficient of primary interest is β.

I estimate two primary versions of this model. In the first, I compare two periods: before ARPA took effect (1991-2000), and after (2001-2008). In this model, β represents the average difference in acres between county groups after ARPA, relative to before. This estimation is shown in the first two columns of Table 2, where price controls are either included or not. The second model differs only in that *Years after ARPA* is replaced with individual years. Instead of comparing periods, the model includes interactions between mixed counties and each year in the study, omitting 2000. In this model, β shows the average difference between counties in the specified year relative to the difference in 2000. These estimates are shown in Table 3. The year by year breakdown features a more detailed depiction of the differences between county groups over time.

Underlying these models is the assumption that the control counties represent a valid counterfactual. This would be questionable under a variety of circumstances. It is possible that evidence of a disproportionate decline in non-program crops might be due to decreasing farmland rather than substitution. Overall acres of farmland in the US have been on the decline. Between 1990 and 2012, planted land fell by about 73 million acres (EPA, 2013). Regardless, a significant result would indicate a bigger decline for non-program crops in mixed counties. This would mean that the presence of revenue insured crops, through some indirect push to reduce acres, corresponded with a decrease in non-program crops. In this case, the effect would be present, but the predicted mechanism may be inaccurate. Further analysis could tease out whether or not an observed decrease in non-program crops was due to substitution or a loss of acres to a different use. This could change some of the policy implications of the study.

Another concern may be that the trend of planting in mixed and control counties was different before the policy change took effect. As Figure 2 demonstrates, this appears to be the case; acres in control counties remain relatively constant while acres in mixed counties are declining throughout. In order to account for this divergence, I include an interaction variable between the mixed counties and a continuous year variable. The nature of this effect is represented as θ in equation 1.

Analysis

Due to the phenomena of substitution outlined in section 3, I expected that planted acres of non-program crops would decrease in mixed counties after the introduction of ARPA. Table 2 displays the estimated difference in acres between mixed and control counties relative to their difference before ARPA. Columns 1 and 2 show the main estimation, with and without price controls. The rest of the columns display estimations for various robustness checks. The chief result of the study can be seen from the coefficients on *Mixed County x Years After ARPA*. In these primary models, the estimates indicate that introduction of ARPA does not correspond with a significant change in acreage for non-program crops in mixed counties. Thus, the results of my primary analysis provide little support for the effect I expected to find.

A more detailed deconstruction of the results can be seen in Table 3. In this model, I take into account the interaction between the differences in counties for each year, instead of the set of years succeeding ARPA. The coefficients represent the average change between county groups from 2000 to the given year. In this model, I find some support for the results I expected. Compared to 2000, I would expect to see positive coefficients increasing in magnitude and significance moving back toward 1991. Succeeding 2000, I would expect to see either increasing negative coefficients with an especially large drop directly after the policy change, or negative coefficients in greater magnitudes than the coefficients before 2000. This prediction aligns with the existing trend of divergence, where non-program crop acreage in mixed counties declined steadily throughout the study period. On top of this, a policy effect could take the form of either a distinct, additional drop right after the policy enactment, or a more general intensification of the loss of acreage in mixed counties after 2000, as indicated by an increase in coefficient magnitudes.

In Table 3, I see elements of the pattern I would expect. From 1991, the coefficients move from large, positive, and significant to smaller and insignificant as they approach 2000. There are significant, negative coefficients directly following 2000 for two years, followed by insignificant coefficients until the last two years in the study period, which are negative. This could indicate that there was a drop in non-program crop acreage in mixed counties right after 2000 as a result of ARPA, followed by a slower continuation of the existing downward trend. The main discrepancy is a negative, significant coefficient in 1999 compared to 2000. It is unclear why the differences between counties would grow between 1999 and 2000, indicating a relative increase in acres in mixed counties right before ARPA was enacted. Regardless, the detail in this analysis suggests that there was a significant change in the years directly following ARPA. However, the other forms of the model demonstrate that this change was not large enough to generate a significant overall loss of non-program crop acreage in mixed counties when considering a longer time span.

To bolster the validity of the results, I perform a range of robustness checks on the estimation model. For the first check, I define the introduction of revenue-based insurance at 1996 instead of 2000. While the legislation that allowed revenue-based insurance on a pilot basis passed in 1994, the first revenue-based options were offered in 1996 (Skees et al., 1998). This estimation accounts for the possibility that the introduction of this program as a pilot serves as a better indicator for a policy effect than its expansion through ARPA. Column 3 in Table 2 displays the estimation, which is insignificant. In brief, redefining the treatment years does not result in a change in the outcome.

A handful of crops were excluded from the study because they received access to revenue-based insurance on a pilot basis during the study period. Among these, there are sufficient data for barley, sorghum, rice, and sunflowers to be included in the study. I perform an estimation of the model where these four crops are contained within the categorization of revenue insured crops. The coefficient, similarly insignificant, can be found in column 5 of Table 2. Due to their sporadic access to the program, the inclusion of these extra crops is hard to justify as the primary model of analysis. It would therefore be surprising if their inclusion led to different results.

I estimate another form of the model where the definition of mixed and control counties is altered. Rather than strictly exclude revenue insured crops from control counties, I allow a small number of acres to be contained within the definition. With a trivial number of existing acres, these crops may not have the power to impact planting patterns for other crops because of a lack of biophysical suitability, infrastructure, or community interest. I use 2,300 acres—the 10^{th} percentile of revenue insured crop acres in the study—as the baseline. As demonstrated in column 4 of Table 2, the coefficient for this estimation is negative and significant at the 1% level.

This is the only version of the primary model with statistically significant results in support of what I expected to see; it finds that mixed counties saw a relative decrease in non-program acreage after ARPA compared to control counties. This means that counties with a large number of revenue insured crop acres saw a steeper decline in non-program crop acreage after ARPA than counties with a small number of or no revenue insured crop acres. Momentum could help explain this result; counties that already plant large numbers of revenue insured crops have the necessary infrastructure and knowledge to more easily convert further land. Hence, the inclusion of counties with small amounts of revenue insured crops may serve as a better control. However, the implications of this estimation are diminished because it is a standalone result. Without significant results using other classifications, this provides a much weaker case for the impact of ARPA.

Next, I estimate the effect of ARPA on the difference between mixed and control counties when outliers are excluded. I run a model where counties with more than 38,710 acres of non-program crops (two standard deviations away from the mean) are not included. This eliminates 18 counties from the study. Column 6 in Table 2 displays that the results are still robust to this change. The coefficient for this model is insignificant.

Finally, I estimate a version of the model where cotton is excluded as a revenue insured crop. Cotton is planted at significantly lower rates than the other three crops in the category.[10] For the same reasons that it could make sense to include some revenue insured crop acreage in control counties, it makes sense to perform an estimation without cotton; having less acreage might detract from its effectiveness in replacing other crops. However, this estimation similarly yields an insignificant result. This can be seen in column 7 of Table 2. In sum, these checks show that the key findings of the study are robust to a wider parameter of classifications than what is specified in the original model.

[10] As displayed in Table 1, the mean acres planted per county were around 5,500 for cotton, compared to 30-40,000 for corn, soy, and wheat.

In addition to the estimation coefficients, Table 2 provides information on the significance of the control variables and their relationship to the dependent variable, non-program crop acres. The *Mixed County x Year* variable accounts for the average existing difference between the county groups over the study period, as discussed in section 5. This control shows a consistent, negative, significant relationship, demonstrating that advancing by a year in mixed counties was significantly correlated with a decrease in non-program acreage across the models.[11] Temperature and precipitation were included because climate projections can influence planting decisions. These variables ranged in significance, but were primarily insignificant.[12] Because the relationship between climate and planting is more nuanced, it is unsurprising that the coefficients on the controls were mostly insignificant. Annual temperature and precipitation averages do not adequately capture the aspects of climate that most affect planting decisions. Farmers care about the duration of the seasons and peak temperatures or rainfall—the distribution is important (Hollinger & Changnon, 1993; Lobell, Cahill, & Field, 2007).

Price variables are included in the study to control for potential impacts of price on planting decisions. In economic terms, the various crops included in the study are primarily substitutes.[13] Rising prices may drive farmers to increase the acreage of one crop in lieu of other crops (Flanders, 2012). This relationship is complicated by the

[11] The coefficients range from about -180 to -245 depending on the model, all at a 5% significance level or higher.
[12] An increase in temperature correlated with a significant decrease of 130 non-program crop acres in the model where outliers were eliminated. An increase in precipitation correlated with a significant increase of 25 acres in the primary estimation without price controls. Otherwise, the coefficients were insignificant.
[13] Some crops are planted in rotations, so they may be complements in places where crop rotations are more common. This further complicates the relationship between crop prices and planting decisions.

aggregate nature of the dependent variable. An increase in the price of oats, for example, may promote the planting of oats while detracting from the acres for other non-program crops. Because acreage for both oats and other non-program crops are included in the value of the dependent variable, the relationship between the price of oats and non-program crop acreage is complex. It should be clearer for the price of revenue insured crops, which likely act as substitutes for all non-program crops. Table 2 shows that corn, soy, and oat prices saw a significant increase in association with non-program crop planting increases, while wheat and potato prices saw a significant decrease.

Conclusion

In the last few decades, crop insurance subsidies have become an increasingly significant feature of the US farm bill. Direct payments to farmers are now seen as politically indefensible and thus more attention and support from farm lobby groups has focused on increasing crop insurance subsidies. Crop insurance plays an important role in reducing risk for farmers. It provides a safety net against threats that can be hard to predict or adapt to, like flooding or pest infestations. Crop insurance requires subsidization in order to be affordable because the complexity of administering the program leads to high overhead costs. Program changes over the last few decades have done an effective job of increasing coverage; more than 85% of eligible acres are now insured (National Crop Insurance Services, 2014).

Recent legislation continues to expand crop insurance. The 2014 farm bill increases the taxpayer cost of insurance programs by $5.7 billion over the next ten years, up to about $9 billion per year (National Sustainable Agriculture Coalition, 2014). As the government allocates more money to the program, policymakers should consider the full range of its impacts. This includes intentional outcomes, like risk reduction, and unintentional effects, like changes in planting patterns that could lead to more erosion or increased chemical inputs.

This study did not find robust evidence that the increased subsidization of revenue-based crop insurance led to such a shift in acreage. In one of six approaches to classifying the data, I saw a significant decrease in non-program crop acres after ARPA went into effect. However, when considering the complete set of results, this link provides little support for a substantial and lasting impact from the increased subsidization. There are several possible explanations for these outcomes. One is that the introduction of ARPA did not have an impact on farmers' planting decisions. Another is that the impact was too small relative to the variation in the data for a statistically significant conclusion to be drawn. It is also possible that a significant change did occur, but it was made insignificant when taking a longer time period into consideration. This explanation is supported by the year-to-year analysis displayed in Table 3. Finally, there were some limitations to the empirical framework of my analysis.

The major limitations of the study fall into two categories. The first is that my framework did not incorporate several significant factors that influence planting decisions. For one, modern agriculture is becoming more knowledge intensive; farmers must manage expensive capital investments, new technologies, increased regulation, and volatile markets, among other challenges (McKenzie, 2014). Because of the investment required to produce a given crop, a farmer may not opt to switch what they are planting simply due to a marginal increase in profit for a different crop. Other elements impact decisions as well. These include input prices, which play a significant role in the expected return on a crop, or the presence of pests, which may influence how much farmers need to spend on inputs or other pest management strategies (Giannini Foundation, 2004).

The other major limitation is that the non-program crops included in the study may not serve as an accurate proxy for all non-program crops that are grown in the US. While they account for a significant number of acres, it is hard to justify generalizing the results of this study beyond the eight crops that are included. While this study was constrained by data availability, future research could potentially circumvent this issue by utilizing other data sources.

This study addresses only one aspect of the agricultural system that could impact crop diversification. Other governmental policies, like restrictions on fruit and vegetable planting in order for commodity crop farmers to receive government support payments (Balagtas et al., 2013), likely play a role. Additionally, individual farmers may choose to engage in more diversified cropping systems for many reasons, including weed control (Liebman, Liedman, Mohler, & Staver, 2001), growing in difficult soils (Qadir et al., 2008), or adapting to environmental change (Lin, 2011). Extension services and other educational outlets can help disseminate information about the options available to farmers.

Future research should continue to examine why the distribution of US farmland has changed so drastically in the past few decades. These changes may have far-reaching consequences for the health and security of our populations and environment. It is particularly important to ensure that government policy is not producing outcomes that are counterproductive to its goals. Good agricultural policy should strive to support the economic viability of farmers, the sustainability of our farmland, and the food security and health of its citizens.

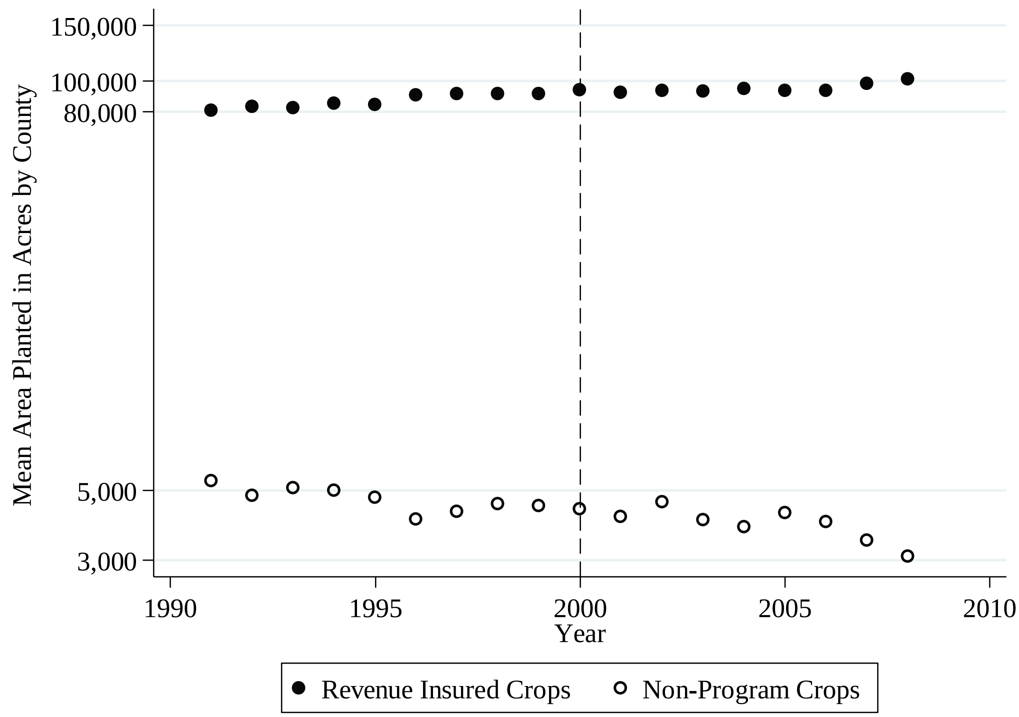
Figures and Tables

Table 1: Summary statistics of study variables by county

Variable	Mean	St. Dev.	Min	Max
Corn - Acres Planted	38,210.64	54,601.05	0	397,000
Soy - Acres Planted	29,974.83	48,476.30	0	540,000
Cotton - Acres Planted	5,578.45	24,969.83	0	412,500
Wheat - Acres Planted	29,108.57	63,622.12	0	764,400
Oats - Acres Planted	2,620.79	5,083.34	0	79,400
Potato - Acres Planted	535.23	3,557.23	0	73,500
Beans - Acres Planted	894.3	5,626.97	0	127,000
Flaxseed - Acres Planted	228.27	2,466.59	0	109,000
Peanuts - Acres Planted	741.69	3,702.30	0	86,600
Sugar beet - Acres Planted	782.34	5,054.53	0	103,200
Sweet Potato - Acres Planted	22.25	300.77	0	9,550
Rye - Acres Planted	278.13	1,830.16	0	71,000
Sum of Non-Program Crop Acres	6,103.00	13,524.28	0	196,400
Temperature	52.69	8.27	37	73
Precipitation	34.38	11.78	7	74
Corn - Price Received	2.14	0.51	1	4
Soy - Price Received	4.9	1.04	3	8
Wheat - Price Received	2.79	0.73	1	5
Oats - Price Received	1.83	0.57	1	4
Potato - Price Received	6.03	2.11	2	20

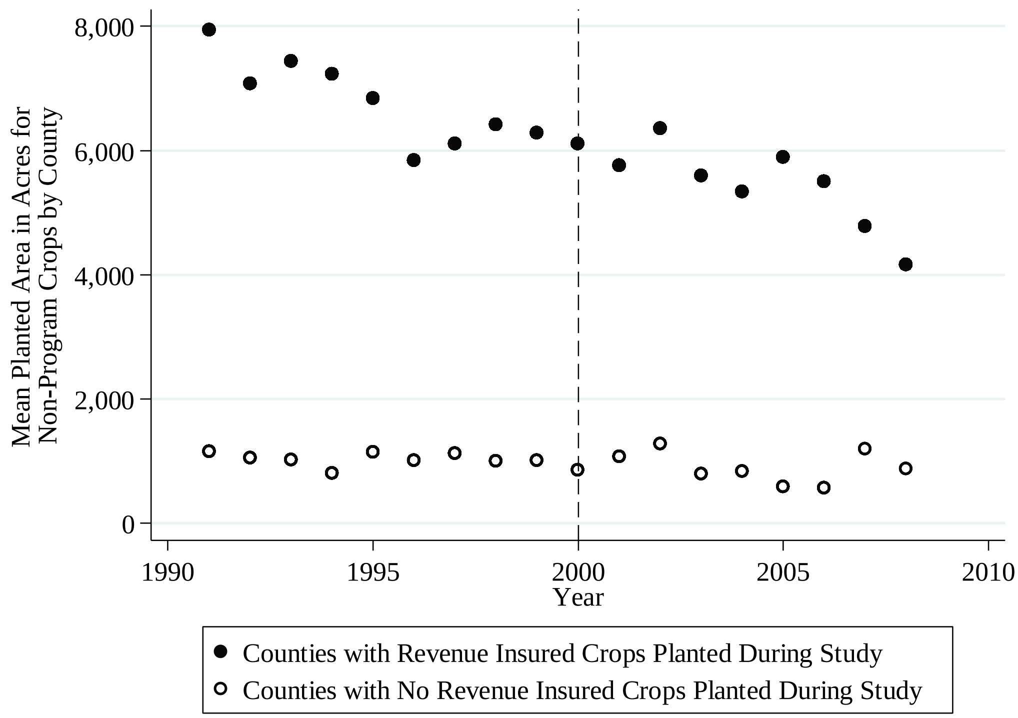
Notes: Data on acreage and price are from the USDA National Agricultural Statistics Service. Data on climate are from the National Climatic Data Center. Summary statistics are based on 31,811 observations in 1,883 counties from 1991-2008. Observations represented in the table are by county and year.

Figure 1: Mean planted acres nationwide for crops with or without access to revenue-based crop insurance from 1991-2008.



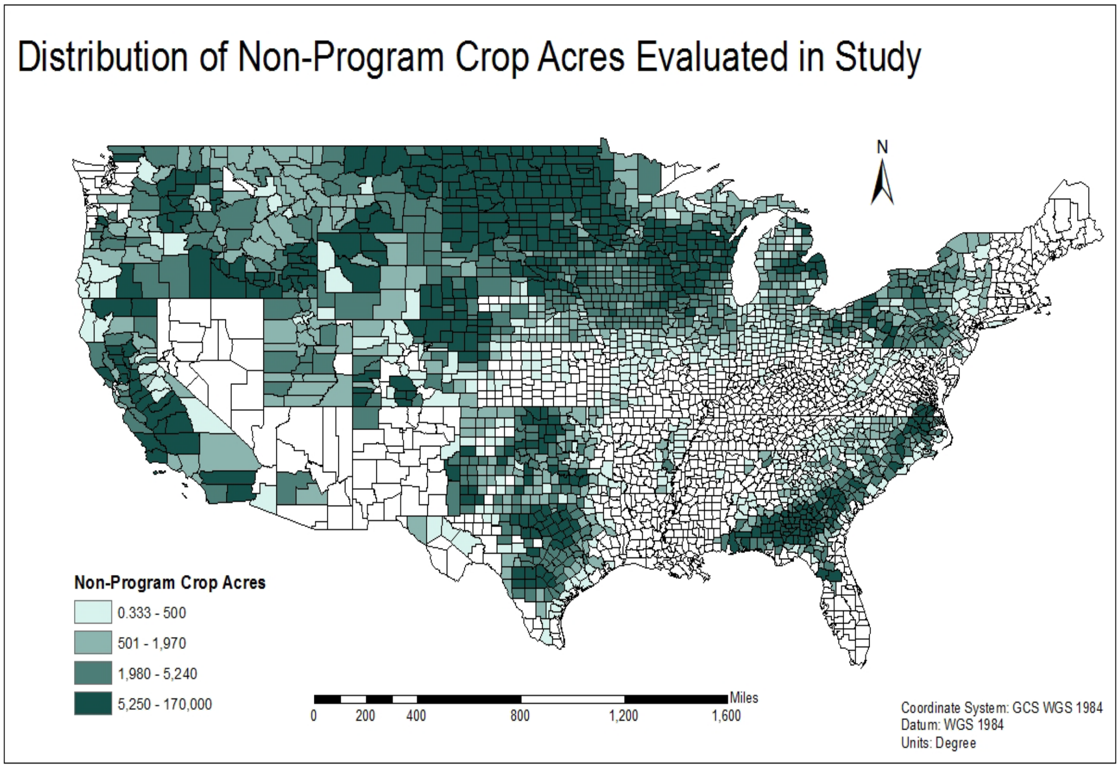
Notes: Filled markers represent the mean area planted for revenue insured crops by county. Hollow markers represent the mean area planted for non-programs crops by county.

Figure 2: Mean planted acres of non-program crops in counties where revenue insured crops were present or not present from 1991-2008.



Notes: Filled markers represent the mean area planted for non-program crops in counties where revenue insured crops were present during the study period. Hollow markers represent the mean area planted in counties where no revenue insured crops were present.

Figure 3: Distribution of non-program crop acres evaluated in study.



Notes: Color gradations represent different concentrations of non-program crop acres by county. Categories represent a quantile method of classification.

Table 2: Estimated difference between mixed and control counties relative to pre-ARPA difference.

			1996 instead of 2000	Low Rev Allowed in Control	More Rev Insured Crops	No Outliers	No Cotton
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mixed County x Years After ARPA	270.001	778.193	(560.149)	-962.950***	1,241.549	964.003	778.193
	(176.50)	(911.46)	(761.15)	(216.80)	(784.56)	(848.79)	(911.46)
Mixed County x Year	-140.117***	-230.650**	-130.660***	-108.760**	-223.582***	-245.045***	-230.65**
	(35.61)	(101.09)	(43.81)	(48.02)	(55.40)	(94.45)	(101.09)
Temperature	25.524	44.970	45.255	46.232	44.766	(35.274)	44.970
	(35.07)	(50.38)	(50.37)	(50.31)	(50.39)	(40.26)	(50.38)
Precipitation	25.370***	4.666	4.656	4.781	4.608	(6.679)	4.666
	(4.32)	(6.32)	(6.32)	(6.32)	(6.33)	(5.04)	(6.32)
Corn - Price Received		1162.892***	1164.161***	1163.681***	1162.846***	1158.303***	1162.892***
		(419.61)	(419.63)	(419.41)	(419.65)	(281.31)	(419.61)
Soy - Price Received		383.076*	382.078*	385.293*	383.001*	415.916***	383.076*
		(220.49)	(220.52)	(220.61)	(220.51)	(160.57)	(220.49)
Wheat - Price Received		-850.462***	-850.435***	-845.624***	-849.959***	-850.588***	-850.462***
		(205.76)	(205.78)	(206.19)	(205.77)	(132.81)	(205.76)
Oats - Price Received		1089.340***	1089.602***	1088.965***	1089.481***	737.254***	1089.340***
		(217.66)	(217.68)	(217.81)	(217.68)	(155.29)	(217.66)
Potato - Price Received		-237.515***	-237.540***	-236.029***	-237.724***	-257.627***	-237.515***
		(57.57)	(57.57)	(57.57)	(57.58)	(43.99)	(57.57)
R-squared	0.076	0.073	0.073	0.073	0.073	0.133	0.073
Observations	31,811	19,456	19,456	19,456	19,456	18,863	19,456

Notes for Table 2: Estimates are based on equation 1. The coefficients represent the estimated differences between mixed counties and control counties relative to differences before ARPA was enacted in 2001, unless otherwise noted. Column 3 uses 1996 as the year that revenue-based insurance was introduced instead of 2000. Column 4 changes the definition of control counties to allow the inclusion of a limited number of revenue insured crop acres. Column 5 expands the definition of revenue insured crops to include barley, sorghum, rice, and sunflower. Column 6 eliminates counties that are more than two standard deviations away from the mean number of non-program crop acres from the analysis. The results are generally robust to more price data. Standard errors are reported in parentheses. One, two, and three stars denote significance at the 10, 5, and 1 percent levels, respectively.

Table 3: Estimated difference between mixed and control counties relative to difference in 2000

	(1)	(2)
Mixed County x 1991	1731.860***	(433.895)
Mixed County x 1992	1240.937***	(430.798)
Mixed County x 1993	1752.653***	(374.330)
Mixed County x 1994	1455.237***	(344.977)
Mixed County x 1995	1066.715***	(332.137)
Mixed County x 1996	144.001	(429.720)
Mixed County x 1997	420.067	(747.264)
Mixed County x 1998	-550.924	(584.283)
Mixed County x 1999	-1979.973***	(138.696)
Mixed County x 2001	-570.626**	(257.505)
Mixed County x 2002	-895.746***	(167.792)
Mixed County x 2003	-673.451	(416.582)
Mixed County x 2004	-7.474	(666.038)
Mixed County x 2005	565.282*	(336.614)
Mixed County x 2006	-37.392	(471.723)
Mixed County x 2007	-1988.482***	(190.924)
Mixed County x 2008	-1758.023***	(331.172)
R-squared	0.073	
Observations	19,456	

Notes: Estimates are based on equation 1. The coefficients represent the estimated differences between mixed counties and control counties relative to the difference in 2000. Estimates control for the same climate and price data as Table 2. Standard errors are reported in parentheses. One, two, and three stars denote significance at the 10, 5, and 1 percent levels, respectively.

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