How does a Fraud Mitigation Program Influence Insurance Claims filing Behavior? Evidence from the "Spot Check List" Program in U.S. Crop Insurance

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Abstract:

The "Spot Check List" (SCL) approach is an important tool developed to help detect and deter fraud, waste, and abuse in the U.S. crop insurance program. This article carefully examines whether the SCL approach affects producers' claims filing behavior and provides insights with regards to the effectiveness of this program. Using proprietary county-level SCL data and panel data econometric procedures (which controls for both observable and unobservable confounding factors), we find evidence that counties with more than three producers included in the SCL tend to have better actuarial performance (i.e., less claims) after being informed about listing in the SCL. This indicates that the SCL procedure seem to be a promising tool for fraud mitigation in the Federal crop insurance program.

Acknowledegment:

JEL Codes: Q14, G22

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Keywords: Spot Check List; Insurance Fraud; Crop Insurance

JEL Classification Numbers: Q18; Q14; G22

1 Introduction

Fraud is a major problem in all lines of insurance because it has the potential to significantly reduce the monetary returns from providing insurance coverage (i.e., it reduces the potential underwriting gains that insurance providers can receive). For government-subsidized insurance programs, like U.S. crop insurance, fraud issues are also of critical importance especially because the government does not want the public to view them as mismanaging the taxpayer dollars used to help support these programs. Hence, the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA), the government agency in charge of administering the US crop insurance program, developed and implemented the "Spot Check List" (SCL) approach in 2001 as part of its efforts to minimize fraud, waste, and abuse in the Federal crop insurance program (USDA-RMA, 2006).

The RMA and their partners use complex algorithms to analyze their large data warehouse, which contains extensive crop insurance-related data records and information from other related databases collected over time (i.e., weather data and/or other administrative data from other USDA agencies), with the aim of detecting individual producers whose claims behaviors demonstrate atypical patterns indicative of potentially fraudulent activity. One of the main outputs from this process is the SCL, a list of insured farmers that investigators believe have a higher probability of engaging in crop insurance fraud and abuse, which may then warrant an on-site inspection during the following season.

The SCL is generated by first computing a fraud probability score for each insured producer. The score is relative to other producers for the same crop, type, and practice within the same county and is automatically adjusted to compensate for years with few losses and years with large losses. A cutoff point is then established and producers with a score above the cutoff point are put into a pool of potential targets for the SCL. In addition, several other potential fraud scenarios are analyzed to identify producers that appear to demonstrate behavior suggestive of fraud, waste, and abuse. For example, the additional scenarios analyzed may pertain to finding producers that have large multi-year losses that are anomalous (i.e., consistently higher than their peers in a county) or finding producers that have large indemnity claims for several years in a row.

Results of the scoring exercise and the scenario analysis are then used to carefully create an initial pool of producers that can be included in the SCL. This initial pool is then forwarded to RMA Regional Compliance Offices for further review (i.e., the regional office can suggest producers that can be added or removed from the initial pool based on "on-the-ground" experience). After this careful regional assessment, a final SCL is created. All producers included in the SCL for a particular crop year (say, in 2017, where data through December 2017 is analyzed) are then typically notified of their inclusion in the list by the middle of the following year (e.g. June 2018) via a formal hard copy letter. The final SCL information is also forwarded to the local USDA county offices (i.e., the Farm Service Agency (FSA) offices) and these county-offices are tasked to send out agents to perform on-site inspections of selected producers in the SCL (i.e., not all SCL producers are inspected).

In light of this SCL procedure, the main objective of this paper is to determine the effect of the SCL program on claims behavior of insured producers and to provide some insights on whether or not the SCL program indeed helps reduce fraud, waste, and abuse in the US crop insurance program. Finding an effective way to reduce fraud, waste, and abuse is critical for the sustainability of the crop insurance program, and, consequently, to the continued vitality of the US agricultural and food system. Thus, carefully evaluating whether or not the SCL program is effective in reducing crop insurance fraud (and abuse) has important public policy implications. If the SCL program is found to be effective in reducing exaggerated claims, then more public funding should be devoted to expand the scale and the scope of the program. On the other hand, if the program is found to be not as effective, then effort should be devoted to searching for other strategies that can help reduce insurance fraud and abuse.

Numerous studies in the literature have examined how the actuarial performance of the

U.S. crop insurance program can be improved either through better rate-making procedures (i.e., to address adverse selection) or contract parameter modifications (i.e., to address ex ante moral hazard). For example, see the studies of Knight and Coble (1999), Borman and Goodwin (2013), and Knight et al. (2010), among others, where different approaches to improve the U.S. crop insurance rate-making process were explored to help address adverse selection problems. The study of Turvey (2012), on the other hand, is an example of one study that explores alternative contract mechanisms that can help curb ex ante moral hazard.

Only a few studies have examined fraud behavior in crop insurance (i.e., also called ex post moral hazard, since this act is typically done after the insured outcome has occurred). One example is the study of Rejesus (2004) where he found evidence of collusion by insurance agents, adjusters, and producers in the crop insurance program. The study of Atwood, Robison-Cox, and Shaik (2006) also examined the possible existence of yield switching fraud in crop insurance (i.e., where farmers switch yields reported across insured fields so as to increase guaranteed yields and increase the likelihood of losses).

However, to the best of our knowledge, there has been no study that carefully examined the economic effectiveness of fraud mitigation policies in crop insurance. This study will contribute to the literature in this regard. Note that USDA-RMA's Program Compliance and Integrity Annual Reports, which were submitted to Congress from 2004 to 2006, all indicated that the SCL approach is an effective method to discourage misrepresentation of crop insurance claim amounts and other types of insurance fraud (USDA-RMA, 2004 to 2006). However, this conclusion was solely based on simple "before-&-after" comparisons of claims behavior (i.e., indemnity amounts before and after receipt of SCL letter), without controlling for possible confounding factors that could have also affected the observed claims behavior (e.g. weather conditions, production inputs, etc.). In addition, these reports also did not address endogeneity issues with respect to the variable that represents inclusion in the SCL due to unobserved heterogeneity. Therefore, in this study, we employ static and dynamic panel data econometric models that can help overcome these issues (i.e., controlling for observable confounding factors and endogeneity due to unobservables), and more accurately identify the effect of the SCL fraud-mitigation procedure on insureds' actuarial performance.[1]

The paper is organized as follows. In the next section, we present a conceptual framework that provides testable hypotheses about the effects of the SCL on insurance claims behavior. In section 3, we describe the proprietary county-level data (and variables) used in our empirical analysis. In section 4, we discuss the econometric model developed to account for the econometric issues above. In section 5, main findings from our estimations are discussed. In section 6, we conduct robustness checks to examine the sensitivity of our results when using alternative specifications. Concluding comments and policy implications are provided in the final section.

2 Conceptual Framework

In the theoretical insurance literature, two paradigms have been widely used to analyze the ex post moral hazard or insurance fraud behavior by an insured (Rejesus, 2003; Picard, 2013; Vercammen and van Kooten, 1994). The first framework is the so-called costly state verification paradigm, attributed to Townsend (1979). In this type of models, the insured knows the actual magnitude of the loss, there is no cost for the insured to file a falsified claim, and the insurer can learn the true loss by incurring a fixed auditing cost. The second framework is the costly state falsification paradigm, attributed to Lacker and Weinberg (1989). In this second type of model, it is assumed that the insured is able to manufacture an observed claim that exceeds the loss actually suffered, by incurring a resource cost. It is also assumed that there is no way for the insurer to learn the true loss.

Crop insurance has features of both models. On one hand, there are some costs for the insured to file a falsified claim. The insured probably needs to incur costs to further damage the crop or bribe the adjuster from the insurance company to help exaggerate his loss. In

[1] As discussed further below, there is also left-censoring in the main SCL variable used in our empirical analysis due to government data reporting rules (i.e., related to privacy laws). Hence, our panel data econometric models also accounted for this issue.

addition, there is a nonzero probability that he will be caught and in that case, he will be banned from participating in any federal programs in the future. On the other hand, with some costs, the insurance company and the government can probably know fairly well the true loss of the producer through a careful audit. In several high-profile real-life cases, charged producers or insurance agents either pleaded guilty to or were convicted of crop insurance fraud after criminal investigations by the authorities. Because of these characteristics, our model below incorporates features from both paradigms.

Formally, assume that a producer participates in the crop insurance program. The insurance contract specifies that the indemnity payment schedule is $t(x)$, where x is the claimed loss at the end of the production season. Due to the large number of producers who purchase crop insurance and the relatively small number of staff at the insurance companies and RMA, each filed claim is only audited with a probability $p(x)$, with $p^{'}(x) > 0$, which means that claims with larger losses are more likely to be audited. Further assume that the producer needs to incur a falsification cost of $C(y - x)$ if his true realized loss is x, but instead he files a claim of y greater than x. To exaggerate his loss, a producer needs to further damage his crops, or falsify yield records, or simply bribe the insurance adjuster/agent. All these activities are costly. Also, we assume that if he is caught, there is a penalty of $f(y - x)$. This function captures the fact that if his fraud behavior is caught, not only does he need to pay back the exaggerated part of his claim, he also faces the possibility of going to prison or being banned from participating in any federal programs in the future. This is likely to be very costly for the insured producer. We further assume that both $\dfrac{\partial C(y-x)}{\partial (y-x)} > 0$ and $\dfrac{\partial f(y-x)}{\partial (y-x)} > 0$, which means both the falsification cost and the penalty are increasing in the amount of the exaggerated claim. For simplicity, we can use the specification $C(y - x) = \dfrac{\gamma}{2}(y - x)^2$ and $f(y - x) = \dfrac{\delta}{2}(y - x)^2$, where $\gamma > 0$ and $\delta > 0$ are the cost parameters. With these assumptions, the producer's objective function can be written as follows,

$$\pi = \big[1 - p(y)\big] \cdot U\big[t(y) - C(y - x)\big] + p(y) \cdot U\big[t(x) - C(y - x) - f(y - x)\big], \tag{1}$$

where $U(\cdot)$ is a twice differentiable von Neumann-Morgenstern utility function with $U^{'}(\cdot) > 0$ and $U^{''}(\cdot) < 0$. $\big[t(y) - C(y - x)\big]$ is the producer's return if he files an exaggerated loss of y and he is not audited. In this case, he will get the indemnity payment of $t(y)$ and pay no fine. The term $[t(x) - C(y - x) - f(y - x]$ is the producer's return if he is audited and caught cheating. In this case, his indemnity payment is $t(x)$ and he pays a fine of $f(y - x)$. The producer's maximization problem is to maximize (1) with respect to y, the amount of loss to claim. The first-order necessary condition for maximization is:

$$\begin{aligned}
&- p^{'}(y) \cdot U[t(y) - \frac{\gamma}{2}(y - x)^2] + [1 - p(y)] \cdot U^{'}[t(y) - \frac{\gamma}{2}(y - x)^2] \cdot [t^{'}(y) - \gamma(y - x)] \\
&+ p^{'}(y) \cdot U[t(x) - \frac{\gamma}{2}(y - x)^2 - \frac{\delta}{2}(y - x)^2] \\
&+ p(y) \cdot U^{'}[t(x) - \frac{\gamma}{2}(y - x)^2 - \frac{\delta}{2}(y - x)^2] \cdot [-\gamma(y - x) - \delta(y - x)] = 0.
\end{aligned} \tag{2}$$

To guarantee that the solution to (2) is the maximum, we also need to impose the following second-order sufficient condition: $FOC_y < 0$, where $FOC(\cdot)$ is the left hand side of (2) and FOC_y is the derivative of $FOC(\cdot)$ with respect to y.

The SCL program increases the producer's falsification cost, which corresponds to the γ parameter in our model. Once a producer is on the SCL, the insurance company or USDA field offices can conduct an on-site inspection during the proceeding production season. The on-site inspection will give the insurance company or USDA-RMA fairly good information on how much the producer has actually planted and the status of his production. This will make it more difficult or more costly for the producer to exaggerate his loss when filing insurance claims. To see the effect of such an increase in falsification cost on the amount of loss to file, we derive the comparative statics of y with respect to γ in our model. Total differentiation of (2) with respect to the two variables yields $FOC_y dy + FOC_\gamma d\gamma = 0$ where FOC_γ is the first derivative of $FOC(\cdot)$ with respect to γ. Therefore, we have $\dfrac{dy}{d\gamma} = -\dfrac{FOC_y}{FOC_\gamma}$. Since $FOC_y < 0$ is the second-order sufficient condition required for the existence of the maximum, the sign of $\dfrac{dy}{d\gamma}$ is determined by the sign of FOC_γ. From (2), it is straightforward to obtain as follows,

$$\begin{aligned}
FOC_\gamma = {} & p'(y) \cdot U'\Big[t(y) - \frac{\gamma}{2}(y-x)^2\Big] \cdot \frac{(y-x)^2}{2} \\
& - \Big[1 - p(y)\Big] \cdot U''\Big[t(y) - \frac{\gamma}{2}(y-x)^2\Big] \cdot \frac{(y-x)^2}{2} \cdot \Big[t'(y) - \gamma(y-x)\Big] \\
& - \Big[1 - p(y)\Big] \cdot U'\Big[t(y) - \frac{\gamma}{2}(y-x)^2\Big] \cdot (y-x) \\
& - p'(y) \cdot U'\Big[t(x) - \frac{\gamma}{2}(y-x)^2 - \frac{\delta}{2}(y-x)^2\Big] \cdot \frac{(y-x)^2}{2} \\
& + p(y) \cdot U''\Big[t(x) - \frac{\gamma}{2}(y-x)^2 - \frac{\delta}{2}(y-x)^2\Big] \cdot \frac{(y-x)^2}{2}(y-x)(\gamma+\delta) \\
& - p(y) \cdot U'\Big[t(x) - \frac{\gamma}{2}(y-x)^2 - \frac{\delta}{2}(y-x)^2\Big] \cdot (y-x).
\end{aligned} \tag{3}$$

With the assumptions made above, it is clear that the first term of (3) is positive, the sign of the second term is unclear and the third, fourth, fifth, and sixth terms are all negative. Therefore, if the sum of the first two terms in (3) is negative, then this is a sufficient condition for $\dfrac{dy}{d\gamma} < 0$. A weaker sufficient condition is simply that (3) is negative. Whether or not these sufficient conditions hold depends on the specifications of $p(\cdot)$, $U(\cdot)$, and $t(\cdot)$, as well as the magnitudes of γ and $(y-x)$. In the special case of a linear utility function with $U'(\cdot) = 1$ and $U''(\cdot) = 0$, (3) is reduced to be $-(y-x)$ and is negative for sure. This leads to one testable hypothesis: *Producers who are on the Spot Check List (SCL) files smaller claims than what they would have if they were not on the Spot Check List (SCL).*

We note, however, that this testable hypothesis can only be empirically validated if one has access to: (i) individual-producer data on whether or not he is on the SCL at a particular point in time, and (ii) the associated claims behavior data over time (preferably claims behavior when the insured was not on the SCL and after he has been put in the SCL (and/or inspected)). Due to the confidentiality reasons explained in more detail below, individual-producers' data relating to our variables of interest (i.e., being on the SCL list, and claims behavior) are not easily accessible. As such (and as discussed further below), only county-level data about SCL listings and claims filing behavior are the only data accessible to us at the moment, and this is the type of data set we use below to test our hypotheses.

Therefore, given the county-level data available, the more "aggregate-level" testable hypothesis that naturally follow from the individual-producer level hypothesis above is as follows: all other things being equal, a county with more producers in the SCL would likely have smaller claims relative to other counties with less (or no) SCL producers.

3 Data

The data used in our study come from several different sources. Each data source is explained in turn below with a focus on the variables used in the econometric estimation. Since the SCL program started in 2001, we restrict our analysis to data from 2001 to 2015. Also, we only focus on yield-based and revenue-based individual policies, the two major crop insurance policies[2] for the following five major US row crops included in our data set: corn, soybeans, wheat, cotton, and tobacco. Therefore, our data still include 78.04% of all crop insurance policies for which acreage has been reported to USDA-RMA from 2001 to 2015. These data come from 2,194 counties across all U.S. states, except in Alaska, Hawaii, and Rhode Island.[3]

The county-level measures of claims behavior used in our study are: (1) the loss ratio (LR), (2) the subsidy adjusted loss ratio (LRsubsidy) and (3) the loss cost ratio (LCR).These are standard measures of actuarial performance and serve as the dependent variables considered in our regression analysis. LR is defined as the ratio between total indemnity and premiums, while LRsubsidy is defined as the ratio of total indemnity and producer paid premiums (total premiums minus government subsidy). Finally, LCR is defined as the ra-

[2]Only Yield-Protection (YP) and Revenue Protection (RP) policies (as these policies are called today) are included in the analysis. Thus, other "less-popular" plans like the Area Risk Protection Insurance (ARPI) and Whole Farm Revenue Protection (WFRP) Insurance policies are not considered in this study.

[3]Crop insurance policies sold from 2001 to 2015 were distributed in 2,832 counties across all 50 U.S. states.

tio between total indemnity and liability. County-level crop insurance experience data such as total insurance premium, indemnity, subsidy, and liability are publicly available from USDA-RMA,[4] and we use this information to compute LR, LRsubsidy, and LCR.

As for the explanatory variables in our regression analysis, the key variable of interest in this study is the number of producers on the SCL in each county (SCL). We obtained this proprietary data from USDA-RMA through a special agreement. Due to government regulations regarding data confidentiality, the number of SCL producers in a county is only reported in our data set if the county has at least four producers on the SCL. We therefore cannot exactly identify the number of producers on the SCL in a county when the number of producers on the SCL is less than 4 (i.e., we only know that the number can be 0, 1, 2, or 3). Therefore, our empirical specification below is designed to accommodate this important data feature. The numbers of counties with more than 3 SCL producers from 2001 to 2015 are presented in Table 1. The numbers ranged from 72 to 186 during the sample period. On average, 123 counties had at least four SCL producers in a particular year and these counties had approximately 7 SCL producers every year. Table 2 summarizes the detailed frequency distribution of counties with each number of SCL producers by year. Figure 1 provides the spatial distribution of the total number of SCL producers from 2001 to 2015 by county.[5] We note that counties with SCL producers are scattered throughout the continental U.S. with some clustering in the upper Midwest, the Dakotas, the Plains (i.e., Kansas, Nebraska and the Texas Panhandle), and the Southeastern States (i.e., North Carolina, South Carolina, Georgia, and Florida). When the SCL program started in 2001, the Dakotas and the Plains were the center of intensive investigation, but the clusterings had gradually disappeared during the 10-year period from 2001 to 2010 as seen in Figure 2. Figure 3 presents the spatial distributions of the number of SCL producers from 2012 to 2015. It appears that for these four years, SCL had been concentrated in a new region including Iowa, Missouri,

[4] See: https://www.rma.usda.gov/data/sob/scc/index.html.

[5] Given the limitation on the number of SCL producers reported in our data, if the number of SCL producers in a year was less than four for a county, then the number of SCL producers in this figure is coded as zero.

Illinois, and Kansas. Figure 4 also demonstrates how indemnities in counties had changed for 3 years since they had at least four producers on the SCL. In most years, there had been a steady decrease in total indemnities paid to counties after they had at least four producers on the SCL. However, in some years, particularly from 2005 to 2010, there had been increases. Indemnities for these years probably were also impacted by worse weather conditions (e.g. severe nationwide drought). The same trend can be seen for LR (Figure 5), LRsubsidy (Figure 6) and LCR (Figure 7).

In addition to the main variable of interest above, claims behavior at the county level is also influenced by characteristics of the insurance policies that farmers in the county purchase. For this reason, we also include the following county-level control variables in our regressions: average number of acres insured per unit insured (*Unit Size*), the ratio of revenue-based relative to yield-based policies (*Insurance Type*), the ratio of buy-up relative to catastrophic coverage (*Coverage Type*), and the average coverage level (*Coverage Level*) weighted by the number of policies at each level. Specifically, producers can purchase minimum catastrophic coverage (CAT) that will protect up to 50% of their expected yield/revenue (at 55% of the price), if a loss occurs. Producers can buy-up to higher levels of coverage with the option to insure up to 85% of the expected yield/revenue. We include the average coverage level for each county and year to take into account the effect of coverage levels on claims. We obtained data on these variables from USDA-RMA's summary of business.[6]

Weather is also an important determinant of agricultural yields and, consequently, the resulting crop insurance claims (or loss) amounts. For this reason, we collected weather data from several sources. First, based on the work of Schlenker and Roberts (2009) and available data from PRISM,[7] we collected monthly county level data on average (averaged across different days in a month as well as different places in a county) precipitation (mm), minimum temperature (°C), maximum temperature (°C), and total degree days above 30 °C

[6]See: https://www.rma.usda.gov/data/sob/scc/index.html.
[7]See: http://www.prism.oregonstate.edu.

for the growing months.[8] Monthly total degree days are defined as the sum of degrees above a certain threshold during a given month.[9] Specifically, Annan and Shenkler (2015) use degree days above 30 °C as a measure of extreme heat because the threshold can be considered harmful for most U.S. field crops. In addition, to take drought and flood conditions into account (i.e., extremely dry and extremely wet conditions), we also collected data on the state-level Palmer Drought Severity Index (PDSI) (also called the Palmer Z index) from the National Oceanic and Atmospheric Administration (NOAA). For ease of interpretation, we constructed two variables based on the PDSI, one that represent dryness (or drought conditions) and the other for wetness (or flood conditions).[10]

Another important determinant of agricultural yields and resulting claims amounts is the production inputs used by insured farmers. Thus, we collected county-level expenditure data on seed, fertilizer and chemicals, labor, and other production expenses, from Bureau of Economic Analysis (BEA).[11] We then divided the expenditure data by the number of acres planted in the county to get the per acre expenditure data.[12] Land rental values for agricultural land per acre are used as the measure of capital cost, and state-level data on this variable was collected from USDA Quick Stats.[13]

Table 3 lists the variables used in our regression analysis below and the corresponding data sources. The summary statistics for these variables are displayed in Table 4.

[8]According to USDA(2010), March to November are the growing months for these five crops.

[9]Ritchie and NeSmith (1991) argue that the most simple and useful definition of thermal time (t_d) is $t_d = \sum_{i=1}^{n} max\{(\overline{T}_i - T_b), 0\}$, where $\overline{T}_i$ is the daily average temperature, T_b is the threshold temperature, and n is the number of days. For details of how this variable was constructed, see Schlenker and Roberts (2006), Schlenker, Hanemann, and Fisher (2007), and SI Appendix of Schlenker and Roberts (2009).

[10]County level data for this index are not publicly available. The Palmer Z index is a short-term drought index that measures the dryness of a region for a particular month. It does not take into account drought conditions in the previous months.

[11]See: https://www.bea.gov/regional/.

[12]The county-level crop acreage planted was approximated by dividing crop acreage insured reported in USDA-RMA's summary of business by the state level percentage of insured acreage as reported by USDA-NASS. Therefore, there could be approximation error if the percentage of acres insured in a county is very different from the state average.

[13]See: http://quickstats.nass.usda.gov/.

4 Empirical Strategy

Since we have a county-level panel data set, we first employ a static linear panel data model with fixed effects to investigate the SCL effects as follows,

$$y_{it} = f(SCL_{i,t-1}, ..., SCL_{i,t-J}) + \gamma \cdot X_{it} + \lambda_t + \delta \cdot t + \mu_i + \epsilon_{it}, \tag{4}$$

where y_{it} is the logarithm of LR (or LRsubsidy or LCR) in county i and year t,[14] and $SCL_{i,t-j}$ $(j = 1, ..., J)$ are the number of SCL producers in county i in year $t-j$ $(j = 1, ..., J)$. The SCL variables are our main variables of interest and meant to capture the effects of the SCL program on farmers' claims filing behavior. Since farmers put on the SCL in year $t-1$ are inspected in year t, we did not include $SCL_{i,t}$ in the model. Further lags of the SCL variable beyond the first lag are included to allow for lagged effects of the SCL program on farmers' claims filing behavior. The empirical specification in (4) also includes X_{it}, a vector of time-varying, county-level control variables such as characteristics of the crop insurance policies sold, weather variables, and production inputs; λ_t, the year fixed effects, to control for effects from macro level variables that do not vary across counties; t, a linear time trend; μ_i, the county fixed effects to control for time-invariant county level factors that influence claims behavior, and ϵ_{it}, the idiosyncratic error for county i in year t. We estimate (4) using the standard fixed effects regression method.

In addition to the static model (4) above, since farmers' claims filing behavior may exhibit state dependence, we also employ a dynamic linear panel data model with fixed effects as follows,

$$y_{it} = \sum_{j=1}^{J} \alpha_j y_{i,t-j} + f(SCL_{i,t-1}, ..., SCL_{i,t-J}) + \gamma \cdot X_{it} + \lambda_t + \delta \cdot t + \mu_i + \epsilon_{it}. \tag{5}$$

[14]For the LR and LCR variables, 513 observations out of 30,457 have a zero value and these observations were dropped from the analysis. For the LRsubsidy variable, 537 observations were dropped since 454 observations have a zero value and the total premiums of 83 additional observations were completely covered from subsidy. In addition, 16 observations which have LCR > 1 were also excluded.

To estimate (5), we first difference (5) to remove the county fixed effects,

$$\Delta y_{it} = \sum_{j=1}^{J} \alpha_j \Delta y_{i,t-j} + \Delta f(SCL_{i,t-1}, ..., SCL_{i,t-J}) + \gamma \cdot \Delta X_{it} + \Delta\lambda_t + \delta + \Delta\epsilon_{it}. \tag{6}$$

By construction, the $\Delta y_{i,t-1}(= y_{i,t-1} - y_{i,t-2})$ variable in (6) is endogenous as it is correlated with $\Delta\epsilon_{it}(= \epsilon_{it} - \epsilon_{it-1})$. Therefore, we use the GMM estimator of Arellano and Bond (1991) to estimate (6). We use three sets of instruments to account for the endogeneity in this specification. First, as suggested by Arellano and Bond (1991), we use the second and feasible higher-order lags of the dependent variable, i.e., $y_{i,t-2}$, $y_{i,t-3}, ..., y_{i,t-14}$[15]. Suppose J in (6) is chosen to be 3 and hence observations in the first three years of our data (2001, 2002, and 2003) cannot be used in estimation, this first set of instruments generate the following set of 88 moment conditions as,

$$\begin{aligned}
\mathbb{E}\left(y_{i,t-2} \cdot \Delta\epsilon_{it}\right) &= 0, \quad \text{for } t = 2005, 2006, 2007, \cdots, 2015 \\
\mathbb{E}\left(y_{i,t-3} \cdot \Delta\epsilon_{it}\right) &= 0, \quad \text{for } t = 2005, 2006, 2007, \cdots, 2015 \\
\mathbb{E}\left(y_{i,t-4} \cdot \Delta\epsilon_{it}\right) &= 0, \quad \text{for } t = 2005, 2006, 2007, \cdots, 2015 \\
\mathbb{E}\left(y_{i,t-5} \cdot \Delta\epsilon_{it}\right) &= 0, \quad \text{for } t = 2006, 2007, \cdots, 2015 \\
\mathbb{E}\left(y_{i,t-14} \cdot \Delta\epsilon_{it}\right) &= 0, \quad \text{for } t = 2015.
\end{aligned}$$

[15] As we have 15 years of data, we can only use 14 lags at most.

In a matrix form, we can stack these moment conditions as,

$$\mathbb{E}\left(\begin{bmatrix} y_{i2003} & 0 & 0 & \cdots & 0 \\ y_{i2002} & 0 & 0 & \cdots & 0 \\ y_{i2001} & 0 & 0 & \cdots & 0 \\ 0 & y_{i2004} & 0 & \cdots & 0 \\ 0 & y_{i2003} & 0 & \cdots & 0 \\ 0 & y_{i2002} & 0 & \cdots & 0 \\ 0 & y_{i2001} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & y_{i2001} \end{bmatrix} \times \begin{bmatrix} \Delta\epsilon_{i2005} \\ \Delta\epsilon_{i2006} \\ \Delta\epsilon_{i2007} \\ \vdots \\ \Delta\epsilon_{i2015} \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{7}$$

which can be written succinctly as $\mathbb{E}(Z_{Di} \cdot \Delta\mathcal{E}_i) = \overrightarrow{0}$, where $\Delta\mathcal{E}_i = [\Delta\epsilon_{i2005}, \Delta\epsilon_{i2006}, \cdots, \Delta\epsilon_{i2015}]^T$ and

$$Z_{Di} = \begin{bmatrix} y_{i2003} & 0 & 0 & \cdots & 0 \\ y_{i2002} & 0 & 0 & \cdots & 0 \\ y_{i2001} & 0 & 0 & \cdots & 0 \\ 0 & y_{i2004} & 0 & \cdots & 0 \\ 0 & y_{i2003} & 0 & \cdots & 0 \\ 0 & y_{i2002} & 0 & \cdots & 0 \\ 0 & y_{i2001} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & y_{i2001} \end{bmatrix}.$$

Second, we can use the differenced explanatory variables to form a second set of moment conditions $\mathbb{E}(\Delta X_{it} \cdot \Delta\epsilon_{it}) = \overrightarrow{0}$, as proposed by Arellano and Bond (1991). In our specification, 78 (or 84 in the case of using SCL grouping dummies) covariates are used and therefore, there are 78 (or 84) moment conditions in this set.

Lastly, following Arellano and Bover (1995), Blundell and Bond (1998), and Blundell, Bond, and Windmeijer (2000), we can also interact the lagged first differenced dependent variable $\Delta y_{i,t-1}$ with the error term in the level equation (5) ϵ_{it} to form the third set of moment conditions $E(\Delta y_{i,t-1}\epsilon_{it}) = 0$ for $t = 2004, ..., 2015$. This yields another 12 moment conditions.

We then stack all three sets of moment conditions together and estimate the model using a two-step optimal GMM method. A total of 178 (or 184 in the case of using SCL grouping dummies) moments conditions are used to estimate 81 (or 87) unknown parameters in (5). Arellano and Bond (1991) suggest that the standard errors estimated by the two-step GMM may be biased downward. Therefore, we follow Windmeijer (2005) to obtain the bias-corrected robust standard errors after estimation.

To complete our empirical specifications, $f(SCL_{i,t-1}, ..., SCL_{i,t-J})$ needs to be specified. As mentioned above, the SCL variable has been censored at three because of confidentiality reasons. To accommodate this data feature, we consider two alternative ways of defining the SCL variables used in estimation. The first one is the linear specification. We simply set each $SCL_{i,t-j}$ at its observed value and if it is censored, it is set to be 0. As a result, $f(SCL_{i,t-1}, ..., SCL_{i,t-J})$ is specified to be,

$$f(SCL_{i,t-1}, ..., SCL_{i,t-J}) = \beta_0 + \beta_1 SCL_{i,t-1} + \beta_2 SCL_{i,t-2} + \cdots + \beta_J SCL_{i,t-J}.$$

Clearly, there are measurement errors for the SCL variables created using this specification as those $SCL_{i,t-j}$s taking values between 1 and 3 are wrongly set to be 0. Our second specification avoids this problem by creating several group dummy variables for the number of SCL producers based on the SCL frequency distribution table (Table 2). Specifically, we create four SCL dummy variables to represent 4 groups of counties: $SCL03_{i,t-j} = 1$ if county i had 0-3 SCL producers in year $t - j$ and 0 otherwise; $SCL456_{i,t-j} = 1$ if county i had 4-6 SCL producers in year $t - j$ and 0 otherwise; $SCL789_{i,t-j} = 1$ if county i had 7-9

SCL producers in year $t-j$ and 0 otherwise; $SCL10Plus_{i,t-j} = 1$ if county i had 10 or more SCL producers in year $t-j$ and 0 otherwise. With this method, $f(SCL_{i,t-1}, ..., SCL_{i,t-J})$ becomes,

$$\begin{aligned}
&f(SCL_{i,t-1}, ..., SCL_{i,t-J}) \\
&\quad = \beta_0 + \beta_1^{456} \cdot SCL456_{i,t-1} + \beta_2^{456} \cdot SCL456_{i,t-2} + \cdots + \beta_J^{456} \cdot SCL456_{i,t-J} \\
&\quad + \beta_1^{789} \cdot SCL789_{i,t-1} + \beta_2^{789} \cdot SCL789_{i,t-2} + \cdots + \beta_J^{789} \cdot SCL789_{i,t-J} \\
&\quad + \beta_1^{10Plus} \cdot SCL10Plus_{i,t-1} + \beta_2^{10Plus} \cdot SCL10Plus_{i,t-2} + \cdots + \beta_J^{10Plus} \cdot SCL10Plus_{i,t-J},
\end{aligned}$$

with SCL^{03} as the omitted category. Compared with the linear specification, one disadvantage of the group dummy method is that with group dummies, we can no longer examine the marginal effect of having one more SCL producer on the claims filing behavior of the farmers. Instead, we can only examine the effect on claims when the number of SCL producers changes from one category to another.

5 Results

The estimation results from the static models are presented in Tables 5 and 6. Table 5 collects the results where the linear specification is used for the SCL variables while Table 6 collects the results where SCL group dummies are used. The regressions include all the variables listed in Table 4, but the coefficients for the weather variables are not reported for brevity. The full results are reported in Tables A.1 and A.2 in the appendix. Also, J is chosen to be 3 in these regressions. In Table 5, we first note that the SCL program has strong deterrence effect. When there are more SCL producers in the county, producers file less claims. For example, having one more producer on the SCL last year decreases the loss ratio (LR), the subsidy adjusted loss ratio (LRsubsidy) and the loss cost ratio (LCR) in the current year by 1.3%, 1.5% and 1.2%, respectively and these effects are all statistically significant at the 1% significance level. In the case when group dummies of SCL are used

(Table 6), we also identify strong negative and significant results for the SCL dummies. More importantly, the magnitudes of the negative effects also become larger (in absolute values) as the number of SCL producers increases from a low to a high category. For example, counties with 4-6 SCL producers last year have lower subsidy adjusted loss ratio (LRsubsidy) by 8.8% while counties with 7-9 and 10 or more SCL producers have lower subsidy adjusted loss ratio by 12.6% and 22.0%, respectively.

Some results associated with control variables are also worth discussing. Regarding the insurance policy characteristics variables, our results show that counties with larger insured units on average have lower LR and LCR. This result is consistent with the empirical regularity in crop insurance where larger insured units tend to have lower risk or more aggregated insured areas tend to have lower variability. Larger insured units have a higher chance of a "portfolio" effect where the part of a large unit with a loss tends to be compensated with another area within the unit that has no loss (see, for example, Knight et al., 2010 and Marra and Schurle, 1994). Moreover, results indicate that counties with higher ratios of revenue-based relative to yield-based insurance policies have lower loss ratio, subsidy adjusted loss ratio and loss cost ratio, which is consistent with the inherent "natural hedge" between prices and yields when revenue is insured instead of just yields. Lastly, counties with producers purchasing more of buy-up coverage (relative to CAT) and counties where producers buy more coverage have higher LRs, LRsubsidys and LCRs, which simply indicates that likelihood of losses increases as insurance coverage increases.

Next, with regards to the production inputs, results show that per acre rent and other expenses than seed, fertilizers and labor have a positive effect on claims filed. This implies that farmers with higher costs on these two items are more likely to file for indemnity payments. However, higher per acre fertilizer, chemicals, and labor costs have a negative effect on claims filed. This may be due to the fact that with more fertilizer, chemicals, and labor, yields are likely to be higher and losses are less likely.

We now turn to the dynamic models. The first set of moment conditions above, $\mathbb{E}(Z_{Di} \cdot$

$\Delta\mathcal{E}_i) = \overrightarrow{0}$, is valid only if there is no second-order autocorrelation in the first-differenced idiosyncratic error term $\Delta\epsilon_{it}$.[16] Therefore, before we present and discuss our estimation results from the dynamic models, we first test for autocorrelation in $\Delta\epsilon_{it}$. This is feasible after estimation since an estimate for $\Delta\epsilon_{it}$ can be recovered from (6) using the data and the parameter estimates. The test results are reported in Table 7. The results clearly reject the null hypothesis that there is no first-order autocorrelation in $\Delta\epsilon_{it}$ and fail to reject the hypothesis that there is no second-order autocorrelation in $\Delta\epsilon_{it}$, which lend support to our empirical specification.

The estimation results from the dynamic models are presented in Tables 8 and 9. Table 8 collects the results where the linear specification is used for the SCL variables while Table 9 collects those where SCL group dummies are used. Again, the coefficients for the weather variables are not reported and the full results are reported in Tables A.3 and A.4 in the appendix. Several results are worth discussing. First, our estimation results clearly show that there is persistence in the LR and LRsubsidy (LCR) variables for at least two (one) years. Tables 8 and 9 indicate that LR and LRsubsidy (LCR) values in the past two (one) years have a positive and statistically significant effect on the LR and LRsubsidy (LCR) values in the current year, with the effect from the last year being larger in magnitude than the effect from two years ago. This result may be capturing state-dependence in losses where unobservable time-varying conditions (like slowly-evolving states of soil nutrient levels and climate trends) have some persistent effects on yield outcomes. This result also shows the importance of using a dynamic specification and including the lagged dependent variables in the empirical model.

Second, with regards to our main SCL variables of interest, we identify stronger deterrence effect compared to the results from the static models. Based on the parameter estimates in Table 8, an additional SCL producer last year decreases this year's LR, LRsubsidy, and LCR by 5.3%, 5.6%, and 4.9%, respectively. These estimated effects are four times larger than

[16]By construction, the first differenced error term is first-order autocorrelated.

those from the static models reported in Table 5. These effects are statistically significant at the 1% significance level. Furthermore, coefficients associated with the SCL group dummies (Table 9) reveal more clear-cut evidence that more SCL producers in a county lead to a much larger reduction in the claims filed. For example, compared with counties with 0-3 SCL producers last year, a county with 4-6, 7-9, and 10 or more SCL producers last year have a LR 32.1%, 49.8%, and 62.2% lower this year, respectively. These effects are again three or four times larger than those from the static models (Table 6) showing the importance of controlling for lagged dependent variables in identifying the SCL effects. There is also evidence that the SCL effects can last for several years. For example, compared with counties with 0-3 SCL producers, a county with 7-9 SCL producers last year has a subsidy adjusted loss cost ratio (LRsubsidy) 50.8% lower this year, 26.2% lower next year, and 25.0% lower two years later, respectively. These results show that the SCL program has strong deterrence effect, i.e., when there are more SCL producers within the same county, producers file much less claims.

Finally, regarding the control variables, the results are almost identical to those from the static models with only a few differences. First, expenses on petroleum products such as gasoline have positive and statistically significant effects on claims filed. Second, expenses on fertilizers, chemicals, and other things no longer have statistically significant effects on claims filed.

6 Robustness Checks

In the analysis so far, we have chosen the lag-depth J in our empirical models to be 3. In this section, we examine different lag-depth specifications and see whether our main results above are robust to alternative lag-depth specifications. We start with $J = 1$ and then go up to $J = 4$ using the logarithm of the loss ratio (LR) as the dependent variable.

Table 10 collects the regression results using the linear SCL specification and alternative lap-depths from $J = 1$ to $J = 4$. The left four columns present the estimation results from the static model and the last four ones come from the dynamic model. For the purpose of brevity, we only report the coefficient estimates for the SCL and lagged dependent variables here.[17] We first note that our main findings continue to hold, both in terms of the signs of the estimates and their statistical significance (except $J = 1$ in the static model). Regarding the magnitudes of the estimates, it is also apparent that the coefficient estimates of the first lagged SCL variable are almost the same across lag-depth specifications: i.e., for the static model, -1.1% for $J = 2$, -1.3% for $J = 3$, and -1.2% for $J = 4$; for the dynamic model, -5.3% for $J = 2$, -5.3% for $J = 3$, and -5.6% for $J = 4$.

We present the regression results using the SCL group dummies specification and alternative lap-depths from $J = 1$ to $J = 4$ in Table 11. In the left four columns for the static model, the finding that the SCL effects become larger for the group dummies that represent more SCL producers still holds across different lag-depth specifications. Regarding the dynamic model, our results show that the loss ratios are persistent over two years. The last three columns of Table 11 show that as long as we specify at least two lagged dependent variables in our dynamic model, the coefficient estimates for the first year deterrence effects across different group dummies are remarkably unchangeable compared to our baseline results. These coefficients are all statistically significant at the 1% level. In sum, we conclude that our results are robust to alternative specifications of the lag-depth J.

Furthermore, we also tried to use different sets of SCL dummies to check how the results change across different specifications of SCL groupings. In particular, we used finer groupings as follows: $SCL03_{i,t-j} = 1$ if $SCL_{i,t-j}$ is between 0 and 3 and 0 otherwise; $SCL4_{i,t-j} = 1$ if $SCL_{i,t-j} = 4$ and 0 otherwise; $SCL5_{i,t-j} = 1$ if $SCL_{i,t-j} = 5$ and 0 otherwise; and so on. We do not present the results here, but the main implications from the estimation results remain the same as those from the coarser groupings of the SCL numbers in section 5.

[17] Full results are available from the authors upon request.

7 Conclusions

Curbing the incidence of fraud, waste, and abuse is a major concern in the U.S. crop insurance program. Reducing the incidence of fraud improves the financial viability of the program (e.g. for participating private insurance providers, as well as the government), and is key to maintaining the integrity and stability of this center-piece U.S. farm safety-net policy. Recognizing this, the USDA-RMA has implemented the SCL approach to help detect producers potentially engaging in these fraudulent activities, and consequently discourage other producers from engaging in this behavior. The SCL fraud-mitigation process was developed with the hope that it reduces incidence of fraud (i.e., leading to more prosecutions and cost avoidance), as well as reduce misrepresentation (or exaggeration) of claimed losses (i.e., encourage truthful revelation).

However, even with the important role that the SCL plays in maintaining the integrity of the U.S. crop insurance program, there have been no rigorous econometric studies that have carefully examined the effectiveness of this fraud-mitigation approach. This study is the first attempt at evaluating the effect of the SCL process on producers' claims behavior. Using proprietary county-level SCL data and controlling for confounding factors that can also influence claims behavior, our econometric analyses over the 2001-2015 period provide strong evidence that the SCL process does indeed statistically affect claims behavior in the counties with SCL producers. Counties with more than three producers listed in the SCL tend to have lower LRs, LRsubsidys, and LCRs in the year the SCL producers are notified about their listing, as compared to counties with less than three (or no) producers included in the SCL. These results suggest that the SCL process may have helped facilitate reduction of potentially fraudulent or exaggerated claims (at least at the county-level). Hence, there is empirical support to the notion that the SCL approach is effective in influencing producer claims behavior.

Given the results in this paper, the SCL approach shows promise as an effective fraud-mitigation tool in U.S. crop insurance. One important policy implication is the need for continued budgetary support for this program. In particular, more resources are needed for conducting more in-season inspections (after notification of SCL listing) in order for producers to believe that USDA-RMA can "credibly" pursue further investigations after SCL listing (thereby improving effectiveness). This will assist in further encouraging truthful claims behavior. Moreover, providing resources to improve the statistical algorithms used for scoring and, ultimately, detecting producers to be included in the SCL also seem to be warranted.

Lastly, even though this article provides important advances to assessing the effectiveness of the SCL fraud-mitigation approach, further research in a couple of dimensions are still needed. First, more accurate inferences about the effectiveness of the SCL can be made if individual level SCL information is analyzed. Availability of this data will allow one to assess whether the SCL notification process actually influences individual farmer behavior. Another direction for further research may be to examine whether the link between people in the SCL directly relates to individuals actually prosecuted for crop insurance fraud in the past. This type of analysis will provide insight on whether the SCL approach at least captures anomalous behavior of those actually prosecuted of crop insurance fraud and can shed light on the effectiveness of SCL as a fraud-detection tool. This kind of research may require linking individual-level SCL data and lawsuit information.

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Table 1: Number of Counties with more than 3 SCL Producers

Year	County	Mean	Std. Dev.	Max
2001	186	14.15	18.25	134
2002	135	7.95	5.00	31
2003	138	7.30	4.47	28
2004	114	7.28	4.04	23
2005	84	6.83	4.29	21
2006	72	6.61	3.93	26
2007	155	5.95	2.65	18
2008	151	5.80	2.19	16
2009	126	5.83	2.22	19
2010	90	5.72	2.18	18
2011	102	5.65	2.29	13
2012	96	5.45	2.13	11
2013	157	5.80	2.03	11
2014	146	6.18	2.14	11
2015	89	5.10	1.64	10

Table 2: The Frequency distribution Table for SCL Counties by Year

	Number of SCL producers										
Year	≤ 3	4	5	6	7	8	9	10	11-20	21-30	>30
2001	1864	48	21	17	7	10	9	8	33	11	22
2002	1902	43	17	14	8	10	6	1	32	3	1
2003	1894	51	16	18	7	13	5	2	25	1	0
2004	1914	37	22	7	3	13	8	5	18	1	0
2005	1926	34	15	10	3	5	3	1	12	1	0
2006	1957	26	19	5	4	3	2	2	10	1	0
2007	1867	62	27	26	9	6	9	7	9	0	0
2008	1872	60	29	19	10	12	9	9	3	0	0
2009	1890	41	31	18	14	9	6	4	3	0	0
2010	1906	30	26	13	4	7	5	4	1	0	0
2011	1910	49	18	9	7	5	2	7	5	0	0
2012	1943	50	17	8	5	4	2	5	5	0	0
2013	1897	60	30	23	8	12	11	11	2	0	0
2014	1906	47	23	22	10	18	8	16	2	0	0
2015	1968	50	14	10	5	4	3	3	0	0	0
Total	28616	688	325	219	104	131	88	85	160	18	23

Table 3: List of Variables used in Estimation and their Sources

Variables	Description and Sources
1. Crop Insurance data[a]	
Average Unit size	Total acres insured/ number of units
Insurance Type	Ratio of revenue-based relative to yield-based policies
Coverage Type	Ratio of buy-up relative to catastrophic type policies
Coverage Level	Avg. coverage level weighted by the number of policies
2. Monthly weather data	
County level[b]	
Precipitation	Precipitation (mm), Jan-Dec
tMin, tMax	Averages of Min. (Max.) temperatures (Celsius), Jan-Dec
dday30C	Total degree days above 30 °C (Celsius and days), Jan-Dec
State level[c]	
Drought	Palmer Z index for drought level
Wetness	Palmer Z index for wetness level
3. Land data[d]	
Rent	Rent per acre
4. Expenses data[e]	
Seed	Seed expenditure per acre[f]
Petroleum Products	Petroleum products expenditure per acre
Fertilizer and Chemicals	Fertilizer and chemicals expenditure per acre
Hired Labor	Hired labor expenditure per acre
All Other Expenses	Expenditure per acre for Machinery, Interest, Tax, etc.

a. Reproduced from Summary of Business (USDA-RMA, County level).

b. Reproduced based on Schlenker and Roberts (2009) and PRISM.

c. Reproduced from Palmer Z Index of NOAA (National Oceanic and Atmospheric Administration).

d. USDA Quick Stats (State level).

e. BEA (Bereau of Economic Analysis): CA45 Farm income and expenses (County level).

f. Reproduced from Summary of Business (USDA-RMA) and USDA-NASS (County level).

Table 4: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Loss (Cost) Ratio				
LR	.85	.96	$5.75 * 10^{-4}$	11.90
LRsubsidy	2.31	2.66	$2.45 * 10^{-3}$	64.28
LCR	.12	.15	$5.95 * 10^{-5}$	1.00
Crop Insurance				
UnitSize	99.61	67.07	2.16	1113.48
InsuranceType	.60	.25	.00	1.00
CoverageType	.87	.16	.00	1.00
CoverageLevel	.67	.06	.50	.83
Precipitation				
Mar_precipitation	68.43	49.17	1.08	359.64
Apr_precipitation	88.82	56.43	.63	584.87
May_precipitation	101.84	59.73	.51	550.42
Jun_precipitation	107.90	62.52	.22	728.44
Jul_precipitation	93.83	54.46	.37	428.86
Aug_precipitation	89.45	56.69	.29	489.99
Sep_precipitation	80.99	59.01	.66	509.47
Oct_precipitation	78.25	56.19	1.20	552.78
Nov_precipitation	62.81	52.63	1.10	379.47
Temperature				
Mar_tMin	.07	5.50	-18.40	17.55
Apr_tMin	5.30	4.41	-8.38	20.81
May_tMin	10.90	4.00	-1.42	22.78
Jun_tMin	16.05	3.66	3.34	24.98
Jul_tMin	18.03	3.20	6.80	28.05
Aug_tMin	17.13	3.51	5.22	27.22
Sep_tMin	13.06	3.91	.46	24.37
Oct_tMin	6.57	4.00	-5.18	21.56
Nov_tMin	.52	4.53	-13.45	16.75
Mar_tMax	12.94	6.43	-6.04	30.86
Apr_tMax	19.04	4.80	1.54	34.31
May_tMax	24.05	3.84	11.38	37.88
Jun_tMax	28.75	3.49	17.91	42.16
Jul_tMax	30.82	3.00	21.17	43.30
Aug_tMax	30.17	3.24	20.24	43.47
Sep_tMax	26.63	3.44	16.39	40.10
Oct_tMax	19.83	4.54	6.26	34.21
Nov_tMax	12.97	5.33	-3.24	28.03
Mar_dday30C	.02	.29	.00	15.97
Apr_dday30C	.30	1.38	.00	35.70
May_dday30C	2.08	4.67	.00	72.28

Table 4: : Continued

Variable	Mean	Std. Dev.	Min.	Max.
Jun_dday30C	9.36	13.47	.00	137.99
Jul_dday30C	16.65	18.81	.00	182.70
Aug_dday30C	14.79	19.32	.00	179.97
Sep_dday30C	4.67	7.93	.00	109.20
Oct_dday30C	.45	1.56	.00	37.20
Nov_dday30C	.01	.11	.00	4.04
Drought				
Mar_Drought	.96	1.13	.00	5.00
Apr_Drought	.66	.95	.00	4.30
May_Drought	.83	1.12	.00	4.66
Jun_Drought	.84	1.18	.00	5.85
Jul_Drought	.77	1.17	.00	5.47
Aug_Drought	.72	1.05	.00	5.10
Sep_Drought	.81	1.08	.00	4.56
Oct_Drought	.44	.73	.00	3.98
Nov_Drought	.71	.88	.00	3.69
Wetness				
Mar_Wetness	.52	.95	.00	6.79
Apr_Wetness	.95	1.45	.00	8.67
May_Wetness	1.08	1.70	.00	9.17
Jun_Wetness	1.21	1.72	.00	6.95
Jul_Wetness	.98	1.48	.00	7.99
Aug_Wetness	.96	1.39	.00	9.99
Sep_Wetness	.85	1.49	.00	9.09
Oct_Wetness	1.32	1.88	.00	10.86
Nov_Wetness	.70	1.24	.00	6.84
Land ($/acre)				
Rent	93.33	55.64	23.00	329.00
Expenses ($/acre)				
Seed	81.29	160.07	.05	6474.83
PetroleumProducts	104.43	233.69	.90	8905.72
AllOtherExpenses	963.94	2426.51	7.25	62968.68
FertilizerChemicals	168.39	314.69	.12	14946.22
HiredLabor	232.70	813.25	1.24	34295.06

Note: The total number of observations in the estimation sample is 23,331 from 2,099 counties and years 2001-2015. When using LRsubsidy as the dependent variable, 8 additional observations were dropped since their total premiums were completely covered from subsidy (i.e., 23,323 observations from 2,098 counties).

Table 5: Estimation Results for Static Models with Linear Specification for SCL Variables

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
SCLProducerCount			
L1.	$-.013^{***}$	$-.015^{***}$	$-.012^{***}$
	(.004)	(.005)	(.004)
L2.	.001	.000	.001
	(.004)	(.004)	(.004)
L3.	$-.003$	$-.003$	$-.003$
	(.003)	(.003)	(.003)
Crop Insurance			
ln(UnitSize)	$-.295^{***}$	$-.043$	$-.362^{***}$
	(.046)	(.045)	(.046)
InsuranceType	$-.979^{***}$	$-.861^{***}$	$-.397^{***}$
	(.120)	(.119)	(.123)
CoverageType	$.854^{***}$	.331	$.440^{**}$
	(.204)	(.211)	(.202)
CoverageLevel	5.866^{***}	5.253^{***}	5.627^{***}
	(.712)	(.709)	(.726)
Land (\$/acre)			
ln(Rent)	$.224^{**}$	$.207^{**}$	$.181^{*}$
	(.109)	(.105)	(.106)
Expenses (\$/acre)			
ln(Seed)	.010	$-.009$	$-.003$
	(.052)	(.052)	(.051)
ln(PetroleumProducts)	.040	.063	.044
	(.069)	(.069)	(.068)
ln(AllOtherExpenses)	$.221^{***}$	$.178^{***}$	$.147^{**}$
	(.068)	(.067)	(.067)
ln(FertilizerChemicals)	$-.152^{**}$	$-.124^{*}$	$-.153^{**}$
	(.068)	(.067)	(.066)
ln(HiredLabor)	$-.112^{**}$	$-.106^{**}$	$-.072$
	(.049)	(.048)	(.048)
Obs.	23331	23323	23331
Counties	2099	2098	2099

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: county-level clustered robust standard errors, *c.* Parameter estimates for weather variables, year dummies, and year trend are omitted for the sake of brevity. See appendix table A.1 for full estimation results.

Table 6: Estimation Results for Static Models with Group Dummies for SCL Variables

	Dependent Variable		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
$SCL456$			
L1.	$-.074^{**}$	$-.088^{***}$	$-.062^{**}$
	(.029)	(.029)	(.029)
L2.	.043	.035	.045
	(.032)	(.032)	(.031)
L3.	$-.097^{***}$	$-.103^{***}$	$-.085^{***}$
	(.032)	(.032)	(.032)
$SCL789$			
L1.	$-.104$	$-.126^{*}$	$-.094$
	(.066)	(.066)	(.066)
L2.	$-.056$	$-.067$	$-.043$
	(.060)	(.061)	(.060)
L3.	$-.194^{***}$	$-.200^{***}$	$-.168^{*}$
	(.068)	(.068)	(.067)
$SCL10Plus$			
L1.	$-.198^{**}$	$-.220^{**}$	$-.211^{**}$
	(.092)	(.092)	(.090)
L2.	$-.028$	$-.032$	$-.042$
	(.086)	(.086)	(.085)
L3.	$-.049$	$-.053$	$-.058$
	(.065)	(.064)	(.063)
Crop Insurance			
ln(UnitSize)	$-.301^{***}$	$-.049$	$-.367^{***}$
	(.046)	(.045)	(.046)
InsuranceType	$-.977^{***}$	$-.859^{***}$	$-.395^{***}$
	(.120)	(.119)	(.123)
CoverageType	$.828^{***}$	.302	$.420^{**}$
	(.204)	(.211)	(.202)
CoverageLevel	5.994^{***}	5.394^{***}	5.731^{***}
	(.713)	(.711)	(.727)
Land ($/acre)			
ln(Rent)	$.224^{**}$	$.207^{**}$	$.181^{*}$
	(.108)	(.105)	(.106)
Expenses ($/acre)			
ln(Seed)	.009	$-.010$	$-.003$
	(.052)	(.052)	(.051)
ln(PetroleumProducts)	.039	.062	.043
	(.069)	(.068)	(.068)
ln(AllOtherExpenses)	$.220^{***}$	$.178^{***}$	$.146^{**}$
	(.068)	(.067)	(.068)
ln(FertilizerChemicals)	$-.152^{**}$	$-.124^{*}$	$-.154^{**}$
	(.068)	(.067)	(.066)

Table 6: : Continued

Variable	Dependent Variable		
	ln(LR)	ln(LRsubsidy)	ln(LCR)
ln(HiredLabor)	$-.110^{**}$	$-.104^{**}$	$-.071$
	(.049)	(.048)	(.048)
Obs.	23331	23323	23331
Counties	2099	2098	2099

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: county-level clustered robust standard errors, *c.* Parameter estimates for weather variables, year dummies, and year trend are omitted for the sake of brevity. See appendix table A.2 for full estimation results.

Table 7: Arellano-Bond Test Results for Autocorrelation after Dynamic Model Estimation

Order	ln(LR)		ln(LRsubsidy)		ln(LCR)	
	z	p-value	z	p-value	z	p-value
SCL linear specification						
1	-25.160	.000	-25.257	.000	-24.910	.000
2	-1.296	.195	-1.060	.289	-.969	.332
SCL group dummies specification						
1	-25.138	.000	-25.226	.000	-24.887	.000
2	-1.262	.207	-1.027	.304	-.925	.355

Table 8: Estimation Results for Dynamic Models with Linear Specification for SCL Variables

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)			
L1.	.083***	.076***	.063***
	(.014)	(.014)	(.015)
L2.	.041***	.031**	.015
	(.013)	(.013)	(.014)
L3.	.004	−.004	−.013
	(.011)	(.011)	(.012)
$SCLProducerCount$			
L1.	−.053***	−.056***	−.049***
	(.009)	(.009)	(.008)
L2.	−.011	−.012	−.009
	(.008)	(.008)	(.008)
L3.	.000	.000	.002
	(.005)	(.005)	(.005)
Crop Insurance			
ln(UnitSize)	−.241**	−.014	−.160
	(.095)	(.095)	(.098)
InsuranceType	−1.826***	−1.666***	−1.098***
	(.298)	(.297)	(.295)
CoverageType	1.661***	.611	1.367**
	(.578)	(.580)	(.557)
CoverageLevel	−1.581	−2.628	−4.006**
	(1.799)	(1.764)	(1.769)
Land ($/acre)			
ln(Rent)	.513***	.466***	.206
	(.151)	(.148)	(.149)
Expenses ($/acre)			
ln(Seed)	.163	.199*	.082
	(.107)	(.109)	(.108)
ln(PetroleumProducts)	.658***	.727***	.711***
	(.154)	(.156)	(.152)
ln(AllOtherExpenses)	−.238	−.273*	−.126
	(.163)	(.162)	(.160)
ln(FertilizerChemicals)	.158	.222	.124
	(.170)	(.167)	(.167)
ln(HiredLabor)	−.552***	−.608***	−.592***
	(.112)	(.111)	(.109)
Obs.	22836	22832	22836
Counties	2073	2072	2073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: Windmeijer (2005) bias-corrected robust standard errors, *c.* Parameter estimates for weather variables, year dummies, and year trend are omitted for the sake of brevity. See appendix table A.3 for full estimation results.

Table 9: Estimation Results for Dynamic Models with Group Dummies for SCL Variables

Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)			
L1.	$.085^{***}$	$.077^{***}$	$.065^{***}$
	(.014)	(.014)	(.015)
L2.	$.042^{***}$	$.033^{**}$	.017
	(.013)	(.013)	(.014)
L3.	.007	.000	$-.009$
	(.011)	(.011)	(.012)
$SCL456$			
L1.	$-.321^{***}$	$-.333^{***}$	$-.304^{***}$
	(.056)	(.056)	(.054)
L2.	$-.098^{*}$	$-.108^{*}$	$-.078$
	(.058)	(.058)	(.057)
L3.	$-.055$	$-.062$	$-.057$
	(.058)	(.058)	(.058)
$SCL789$			
L1.	$-.498^{***}$	$-.508^{***}$	$-.440^{***}$
	(.134)	(.134)	(.131)
L2.	$-.259^{**}$	$-.262^{**}$	$-.216^{*}$
	(.121)	(.120)	(.116)
L3.	$-.259^{**}$	$-.250^{**}$	$-.172$
	(.128)	(.127)	(.123)
$SCL10Plus$			
L1.	$-.622^{***}$	$-.650^{***}$	$-.564^{***}$
	(.151)	(.149)	(.145)
L2.	$-.197$	$-.213$	$-.169$
	(.154)	(.150)	(.147)
L3.	$-.013$	$-.022$	.012
	(.130)	(.127)	(.124)
Crop Insurance			
ln(UnitSize)	$-.246^{***}$	$-.020$	$-.165^{*}$
	(.095)	(.094)	(.098)
InsuranceType	-1.799^{***}	-1.643^{***}	-1.089^{***}
	(.297)	(.296)	(.294)
CoverageType	1.630^{***}	.582	1.352^{**}
	(.577)	(.579)	(.556)
CoverageLevel	-1.479	-2.509	-3.944^{**}
	(1.797)	(1.761)	(1.768)
Land (\$/acre)			
ln(Rent)	$.511^{***}$	$.462^{***}$	.209
	(.151)	(.148)	(.149)
Expenses (\$/acre)			
ln(Seed)	.150	$.187^{*}$	.073

Table 9: : Continued

Variable	Dependent Variable		
	ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.107)	(.109)	(.108)
ln(PetroleumProducts)	.655***	.726***	.709***
	(.154)	(.156)	(.153)
ln(AllOtherExpenses)	−.231	−.265	−.122
	(.163)	(.162)	(.159)
ln(FertilizerChemicals)	.159	.222	.127
	(.170)	(.167)	(.167)
ln(HiredLabor)	−.545***	−.604***	−.587***
	(.112)	(.111)	(.110)
Obs.	22836	22832	22836
Counties	2073	2072	2073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: Windmeijer (2005) bias-corrected robust standard errors, *c.* Parameter estimates for weather variables, year dummies, and year trend are omitted for the sake of brevity. See appendix table A.4 for full estimation results.

Table 10: Robustness Check: SCL linear specification

	Dependent variable: ln(Loss Ratio)							
	Static model				Dynamic model			
Variable	$J=1$	$J=2$	$J=3$	$J=4$	$J=1$	$J=2$	$J=3$	$J=4$
Lagged dependent variable ($\widehat{\alpha}$)								
L1.					$.069^{***}$	$.079^{***}$	$.083^{***}$	$.092^{***}$
					(.012)	(.012)	(.014)	(.016)
L2.						$.034^{***}$	$.041^{***}$	$.031^{**}$
						(.012)	(.013)	(.014)
L3.							.004	.010
							(.011)	(.012)
L4.								$.033^{***}$
								(.012)
$SCLProducerCount$								
L1.	$-.002$	$-.011^{***}$	$-.013^{***}$	$-.012^{**}$	$-.029^{***}$	$-.053^{***}$	$-.053^{***}$	$-.056^{***}$
	(.002)	(.004)	(.004)	(.005)	(.007)	(.008)	(.009)	(.009)
L2.		$-.001$	.001	.002		$-.007$	$-.011$	$-.019^{**}$
		(.002)	(.004)	(.004)		(.005)	(.008)	(.008)
L3.			$-.003$	$-.010^{**}$			.000	$-.012^{*}$
			(.003)	(.004)			(.005)	(.007)
L4.				$-.001$				.001
				(.003)				(.004)

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: robust standard errors, *c.* Parameter estimates for covariates, year dummies, and year trend are omitted for the sake of brevity.

Table 11: Robustness Check: SCL group dummies specification

	Dependent variable: ln(Loss Ratio)							
	Static model				Dynamic model			
Variable	$J = 1$	$J = 2$	$J = 3$	$J = 4$	$J = 1$	$J = 2$	$J = 3$	$J = 4$
Lagged dependent variable ($\widehat{\alpha}$)								
L1.					$.072^{***}$	$.080^{***}$	$.085^{***}$	$.092^{***}$
					(.012)	(.012)	(.014)	(.016)
L2.						$.034^{***}$	$.042^{***}$	$.032^{**}$
						(.012)	(.013)	(.014)
L3.							.007	.010
							(.011)	(.012)
L4.								$.034^{***}$
								(.013)
$SCL456$								
L1.	$-.062^{**}$	$-.069^{**}$	$-.074^{**}$	$-.089^{***}$	$-.276^{***}$	$-.326^{***}$	$-.321^{***}$	$-.325^{***}$
	(.027)	(.028)	(.029)	(.031)	(.052)	(.052)	(.056)	(.056)
L2.		.035	.043	.022		$-.064$	$-.098^{*}$	$-.121^{**}$
		(.030)	(.032)	(.032)		(.055)	(.058)	(.060)
L3.			$-.097^{***}$	$-.090^{***}$			$-.055$	$-.104^{*}$
			(.032)	(.033)			(.058)	(.059)
L4.				$-.116^{***}$				$-.063$
				(.035)				(.064)
$SCL789$								
L1.	$-.070$	$-.084$	$-.104$	$-.108$	$-.401^{***}$	$-.481^{***}$	$-.498^{***}$	$-.499^{***}$
	(.061)	(.063)	(.066)	(.069)	(.119)	(.130)	(.134)	(.137)
L2.		$-.072$	$-.056$	$-.096$		$-.116$	$-.259^{**}$	$-.238^{*}$
		(.057)	(.060)	(.060)		(.109)	(.121)	(.124)
L3.			$-.194^{***}$	$-.188^{**}$			$-.259^{**}$	$-.174$
			(.068)	(.074)			(.128)	(.122)
L4.				$-.125^{**}$				$-.007$
				(.064)				(.123)
$SCL10Plus$								
L1.	$-.092$	$-.195^{**}$	$-.198^{**}$	$-.159^{*}$	$-.472^{***}$	$-.600^{***}$	$-.622^{***}$	$-.572^{***}$
	(.068)	(.081)	(.092)	(.094)	(.125)	(.143)	(.151)	(.165)
L2.		$-.027$	$-.028$	.007		$-.128$	$-.197$	$-.234$
		(.068)	(.086)	(.083)		(.130)	(.154)	(.156)
L3.			$-.049$	$-.017$			$-.013$	$-.114$
			(.065)	(.078)			(.130)	(.138)
L4.				.004				.059
				(.068)				(.112)

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: robust standard errors, *c.* Parameter estimates for covariates, year dummies, and year trend are omitted for the sake of brevity.

Figure 1: Spatial Distribution: Total Number of SCL Producers from 2001 to 2015

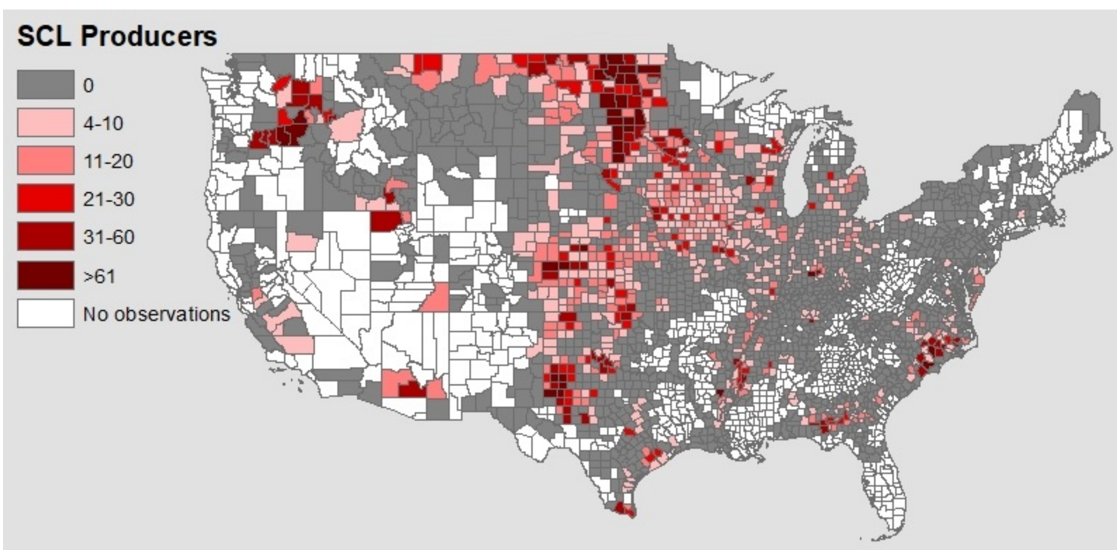


Figure 2: Spatial Distributions of Number of SCL Producers for Selected Years between 2001 and 2010

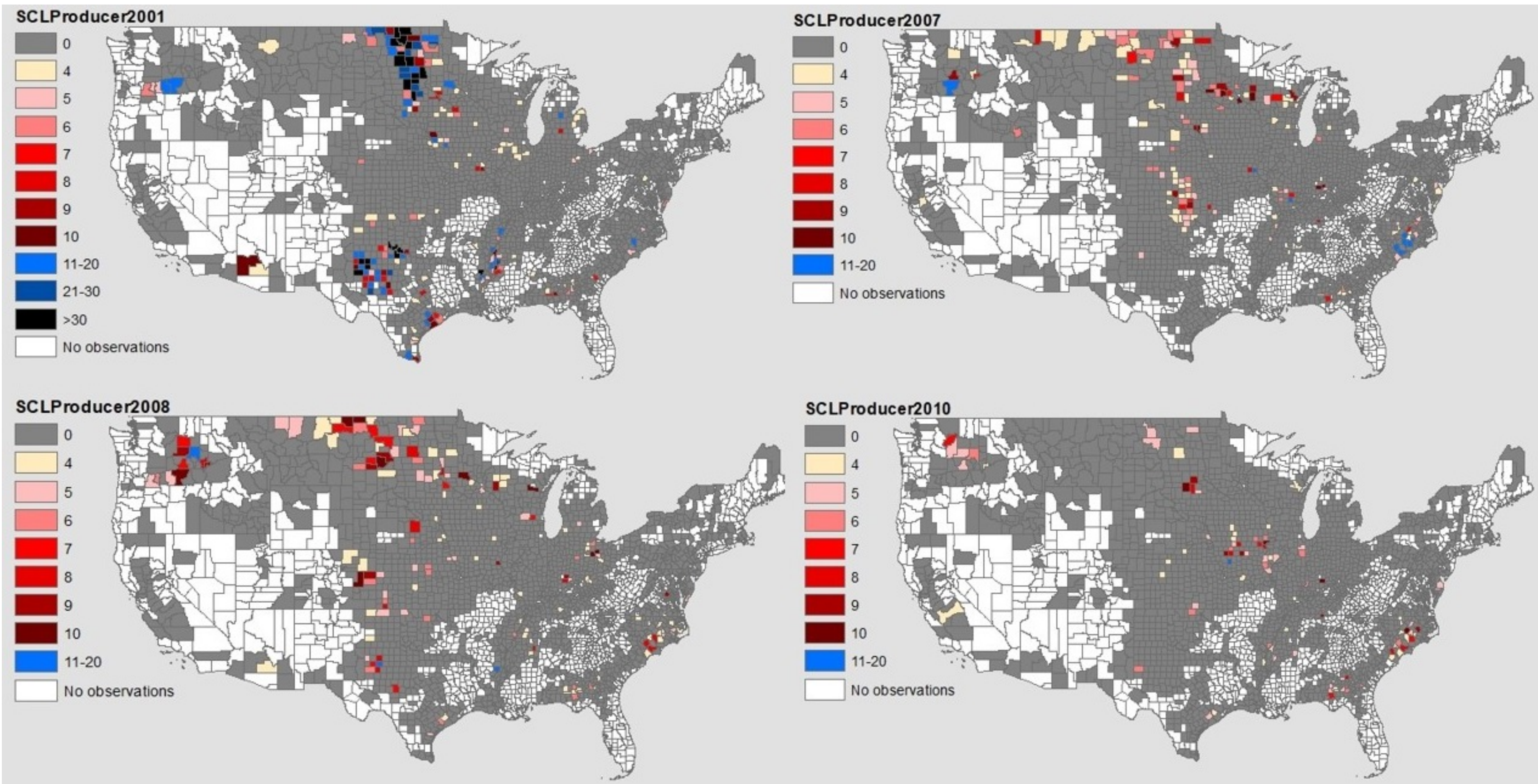


Figure 3: Spatial Distributions of Number of SCL Producers from 2012 to 2015

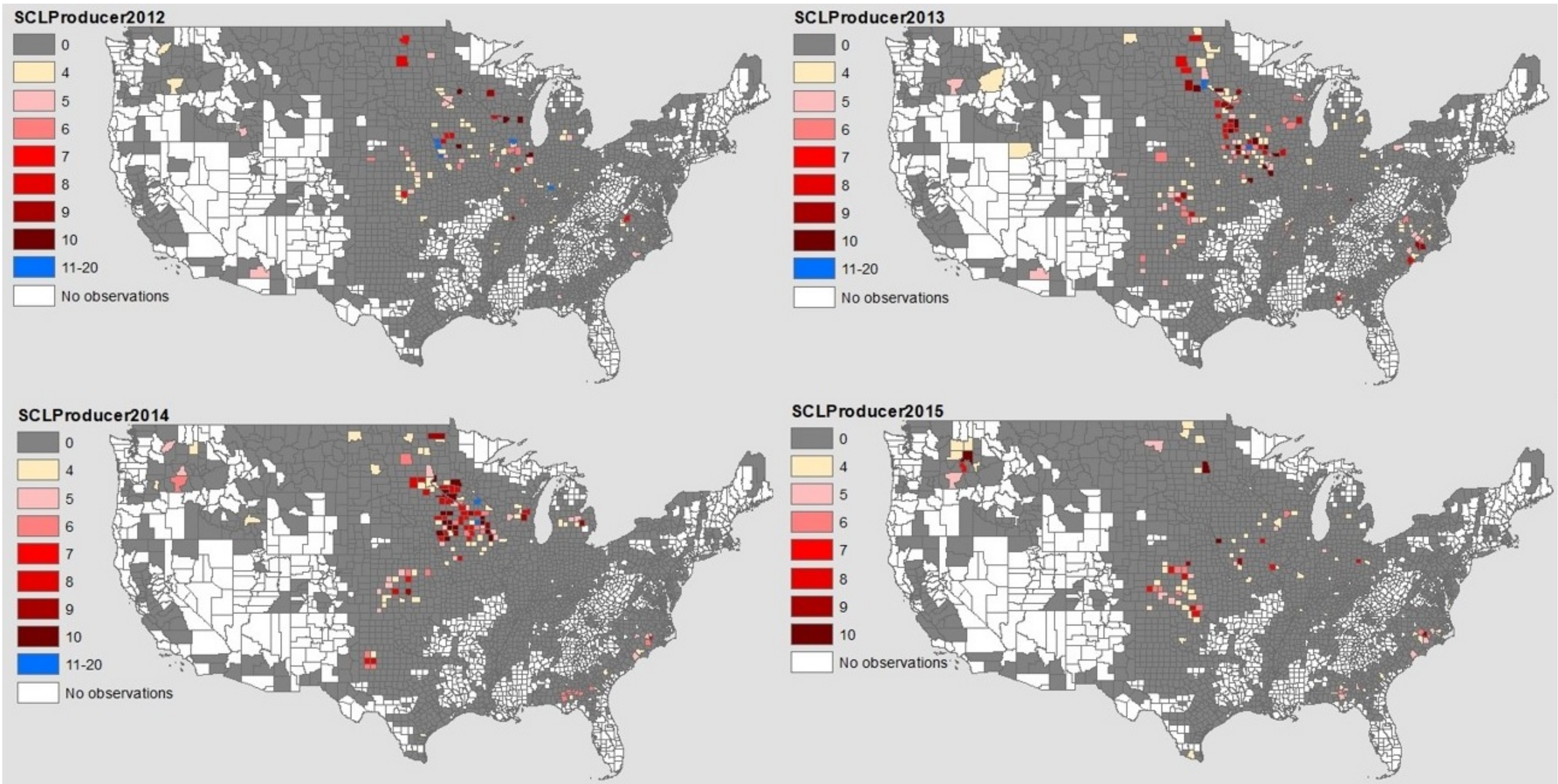


Figure 4: Indemnity Trend for Counties over 3 years after Having at least 4 SCL Producers

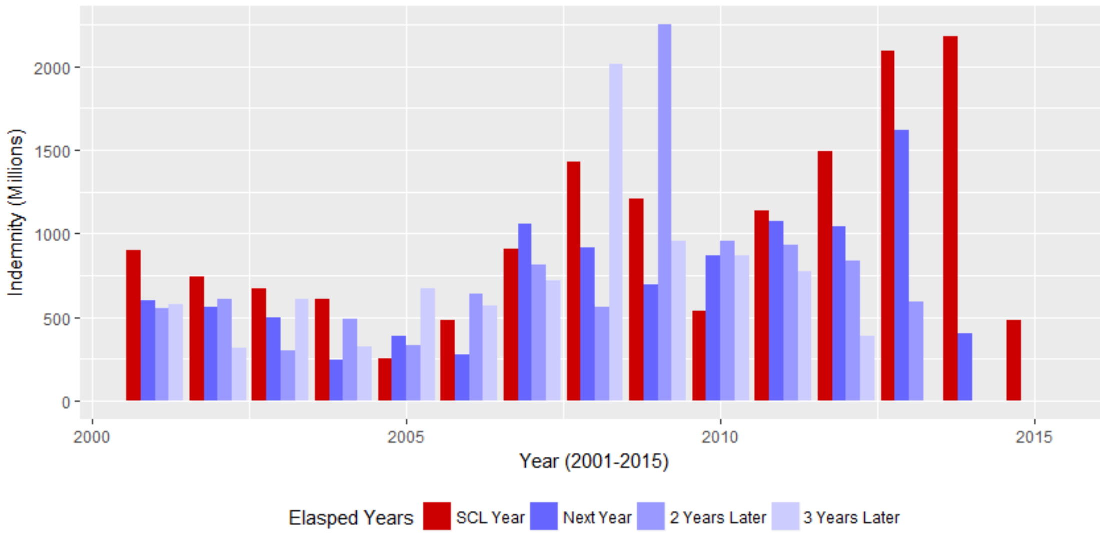


Figure 5: LR Trend for Counties over 3 years after Having at least 4 SCL Producers

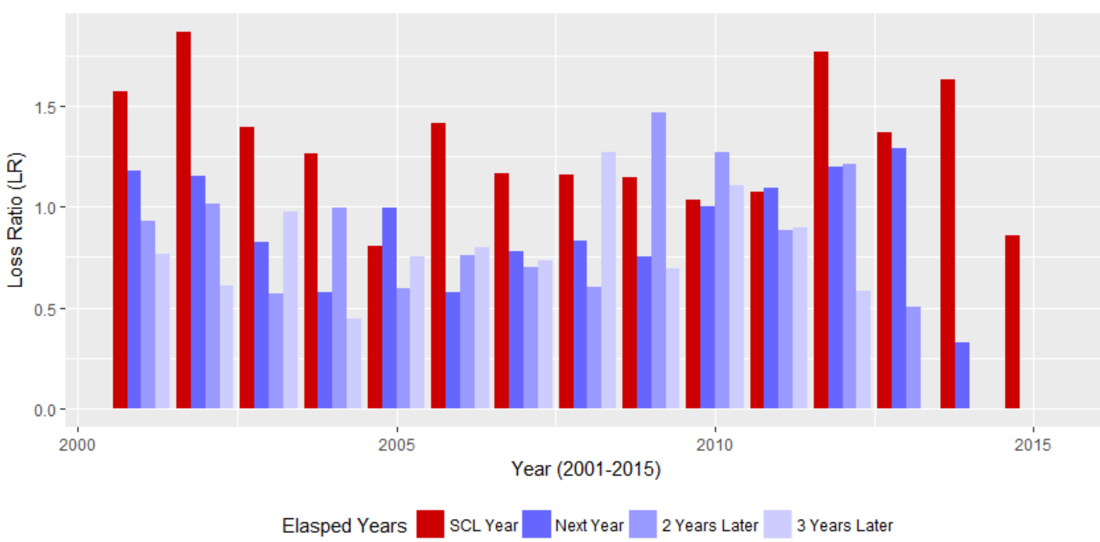


Figure 6: LRsubsidy Trend for Counties over 3 years after Having at least 4 SCL Producers

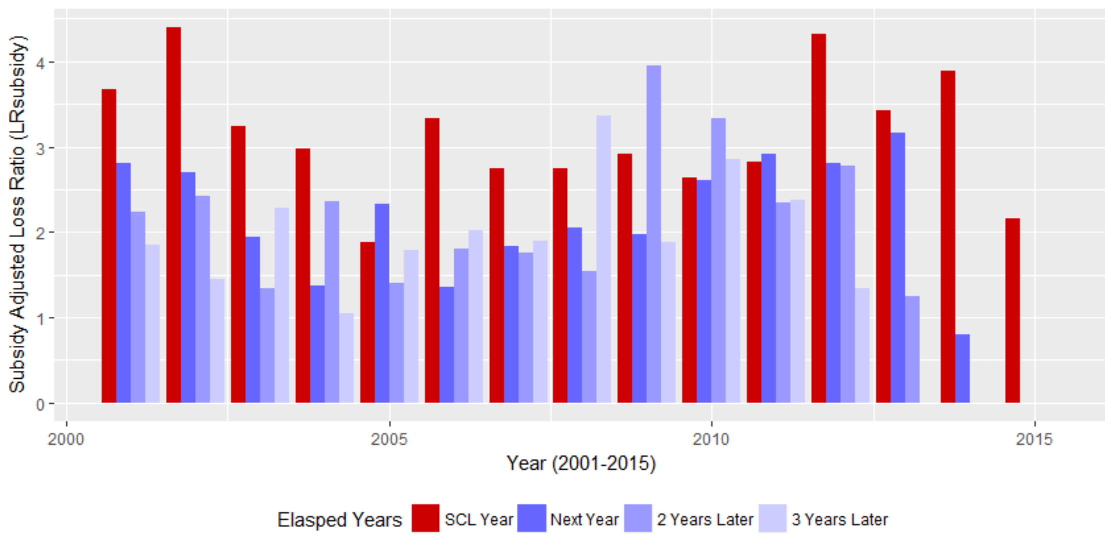
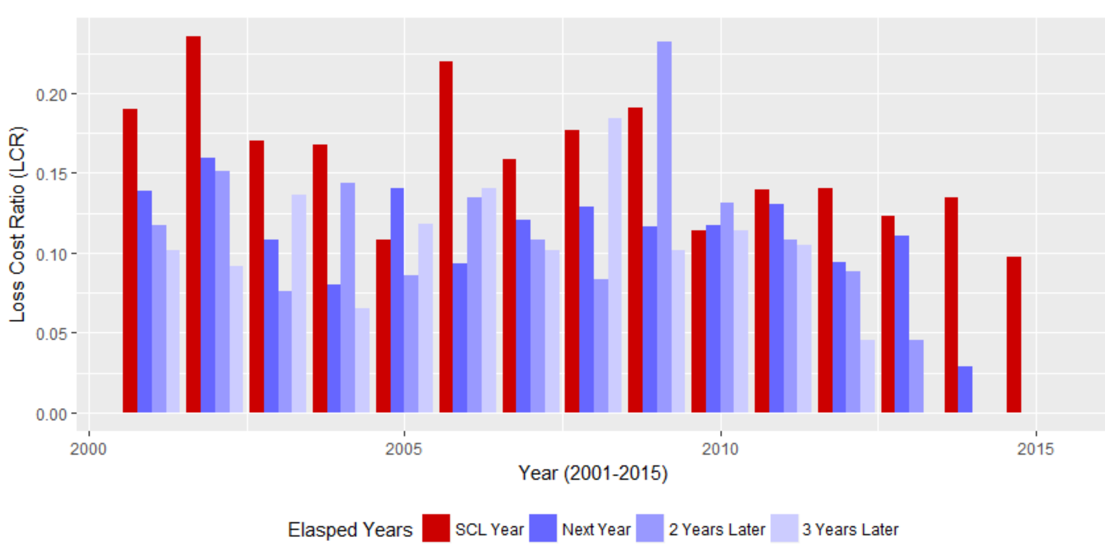


Figure 7: LCR Trend for Counties over 3 years after Having at least 4 SCL Producers



Appendix

Table A.1: Full Estimation Results for Table 5

Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
	Dependent Variable		
SCLProducerCount			
L1.	$-.013^{***}$	$-.015^{***}$	$-.012^{***}$
	(.004)	(.005)	(.004)
L2.	.001	.000	.001
	(.004)	(.004)	(.004)
L3.	−.003	−.003	−.003
	(.003)	(.003)	(.003)
Crop Insurance			
ln(UnitSize)	$-.295^{***}$	−.043	$-.362^{***}$
	(.046)	(.045)	(.046)
InsuranceType	$-.979^{***}$	$-.861^{***}$	$-.397^{***}$
	(.120)	(.119)	(.123)
CoverageType	$.854^{***}$	.331	$.440^{**}$
	(.204)	(.211)	(.202)
CoverageLevel	5.866^{***}	5.253^{***}	5.627^{***}
	(.712)	(.709)	(.726)
Precipitation			
ln(Mar_precipitation)	$-.044^{**}$	$-.041^{**}$	$-.053^{***}$
	(.017)	(.017)	(.017)
ln(Apr_precipitation)	$-.067^{***}$	$-.074^{***}$	$-.070^{***}$
	(.020)	(.020)	(.020)
ln(May_precipitation)	$.074^{***}$	$.076^{***}$	$.086^{***}$
	(.021)	(.021)	(.021)
ln(Jun_precipitation)	$.100^{***}$	$.097^{***}$	$.102^{***}$
	(.023)	(.022)	(.023)
ln(Jul_precipitation)	$-.120^{***}$	$-.115^{***}$	$-.113^{***}$
	(.020)	(.020)	(.020)
ln(Aug_precipitation)	$-.060^{***}$	$-.065^{***}$	$-.054^{***}$
	(.018)	(.018)	(.018)
ln(Sep_precipitation)	$.112^{***}$	$.112^{***}$	$.108^{***}$
	(.016)	(.016)	(.016)
ln(Oct_precipitation)	$.031^{*}$	$.028^{*}$	.026
	(.017)	(.017)	(.017)
ln(Nov_precipitation)	$-.134^{***}$	$-.131^{***}$	$-.122^{***}$
	(.017)	(.017)	(.017)
Temperature			
Mar_tMin	$.019^{**}$	$.017^{*}$	.013
	(.010)	(.009)	(.009)
Apr_tMin	$-.019^{*}$	−.012	$-.022^{**}$
	(.011)	(.011)	(.010)
May_tMin	$-.080^{***}$	$-.075^{***}$	$-.094^{***}$
	(.011)	(.011)	(.011)
Jun_tMin	$-.076^{***}$	$-.082^{***}$	$-.055^{***}$

Table A.1: Continued

Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
	Dependent Variable		
	(.016)	(.016)	(.016)
Jul_tMin	.107***	.104***	.117***
	(.015)	(.015)	(.015)
Aug_tMin	−.119***	−.121***	−.113***
	(.013)	(.013)	(.013)
Sep_tMin	.018*	.016	.032***
	(.011)	(.011)	(.011)
Oct_tMin	−.016	−.017	−.012
	(.011)	(.011)	(.011)
Nov_tMin	.037***	.039***	.037***
	(.010)	(.010)	(.010)
Mar_tMax	−.032***	−.029***	−.028***
	(.008)	(.008)	(.008)
Apr_tMax	−.056***	−.058***	−.062***
	(.008)	(.008)	(.008)
May_tMax	−.007	−.005	−.005
	(.012)	(.012)	(.011)
Jun_tMax	.057***	.063***	.041***
	(.014)	(.014)	(.014)
Jul_tMax	.052***	.052***	.048***
	(.016)	(.016)	(.016)
Aug_tMax	.129***	.125***	.130***
	(.014)	(.014)	(.014)
Sep_tMax	.046***	.045***	.048***
	(.010)	(.010)	(.010)
Oct_tMax	.032***	.034***	.025**
	(.010)	(.010)	(.010)
Nov_tMax	−.064***	−.065***	−.063***
	(.009)	(.009)	(.009)
Mar_dday30C	.215***	.208***	.208***
	(.061)	(.059)	(.060)
Apr_dday30C	−.019*	−.019*	−.023*
	(.011)	(.011)	(.012)
May_dday30C	.051***	.049***	.054***
	(.005)	(.005)	(.005)
Jun_dday30C	.012***	.010***	.013***
	(.002)	(.002)	(.002)
Jul_dday30C	.005***	.005***	.006***
	(.002)	(.002)	(.002)
Aug_dday30C	.003	.003**	.003
	(.002)	(.002)	(.002)
Sep_dday30C	−.012***	−.012***	−.010***
	(.002)	(.002)	(.002)
Oct_dday30C	.063***	.055***	.069***
	(.015)	(.015)	(.016)
Nov_dday30C	.231**	.257***	.193*
	(.099)	(.083)	(.112)
Drought			
Mar_Drought	−.052***	−.053***	−.066***

Table A.1: Continued

Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
	Dependent Variable		
	(.010)	(.010)	(.010)
Apr_Drought	−.007	−.003	−.007
	(.014)	(.013)	(.014)
May_Drought	−.024**	−.021**	−.017
	(.011)	(.011)	(.011)
Jun_Drought	.197***	.194***	.198***
	(.014)	(.014)	(.014)
Jul_Drought	.194***	.187***	.186***
	(.012)	(.012)	(.012)
Aug_Drought	.021**	.024**	.021**
	(.010)	(.010)	(.010)
Sep_Drought	.048***	.048***	.048***
	(.010)	(.010)	(.010)
Oct_Drought	−.026*	−.026*	−.027*
	(.015)	(.015)	(.015)
Nov_Drought	.111***	.116***	.097***
	(.014)	(.014)	(.014)
Wetness			
Mar_Wetness	−.044***	−.043***	−.044***
	(.010)	(.010)	(.010)
Apr_Wetness	.037***	.039***	.035***
	(.007)	(.007)	(.007)
May_Wetness	.109***	.110***	.112***
	(.006)	(.006)	(.006)
Jun_Wetness	.133***	.132***	.129***
	(.006)	(.006)	(.006)
Jul_Wetness	.025***	.024***	.025***
	(.008)	(.008)	(.008)
Aug_Wetness	.001	.001	.001
	(.008)	(.008)	(.008)
Sep_Wetness	.047***	.046***	.053***
	(.006)	(.006)	(.006)
Oct_Wetness	.008	.011*	.008
	(.006)	(.006)	(.006)
Nov_Wetness	−.020**	−.020**	−.029***
	(.009)	(.009)	(.009)
Land ($/acre)			
ln(Rent)	.224**	.207**	.181*
	(.109)	(.105)	(.106)
Expenses ($/acre)			
ln(Seed)	.010	−.009	−.003
	(.052)	(.052)	(.051)
ln(PetroleumProducts)	.040	.063	.044
	(.069)	(.069)	(.068)
ln(AllOtherExpenses)	.221***	.178***	.147**
	(.068)	(.067)	(.067)
ln(FertilizerChemicals)	−.152**	−.124*	−.153**
	(.068)	(.067)	(.066)
ln(HiredLabor)	−.112**	−.106**	−.072

Table A.1: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.049)	(.048)	(.048)
Year			
Year2005	$-.898^{***}$	$-.860^{***}$	$-.923^{***}$
	(.059)	(.059)	(.058)
Year2006	$-.851^{***}$	$-.834^{***}$	$-.760^{***}$
	(.060)	(.060)	(.060)
Year2007	$-.787^{***}$	$-.792^{***}$	$-.702^{***}$
	(.059)	(.059)	(.059)
Year2008	$-.244^{***}$	$-.243^{***}$	$-.099^{**}$
	(.051)	(.051)	(.050)
Year2009	$-.069$	$-.029$	$.132^{**}$
	(.054)	(.054)	(.055)
Year2010	$-.674^{***}$	$-.625^{***}$	$-.595^{***}$
	(.054)	(.054)	(.054)
Year2011	-1.194^{***}	-1.146^{***}	-1.099^{***}
	(.063)	(.062)	(.062)
Year2012	$-.836^{***}$	$-.835^{***}$	$-.725^{***}$
	(.071)	(.073)	(.070)
Year2013	$-.371^{***}$	$-.346^{***}$	$-.390^{***}$
	(.042)	(.042)	(.042)
Year2014	(omitted)	(omitted)	(omitted)
Year2015	$-.334^{***}$	$-.360^{***}$	$-.309^{***}$
	(.064)	(.064)	(.064)
Trend	$-.011$	.000	$-.025^{***}$
	(.009)	(.009)	(.009)
Constant	12.453	-7.880	39.533^{**}
	(17.649)	(17.389)	(17.712)
Obs.	23331	23323	23331
Counties	2099	2098	2099

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: county-level clustered robust standard errors.

Table A.2: Full Estimation Results for Table 6

	Dependent Variable		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
SCL456			
L1.	$-.074^{**}$	$-.088^{***}$	$-.062^{**}$
	(.029)	(.029)	(.029)
L2.	.043	.035	.045
	(.032)	(.032)	(.031)
L3.	$-.097^{***}$	$-.103^{***}$	$-.085^{***}$
	(.032)	(.032)	(.032)
SCL789			
L1.	$-.104$	$-.126^{*}$	$-.094$
	(.066)	(.066)	(.066)
L2.	$-.056$	$-.067$	$-.043$
	(.060)	(.061)	(.060)
L3.	$-.194^{***}$	$-.200^{***}$	$-.168^{*}$
	(.068)	(.068)	(.067)
SCL10Plus			
L1.	$-.198^{**}$	$-.220^{**}$	$-.211^{**}$
	(.092)	(.092)	(.090)
L2.	$-.028$	$-.032$	$-.042$
	(.086)	(.086)	(.085)
L3.	$-.049$	$-.053$	$-.058$
	(.065)	(.064)	(.063)
Crop Insurance			
ln(UnitSize)	$-.301^{***}$	$-.049$	$-.367^{***}$
	(.046)	(.045)	(.046)
InsuranceType	$-.977^{***}$	$-.859^{***}$	$-.395^{***}$
	(.120)	(.119)	(.123)
CoverageType	$.828^{***}$	.302	$.420^{**}$
	(.204)	(.211)	(.202)
CoverageLevel	5.994^{***}	5.394^{***}	5.731^{***}
	(.713)	(.711)	(.727)
Precipitation			
ln(Mar_precipitation)	$-.044^{**}$	$-.041^{**}$	$-.053^{***}$
	(.017)	(.017)	(.017)
ln(Apr_precipitation)	$-.067^{***}$	$-.074^{***}$	$-.070^{***}$
	(.020)	(.020)	(.020)
ln(May_precipitation)	$.073^{***}$	$.075^{***}$	$.086^{***}$
	(.021)	(.021)	(.021)
ln(Jun_precipitation)	$.099^{***}$	$.095^{***}$	$.101^{***}$
	(.022)	(.022)	(.023)
ln(Jul_precipitation)	$-.120^{***}$	$-.115^{***}$	$-.113^{***}$
	(.020)	(.020)	(.020)
ln(Aug_precipitation)	$-.060^{***}$	$-.064^{***}$	$-.053^{***}$
	(.018)	(.018)	(.018)
ln(Sep_precipitation)	$.111^{***}$	$.112^{***}$	$.108^{***}$
	(.016)	(.016)	(.016)
ln(Oct_precipitation)	$.032^{*}$	$.029^{*}$	.026
	(.017)	(.017)	(.017)
ln(Nov_precipitation)	$-.133^{***}$	$-.131^{***}$	$-.122^{***}$

Table A.2: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.017)	(.017)	(.017)
Temperature			
Mar_tMin	.019**	.018*	.013
	(.010)	(.009)	(.009)
Apr_tMin	−.019*	−.012	−.021**
	(.011)	(.011)	(.010)
May_tMin	−.079***	−.075***	−.093***
	(.011)	(.011)	(.011)
Jun_tMin	−.074***	−.080***	−.053***
	(.016)	(.016)	(.016)
Jul_tMin	.105***	.102***	.116***
	(.015)	(.015)	(.015)
Aug_tMin	−.120***	−.121***	−.114***
	(.013)	(.013)	(.013)
Sep_tMin	.018*	.016	.032***
	(.011)	(.011)	(.011)
Oct_tMin	−.016	−.017	−.011
	(.011)	(.011)	(.011)
Nov_tMin	.036***	.039***	.037***
	(.010)	(.010)	(.010)
Mar_tMax	−.033***	−.029***	−.029***
	(.008)	(.008)	(.008)
Apr_tMax	−.055***	−.058***	−.062***
	(.008)	(.008)	(.008)
May_tMax	−.007	−.005	−.005
	(.012)	(.012)	(.011)
Jun_tMax	.056***	.062***	.040***
	(.014)	(.014)	(.014)
Jul_tMax	.052***	.053***	.049***
	(.016)	(.016)	(.016)
Aug_tMax	.128***	.123***	.129***
	(.014)	(.014)	(.014)
Sep_tMax	.046***	.044***	.048***
	(.010)	(.010)	(.010)
Oct_tMax	.032***	.033***	.025**
	(.011)	(.010)	(.010)
Nov_tMax	−.064***	−.065***	−.063***
	(.009)	(.009)	(.009)
Mar_dday30C	.217***	.210***	.210***
	(.061)	(.059)	(.060)
Apr_dday30C	−.020*	−.020*	−.024**
	(.011)	(.011)	(.012)
May_dday30C	.052***	.050***	.054***
	(.005)	(.005)	(.005)
Jun_dday30C	.011***	.010***	.013***
	(.002)	(.002)	(.002)
Jul_dday30C	.005***	.005***	.006***
	(.002)	(.002)	(.002)
Aug_dday30C	.003*	.004**	.003

Table A.2: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.002)	(.002)	(.002)
Sep_dday30C	−.012***	−.012***	−.010***
	(.002)	(.002)	(.002)
Oct_dday30C	.063***	.055***	.069***
	(.015)	(.014)	(.015)
Nov_dday30C	.229**	.255***	.192*
	(.100)	(.084)	(.113)
Drought			
Mar_Drought	−.052***	−.052***	−.066***
	(.010)	(.010)	(.010)
Apr_Drought	−.007	−.003	−.007
	(.014)	(.013)	(.014)
May_Drought	−.024**	−.021**	−.017
	(.011)	(.011)	(.011)
Jun_Drought	.198***	.194***	.198***
	(.014)	(.014)	(.014)
Jul_Drought	.193***	.187***	.185***
	(.012)	(.012)	(.012)
Aug_Drought	.020**	.023**	.020**
	(.010)	(.010)	(.010)
Sep_Drought	.048***	.048***	.048***
	(.010)	(.010)	(.010)
Oct_Drought	−.026*	−.026*	−.028*
	(.015)	(.015)	(.015)
Nov_Drought	.112***	.117***	.098***
	(.014)	(.014)	(.014)
Wetness			
Mar_Wetness	−.044***	−.043***	−.045***
	(.010)	(.010)	(.010)
Apr_Wetness	.037***	.038***	.035***
	(.007)	(.007)	(.007)
May_Wetness	.110***	.111***	.112***
	(.006)	(.006)	(.006)
Jun_Wetness	.133***	.132***	.130***
	(.006)	(.006)	(.006)
Jul_Wetness	.025***	.025***	.025***
	(.008)	(.008)	(.008)
Aug_Wetness	.000	.001	.001
	(.008)	(.008)	(.008)
Sep_Wetness	.047***	.046***	.053***
	(.006)	(.006)	(.006)
Oct_Wetness	.008	.010*	.008
	(.006)	(.006)	(.006)
Nov_Wetness	−.019**	−.019**	−.028***
	(.009)	(.009)	(.009)
Land ($/acre)			
ln(Rent)	.224**	.207**	.181*
	(.108)	(.105)	(.106)
Expenses ($/acre)			

Table A.2: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
ln(Seed)	.009	−.010	−.003
	(.052)	(.052)	(.051)
ln(PetroleumProducts)	.039	.062	.043
	(.069)	(.068)	(.068)
ln(AllOtherExpenses)	.220***	.178***	.146**
	(.068)	(.067)	(.068)
ln(FertilizerChemicals)	−.152**	−.124*	−.154**
	(.068)	(.067)	(.066)
ln(HiredLabor)	−.110**	−.104**	−.071
	(.049)	(.048)	(.048)
Year			
Year2005	−.891***	−.852***	−.917***
	(.059)	(.059)	(.058)
Year2006	−.844***	−.826***	−.754***
	(.060)	(.060)	(.060)
Year2007	−.779***	−.783***	−.695***
	(.059)	(.059)	(.059)
Year2008	−.238***	−.236***	−.094*
	(.051)	(.051)	(.051)
Year2009	−.067	−.027	.134**
	(.054)	(.054)	(.055)
Year2010	−.666***	−.616***	−.590***
	(.054)	(.054)	(.054)
Year2011	−1.184***	−1.134***	−1.091***
	(.063)	(.063)	(.063)
Year2012	−.825***	−.823***	−.716***
	(.071)	(.073)	(.070)
Year2013	−.367***	−.342***	−.387***
	(.042)	(.042)	(.042)
Year2014	(omitted)	(omitted)	(omitted)
Year2015	−.336***	−.362***	−.311***
	(.064)	(.064)	(.064)
Trend	−.011	.000	−.025***
	(.009)	(.009)	(.009)
Constant	12.122	−8.421	39.429**
	(17.635)	(17.370)	(17.705)
Obs.	23331	23323	23331
Counties	2099	2098	2099

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: county-level clustered robust standard errors.

Table A.3: Full Estimation Results for Table 8

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)			
L1.	.083***	.076***	.063***
	(.014)	(.014)	(.015)
L2.	.041***	.031**	.015
	(.013)	(.013)	(.014)
L3.	.004	−.004	−.013
	(.011)	(.011)	(.012)
SCLProducerCount			
L1.	−.053***	−.056***	−.049***
	(.009)	(.009)	(.008)
L2.	−.011	−.012	−.009
	(.008)	(.008)	(.008)
L3.	.000	.000	.002
	(.005)	(.005)	(.005)
Crop Insurance			
ln(UnitSize)	−.241**	−.014	−.160
	(.095)	(.095)	(.098)
InsuranceType	−1.826***	−1.666***	−1.098***
	(.298)	(.297)	(.295)
CoverageType	1.661***	.611	1.367**
	(.578)	(.580)	(.557)
CoverageLevel	−1.581	−2.628	−4.006**
	(1.799)	(1.764)	(1.769)
Precipitation			
ln(Mar_precipitation)	−.010	−.013	−.016
	(.027)	(.027)	(.027)
ln(Apr_precipitation)	−.130***	−.131***	−.127***
	(.032)	(.032)	(.032)
ln(May_precipitation)	.087**	.076**	.097***
	(.036)	(.036)	(.035)
ln(Jun_precipitation)	.115***	.115***	.120***
	(.037)	(.037)	(.036)
ln(Jul_precipitation)	−.040	−.046	−.020
	(.031)	(.031)	(.031)
ln(Aug_precipitation)	−.018	−.023	−.007
	(.029)	(.029)	(.028)
ln(Sep_precipitation)	.113***	.122***	.103***
	(.029)	(.029)	(.028)
ln(Oct_precipitation)	.049*	.050*	.065**
	(.027)	(.027)	(.026)
ln(Nov_precipitation)	−.125***	−.116***	−.128***
	(.027)	(.028)	(.026)
Temperature			
Mar_tMin	.017	.013	.011
	(.014)	(.014)	(.013)
Apr_tMin	.002	−.001	−.001
	(.015)	(.016)	(.015)
May_tMin	−.096***	−.090***	−.084***

Table A.3: Continued

Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)
	Dependent Variable		
	(.019)	(.019)	(.019)
Jun_tMin	−.097***	−.086***	−.080***
	(.025)	(.025)	(.025)
Jul_tMin	.169***	.164***	.165***
	(.021)	(.021)	(.020)
Aug_tMin	−.075***	−.069***	−.088***
	(.021)	(.021)	(.021)
Sep_tMin	−.036**	−.036**	−.013
	(.017)	(.017)	(.016)
Oct_tMin	.056***	.048***	.048***
	(.017)	(.016)	(.017)
Nov_tMin	.063***	.058***	.066***
	(.015)	(.016)	(.015)
Mar_tMax	−.056***	−.051***	−.053***
	(.012)	(.012)	(.011)
Apr_tMax	−.072***	−.070***	−.077***
	(.013)	(.013)	(.013)
May_tMax	.041**	.035*	.031*
	(.018)	(.018)	(.018)
Jun_tMax	.069***	.072***	.060***
	(.023)	(.023)	(.023)
Jul_tMax	.039*	.036	.046**
	(.024)	(.023)	(.023)
Aug_tMax	.161***	.159***	.161***
	(.024)	(.024)	(.023)
Sep_tMax	.050***	.046***	.051***
	(.015)	(.015)	(.014)
Oct_tMax	−.060***	−.050***	−.053***
	(.016)	(.016)	(.016)
Nov_tMax	−.061***	−.055***	−.067***
	(.014)	(.014)	(.014)
Mar_dday30C	.342**	.311**	.333**
	(.150)	(.128)	(.156)
Apr_dday30C	−.057***	−.058***	−.068***
	(.021)	(.020)	(.021)
May_dday30C	.046***	.047***	.057***
	(.009)	(.009)	(.010)
Jun_dday30C	.018***	.015***	.014***
	(.004)	(.004)	(.004)
Jul_dday30C	.003	.003	.005*
	(.003)	(.003)	(.003)
Aug_dday30C	.003	.003	.005*
	(.003)	(.003)	(.003)
Sep_dday30C	−.013***	−.012***	−.011***
	(.003)	(.003)	(.003)
Oct_dday30C	.031	.026	.035
	(.027)	(.027)	(.027)
Nov_dday30C	.245	.282	.342
	(.196)	(.184)	(.248)

Table A.3: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
Drought			
Mar_Drought	$-.043^{**}$	$-.040^{**}$	$-.041^{**}$
	(.017)	(.018)	(.017)
Apr_Drought	$-.002$	$-.011$	$-.011$
	(.022)	(.022)	(.021)
May_Drought	$-.097^{***}$	$-.093^{***}$	$-.084^{***}$
	(.018)	(.018)	(.017)
Jun_Drought	$.175^{***}$	$.185^{***}$	$.202^{***}$
	(.023)	(.023)	(.023)
Jul_Drought	$.227^{***}$	$.220^{***}$	$.194^{***}$
	(.020)	(.020)	(.020)
Aug_Drought	.004	.002	.003
	(.016)	(.016)	(.016)
Sep_Drought	$.088^{***}$	$.093^{***}$	$.091^{***}$
	(.017)	(.017)	(.017)
Oct_Drought	.022	.023	$.041^{*}$
	(.023)	(.023)	(.022)
Nov_Drought	$.142^{***}$	$.134^{***}$	$.130^{***}$
	(.022)	(.022)	(.022)
Wetness			
Mar_Wetness	$-.028^{*}$	$-.020$	$-.030^{*}$
	(.017)	(.017)	(.016)
Apr_Wetness	.008	.008	.008
	(.011)	(.012)	(.011)
May_Wetness	$.107^{***}$	$.109^{***}$	$.105^{***}$
	(.010)	(.010)	(.010)
Jun_Wetness	$.145^{***}$	$.142^{***}$	$.149^{***}$
	(.010)	(.010)	(.010)
Jul_Wetness	$.029^{**}$	$.030^{**}$	$.030^{**}$
	(.013)	(.013)	(.012)
Aug_Wetness	.006	.009	.017
	(.012)	(.012)	(.012)
Sep_Wetness	$.075^{***}$	$.073^{***}$	$.075^{***}$
	(.010)	(.010)	(.010)
Oct_Wetness	$-.008$	$-.003$	$-.011$
	(.010)	(.010)	(.010)
Nov_Wetness	$-.011$	$-.015$	$-.007$
	(.014)	(.014)	(.014)
Land ($/acre)			
ln(Rent)	$.513^{***}$	$.466^{***}$	.206
	(.151)	(.148)	(.149)
Expenses ($/acre)			
ln(Seed)	.163	$.199^{*}$	.082
	(.107)	(.109)	(.108)
ln(PetroleumProducts)	$.658^{***}$	$.727^{***}$	$.711^{***}$
	(.154)	(.156)	(.152)
ln(AllOtherExpenses)	$-.238$	$-.273^{*}$	$-.126$
	(.163)	(.162)	(.160)
ln(FertilizerChemicals)	.158	.222	.124

Table A.3: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.170)	(.167)	(.167)
ln(HiredLabor)	$-.552^{***}$	$-.608^{***}$	$-.592^{***}$
	(.112)	(.111)	(.109)
Year			
Year2005	-1.005^{***}	-1.059^{***}	-1.012^{***}
	(.081)	(.083)	(.080)
Year2006	-1.027^{***}	-1.085^{***}	$-.949^{***}$
	(.085)	(.085)	(.085)
Year2007	$-.901^{***}$	-1.001^{***}	$-.893^{***}$
	(.088)	(.087)	(.088)
Year2008	$-.621^{***}$	$-.717^{***}$	$-.512^{***}$
	(.085)	(.087)	(.084)
Year2009	$-.415^{***}$	$-.411^{***}$	$-.188^{**}$
	(.078)	(.078)	(.079)
Year2010	$-.925^{***}$	$-.929^{***}$	$-.881^{***}$
	(.073)	(.073)	(.073)
Year2011	-1.589^{***}	-1.563^{***}	-1.506^{***}
	(.095)	(.096)	(.094)
Year2012	-1.187^{***}	-1.139^{***}	-1.118^{***}
	(.093)	(.093)	(.089)
Year2013	$-.646^{***}$	$-.627^{***}$	$-.648^{***}$
	(.059)	(.060)	(.057)
Year2014	(omitted)	(omitted)	(omitted)
Year2015	$-.208^{***}$	$-.174^{**}$	$-.213^{***}$
	(.073)	(.073)	(.071)
Trend	$-.004^{***}$	$-.003^{***}$	$-.004^{***}$
	(.001)	(.001)	(.001)
Obs.	22836	22832	22836
Counties	2073	2072	2073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: Windmeijer (2005) bias-corrected robust standard errors.

Table A.4: Full Estimation Results for Table 9

Variable	Dependent Variable		
	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)			
L1.	.085***	.077***	.065***
	(.014)	(.014)	(.015)
L2.	.042***	.033**	.017
	(.013)	(.013)	(.014)
L3.	.007	.000	−.009
	(.011)	(.011)	(.012)
$SCL456$			
L1.	−.321***	−.333***	−.304***
	(.056)	(.056)	(.054)
L2.	−.098*	−.108*	−.078
	(.058)	(.058)	(.057)
L3.	−.055	−.062	−.057
	(.058)	(.058)	(.058)
$SCL789$			
L1.	−.498***	−.508***	−.440***
	(.134)	(.134)	(.131)
L2.	−.259**	−.262**	−.216*
	(.121)	(.120)	(.116)
L3.	−.259**	−.250**	−.172
	(.128)	(.127)	(.123)
$SCL10Plus$			
L1.	−.622***	−.650***	−.564***
	(.151)	(.149)	(.145)
L2.	−.197	−.213	−.169
	(.154)	(.150)	(.147)
L3.	−.013	−.022	.012
	(.130)	(.127)	(.124)
Crop Insurance			
ln(UnitSize)	−.246***	−.020	−.165*
	(.095)	(.094)	(.098)
InsuranceType	−1.799***	−1.643***	−1.089***
	(.297)	(.296)	(.294)
CoverageType	1.630***	.582	1.352**
	(.577)	(.579)	(.556)
CoverageLevel	−1.479	−2.509	−3.944**
	(1.797)	(1.761)	(1.768)
Precipitation			
ln(Mar_precipitation)	−.010	−.013	−.015
	(.027)	(.027)	(.027)
ln(Apr_precipitation)	−.129***	−.130***	−.127***
	(.032)	(.032)	(.032)
ln(May_precipitation)	.088**	.077**	.097***
	(.036)	(.036)	(.035)
ln(Jun_precipitation)	.114***	.114***	.119***
	(.037)	(.037)	(.036)
ln(Jul_precipitation)	−.040	−.047	−.020
	(.031)	(.031)	(.031)

Table A.4: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
ln(Aug_precipitation)	−.018	−.023	−.007
	(.029)	(.029)	(.028)
ln(Sep_precipitation)	.112***	.121***	.102***
	(.029)	(.029)	(.028)
ln(Oct_precipitation)	.051*	.051*	.066**
	(.027)	(.027)	(.026)
ln(Nov_precipitation)	−.125***	−.117***	−.129***
	(.027)	(.028)	(.026)
Temperature			
Mar_tMin	.017	.013	.011
	(.014)	(.014)	(.013)
Apr_tMin	.003	.000	−.001
	(.015)	(.016)	(.015)
May_tMin	−.096***	−.090***	−.083***
	(.019)	(.019)	(.019)
Jun_tMin	−.098***	−.087***	−.081***
	(.025)	(.025)	(.025)
Jul_tMin	.167***	.161***	.164***
	(.021)	(.021)	(.020)
Aug_tMin	−.074***	−.069***	−.088***
	(.021)	(.021)	(.021)
Sep_tMin	−.035**	−.035**	−.012
	(.017)	(.017)	(.016)
Oct_tMin	.057***	.049***	.049***
	(.017)	(.016)	(.017)
Nov_tMin	.062***	.058***	.065***
	(.015)	(.016)	(.015)
Mar_tMax	−.057***	−.051***	−.054***
	(.012)	(.012)	(.011)
Apr_tMax	−.072***	−.070***	−.077***
	(.013)	(.013)	(.013)
May_tMax	.040**	.034*	.031*
	(.018)	(.018)	(.018)
Jun_tMax	.069***	.073***	.060***
	(.023)	(.023)	(.023)
Jul_tMax	.040*	.037	.046**
	(.023)	(.023)	(.023)
Aug_tMax	.159***	.157***	.159***
	(.024)	(.024)	(.023)
Sep_tMax	.049***	.045***	.049***
	(.015)	(.015)	(.014)
Oct_tMax	−.060***	−.051***	−.053***
	(.016)	(.016)	(.016)
Nov_tMax	−.061***	−.055***	−.067***
	(.014)	(.014)	(.014)
Mar_dday30C	.346**	.314**	.337**
	(.150)	(.128)	(.156)
Apr_dday30C	−.058***	−.060***	−.069***
	(.021)	(.020)	(.021)

Table A.4: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
May_dday30C	.046***	.048***	.057***
	(.009)	(.009)	(.010)
Jun_dday30C	.018***	.015***	.014***
	(.004)	(.004)	(.004)
Jul_dday30C	.003	.003	.005*
	(.003)	(.003)	(.003)
Aug_dday30C	.003	.003	.005*
	(.003)	(.003)	(.003)
Sep_dday30C	−.013***	−.012***	−.011***
	(.004)	(.003)	(.003)
Oct_dday30C	.031	.025	.035
	(.027)	(.026)	(.027)
Nov_dday30C	.246	.278	.343
	(.197)	(.185)	(.249)
Drought			
Mar_Drought	−.043**	−.039**	−.040**
	(.017)	(.018)	(.017)
Apr_Drought	−.001	−.010	−.012
	(.022)	(.022)	(.021)
May_Drought	−.097***	−.093***	−.084***
	(.018)	(.018)	(.017)
Jun_Drought	.175***	.184***	.202***
	(.023)	(.023)	(.023)
Jul_Drought	.227***	.221***	.194***
	(.020)	(.020)	(.020)
Aug_Drought	.004	.002	.004
	(.016)	(.016)	(.016)
Sep_Drought	.088***	.093***	.092***
	(.017)	(.017)	(.017)
Oct_Drought	.021	.022	.040*
	(.023)	(.023)	(.022)
Nov_Drought	.142***	.134***	.130***
	(.022)	(.022)	(.022)
Wetness			
Mar_Wetness	−.028*	−.020	−.030*
	(.017)	(.017)	(.016)
Apr_Wetness	.008	.008	.008
	(.011)	(.012)	(.011)
May_Wetness	.107***	.109***	.105***
	(.010)	(.010)	(.010)
Jun_Wetness	.145***	.142***	.149***
	(.010)	(.010)	(.010)
Jul_Wetness	.029**	.031**	.031**
	(.013)	(.013)	(.012)
Aug_Wetness	.006	.009	.017
	(.012)	(.012)	(.012)
Sep_Wetness	.075***	.074***	.075***
	(.010)	(.010)	(.010)
Oct_Wetness	−.009	−.004	−.012

Table A.4: Continued

Variable	Dependent Variable ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.010)	(.010)	(.010)
Nov_Wetness	−.011	−.014	−.007
	(.014)	(.014)	(.014)
Land ($/acre)			
ln(Rent)	.511***	.462***	.209
	(.151)	(.148)	(.149)
Expenses ($/acre)			
ln(Seed)	.150	.187*	.073
	(.107)	(.109)	(.108)
ln(PetroleumProducts)	.655***	.726***	.709***
	(.154)	(.156)	(.153)
ln(AllOtherExpenses)	−.231	−.265	−.122
	(.163)	(.162)	(.159)
ln(FertilizerChemicals)	.159	.222	.127
	(.170)	(.167)	(.167)
ln(HiredLabor)	−.545***	−.604***	−.587***
	(.112)	(.111)	(.110)
Year			
Year2005	−1.001***	−1.053***	−1.007***
	(.081)	(.083)	(.080)
Year2006	−1.022***	−1.081***	−.946***
	(.084)	(.085)	(.084)
Year2007	−.898***	−.996***	−.893***
	(.087)	(.087)	(.087)
Year2008	−.614***	−.709***	−.506***
	(.085)	(.087)	(.084)
Year2009	−.406***	−.401***	−.183**
	(.078)	(.078)	(.079)
Year2010	−.907***	−.911***	−.866***
	(.074)	(.074)	(.074)
Year2011	−1.574***	−1.547***	−1.494***
	(.096)	(.096)	(.095)
Year2012	−1.171***	−1.122***	−1.106***
	(.093)	(.093)	(.090)
Year2013	−.641***	−.621***	−.644***
	(.060)	(.060)	(.058)
Year2014	(omitted)	(omitted)	(omitted)
Year2015	−.202***	−.168**	−.207***
	(.073)	(.073)	(.071)
Trend	−.004***	−.003***	−.004***
	(.001)	(.001)	(.001)
Obs.	22836	22832	22836
Counties	2073	2072	2073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: Windmeijer (2005) bias-corrected robust standard errors.