Somebody's Watching Me! Impacts of the Spot Check List Program in U.S. Crop Insurance

Sungkwol Park, Korean Ministry of Strategy and Finance (sungkwol@gmail.com)

Roderick M. Rejesus, North Carolina State University (rmrejesu@ncsu.edu)

Xiaoyong Zheng, North Carolina State University (xzheng@ncsu.edu)

Barry K. Goodwin, North Carolina State University (bkgoodwi@ncsu.edu)

Selected Paper prepared for presentation at the 2019 Agricultural & Applied Economics Association Annual Meeting, Atlanta, GA, July 21 – July 23

Somebody's Watching Me! Impacts of the Spot Check List Program in U.S. Crop Insurance

May 13, 2019

Abstract

The "Spot Check List" (SCL) is an important tool developed to help detect and deter fraud, waste, and abuse in the U.S. crop insurance program. This article examines whether the SCL program affects producers' claims filing behavior and provides insights on the effectiveness of this program. Using proprietary, county-level SCL data and panel data econometric procedures (which control for both observable and unobservable confounding factors), we find evidence that counties with producers included in the SCL tend to have better actuarial performance (i.e., lower indemnity payment amounts) after being informed about their listing on the SCL. This indicates that the SCL procedure is a valuable tool for maintaining integrity in the federal crop insurance program.

Keywords: Spot Check List; Insurance Fraud; Crop Insurance
JEL Classification Numbers: H59; Q18

1 Introduction

Fraud, waste, and abuse in the insurance industry is a serious problem for consumers, regulators, and insurance companies because it has the potential to significantly increase the cost of providing coverage and may eventually lead to the collapse of different kinds of insurance programs. For example, in 2014, the U.S. spent approximately $3 trillion on health care. Medicare accounted for $554 billion of these costs and around $60 billion may have been squandered due to incorrect billing methods, abuse, and fraud (Bush et al., 2017). For government-subsidized insurance programs, like Medicare, Medicaid and U.S. crop insurance, maintaining program integrity is also of critical importance because governments do not want the public to view them as mismanaging taxpayer dollars.

In 2000, the U.S. Congress enacted the Agricultural Risk Protection Act (ARPA), which expanded the authorities of the U.S. Department of Agriculture's (USDA's) Risk Management Agency (RMA)[1] and directed them to utilize cutting-edge data mining methods and related technologies to maintain and improve integrity in the US crop insurance program. As part of these efforts and to comply with the directives in ARPA, the RMA and their partners use complex and proprietary algorithms to analyze their large data warehouse containing extensive crop insurance data and information from other related databases collected over time (e.g. weather data and other administrative data from other USDA agencies). The aim is to detect individual producers whose claims behaviors demonstrate atypical patterns that may indicate fraud, waste, or abuse. One of the main outputs from this process is the "Spot Check List" (SCL) – an annual list of insured farmers, identified using objective and data-driven statistical techniques, whose loss experience is considered "anomalous" relative to similarly-situated producers in the same geographic area (i.e., typically within a county), producing the same crop and using the same cropping practices.

To develop the SCL, previous research and "on-the-ground" observations gathered from

[1]USDA-RMA is the government agency in charge of administering the US crop insurance program.

RMA field staff and partner insurance companies (called Approved Insurance Providers (AIPs)) are first utilized to identify different "scenarios" that suggest potential fraud, waste, or abuse. For example, one algorithm may pertain to finding those producers that have large multi-year losses that are consistently higher than their peers in the county. Another algorithm may aim to detect behavior consistent with known fraud schemes that have previously been recognized.

All producers flagged by these detection procedures are then used to create a pool to be included in the SCL. The SCL developed for producers of spring-planted crops (e.g. corn, soybeans), that is based on data analyzed through a particular crop year (say, in 2017, where data through December 2017 is analyzed), is typically finalized no later than the first quarter of the following year (i.e., no later than April 1, 2018). Each farmer in the SCL is then assigned either to the USDA Farm Service Agency (FSA) county office where the SCL is located or to the AIP who serviced the SCL producer. Soon after, the concerned FSA county office or AIP sends a formal written letter to the SCL farmers assigned to them, informing them of their inclusion in the SCL and that their operations are subject to inspection and policy review during the growing season.[2] The FSA county offices or the AIPs then conduct infield inspections or policy reviews of the SCL producers, although on occasion a small number of SCL farmers are not inspected or reviewed (i.e., due to time and resource constraints).

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 as to whether the SCL program indeed helps reduce fraud, waste, and abuse. Finding an

[2]Note that from 2001 to 2011 the FSA had the sole responsibility for conducting infield inspections of all SCL producers (i.e., both growing season and pre-harvest inspections) to assess whether the condition of the insured crop was consistent with other non-SCL producers in the area. Beginning in 2012, AIPs assumed responsibility for inspecting a subset of producers in the SCL (with the FSA still responsible for the remaining producers). The AIP inspection is more comprehensive than the FSA in the sense that they perform both infield inspections and a full policy review. Moreover, the AIPs inspect and review all the SCL producers assigned to them given their contractual obligation to the Federal crop insurance program. For a more detailed description of what is involved in an AIP inspection and full policy review, see: https://www.rma.usda.gov/pubs/ra/sraarchives/19sra.pdf.

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 the SCL program is effective in helping maintain the integrity of the US crop insurance program is an important public policy issue. If the SCL program is effective in reducing exaggerated claims, then more public funding should be devoted to develop better data-driven algorithms and statistical techniques for identifying insured producers to be included in the SCL. On the other hand, if the program is found to be ineffective, then effort should be devoted to searching for other strategies that can help deter potential crop insurance fraud, waste, or 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. Turvey (2012), on the other hand, is an example of one study that explores alternative contract mechanisms that may help curb ex ante moral hazard.

Only a few studies have examined potential fraud behavior in crop insurance (i.e., also called ex post moral hazard, since this typically ocurs after the insured outcome is realized).[3] Rejesus et al. (2004) 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 indemnity payments). A recent study of Zhang, Cao, and Wang (2018) suggest that there is underreporting of insurable hogs in a pilot hog insurance program in China (i.e., to lower producer paid premiums,

[3] It is important to note here that the SCL approach examined in this study aims to not only detect and deter potentially fraudulent actions, but also other "anomalous" behavior that is suggestive of waste or abuse (i.e., actions taking advantage of a loophole). As such, the scope of the SCL program covers both ex ante and ex post moral hazard behavior.

relative to expected indemnities).

To the best of our knowledge, no study has carefully examined the economic effectiveness of policies that aim to mitigate fraud, waste, and abuse 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 (USDA-RMA, 2004 to 2006). However, this conclusion was primarily based on simple "before-and-after" comparisons of claims behavior (i.e., indemnity amounts of SCL producers before and after receipt of the SCL letter), without controlling for possible confounding factors that could have also affected the observed claims behavior (e.g. weather conditions, production inputs).[4] In addition, these reports also did not address endogeneity issues with respect to the variable that represents inclusion in the SCL due to time-invariant unobserved heterogeneity. Therefore, in this study, we employ static and dynamic panel data models that help overcome these issues (i.e., controlling for observable confounding factors and time-invariant unobserved heterogeneity), and provide a robust estimate of the SCL's impact on actuarial performance.[5]

This paper also contributes to the literature on evaluating strategies to prevent and mitigate potential fraud, waste, and abuse in various public and private programs such as tax collection (Slemrod, Blumenthal and Christian, 2001; Lyer, Reckers and Sanders, 2010; Kleven et al., 2011; Pomeranz, 2015; Bott et al., 2017; Mascagni, 2017), TV license fees (Rincke and Traxler, 2011; Fellner, Sausgruber and Traxler, 2013; Drago, Mengel and Traxler, 2015), health insurance (Becker, Kessler and McClellan, 2005; Kang et al., 2009;

[4]The "before-and-after" indemnity comparison is considered by RMA as a measure of "cost avoidance" attributable to the SCL. Over the years there has been refinements to this cost avoidance calculation (i.e., accounting for price changes before and after listing, and accounting for "background" losses common to all producers in an area), but the basic "before-and-after" procedure remains unchanged. While the reports that detail the calculation procedures over time remains internal to RMA, the resulting annual cost avoidance measure is typically made publicly available.

[5]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.

Rashidian, Joudaki and Vian, 2012) and auto insurance (Hoyt, Mustard and Powell, 2006). Of particular relevance are the studies that evaluate the effects of sending warning letters to suspicious individuals (Slemrod, Blumenthal and Christian, 2001; Lyer, Reckers and Sanders, 2010; Kleven et al., 2011; Bott et al., 2017; Fellner, Sausgruber and Traxler, 2013). To the best of our knowledge, our study is the first to evaluate a similar program in the context of U.S. crop insurance.

The rest of 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, the 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 model, the insured knows the actual magnitude of the loss, there is no cost for the insured to file a false 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 paradigms. On one hand, there are some costs for the insured to file a false claim. The insured probably needs to incur costs to falsely represent a claim. In addition, there is a nonzero probability that they will be caught and banned from participating in any federal programs in the future. On the other hand, with some costs, the insurance company and the government can discern the true loss of the producer through a careful audit. In several high-profile cases, 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 low frequency of audits, 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 $C(y-x,\gamma)$ if his/her true realized loss is x, but instead he/she files a claim of y greater than x. The exaggeration activities are costly and $\gamma > 0$ is the cost parameter. $C(y-x,\gamma)$ is assumed to have the following properties: $\frac{\partial C(y-x,\gamma)}{\partial(y-x)} > 0$, $\frac{\partial C(y-x,\gamma)}{\partial\gamma} > 0$ and $\frac{\partial^2 C(y-x,\gamma)}{\partial(y-x)\partial\gamma} > 0$. These imply that the falsification cost increases in the amount of the exaggerated claim and the cost parameter. In addition, the effect of the exaggerated claim amount on falsification cost increases with the cost parameter. For example, a quadratic cost function $C(y-x,\gamma) = \gamma(y-x)^2$ satisfies all these properties. In addition, we assume that if fraud is detected and proven, there is a penalty of $f(y-x)$. This function captures the fact that if fraud behavior is detected and proven, not only does the insured need to pay back the exaggerated part of the claim, but also faces the possibility of legal penalties, including imprisonment, fines, and exclusion from federal programs. This is likely to be very costly for the insured producer. We further assume that $\frac{\partial f(y-x)}{\partial(y-x)} > 0$, which means the penalty is increasing in the amount of the exaggerated claim.

With these assumptions, the producer's objective function can be written as follows,

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

where $U(\cdot)$ is a twice differentiable von Neumann-Morgenstern utility function with $U^{'}(\cdot) > 0$ and $U^{''}(\cdot) < 0$. $\big[t(y) - C(y-x,\gamma)\big]$ is the producer's return if he files an exaggerated loss of y and he is not audited. In this case, the producer will get an indemnity payment of $t(y)$ and pay no fine. The producer will also receive $t(y)$ in the case where he/she is audited but no sufficient evidence of fraud is found. The term $[t(x) - C(y-x,\gamma) - f(y-x)]$ is then the producer's return if audited and found to be cheating. In this case, the indemnity payment is $t(x)$ and the producer 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, with the restriction $y > x$.[6] The first-order necessary condition for maximization is:

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

To guarantee that the solution to (2) is a 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 the SCL is finalized and the producers included are informed, the concerned insurance companies or the USDA FSA field offices can conduct growing season

[6]Under the assumption that reporting a claim less than the true loss incurs no falsification and penalty cost, it is easy to show that filing a claim less than the true loss is never optimal. And for simplicity, we rule out the corner solution case, that is, the case where reporting the true loss is optimal. When falsification and penalty costs are prohibitively high, it is possible that reporting the true loss is the optimal choice.

or pre-harvest infield inspections of the SCL producers assigned to them. In addition, the insurance companies, in particular, can can also perform a more comprehensive policy review of the SCL producers they are designated to inspect. The infield inspection (or policy review) will give the insurance company or USDA FSA/RMA information on how much the producer has actually planted/produced and the status of their production. This will make it more costly for the producer to exaggerate their loss when filing claims. To see the effect of such an increase in falsification cost on the amount of loss claimed, 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 $\frac{dy}{d\gamma} = -\frac{FOC_\gamma}{FOC_y}$. Since $FOC_y < 0$ is the second-order sufficient condition required for the existence of the maximum, the sign of $\frac{dy}{d\gamma}$ is determined by the sign of FOC_γ. From (2), it is straightforward to show,

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

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 $\frac{dy}{d\gamma} < 0$. A weaker sufficient condition is simply that (3) is negative. Whether or not these sufficient conditions hold depends on the specifications of $p(\cdot)$, $U(\cdot)$, $t(\cdot)$, $C(\cdot,\cdot)$ and $f(\cdot)$ as well as the magnitudes of γ and $(y-x)$. In the special case of a linear utility function with $U(x) = ax + b$ $(a > 0)$ and hence $U^{'}(\cdot) = a$ and $U^{''}(\cdot) = 0$, (3) is reduced to be $-a\frac{\partial^2 C(y-x,\gamma)}{\partial(y-x)\partial\gamma}$ which is negative. This leads to one testable hypothesis: *Producers who are on the Spot Check List (SCL) will file smaller claim amounts than what they would have if they were not on the SCL.*

We note, however, that this testable hypothesis can only be empirically validated if one has access to: (i) individual-producer data on whether the grower is on the SCL at a particular point in time, and (ii) the associated claims data over time (preferably claims behavior when the insured was not on the SCL and after they were put on the SCL (and/or inspected)). Due to the confidentiality considerations 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 accessible. As such (and as discussed further below), county-level data about SCL listings and claims filing behavior are the only data accessible, and therefore this is the type of data we use to test our hypothesis. Therefore, the more "aggregate-level" testable hypothesis that naturally follows from the individual-producer level hypothesis above is as follows: *all other things being equal, a county with more producers on the SCL will have smaller claim amounts than other similar counties with less (or no) SCL producers.*

3 Data

The data used in our study come from several different sources. Each source is explained below with a focus on the variables used in the empirical analysis. Because the SCL program formally 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[7] for the following four major US row crops: corn, soybeans, wheat, and cotton, in

[7]Only Yield-Protection (YP) and Revenue Protection (RP) policies (as these policies are called today) are considered in the SCL process, as such, these are the only two policies included in the analysis here. 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 (and in the SCL program).

addition to tobacco. Therefore, our data include 78.7% of all crop insurance policies for which acreage has been reported to USDA-RMA from 2001 to 2015. These data come from 2,200 counties across all U.S. states, except Alaska, Hawaii, and Rhode Island.[8]

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 of total indemnities to premiums, while LRsubsidy is defined as the ratio of total indemnities to producer paid premiums (total premiums minus subsidy). Finally, LCR is defined as the ratio of total indemnities to liability. County-level crop insurance experience data such as total insurance premium, indemnity, subsidy, and liability are publicly available from USDA-RMA.[9]

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 these 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).[10] 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

[8]Crop insurance policies sold from 2001 to 2015 were distributed in 2,832 counties across all 50 U.S. states. For the five crops we focus on (i.e., corn, soybeans, wheat, cotton, and tobacco), crop insurance policies were sold to producers in 2,213 counties across 47 states during the same period. An additional 13 counties were lost due to missing data and counties being merged and consolidated.

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

[10]In other words, the data are censored from below at 4.

spatial distribution of the total number of SCL producers from 2001 to 2015.[11] We note that counties with substantial 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 was started in 2001, the Dakotas and the Plains have larger numbers of SCL producers, but the clusterings 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, a number of SCL producers were in Iowa, Missouri, Illinois, and Kansas.[12] Figure 4 demonstrates how indemnities in counties changed over the 3 years after they had at least four producers on the SCL. It shows that there was 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 were increases. Indemnities for these years probably were also impacted by unfavorable weather conditions (e.g. severe nationwide drought). The same trend can be seen for the loss ratio (Figure 5), the subsidy adjusted loss ratio (Figure 6) and the loss cost ratio (Figure 7).

In addition to the main variable of interest above, weather is another 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,[13] 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

[11] 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.

[12] It is important to emphasize here that the SCL procedure is national in scope. Even with these geographical SCL "clusterings" observed over time, there was no explicit attempt to "target" a specific region in the US or a particular set of crops. These SCL "clusterings" over time are simply a result of objective, data-driven algorithms applied nationally in order to detect anomalous behavior.

[13] See: http://www.prism.oregonstate.edu.

temperature (°C), and total degree days above 30 °C for the growing months.[14] Monthly total degree days are defined as the sum of degrees above a certain threshold during a given month.[15] 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) from the National Oceanic and Atmospheric Administration (NOAA). For ease of interpretation, we constructed two variables based on the PDSI, one that represents dryness (or drought conditions) and the other for wetness (or flood conditions).[16]

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 collected county-level data for the following control variables: the average number of acres insured per unit (*Unit Size*), the ratio of revenue-based policies relative to yield-based policies (*Insurance Type*), the ratio of policies with buy-up coverage relative to catastrophic coverage (*Coverage Type*), and the average coverage level (*Coverage Level*) weighted by the number of acres insured. 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. These data were collected from the USDA-RMA's summary of business.[17]

Another important determinant of agricultural yields and resulting claims amounts is the

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

[15]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).

[16]The county level data for this index were not publicly available (at the time the data set was constructed). PDSI 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.

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

production inputs used by insured farmers. Thus, we collected county-level expenditure data on seed, fertilizer and chemicals, labor, and other production expenses, from the Bureau of Economic Analysis (BEA).[18] We then divided the expenditure data by the number of acres planted in the county to get the per acre expenditure data.[19] Land rental values for agricultural land are used as the measure of capital cost, and state-level data on this variable are collected from the USDA's Quick Stats.[20]

It is worth noting that insurance characteristics and input expenditure (with the exception of land rental values) are farmers' decision variables and hence are likely to be endogenous in a regression model for claims filed. Therefore, in the main specification of our regression analysis below, we only include the number of producers on the SCL, the weather variables, and land rental values as independent variables. Other insurance characteristics and input expenditure variables are only included in one of the robustness check regressions. Table 3 lists the variables used in our empirical analysis below and the corresponding data sources, while the summary statistics for these variables are then displayed in Table 4.

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 impact as follows,

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

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

[19]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.

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

where y_{it} is the logarithm of LR (or LRsubsidy or LCR) in county i and year t,[21] 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 are 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 the weather variables and land rental values; λ_t, the year fixed effects, to control for effects from variables that do not vary across counties; t, a linear time trend; μ_i, the county fixed effects that control for time-invariant county level factors that influence claims behavior, and ϵ_{it}, the idiosyncratic error for county i in year t. We first 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,

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

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

[21]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.

specification. First, as suggested by Arellano and Bond (1991), we use the second and feasible higher-order lags of the dependent variable, i.e., $y_{i,t-2}$, $y_{i,t-3}$, ..., $y_{i,t-14}$[22]. 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,

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

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 spec-

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

ification, 69 (or 75 in the case of using SCL grouping dummies) covariates are used and therefore, there are 69 (or 75) moment conditions in this set.

Finally, following Arellano and Bover (1995), Blundell and Bond (1998), and Blundell, Bond, and Windmeijer (2000), we 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 a 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 169 (or 175 in the case of using SCL grouping dummies) moments conditions are used to estimate 72 (or 78) 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

5.1 Estimation results

The main estimation results from the static and dynamic models are presented in Tables 5-6. The regressions include lagged dependent variables (only in the dynamic models), SCL variables, weather variables, a land rental value variable, and a trend variable. But note that the coefficients for the weather and trend variables are not reported in Tables 5-6 for brevity. The full results are reported in Tables A.1-A.2 in the appendix. Also, J is chosen to be 3 in these regressions. Before we present and discuss our estimation results, we first must test for autocorrelation in $\Delta\epsilon_{it}$ for the dynamic models. This is because 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 $\Delta\epsilon_{it}$.[23] This test 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 the bottom part of Table 6. 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 $\Delta\epsilon_{it}$ at the conventional significance levels. These results lend support to our empirical specifications.

Several results are notable. First, our estimation results clearly show that there is persistence in the LR, LRsubsidy, and LCR variables for at least two years. Table 6 indicates that LR, LRsubsidy, and LCR values in the past two years have a positive and statistically significant effect on the LR, LRsubsidy, and 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 unobserved time-varying conditions (like slowly-evolving states of soil nutrient levels and climate trends) have persistent effects on yields. This result may also reflect state-dependence due to the relatively stable crop insurance participation in the sample period, suggesting that premiums and/or liabilities inherent in the actuarial performance variables are fairly "slow-moving." This result shows the importance of using a dynamic specification instead of a static one and including the lagged dependent variables in the empirical model.

Second, regarding our main SCL variables of interest, we identify strong deterrence effect in the results from the dynamic models. Based on the SCL linear specification, it appears that an additional SCL producer in a county (i.e., identified using data through year $t-1$ and notified of inclusion in year t), decreases the county's LR, LRsubsidy, and LCR in year t by 5.8%, 6.1%, and 5.4%, respectively. These estimated effects are much larger than those from the static models reported in Table 5 and are statistically significant at the 1% significance level. It shows the importance of controlling for lagged dependent variables in identifying the SCL effects using county-level data.

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

Furthermore, coefficients associated with the SCL group dummies (Table 6) reveal additional evidence that more SCL producers in a county leads to a much larger reduction in the amount of 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 that is 35.9%, 53.9%, and 66.1% lower this year, respectively. These effects are again much larger than those from the static models (Table 5), 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 in the previous year has a loss cost ratio (LCR) 47.9% lower this year, 22.7% lower next year, and 21.4% lower two years later, respectively. These results show that the SCL program has strong deterrence effect, which implies that when there are more SCL producers in a county, producers file much lower claim amounts and the deterrence effect tends to last longer than just during the year they were informed.

Lastly, our results show that rental rates have a positive effect on claims filed. This indicates that farmers with higher costs on cropland are more likely to file for indemnity payments.

5.2 Cost Avoidance Estimates

To put further context on the deterrence effects estimated in Table 6, we also calculate a "cost avoidance" measure (in dollar terms) that reflect the indemnities that could have been incurred had the SCL program not been in place (i.e., or alternatively, an estimate of the indemnities avoided due to the presence of the SCL program). Based on the SCL linear specification in Table 6, the average short-run (or "single year") effects of notifying one additional producer in a county that they are on the SCL are: (a) lower county-level LR (by -5.8%), (b) lower county-level LRsubsidy (by -6.1%), and (c) lower LCR (by -5.4%). The first step in calculating a short-run, dollar-valued cost avoidance measure is to multiply the estimated percentage deterrence effect with the average number of of SCL producers in a county for a given year.[24] For example, consider the 2004 crop year where the average number of SCL producers for all counties in our sample is 0.434, and the -5.8% deterrence effect for LR from Table 6. The initial step in the cost avoidance calculation is then to multiply 0.434 by 0.058, to get the average percentage reduction in LR (i.e., for all counties) for the year 2004, which is equal to 0.025 ($= 0.434 \times 0.058$).

Following our example above, the second step in the cost avoidance calculation is to use the average percentage reduction in LR (from the first step) to get an estimate of what the average LR should have been had the SCL program not been present (for a given year). For the 2004 crop year, we know from our data that the actual observed average LR (across all counties) was 0.685, with the SCL program present for that year. Thus, the average county-level LR in 2004 had the SCL program <u>not</u> been in place is calculated as follows ($\frac{0.685}{1-0.025}$=0.703). This suggests that the average county-level LR for 2004 should have been 0.703 (rather than 0.685) had the SCL program not been in place. This implies that the average LR for all counties in our sample would have been 0.018 higher in 2004 had the SCL program not been present ($0.018 = 0.703 - 0.685$).

The third step in our cost avoidance calculation is to then translate the estimated average LR avoided (0.018, in our example) to a total indemnity avoided measure for a particular year (in dollar terms) . Since LR is calculated as LR=Indemnities/Premiums, we determine the average indemnity avoided by multiplying the average LR avoided (across all counties for a given year) with the observed total premiums collected (for all counties for a given year). Therefore, for crop year 2004, the average indemnity avoided is \$57 million (i.e., calculated as $0.018 \times \$3.180$ billion = \$57 million, where \$3.180 billion is the observed total premiums for all counties in the data for 2004) (See Table 7).

The same computational procedure described above is then applied for each year based

[24] The average number of SCL producers for a given year is calculated for <u>all</u> counties in the sample (which includes counties with no SCL producers and counties with SCL producers). That is, $\frac{1}{n_{all}} \sum_{i=1}^{n_{all}} SCL_i$, where n_{all} is the total number of counties in the sample and SCL_i is the total number of SCL producers for each county i (i.e., SCL_i can be zero for some counties). The average number of SCL producers across all counties is considered here because the deterrent effect estimated from dynamic model pertains to the "average" effect across all counties in the sample (not just the effect on the counties with SCL producers).

on the estimated short-run LR (-5.8%), LRsubsidy (-6.1%), and LCR (-5.4%) deterrent effects. The resulting average yearly cost avoidance (or average indemnity avoided) for all counties in each year are reported in Table 7. Graphically, the trends in the estimated yearly total indemnity avoided due to the presence of the SCL program is depicted in Figure 8. The cost avoidance estimates range from a low of $25 million in 2005 (based on the LR deterrent effect) to a high of $319 million for 2013 (based on the LCR deterrent effect). Averaging across all years (from 2004-2015), the average yearly cost avoidance (or average yearly indemnities avoided) is $127 million for the LR specification, $141 million for the LRsubsidy specification, and $153 million for the LCR specification, respectively (Table 7).

Given that the average yearly indemnities paid out to farmers of the five crops considered in this study (for the 2004-2015 period) is about $5.7 billion, the average yearly cost avoidance (or indemnity avoided) based on the LR model specification is about 2.2% of the annual average indemnities paid out (i.e., $127 million/$5.7 billion = 0.022 or 2.2%). Accordingly, the average yearly cost avoidance (or indemnity avoided) based on the LRsubsidy and LCR models are 2.5% and 2.7%, respectively (i.e., $141 million/$5.7 billion = 0.025 or 2.5%, and $153 million/$5.7 billion = 0.027 or 2.7%). These figures imply that the average yearly indemnities paid out for the period 2004-2015 would on average have been 2.2% to 2.7% higher had the SCL program not been in place at that time. Interpreted another way, these figures suggest that the average yearly indemnities avoided (or average yearly cost avoidance) for the period 2004-2015 (across all counties) range from about 2.2% to 2.7% of the average yearly indemnities paid out.

To further validate the estimated 2.2% to 2.7% magnitude of the average yearly cost avoidance (or indemnity avoidance), we examine existing literature that investigated the effectiveness of notification strategies (similar to the SCL program) that is used in other contexts/industries. The majority of studies in this vein specifically look at the effects of "threat-of-audit" letters in tax reporting situations (Slemrod, Blumenthal and Christian 2001; Kleven et al., 2011; Agostini and Martinez 2014; Doerrenberg and Schmitz 2015;

Mazzolini, Pagani, and Santoro 2017). The deterrence effects estimated in these tax studies ranged from 8.2% (Mazzolini, Pagani, and Santoro, 2017) to 19% (Kleven et al., 2011).[25] In addition, although we did not find any explicit figures about the effects of inspection letters (like the SCL approach) in other lines of insurance, Viaene and Dedene (2004) report that in most European countries fraud, waste, and abuse may represent between 5% to 10% of the yearly indemnities paid in non-life insurance lines. Therefore, given the deterrence effect magnitudes in other contexts (as reported above), the cost avoidance (or indemnity avoidance) estimates for the SCL program as calculated in this study seem reasonable.

Notwithstanding the consistency of our SCL cost avoidance estimates to those reported in related studies (e.g., tax setting), it is important to acknowledge here that the deterrence effects in the present study is based on aggregate county-level data rather than individual insured producer data. The parameter estimates for SCL linear specification in Table 6 demonstrate the effect of an additional SCL producer on county-level actuarial performance, rather than individual performance. Therefore, our county-level analysis does not precisely reveal the direct impact of SCL notification on the same SCL producer's claims filing behavior. With the county-level data utilized, the deterrence effects in Table 6 and the cost avoidance measures calculated above also capture "spillover effects" of SCL notification on other neighboring non-SCL producers in the county (who could have heard that their neighbor is in the SCL). It is possible that non-SCL producers in the county, who learned that their neighbor is on the SCL, could also alter their behavior to avoid being included in the list in the future. For example, neighboring non-SCL farmers may decide not to exaggerate their claims if they know that their neighbor is in the SCL, so as to reduce the likelihood of

[25]Detailed calculations of how these percentage deterrence effects are calculated from the results reported in each study are available from the authors upon request. Typically, the effect of "threat-of-audit" letters is to increase reporting of tax liability. Note that most of these tax studies cited utilized controlled experiments (e.g., randomly sending audit letters) or quasi-experimental methods, although there are some that used administrative data similar to the present study. Another context where the effects of "threat-of-audit" letters are examined is TV access license setting, where households that do not have license to access TV broadcasts are sent these letters and the effect is an increase in license registration (See Rincke and Traxler, 2011 and Drago, Mengel, and Traxler, 2015). The magnitude of effects in these TV license studies are similar to the ones reported here for taxes and for the SCL program.

being on the SCL in the future.

6 Robustness Checks

In the analysis so far, we have chosen the dependent variable lag length J to be 3. In this section, we examine whether our main results are robust to alternative lag length specifications. We consider $J = 1$, 2, and 4. Tables 8-9 collects the regression results using the dynamic specification and alternative lag lengths. For the purpose of brevity, we only report the coefficient estimates for the SCL and lagged dependent variables.[26] The results show that our main findings continue to hold, both in terms of the signs of the estimates and their statistical significance. The coefficient estimates for the lagged dependent variables are statistically significant for the first two lagged terms across all lag-depth alternatives. Regarding the SCL effects, the coefficient estimates of the lagged SCL variables indicate that the strong and persistent SCL effects are robust across different lag-depth specifications. Given that the coefficient estimates for the first, second, and third lagged SCL variables are all statistically significant across different lag-depth specifications, but the fourth lag term for the SCL variable is not statistically significant, setting J at 3 in the main specification can be justified. In sum, we conclude that our results are robust to alternative specifications of the lag-depth J.

Next, we investigate whether the main findings are sensitive to the loss of observations from taking the logarithm of the dependent variable. For this purpose, we add a small positive constant (e.g. 0.001) to the dependent variable and then take the logarithm, which is known as "started logs" (Tukey, 1977; Treiman, 2014).[27] This way, we can include those observations with zero value for the dependent variable in estimation. Table 10 shows that using started logs in the dynamic models yields very similar estimates of the SCL deterrence

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

[27]Further discussions (e.g. the nature and characteristics of estimates of log-linear relationships in the presence of zero observations for the regressand) can be found in Johnson and Rausser (1971), Hu (1972), Smith and Cicchetti (1974).

effects compared to those in section 5.

Furthermore, we considered additional alternative SCL specifications. As a third specification, we create two SCL variables: $SCL1_{i,t-j} = SCLProducerCount$ if the number of producers on the SCL > 3 and 0 otherwise; $SCL2_{i,t-j} = 1$ if $SCLProducerCount < 4$ and 0 otherwise. This specification is the same as the SCL group dummies specification for the $0-3$ category but linear for the part where $SCL > 3$. Therefore, this is like a combination of the two previous SCL specifications. Table 11 collects the main findings from the dynamic models with a third SCL specification from $J = 2$ to $J = 3$. Once again, consistently strong SCL deterrence effects are found. More specifically, in the case of $J = 2$, counties with $0-3$ SCL producers ($SCL2$) in the preceding year have a higher LR, LRsubsidy, and LCR in the current year by 27.5%, 27.0%, and 24.5% compared to those with 4 or more SCL producers. Moreover, as seen in the estimates in $SCL1$ variable, one more producer on the SCL ($SCL1$) has an additional negative impact on the LR, LRsubsidy, and LCR by 2.3%, 2.7%, and 2.7%, respectively.

Different sets of SCL dummies were also examined to evaluate results across different 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 forth. 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.

Finally, we included additional categories of control variables in the regression to evaluate the sensitivity of our results. The additional control variables included are insurance characteristics and input expenditure variables. As discussed above in section 3, these variables are potentially endogenous. Table 12 collects the estimates for the key variables.[28] We note that the coefficient estimates for the lagged dependent variables and SCL deterrence effects are nearly identical to our baseline results in section 5 with slightly lower magnitudes.[29]

[28]The full regression results are available from authors upon request.

[29]Table A.3 in the appendix shows the resulting costs avoided for all counties in each year, which are

In addition, regarding the insurance policy characteristics variables, our results show that counties with larger insured units on average have better actuarial performance. 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 better actuarial performance, which is consistent with the inherent "natural hedge" between prices and yields when revenue is insured instead of just yields being insured.

Lastly, counties with producers purchasing more buy-up coverage (relative to CAT) and counties where producers buy more coverage have poorer actuarial performance, which simply indicates that the likelihood of losses increases as insurance coverage increases. Next, with regards to the production inputs, our results show that rental rates and fuel expenditure 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 (and higher indemnity amounts). However, higher per acre labor cost have a negative effect on claims amount. This may be due to the fact that with more labor, yields are likely to be higher and losses are less likely.

7 Conclusions

Fraud, waste, and abuse are major concerns in the U.S. crop insurance program. Reducing the incidence of fraud, waste, and abuse improves the financial viability of the program, and provides benefits for both the participating private insurance providers and taxpayers. Such improvements are key to maintaining the integrity and stability of this centerpiece U.S. farm safety-net policy. Recognizing this, the USDA RMA implemented the SCL approach to help

based on the estimation results from the SCL linear specification in Table 12. Figure A.1 also illustrates the trends in the estimated costs avoided due to the presence of the SCL program.

detect producers potentially engaging in fraud, waste, and abuse, and consequently mitigate overall moral hazard behavior in the US crop insurance program. Specifically, the SCL is designed to help discourage 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 examined its effectiveness. This study is the first to evaluate the effect of the SCL process on producers' claims behavior. Using proprietary county-level SCL data and controlling for confounding factors that may also influence claims behavior, our econometric analyses over the 2001-2015 period provide strong statistical evidence that the SCL process does indeed affect claim amounts in the counties with SCL producers. Counties with producers listed on the SCL tend to have lower LRs, LRsubsidys, and LCRs in the year when the SCL producers are notified about their listing, and this effect carries over in subsequent years. For example, an additional producer informed of inclusion in the SCL in a county will result in approximately 5.8% lower county-level loss ratio (LR) in the year of notification. These results suggest that the SCL process may have facilitated a reduction in moral hazard behavior and is indeed a major factor in maintaining the integrity of the US crop insurance program. Hence, there is empirical support for the notion that the SCL procedure is effective in influencing producer claims behavior.

Given the results in this paper, the SCL approach seems to be a valuable and effective tool for mitigating fraud, waste, and abuse in the U.S. crop insurance program. One important policy implication is the need for continued budgetary support for this program. In particular, more resources are needed to conduct more in-season inspections and policy reviews (i.e., after notification of SCL listing), in order for producers to believe that the USDA-RMA can "credibly" pursue further investigations. This will assist in further encouraging truthful claims behavior. Moreover, providing resources to improve the statistical algorithms used for detecting "anomalous" producers potentially engaging in fraud, waste, and abuse also seems to be warranted.

Finally, even though this article provides important advances to assessing the effectiveness of the SCL fraud-mitigation approach, further research in a couple of dimensions is still needed. More accurate inferences about the effectiveness of the SCL could be made if individual level SCL data were analyzed. Availability of such data would allow one to assess whether the SCL notification process actually influences individual farmer behavior and (as mentioned in Section 5) would likely enable one to calculate more precise cost avoidance measures.

References

Agostini, C.A., Martinez, C.A., 2014. Response of Tax Credit Claims to Tax Enforcement: Evidence from a Quasi-Experiment in Chile. Fiscal Studies 35(1), 41-65-297.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277-297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68 (1), 29-51.

Annan, F., Schlenker, W., 2015. Federal crop insurance and the disincentive to adapt to extreme heat. American Economic Review: Papers & Proceedings 105 (5), 262-266.

Atwood, J. A., Robison-Cox, J. F., Shaik, S., 2006. Estimating the prevalence and cost of yield-switching fraud in the federal crop insurance program. American Journal of Agricultural Economics 88 (2), 365-381.

Becker, D., Kessler, D., McClellan, M., 2005. Detecting Medicare abuse. Journal of Health Economics 24, 189-210.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87 (1), 115-143.

Blundell, R., Bond, S., Windmeijer, F., 2000. Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. in Badi H. Baltagi, Thomas B. Fomby, R. Carter Hill (ed.) Nonstationary panels, panel cointegration, and dynamic panels (Advances in Econometrics, Volume 15) Emerald Group Publishing Limited, 53 - 91.

Borman, J. I., Goodwin, B. K., 2013. Accounting for short samples and heterogeneous experience in rating crop insurance. Agricultural Finance Review, 73 (1), 88-101.

Bott, K. M., Cappelen, A. W., Sorensen, E. O., Tungodden, B., 2017. You've got mail: a randomised field experiment on tax evasion. Norwegian School of Economics Working Paper.

Bush, J., Sandridge, L., Treadway, C., Vance, K., and Coustasse, A., 2017. Medicare fraud, waste, and abuse. in Avinandan Mukherjee (ed.) Business & health administration proceedings, 17-26.

Doerrenberg, P., Schmitz, J., 2015. Tax Compliance and Information Provision: A Field Experiment with Small Firms. ZEW Discussion Paper No. 15-028, Center for European Economic Research.

Drago, F., Mengel, F., Traxler, C., 2015. Compliance behavior in networks: evidence from a field experiment. IZA Discussion Paper No. 9443.

Fellner, G., Sausgruber, R., Traxler, C., 2013. Testing enforcement strategies in the field: threat, moral appeal and social information. Journal of the European Economic Association 11 (3), 634-660.

Hoyt, R. E., Mustard, D. B., Powell, L. S., 2006. The effectiveness of state legislation in mitigating moral hazard: evidence from automobile insurance. Journal of Law and Economics 49 (2), 427-450.

Hu, T., 1972. The fitting of log-regression functions when some observations in the regressand are zero or negative. Metroeconomica, 24 (1), 86-90.

Johnson, S. R., Rausser, G.C., 1971. Effects of misspecification of log-linear functions when sample values are zero or negative. American Journal of Agricultural Economics, 53 (1), 120-124.

Kang, H., Hong, J., Lee, K., Kim, S., 2009. The effects of the fraud and abuse enforcement program under the national health insurance program in Korea. Health Policy 95, 41-49.

Kleven, H. J., Knudsen, M. B., Kreiner, C. T., Pedersen, S., Saez, E., 2011. Unwilling or unable to chear? Evidence from a tax audit experiment in Denmark. Econometrica 79 (3), 651-692.

Knight, T. O., Coble, K. H., 1999. Actuarial effects of unit structure in the U.S. actual production history crop insurance program. Journal of Agricultural and Applied Economics, 31 (3), 519-535.

Knight, T. O., Coble, K. H., Goodwin, B. K., Rejesus, R. M., Seo, S., 2010. Developing variable unit-structure premium rate differentials in crop insurance. American Journal of Agricultural Economics, 92 (1), 141-151.

Lacker, J. M., Weinberg, J. A., 1989. Optimal contracts under costly state falsification. Journal of Political Economy, 97 (6), 1345-1363.

Lyer, G. S., Reckers, P. M. J., Sanders, D. L., 2010. Increasing tax compliance in Washington state: a field experiment. National Tax Journal 63 (1), 7-32.

Marra, M. C., Schurle, B. W., 1994. Kansas wheat yield risk measures and aggregation: a meta-analysis approach. Journal of Agricultural and Resource Economics, 19 (1), 69-77.

Mascagni, G., 2017. From the lab to the field: a review of tax experiments. Journal of Economic Surveys, 1-29.

Mazzolini, G., Pagani, L., Santoro, A., 2017. The deterrence effect of real-world operational tax audits. DEMS Working Paper Series No. 359, Dept. of Economics, Management, and Statistics, U. of Milan Bicocca.

NOAA (National Oceanic and Atmospheric Administration), Palmer Drought Severity Index (https://www7.ncdc.noaa. gov/CDO/CDODivisionalSelect.jsp♯).

Picard, P., 2013. Economic analysis of insurance fraud. In: Georges, D. (eds) Handbook of Insurance. Springer: New York, NY, 349-395.

Pomeranz, D. 2015. No taxation without information: deterrence and self-enforcement in the value added tax. American Economic Review, 105 (8), 2539-2569.

PRISM Climate Group, Oregon State University (http://prism.oregonstate.edu).

Rashidian, A., Joudaki, H., Vian, T., 2012. No evidence of the effect of the interventions to combat health care fraud and abuse: a systematic review of literature. PLoS ONE 7 (8): e41988.

Rejesus, R. M., 2003. Ex-post moral hazard in the U.S. crop insurance program: costly state verification or falsification? Economic Issues, 8 (2), 29-45.

Rejesus, R. M., Little, B. B., Lovell, A. C., Cross, M., 2004. Patterns of collusion in the U.S. crop insurance program: an empirical analysis. Journal of Agricultural and Applied Economics, 36 (2), 449-465.

Ritchie, J. T., NeSmith, D.S., 1991. Temperature and crop development. In: Hanks, J., Richie, J. T. (eds) Modeling plant and soil systems, 5-29. Madison, WI: American Society of Agronomy.

Rincke, J., Traxler, C., 2011. Enforcement spillovers. Review of Economics and Statistics 93 (4), 1224-1234.

Schlenker, W., Roberts, M. J., 2006. Nonlinear effects of weather on corn yields. Review of Agricultural Economics, 28 (3), 391-398.

Schlenker, W., Hanemann, W. M., Fisher, A. C., 2007. Water availability, degree days, and the potential impact of climate change on irrigated agriculture in California. Climatic Change, 81 (1), 19-38.

Schlenker, W., Roberts, M. J., 2009. Nonlinear temperature effects indicate severe damages to U.S. Crop yields under climate change. Proceedings of the National Academy of Sciences, 106 (37), 15594-15598.

Slemrod, J., Blumenthal, M., Christian, C., 2001. Taxpayer response to an increased probability of audit: evidence from a controlled experiment in Minnesota. Journal of Public Economics 79, 455-483.

Smith, V. K., Cicchetti, C. J., 1974. A note on fitting log-linear regression with some zero observations for the regressand. Metroeconomica, 26 (1-3), 282-284.

Townsend, R. M., 1979. Optimal contracts and competitive markets with costly state verification. Journal of Economic Theory, 21 (2), 265-293.

Treiman, D. J., 2014. Quantitative Data Analysis: Doing Social Research to Test Ideas. John Wiley & Sons, Inc.

Tukey, J. W., 1977. Exploratory data analysis. Reading, MA: Addison-Wesley Pub. Co.

Turvey, C. G., 2012. Whole farm income insurance. Journal of Risk and Insurance, 79 (2), 515-540.

U.S. Department of Commerce-BEA (Bureau of Economic Analysis), Regional economic accounts, CA45 farm income and expenses (https://www.bea.gov/regional/).

USDA (United States Department of Agriculture), 2007. Risk management agency program compliance and integrity. Annual Report to Congress, January-December 2004.

USDA (United States Department of Agriculture), 2010. Program compliance and integrity. Annual Report to Congress, January-December 2005.

USDA (United States Department of Agriculture), 2011. Program compliance and integrity. Annual Report to Congress, January-December 2006.

USDA (United States Department of Agriculture), 2010. Field crops - usual planting and harvesting dates. Agricultural Handbook, Number 628.

USDA-NASS (National Agricultural Statistics Service), USDA Quick Stats (http://quickstats.nass.usda.gov/).

USDA-RMA (Risk Management Agency), 2018. Federal Crop Insurance Program - Spot Check List Study.

USDA-RMA (Risk Management Agency), Summary of business (1989-2015) (https://www.rma.usda.gov/data/sob/scc/index.html).

Vercammen, J., van Kooten, C. G., 1994. Moral hazard cycles in individual-coverage crop insurance. American Journal of Agricultural Economics, 76 (2), 250-261.

Viaene, S., Dedene, G., 2004. Insurance Fraud: Issues and Challenges. The Geneva Papers on Risk and Insurance, 29 (2), 313-333.

Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics, 126, 25-51.

Zhang, Y., Cao, Y., Wang, H. H., 2018. Cheating? The Case of Producers' Under-Reporting Behavior in Hog Insurance in China. Canadian Jounal of Agricultural Economics, 66(3), 489-510.

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: Frequency Distribution of Counties with Different Numbers of SCL Producers

	Number of SCL producers										
Year	≤ 3	4	5	6	7	8	9	10	11-20	21-30	>30
2001	1,864	48	21	17	7	10	9	8	33	11	22
2002	1,902	43	17	14	8	10	6	1	32	3	1
2003	1,894	51	16	18	7	13	5	2	25	1	0
2004	1,914	37	22	7	3	13	8	5	18	1	0
2005	1,926	34	15	10	3	5	3	1	12	1	0
2006	1,957	26	19	5	4	3	2	2	10	1	0
2007	1,867	62	27	26	9	6	9	7	9	0	0
2008	1,872	60	29	19	10	12	9	9	3	0	0
2009	1,890	41	31	18	14	9	6	4	3	0	0
2010	1,906	30	26	13	4	7	5	4	1	0	0
2011	1,910	49	18	9	7	5	2	7	5	0	0
2012	1,943	50	17	8	5	4	2	5	5	0	0
2013	1,897	60	30	23	8	12	11	11	2	0	0
2014	1,906	47	23	22	10	18	8	16	2	0	0
2015	1,968	50	14	10	5	4	3	3	0	0	0

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

Variables	Description and Sources
1. Monthly weather data	
County level[a]	
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[b]	
Drought	Palmer Z index for drought level
Wetness	Palmer Z index for wetness level
2. Land data[c]	
Rent	Rent per acre
3. Insurance characteristics data[d]	
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 acres insured
4. Input expenditure 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 based on Schlenker and Roberts (2009) and PRISM.

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

c. USDA Quick Stats (State level).

d. Reproduced from Summary of Business (USDA-RMA, County 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
Precipitation				
Mar_prec	68.43	49.17	1.08	359.64
Apr_prec	88.82	56.43	.63	584.87
May_prec	101.84	59.73	.51	550.42
Jun_prec	107.90	62.52	.22	728.44
Jul_prec	93.83	54.46	.37	428.86
Aug_prec	89.45	56.69	.29	489.99
Sep_prec	80.99	59.01	.66	509.47
Oct_prec	78.25	56.19	1.20	552.78
Nov_prec	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
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

Table 4: Continued

Variable	Mean	Std. Dev.	Min.	Max.
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 ($/acre)				
Rent	93.33	55.64	23.00	329.00
Insurance characteristics data				
UnitSize	99.61	67.07	2.16	1113.48
InsuranceType	.60	.25	.00	1.00
CoverageType	.87	.16	.00	1.00
CoverageLevel	.68	.07	.50	.84
Input expenditure data ($/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: Main Estimation Results from Static Models

	Dependent variable					
	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
SCLProducerCount						
L1.	$-.008^{*}$	$-.012^{***}$	$-.007^{*}$			
	(.004)	(.004)	(.004)			
L2.	.004	.002	.004			
	(.004)	(.004)	(.004)			
L3.	$-.001$	$-.002$	$-.001$			
	(.003)	(.003)	(.002)			
*SCL*456						
L1.				$-.053^{*}$	$-.076^{***}$	$-.037$
				(.029)	(.029)	(.029)
L2.				$.061^{*}$	.046	$.065^{**}$
				(.032)	(.032)	(.031)
L3.				$-.076^{**}$	$-.091^{***}$	$-.062^{*}$
				(.032)	(.032)	(.032)
*SCL*789						
L1.				$-.059$	$-.089$	$-.046$
				(.065)	(.065)	(.065)
L2.				$-.037$	$-.052$	$-.014$
				(.061)	(.061)	(.060)
L3.				$-.173^{**}$	$-.190^{***}$	$-.139^{**}$
				(.069)	(.068)	(.067)
*SCL*10*Plus*						
L1.				$-.137$	$-.175^{*}$	$-.149^{*}$
				(.091)	(.092)	(.090)
L2.				$-.002$	$-.018$	$-.004$
				(.089)	(.088)	(.087)
L3.				$-.015$	$-.037$	$-.016$
				(.065)	(.064)	(.065)
Land ($/acre)						
ln(Rent)	$.333^{***}$	$.336^{***}$	$.277^{***}$	$.337^{***}$	$.340^{***}$	$.280^{***}$
	(.108)	(.104)	(.106)	(.108)	(.104)	(.106)
Obs.	23,331	23,323	23,331	23,331	23,323	23,331
Counties	2,099	2,098	2,099	2,099	2,098	2,099

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 trend are omitted for the sake of brevity. See appendix table A.1 for full estimation results.

Table 6: Main Estimation Results from Dynamic Models

	Dependent variable					
	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)						
L1.	.090***	.079***	.067***	.092***	.081***	.070***
	(.013)	(.013)	(.014)	(.013)	(.013)	(.014)
L2.	.039***	.027**	.016	.042***	.030**	.018
	(.012)	(.012)	(.013)	(.012)	(.012)	(.013)
L3.	.005	−.003	−.010	.009	.001	−.006
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
$SCLProducerCount$						
L1.	−.058***	−.061***	−.054***			
	(.009)	(.009)	(.008)			
L2.	−.013*	−.015**	−.011			
	(.008)	(.008)	(.007)			
L3.	−.001	−.003	.000			
	(.005)	(.005)	(.005)			
$SCL456$						
L1.				−.359***	−.374***	−.333***
				(.055)	(.055)	(.054)
L2.				−.109*	−.121**	−.090
				(.058)	(.057)	(.056)
L3.				−.070	−.086	−.078
				(.057)	(.057)	(.057)
$SCL789$						
L1.				−.539***	−.556***	−.479***
				(.131)	(.130)	(.127)
L2.				−.276**	−.292**	−.227*
				(.122)	(.120)	(.116)
L3.				−.290**	−.290**	−.214*
				(.126)	(.124)	(.120)
$SCL10Plus$						
L1.				−.661***	−.699***	−.603***
				(.147)	(.143)	(.141)
L2.				−.240	−.272*	−.210
				(.153)	(.146)	(.144)
L3.				−.010	−.033	.014

Table 6 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
				(.129)	(.124)	(.121)
Land ($/acre)						
ln(Rent)	.419***	.342***	.055	.418***	.342***	.058
	(.083)	(.086)	(.086)	(.083)	(.086)	(.086)
Arellano-Bond test						
Order 1	-25.554	-25.731	-25.309	-25.516	-25.686	-25.275
(p-value)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Order 2	-1.482	-1.230	-1.382	-1.457	-1.201	-1.344
(p-value)	(.138)	(.219)	(.167)	(.145)	(.230)	(.179)
Obs.	22,836	22,832	22,836	22,836	22,832	22,836
Counties	2,073	2,072	2,073	2,073	2,072	2,073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parentheses: Windmeijer (2005) bias-corrected robust standard errors, *c.* Parameter estimates for weather variables, year dummies, and trend are omitted for the sake of brevity. See appendix table A.2 for full estimation results.

Table 7: Costs Avoided in $ million by Year

Year	LR specification	LRsubsidy specification	LCR specification
2004	57	64	71
2005	25	30	31
2006	39	45	53
2007	109	127	129
2008	207	231	234
2009	120	137	147
2010	64	71	76
2011	162	188	221
2012	215	230	225
2013	250	276	319
2014	190	206	233
2015	82	90	98
Average	127	141	153

Table 8: Robustness Check of Dynamic Models for SCL linear specification with Lag-depths from $J = 1$, 2, and 4

	Dependent Variable								
	Loss Ratio (LR)			LRsubsidy			Loss Cost Ratio (LCR)		
Variable	$J = 1$	$J = 2$	$J = 4$	$J = 1$	$J = 2$	$J = 4$	$J = 1$	$J = 2$	$J = 4$
Lagged dependent variable ($\widehat{\alpha}$)									
L1.	$.074^{***}$	$.082^{***}$	$.094^{***}$	$.070^{***}$	$.074^{***}$	$.087^{***}$	$.065^{***}$	$.072^{***}$	$.089^{***}$
	(.011)	(.012)	(.014)	(.011)	(.011)	(.014)	(.012)	(.012)	(.016)
L2.		$.033^{***}$	$.030^{**}$		$.026^{**}$	$.025^{*}$		.015	$.032^{**}$
		(.012)	(.013)		(.012)	(.013)		(.012)	(.014)
L3.			.007			.002			.017
			(.012)			(.012)			(.013)
L4.			$.033^{***}$			$.031^{**}$			$.044^{***}$
			(.012)			(.012)			(.013)
$SCLProducerCount$									
L1.	$-.030^{***}$	$-.057^{***}$	$-.064^{***}$	$-.033^{***}$	$-.060^{***}$	$-.068^{***}$	$-.032^{***}$	$-.057^{***}$	$-.062^{***}$
	(.007)	(.008)	(.009)	(.008)	(.008)	(.009)	(.007)	(.008)	(.009)
L2.		$-.008^{*}$	$-.023^{***}$		$-.010^{**}$	$-.026^{***}$		$-.009^{**}$	$-.023^{***}$
		(.005)	(.008)		(.005)	(.008)		(.004)	(.008)
L3.			$-.017^{**}$			$-.019^{**}$			$-.018^{**}$
			(.007)			(.007)			(.007)
L4.			.001			$-.001$			.000
			(.004)			(.004)			(.004)
Number of Parameters	70	71	73	70	71	73	70	71	73
Number of Moments	173	172	165	173	172	165	173	172	165
Arellano-Bond test									
Order 1	-27.061	-26.670	-24.185	-27.218	-26.715	-24.426	-26.886	-26.576	-23.716
(p-value)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Order 2	-.106	-1.086	-.954	-.110	-.852	-.898	-.659	-.272	-1.310
(p-value)	(.915)	(.278)	(.340)	(.913)	(.394)	(.369)	(.510)	(.786)	(.190)
Obs.	27,407	25,064	20,688	27,394	25,057	20,685	27,407	25,064	20,688
Counties	2,144	2,108	2,025	2,143	2,106	2,024	2,144	2,108	2,025

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, land, year dummies, and trend are omitted for the sake of brevity.

Table 9: Robustness Check of Dynamic Models for SCL group dummies Specification with Lag-depths from $J = 1$, 2, and 4

	Dependent Variable								
	Loss Ratio (LR)			LRsubsidy			Loss Cost Ratio (LCR)		
Variable	$J=1$	$J=2$	$J=4$	$J=1$	$J=2$	$J=4$	$J=1$	$J=2$	$J=4$
Lagged dependent variable ($\widehat{\alpha}$)									
L1.	.078***	.084***	.094***	.074***	.076***	.088***	.069***	.074***	.090***
	(.011)	(.012)	(.014)	(.011)	(.011)	(.014)	(.012)	(.012)	(.016)
L2.		.034***	.031**		.028**	.026**		.017	.033**
		(.012)	(.013)		(.012)	(.013)		(.012)	(.014)
L3.			.008			.003			.018
			(.012)			(.012)			(.013)
L4.			.034***			.033***			.045***
			(.012)			(.012)			(.013)
$SCL456$									
L1.	−.303***	−.360***	−.367***	−.315***	−.371***	−.391***	−.307***	−.351***	−.367***
	(.051)	(.052)	(.057)	(.051)	(.052)	(.058)	(.050)	(.050)	(.056)
L2.		−.069	−.136**		−.076	−.148**		−.062	−.133**
		(.054)	(.059)		(.054)	(.060)		(.053)	(.059)
L3.			−.125**			−.142**			−.136**
			(.057)			(.058)			(.057)
L4.			−.060			−.070			−.055
			(.063)			(.064)			(.063)
$SCL789$									
L1.	−.430***	−.514***	−.561***	−.445***	−.531***	−.580***	−.437***	−.509***	−.515***
	(.118)	(.130)	(.134)	(.118)	(.131)	(.136)	(.114)	(.127)	(.133)
L2.		−.114	−.270**		−.139	−.301**		−.128	−.239**
		(.108)	(.122)		(.109)	(.123)		(.104)	(.120)
L3.			−.243**			−.263**			−.215*
			(.117)			(.118)			(.113)
L4.			−.020			−.041			−.020
			(.118)			(.119)			(.115)

Table 9 (continued)

	Dependent Variable								
	Loss Ratio (LR)			LRsubsidy			Loss Cost Ratio (LCR)		
Variable	$J = 1$	$J = 2$	$J = 4$	$J = 1$	$J = 2$	$J = 4$	$J = 1$	$J = 2$	$J = 4$
SCL10Plus									
L1.	$-.481^{***}$	$-.637^{***}$	$-.657^{***}$	$-.533^{***}$	$-.689^{***}$	$-.718^{***}$	$-.537^{***}$	$-.672^{***}$	$-.622^{***}$
	(.124)	(.141)	(.166)	(.124)	(.141)	(.167)	(.120)	(.137)	(.164)
L2.		$-.163$	$-.299^{*}$		$-.217^{*}$	$-.346^{**}$		$-.208^{*}$	$-.329^{**}$
		(.129)	(.152)		(.128)	(.152)		(.124)	(.148)
L3.			$-.141$			$-.176$			$-.189$
			(.136)			(.135)			(.130)
L4.			.033			$-.017$			.008
			(.110)			(.110)			(.107)
Number of Parameters	72	75	81	72	75	81	72	75	81
Number of Moments	175	176	173	175	176	173	175	176	173
Arellano-Bond test									
Order 1	-27.039	-26.646	-24.138	-27.201	-26.686	-24.376	-26.861	-26.559	-23.663
(p-value)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Order 2	-.047	-1.116	-.969	-.047	-.905	-.912	-.593	-.296	-1.326
(p-value)	(.963)	(.265)	(.333)	(.963)	(.365)	(.362)	(.553)	(.768)	(.185)
Obs.	27,407	25,064	20,688	27,394	25,057	20,685	27,407	25,064	20,688
Counties	2,144	2,108	2,025	2,143	2,106	2,024	2,144	2,108	2,025

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, land, year dummies, and trend are omitted for the sake of brevity.

Table 10: Robustness Check of Dynamic Model with Started Logs

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)						
L1.	.094***	.076***	.078***	.095***	.078***	.080***
	(.016)	(.016)	(.015)	(.016)	(.016)	(.015)
L2.	.038***	.023	.024*	.040***	.025*	.027**
	(.013)	(.014)	(.013)	(.013)	(.014)	(.013)
L3.	−.019	−.022	−.009	−.006	−.019	−.005
	(.013)	(.013)	(.012)	(.013)	(.014)	(.012)
$SCLProducerCount$						
L1.	−.063***	−.064***	−.055***			
	(.008)	(.008)	(.008)			
L2.	−.015**	−.017**	−.013*			
	(.007)	(.007)	(.007)			
L3.	−.002	−.003	−.001			
	(.005)	(.005)	(.005)			
$SCL456$						
L1.				−.366***	−.369***	−.318***
				(.050)	(.049)	(.049)
L2.				−.110**	−.113**	−.103**
				(.051)	(.050)	(.051)
L3.				−.067	−.074	−.078
				(.053)	(.053)	(.053)
$SCL789$						
L1.				−.608***	−.616***	−.531***
				(.113)	(.111)	(.113)
L2.				−.310***	−.327***	−.265**
				(.108)	(.105)	(.107)
L3.				−.268**	−.268**	−.230**
				(.112)	(.109)	(.113)
$SCL10Plus$						
L1.				−.693***	−.703***	−.610***
				(.129)	(.125)	(.127)
L2.				−.254*	−.258*	−.212
				(.139)	(.133)	(.136)
L3.				−.062	−.063	−.017
				(.120)	(.114)	(.119)
Obs.	23,620	23,539	23,620	23,620	23,539	23,620
Counties	2,106	2,105	2,106	2,106	2,105	2,106

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

Table 11: Robustness Check of Dynamic Model with Alternative SCL Specification

	$J=2$			$J=3$		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)						
L1.	.083***	.075***	.073***	.090***	.080***	.068***
	(.012)	(.011)	(.012)	(.013)	(.013)	(.014)
L2.	.033***	.027**	.016	.040***	.028**	.017
	(.012)	(.012)	(.012)	(.012)	(.012)	(.013)
L3.				.008	.000	−.007
				(.011)	(.011)	(.011)
$SCL1$						
L1.	−.023*	−.027**	−.027**	−.022	−.026*	−.022
	(.014)	(.014)	(.014)	(.015)	(.015)	(.014)
L2.	−.003	−.005	−.006	.001	−.003	−.003
	(.006)	(.006)	(.006)	(.015)	(.014)	(.014)
L3.				.008	.007	.009
				(.006)	(.006)	(.006)
$SCL2$						
L1.	.275**	.270**	.245**	.285***	.283***	.252***
	(.091)	(.092)	(.088)	(.095)	(.095)	(.092)
L2.	.064	.066	.048	.153	.145	.106
	(.062)	(.061)	(.060)	(.101)	(.098)	(.097)
L3.				.148**	.157**	.143**
				(.063)	(.062)	(.061)
Arellano-Bond test						
Order 1	-26.644	-26.685	-26.558	-25.510	-25.689	-25.274
(p-value)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Order 2	-1.113	-.897	-.294	-1.465	-1.204	-1.347
(p-value)	(.266)	(.370)	(.769)	(.143)	(.229)	(.178)
Obs.	25,064	25,057	25,064	22,836	22,832	22,836
Counties	2,108	2,106	2,108	2,073	2,072	2,073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parenthesis: robust standard errors, *c.* $SCL1 = SCLProducerCount$ if the number of producers on the SCL > 3 and 0 otherwise; $SCL2$ = 1 if $SCLProducerCount < 4$ and 0 otherwise, *d.* Parameter estimates for weather variables, land, year dummies, and trend are omitted for the sake of brevity.

Table 12: Robustness Check of Dynamic Models with Additional Control variables

	Dependent variable					
	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable ($\widehat{\alpha}$)						
L1.	.082***	.076***	.058***	.084***	.078***	.060***
	(.013)	(.013)	(.014)	(.013)	(.013)	(.014)
L2.	.039***	.030**	.010	.041***	.032**	.012
	(.013)	(.013)	(.014)	(.013)	(.013)	(.014)
L3.	.001	−.006	−.017	.005	−.002	−.013
	(.011)	(.011)	(.011)	(.011)	(.011)	(.012)
$SCLProducerCount$						
L1.	−.055***	−.057***	−.051***			
	(.009)	(.009)	(.008)			
L2.	−.011	−.012	−.009			
	(.008)	(.008)	(.007)			
L3.	.001	.000	.002			
	(.005)	(.005)	(.005)			
$SCL456$						
L1.				−.329***	−.341***	−.311***
				(.055)	(.056)	(.054)
L2.				−.099*	−.111*	−.082
				(.058)	(.058)	(.056)
L3.				−.055	−.063	−.061
				(.057)	(.057)	(.057)
$SCL789$						
L1.				−.515***	−.523***	−.457***
				(.134)	(.134)	(.131)
L2.				−.262**	−.265**	−.220*
				(.120)	(.119)	(.116)
L3.				−.252**	−.242*	−.166
				(.127)	(.126)	(.122)
$SCL10Plus$						
L1.				−.639***	−.663***	−.584***
				(.150)	(.148)	(.145)
L2.				−.190	−.207	−.166
				(.153)	(.148)	(.144)
L3.				.001	−.011	.021
				(.129)	(.126)	(.122)
Land ($/acre)						
ln_Rent	.396***	.356***	−.025	.398***	.357***	−.020
	(.138)	(.136)	(.134)	(.137)	(.135)	(.134)
Insurance characteristics data						
ln(UnitSize)	−.236**	−.005	−.154	−.242**	−.010	−.159
	(.097)	(.095)	(.099)	(.097)	(.095)	(.099)
InsuranceType	−1.895***	−1.683***	−1.236***	−1.865***	−1.658***	−1.225***
	(.300)	(.296)	(.295)	(.298)	(.295)	(.294)
CoverageType	1.154**	.204	.462	1.139**	.196	.455
	(.499)	(.513)	(.484)	(.497)	(.511)	(.483)
CoverageLevel	1.013	−.347	.937	1.020	−.338	.940

Table 12 (continued)

Variable	Linear Specification ln(LR)	ln(LRsubsidy)	ln(LCR)	Group Dummies Specification ln(LR)	ln(LRsubsidy)	ln(LCR)
	(1.045)	(1.017)	(.983)	(1.044)	(1.017)	(.984)
Input expenditure data ($/acre)						
ln(Seed)	.125	.169	.036	.113	.158	.027
	(.106)	(.108)	(.107)	(.106)	(.108)	(.106)
ln(PetroleumProducts)	.696***	.759***	.769***	.693***	.756***	.767***
	(.152)	(.154)	(.149)	(.152)	(.154)	(.150)
ln(FertilizerChemicals)	.161	.226	.119	.162	.227	.122
	(.168)	(.165)	(.164)	(.168)	(.165)	(.164)
ln(HiredLabor)	−.529***	−.592***	−.548***	−.523***	−.589***	−.544***
	(.111)	(.109)	(.108)	(.111)	(.109)	(.108)
ln(AllOtherExpenses)	−.267*	−.301*	−.185	−.259	−.293*	−.182
	(.161)	(.160)	(.155)	(.161)	(.159)	(.155)
Arellano-Bond test						
Order 1	-25.246	-25.354	-25.076	-25.221	-25.319	-25.051
(p-value)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Order 2	-1.311	-1.085	-.971	-1.270	-1.048	-.919
(p-value)	(.190)	(.278)	(.332)	(.204)	(.295)	(.358)
Obs.	22,836	22,832	22,836	22,836	22,832	22,836
Counties	2,073	2,072	2,073	2,073	2,072	2,073

Notes: *a.* *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$, *b.* Parentheses: Windmeijer (2005) bias-corrected robust standard errors, *c.* Parameter estimates for weather variables, year dummies, and trend are omitted for the sake of brevity.

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

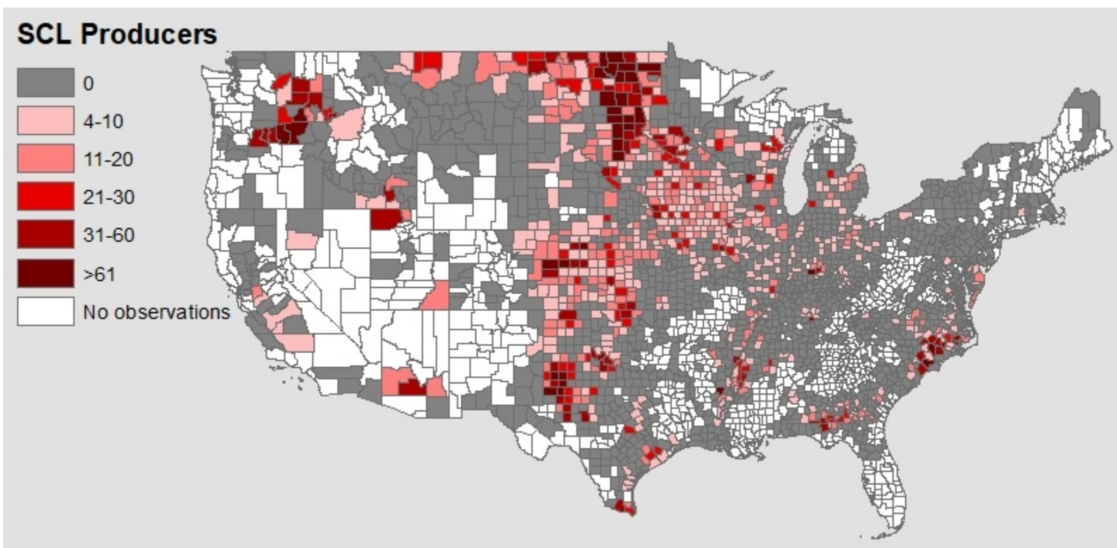


Figure 2: Spatial Distributions of Number of SCL Producers for Selected Years between 2001 and 2010

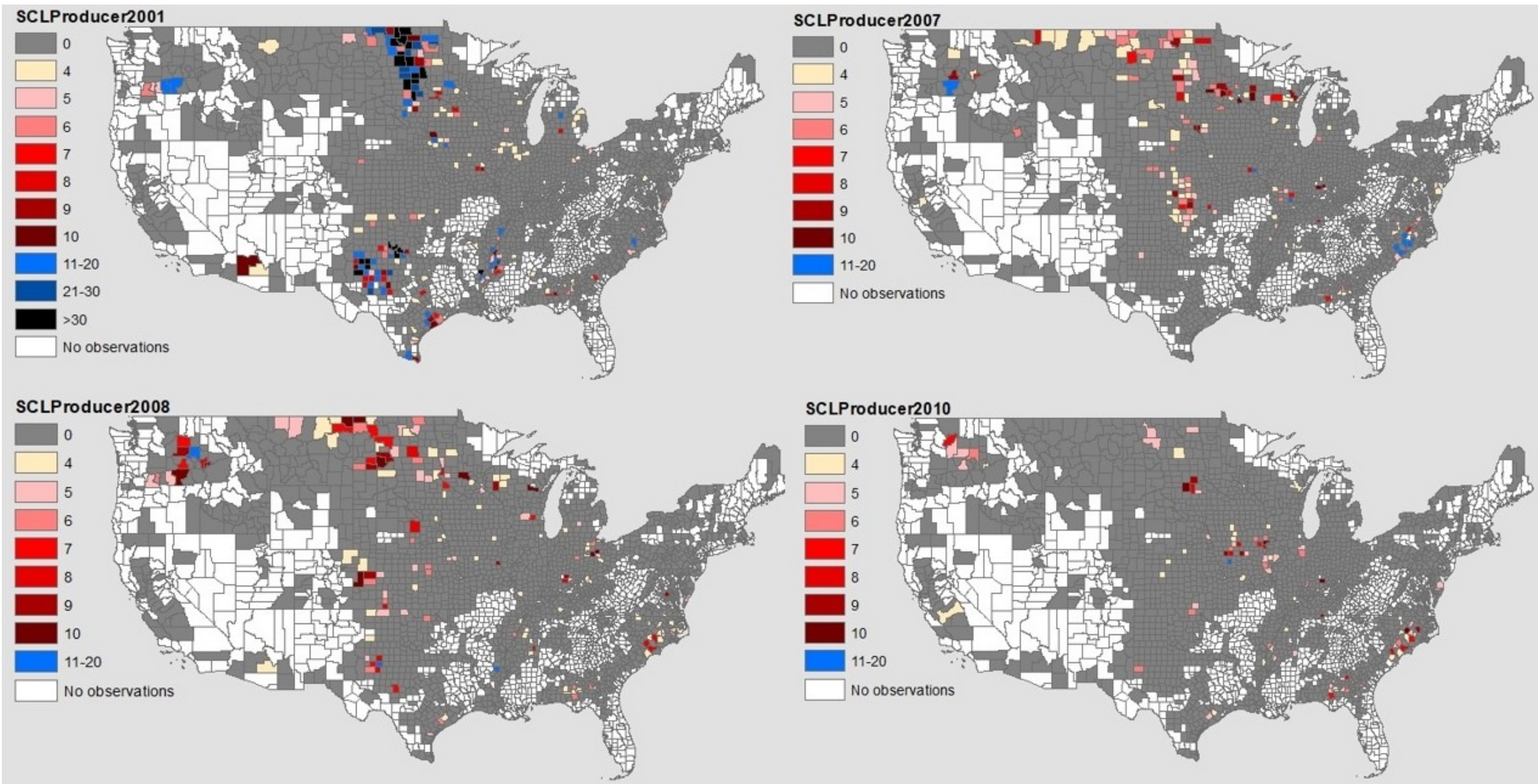


Figure 3: Spatial Distributions of Number of SCL Producers from 2012 to 2015

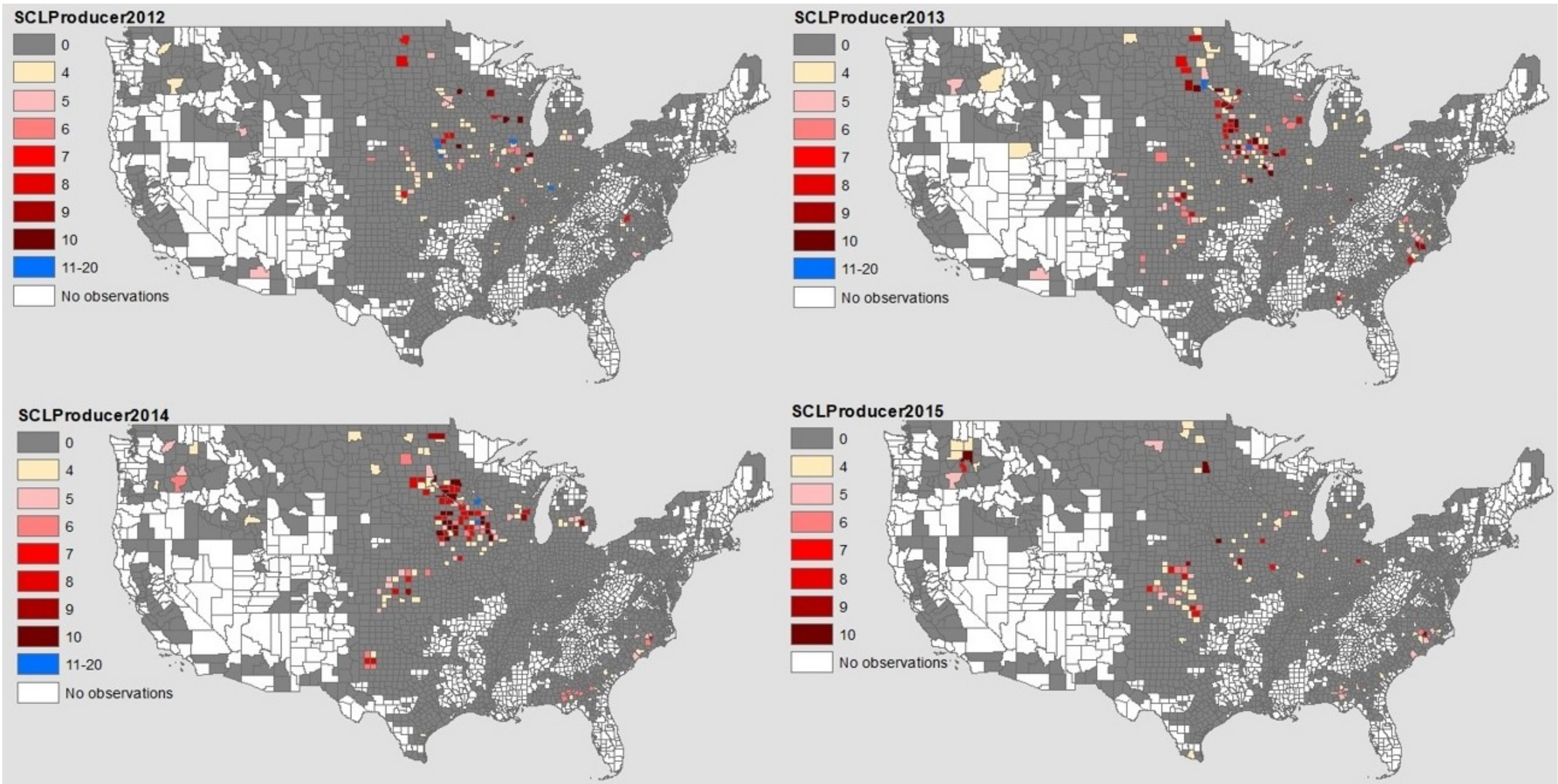


Figure 4: Indemnity Trend for Counties over 3 years after Having at least 4 SCL Producers

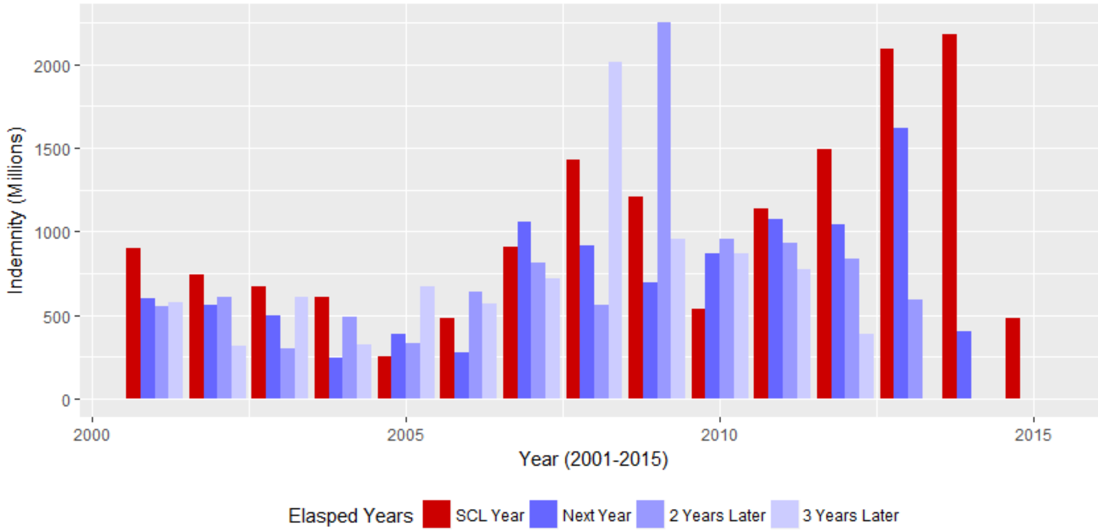


Figure 5: LR Trend for Counties over 3 years after Having at least 4 SCL Producers

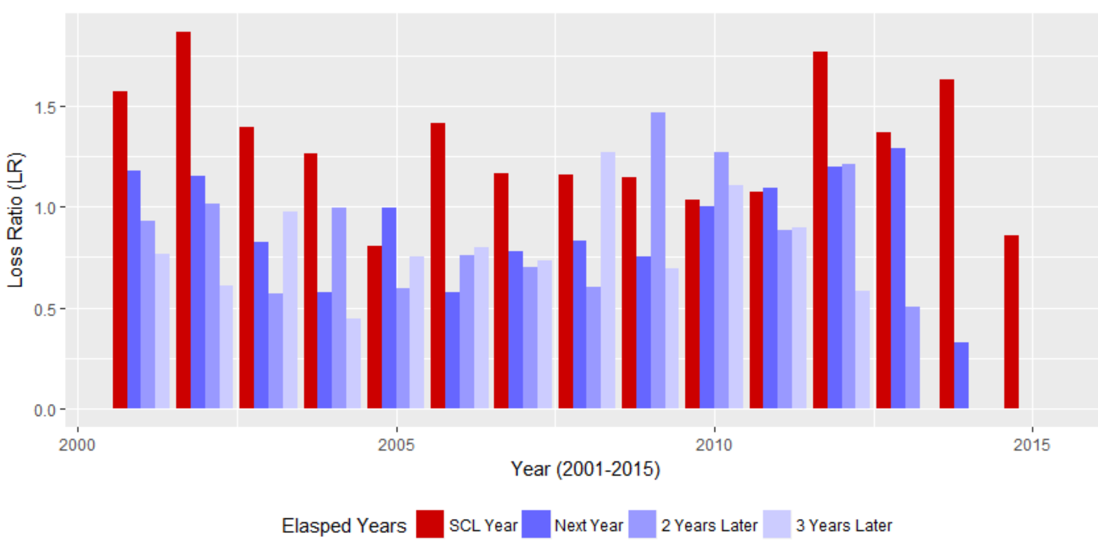


Figure 6: LRsubsidy Trend for Counties over 3 years after Having at least 4 SCL Producers

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

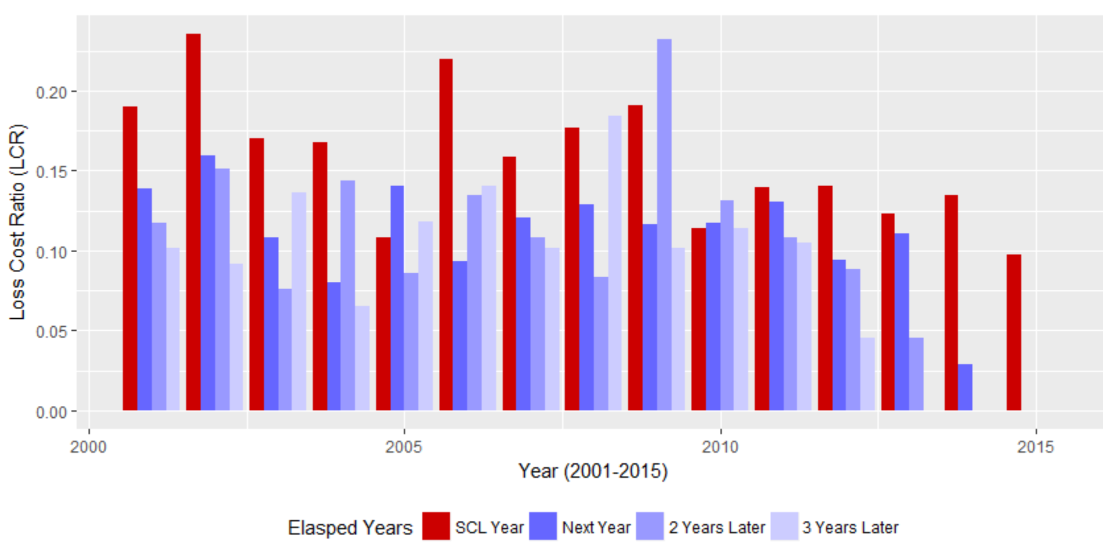
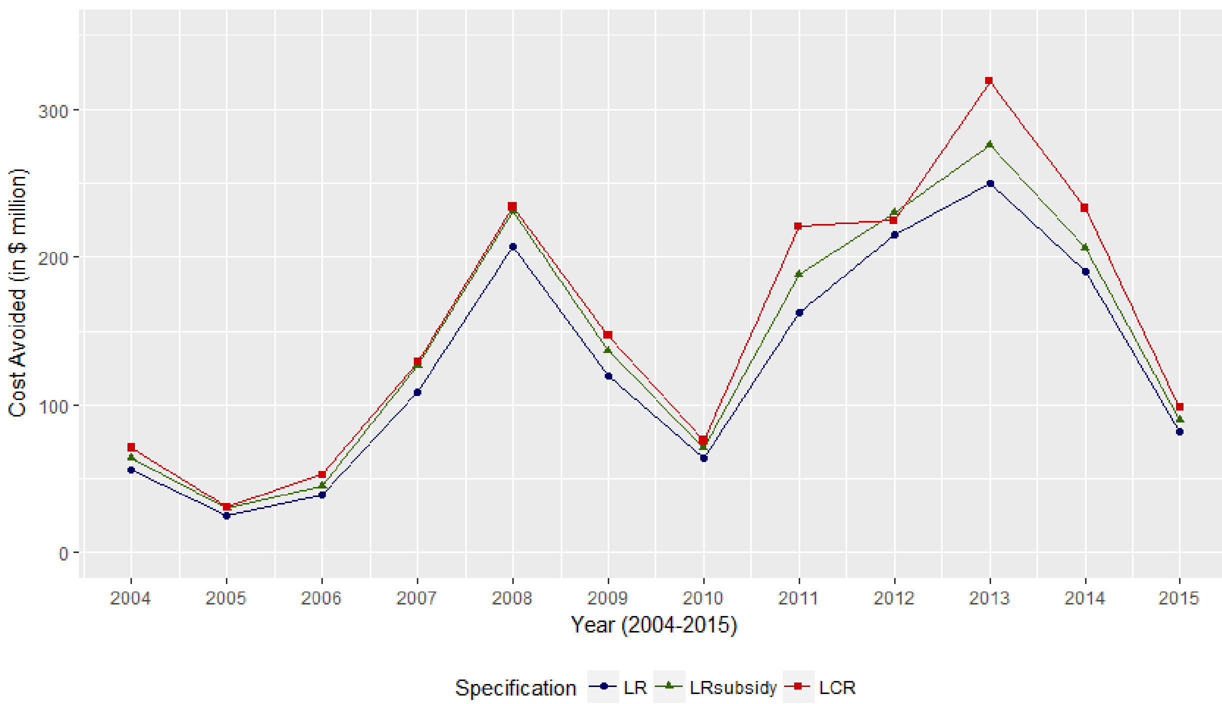


Figure 8: Costs Avoided in $ million by Year



Appendix

Table A.1: Full Estimation Results for Table 5

	Dependent variable					
	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
SCLProducerCount						
L1.	$-.008^{*}$	$-.012^{***}$	$-.007^{*}$			
	(.004)	(.004)	(.004)			
L2.	.004	.002	.004			
	(.004)	(.004)	(.004)			
L3.	$-.001$	$-.002$	$-.001$			
	(.003)	(.003)	(.002)			
*SCL*456						
L1.				$-.053^{*}$	$-.076^{***}$	$-.037$
				(.029)	(.029)	(.029)
L2.				$.061^{*}$	.046	$.065^{**}$
				(.032)	(.032)	(.031)
L3.				$-.076^{**}$	$-.091^{***}$	$-.062^{*}$
				(.032)	(.032)	(.032)
*SCL*789						
L1.				$-.059$	$-.089$	$-.046$
				(.065)	(.065)	(.065)
L2.				$-.037$	$-.052$	$-.014$
				(.061)	(.061)	(.060)
L3.				$-.173^{**}$	$-.190^{***}$	$-.139^{**}$
				(.069)	(.068)	(.067)
*SCL*10*Plus*						
L1.				$-.137$	$-.175^{*}$	$-.149^{*}$
				(.091)	(.092)	(.090)
L2.				$-.002$	$-.018$	$-.004$
				(.089)	(.088)	(.087)
L3.				$-.015$	$-.037$	$-.016$
				(.065)	(.064)	(.065)
Precipitation						
ln(Mar_prec)	$-.035^{**}$	$-.034^{*}$	$-.044^{**}$	$-.034^{**}$	$-.033^{*}$	$-.043^{**}$
	(.017)	(.017)	(.017)	(.017)	(.017)	(.017)
ln(Apr_prec)	$-.063^{***}$	$-.072^{***}$	$-.062^{***}$	$-.063^{***}$	$-.071^{***}$	$-.062^{***}$
	(.020)	(.020)	(.020)	(.020)	(.020)	(.020)
ln(May_prec)	$.062^{***}$	$.066^{***}$	$.079^{***}$	$.061^{***}$	$.065^{***}$	$.078^{***}$
	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)
ln(Jun_prec)	$.105^{***}$	$.101^{***}$	$.105^{***}$	$.104^{***}$	$.099^{***}$	$.104^{***}$
	(.023)	(.022)	(.023)	(.023)	(.022)	(.023)
ln(Jul_prec)	$-.118^{***}$	$-.112^{***}$	$-.112^{***}$	$-.118^{***}$	$-.112^{***}$	$-.112^{***}$
	(.020)	(.020)	(.020)	(.020)	(.020)	(.020)
ln(Aug_prec)	$-.065^{***}$	$-.070^{***}$	$-.060^{***}$	$-.065^{***}$	$-.070^{***}$	$-.060^{***}$

Table A.1 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.018)	(.018)	(.018)	(.018)	(.018)	(.018)
ln(Sep_prec)	$.115^{***}$	$.115^{***}$	$.112^{***}$	$.115^{***}$	$.115^{***}$	$.112^{***}$
	(.017)	(.016)	(.016)	(.017)	(.016)	(.016)
ln(Oct_prec)	$.032^{*}$	$.029^{*}$	.026	$.033^{*}$	$.030^{*}$	.027
	(.017)	(.017)	(.017)	(.017)	(.017)	(.017)
ln(Nov_prec)	$-.132^{***}$	$-.131^{***}$	$-.118^{***}$	$-.132^{***}$	$-.130^{***}$	$-.117^{***}$
	(.018)	(.017)	(.017)	(.018)	(.017)	(.017)
Temperature						
Mar_tMin	$.025^{**}$	$.019^{**}$	$.017^{*}$	$.025^{***}$	$.019^{**}$	$.018^{*}$
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Apr_tMin	$-.022^{**}$	$-.018^{*}$	$-.024^{**}$	$-.022^{**}$	$-.018$	$-.024^{**}$
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
May_tMin	$-.068^{***}$	$-.063^{***}$	$-.086^{***}$	$-.068^{***}$	$-.062^{***}$	$-.085^{***}$
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Jun_tMin	$-.086^{***}$	$-.088^{***}$	$-.061^{***}$	$-.084^{***}$	$-.087^{***}$	$-.059^{***}$
	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
Jul_tMin	$.092^{***}$	$.091^{***}$	$.103^{***}$	$.090^{***}$	$.089^{***}$	$.102^{***}$
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
Aug_tMin	$-.108^{***}$	$-.111^{***}$	$-.102^{***}$	$-.108^{***}$	$-.111^{***}$	$-.102^{***}$
	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)
Sep_tMin	$.026^{**}$	$.021^{*}$	$.038^{***}$	$.026^{**}$	$.021^{**}$	$.038^{***}$
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Oct_tMin	$-.021^{*}$	$-.022^{**}$	$-.014$	$-.021^{*}$	$-.022^{**}$	$-.014$
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Nov_tMin	$.036^{***}$	$.036^{***}$	$.037^{***}$	$.036^{***}$	$.036^{***}$	$.037^{***}$
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Mar_tMax	$-.036^{***}$	$-.030^{***}$	$-.033^{***}$	$-.037^{***}$	$-.031^{***}$	$-.034^{***}$
	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Apr_tMax	$-.050^{***}$	$-.052^{***}$	$-.054^{***}$	$-.049^{***}$	$-.052^{***}$	$-.054^{***}$
	(.009)	(.008)	(.008)	(.009)	(.008)	(.008)
May_tMax	$-.019$	$-.013$	$-.011$	$-.019^{*}$	$-.014$	$-.011$
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Jun_tMax	$.058^{***}$	$.065^{***}$	$.036^{**}$	$.057^{***}$	$.064^{***}$	$.036^{**}$
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Jul_tMax	$.050^{***}$	$.051^{***}$	$.048^{***}$	$.050^{***}$	$.051^{***}$	$.048^{***}$
	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
Aug_tMax	$.121^{***}$	$.114^{***}$	$.124^{***}$	$.120^{***}$	$.112^{***}$	$.124^{***}$
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Sep_tMax	$.053^{***}$	$.048^{***}$	$.052^{***}$	$.053^{***}$	$.048^{***}$	$.052^{***}$
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Oct_tMax	$.031^{***}$	$.033^{***}$	$.021^{**}$	$.031^{***}$	$.033^{***}$	$.021^{**}$
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Nov_tMax	$-.065^{***}$	$-.064^{***}$	$-.064^{***}$	$-.065^{***}$	$-.064^{***}$	$-.063^{***}$
	(.010)	(.009)	(.009)	(.010)	(.009)	(.009)
Mar_dday30C	$.217^{***}$	$.214^{***}$	$.209^{***}$	$.219^{***}$	$.215^{***}$	$.210^{***}$
	(.063)	(.061)	(.062)	(.062)	(.061)	(.062)
Apr_dday30C	$-.024^{**}$	$-.021^{*}$	$-.028^{**}$	$-.025^{**}$	$-.023^{*}$	$-.029^{**}$
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
May_dday30C	$.052^{***}$	$.050^{***}$	$.054^{***}$	$.053^{***}$	$.051^{***}$	$.054^{***}$

Table A.1 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Jun_dday30C	.012***	.010***	.014***	.012***	.010***	.014***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Jul_dday30C	.006***	.006***	.007***	.006***	.006***	.007***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Aug_dday30C	.001	.002	.000	.001	.002	.000
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Sep_dday30C	−.012***	−.012***	−.009***	−.012***	−.012***	−.009***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Oct_dday30C	.071***	.062***	.076***	.071***	.062***	.076***
	(.016)	(.015)	(.016)	(.016)	(.015)	(.016)
Nov_dday30C	.279***	.280***	.220*	.277***	.278***	.218*
	(.105)	(.085)	(.118)	(.107)	(.086)	(.119)
Drought						
Mar_Drought	−.051***	−.049***	−.066***	−.051***	−.049***	−.066***
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Apr_Drought	−.007	−.005	−.005	−.007	−.005	−.005
	(.014)	(.014)	(.014)	(.014)	(.013)	(.014)
May_Drought	−.022**	−.019*	−.017	−.022**	−.019*	−.017
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Jun_Drought	.204***	.197***	.203***	.205***	.198***	.204***
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Jul_Drought	.188***	.181***	.183***	.187***	.180***	.182***
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Aug_Drought	.025**	.028***	.020**	.024**	.028***	.019*
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Sep_Drought	.049***	.049***	.048***	.049***	.050***	.048***
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Oct_Drought	−.039***	−.036**	−.037**	−.039***	−.037**	−.037**
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
Nov_Drought	.121***	.121***	.105***	.122***	.121***	.106***
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Wetness						
Mar_Wetness	−.052***	−.050***	−.051***	−.052***	−.050***	−.052***
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Apr_Wetness	.037***	.042***	.035***	.037***	.041***	.035***
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
May_Wetness	.105***	.107***	.108***	.105***	.107***	.108***
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Jun_Wetness	.138***	.136***	.133***	.138***	.136***	.133***
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Jul_Wetness	.025***	.025***	.026***	.025***	.026***	.027***
	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Aug_Wetness	−.009	−.007	−.009	−.009	−.007	−.010
	(.008)	(.007)	(.007)	(.008)	(.007)	(.007)
Sep_Wetness	.051***	.049***	.055***	.051***	.049***	.056***
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Oct_Wetness	.002	.007	.004	.002	.006	.004
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)

Table A.1 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Nov_Wetness	−.008	−.013	−.019**	−.007	−.011	−.018**
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Land ($/acre)						
ln(Rent)	.333***	.336***	.277***	.337***	.340***	.280***
	(.108)	(.104)	(.106)	(.108)	(.104)	(.106)
Year						
Year_2005	−.816***	−.785***	−.863***	−.810***	−.778***	−.859***
	(.059)	(.058)	(.058)	(.059)	(.058)	(.057)
Year_2006	−.737***	−.754***	−.679***	−.732***	−.747***	−.675***
	(.059)	(.058)	(.058)	(.059)	(.058)	(.058)
Year_2007	−.714***	−.750***	−.624***	−.707***	−.742***	−.618***
	(.056)	(.055)	(.056)	(.056)	(.055)	(.056)
Year_2008	−.213***	−.232***	−.080*	−.208***	−.227***	−.076*
	(.045)	(.045)	(.045)	(.045)	(.045)	(.045)
Year_2009	−.033	−.001	.121**	−.033	.000	.121**
	(.054)	(.053)	(.054)	(.054)	(.053)	(.054)
Year_2010	−.645***	−.586***	−.594***	−.640***	−.579***	−.591***
	(.053)	(.053)	(.053)	(.053)	(.053)	(.053)
Year_2011	−1.164***	−1.095***	−1.093***	−1.156***	−1.086***	−1.087***
	(.061)	(.061)	(.060)	(.061)	(.061)	(.060)
Year_2012	−.880***	−.847***	−.765***	−.872***	−.838***	−.759***
	(.071)	(.072)	(.070)	(.071)	(.072)	(.070)
Year_2013	−.395***	−.355***	−.415***	−.392***	−.352***	−.412***
	(.042)	(.042)	(.042)	(.042)	(.042)	(.042)
Year_2014	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Year_2015	−.342***	−.342***	−.316***	−.344***	−.343***	−.317***
	(.064)	(.064)	(.064)	(.064)	(.064)	(.064)
Trend	−.007	.003	−.018**	−.007	.003	−.019**
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Constant	8.380	−11.089	28.560	8.544	−11.196	28.906*
	(17.722)	(17.192)	(17.484)	(17.713)	(17.180)	(17.477)
Obs.	23,331	23,323	23,331	23,331	23,323	23,331
Counties	2,099	2,098	2,099	2,099	2,098	2,099

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

Table A.2: Full Estimation Results for Table 6

	Dependent variable					
	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Lagged dependent variable (α)						
L1.	.090***	.079***	.067***	.092***	.081***	.070***
	(.013)	(.013)	(.014)	(.013)	(.013)	(.014)
L2.	.039***	.027**	.016	.042***	.030**	.018
	(.012)	(.012)	(.013)	(.012)	(.012)	(.013)
L3.	.005	−.003	−.010	.009	.001	−.006
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
$SCLProducerCount$						
L1.	−.058***	−.061***	−.054***			
	(.009)	(.009)	(.008)			
L2.	−.013*	−.015**	−.011			
	(.008)	(.008)	(.007)			
L3.	−.001	−.003	.000			
	(.005)	(.005)	(.005)			
$SCL456$						
L1.				−.359***	−.374***	−.333***
				(.055)	(.055)	(.054)
L2.				−.109*	−.121**	−.090
				(.058)	(.057)	(.056)
L3.				−.070	−.086	−.078
				(.057)	(.057)	(.057)
$SCL789$						
L1.				−.539***	−.556***	−.479***
				(.131)	(.130)	(.127)
L2.				−.276**	−.292**	−.227*
				(.122)	(.120)	(.116)
L3.				−.290**	−.290**	−.214*
				(.126)	(.124)	(.120)
$SCL10Plus$						
L1.				−.661***	−.699***	−.603***
				(.147)	(.143)	(.141)
L2.				−.240	−.272*	−.210
				(.153)	(.146)	(.144)
L3.				−.010	−.033	.014
				(.129)	(.124)	(.121)
Precipitation						
ln(Mar_prec)	−.007	−.014	−.019	−.006	−.014	−.018
	(.027)	(.027)	(.026)	(.027)	(.027)	(.026)
ln(Apr_prec)	−.137***	−.144***	−.136***	−.137***	−.144***	−.136***
	(.031)	(.032)	(.031)	(.031)	(.032)	(.031)
ln(May_prec)	.081**	.067*	.091***	.082**	.068*	.091***
	(.035)	(.035)	(.034)	(.035)	(.035)	(.034)
ln(Jun_prec)	.119***	.103***	.129***	.118***	.102***	.127***
	(.037)	(.037)	(.036)	(.037)	(.037)	(.036)

Table A.2 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
ln(Jul_prec)	−.006	−.012	.004	−.007	−.013	.003
	(.031)	(.031)	(.030)	(.031)	(.031)	(.030)
ln(Aug_prec)	.003	.001	.014	.003	.001	.015
	(.029)	(.029)	(.028)	(.029)	(.029)	(.028)
ln(Sep_prec)	.127***	.121***	.114***	.125***	.119***	.113***
	(.028)	(.028)	(.027)	(.028)	(.028)	(.027)
ln(Oct_prec)	.046*	.045*	.065**	.047*	.046*	.065**
	(.027)	(.027)	(.026)	(.027)	(.027)	(.026)
ln(Nov_prec)	−.109***	−.102***	−.111***	−.110***	−.103***	−.112***
	(.026)	(.026)	(.025)	(.026)	(.026)	(.025)
Temperature						
Mar_tMin	.016	.013	.008	.017	.012	.009
	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)
Apr_tMin	.006	.007	.004	.007	.007	.004
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
May_tMin	−.088***	−.084***	−.083***	−.087***	−.083***	−.082***
	(.019)	(.019)	(.018)	(.019)	(.019)	(.018)
Jun_tMin	−.081***	−.063***	−.055**	−.081***	−.064***	−.056**
	(.023)	(.024)	(.024)	(.023)	(.024)	(.023)
Jul_tMin	.175***	.169***	.169***	.174***	.167***	.168***
	(.021)	(.021)	(.020)	(.021)	(.021)	(.020)
Aug_tMin	−.070***	−.065***	−.078***	−.070***	−.065***	−.078***
	(.021)	(.021)	(.020)	(.021)	(.021)	(.020)
Sep_tMin	−.022	−.013	.002	−.021	−.012	.003
	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
Oct_tMin	.057***	.055***	.049***	.058***	.056***	.050***
	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
Nov_tMin	.051***	.045***	.048***	.051***	.045***	.048***
	(.014)	(.015)	(.014)	(.014)	(.015)	(.014)
Mar_tMax	−.052***	−.043***	−.047***	−.052***	−.043***	−.048***
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Apr_tMax	−.076***	−.080***	−.083***	−.075***	−.080***	−.083***
	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)
May_tMax	.034*	.029	.028	.034*	.029	.027
	(.018)	(.018)	(.017)	(.018)	(.018)	(.017)
Jun_tMax	.064***	.067***	.055**	.064***	.067***	.055**
	(.022)	(.023)	(.022)	(.022)	(.022)	(.022)
Jul_tMax	.024	.019	.033	.025	.020	.033
	(.023)	(.023)	(.022)	(.023)	(.023)	(.022)
Aug_tMax	.162***	.167***	.169***	.160***	.165***	.167***
	(.023)	(.024)	(.023)	(.023)	(.024)	(.023)
Sep_tMax	.059***	.044***	.049***	.058***	.043***	.048***
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Oct_tMax	−.058***	−.049***	−.044***	−.059***	−.050***	−.045***
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
Nov_tMax	−.057***	−.050***	−.058***	−.057***	−.051***	−.058***
	(.014)	(.014)	(.013)	(.014)	(.014)	(.013)
Mar_dday30C	.325**	.276***	.321**	.328**	.279***	.324**
	(.131)	(.107)	(.141)	(.131)	(.106)	(.141)

Table A.2 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
Apr_dday30C	−.059***	−.057***	−.071***	−.061***	−.059***	−.071***
	(.020)	(.020)	(.021)	(.020)	(.020)	(.021)
May_dday30C	.041***	.042***	.055***	.042***	.043***	.055***
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Jun_dday30C	.017***	.015***	.014***	.017***	.015***	.014***
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Jul_dday30C	.004*	.005*	.006**	.004*	.004*	.006**
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Aug_dday30C	.003	.003	.004	.003	.003	.004
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Sep_dday30C	−.014***	−.013***	−.010***	−.014***	−.014***	−.010***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Oct_dday30C	.027	.025	.033	.026	.024	.032
	(.026)	(.026)	(.026)	(.026)	(.026)	(.026)
Nov_dday30C	.288	.283	.353	.280	.271	.347
	(.177)	(.175)	(.230)	(.179)	(.176)	(.232)
Drought						
Mar_Drought	−.040**	−.039**	−.041**	−.039**	−.038**	−.040**
	(.017)	(.017)	(.017)	(.017)	(.017)	(.017)
Apr_Drought	.001	−.007	−.012	.001	−.007	−.012
	(.022)	(.022)	(.021)	(.022)	(.021)	(.021)
May_Drought	−.096***	−.095***	−.084***	−.095***	−.095***	−.083***
	(.018)	(.018)	(.017)	(.018)	(.018)	(.017)
Jun_Drought	.179***	.179***	.198***	.178***	.178***	.198***
	(.022)	(.022)	(.022)	(.022)	(.022)	(.022)
Jul_Drought	.225***	.224***	.196***	.226***	.224***	.196***
	(.020)	(.020)	(.020)	(.020)	(.020)	(.020)
Aug_Drought	.013	.014	.014	.013	.014	.015
	(.016)	(.016)	(.015)	(.016)	(.016)	(.015)
Sep_Drought	.079***	.080***	.084***	.080***	.080***	.085***
	(.017)	(.017)	(.016)	(.017)	(.017)	(.016)
Oct_Drought	−.005	−.004	.011	−.006	−.004	.010
	(.022)	(.022)	(.022)	(.022)	(.022)	(.022)
Nov_Drought	.146***	.137***	.133***	.145***	.137***	.132***
	(.022)	(.022)	(.021)	(.022)	(.022)	(.021)
Wetness						
Mar_Wetness	−.025	−.012	−.023	−.025	−.013	−.023
	(.017)	(.017)	(.016)	(.017)	(.017)	(.016)
Apr_Wetness	.008	.009	.010	.009	.009	.010
	(.011)	(.012)	(.011)	(.011)	(.012)	(.011)
May_Wetness	.105***	.105***	.103***	.106***	.105***	.103***
	(.010)	(.009)	(.009)	(.010)	(.009)	(.009)
Jun_Wetness	.143***	.140***	.143***	.143***	.139***	.143***
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Jul_Wetness	.019	.023*	.027**	.020	.023*	.027**
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Aug_Wetness	−.005	−.004	.007	−.005	−.004	.007
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Sep_Wetness	.077***	.071***	.073***	.077***	.071***	.074***

Table A.2 (continued)

	Linear Specification			Group Dummies Specification		
Variable	ln(LR)	ln(LRsubsidy)	ln(LCR)	ln(LR)	ln(LRsubsidy)	ln(LCR)
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Oct_Wetness	−.014	−.007	−.012	−.015	−.008	−.012
	(.010)	(.010)	(.009)	(.010)	(.010)	(.009)
Nov_Wetness	−.020	−.031**	−.019	−.019	−.030**	−.018
	(.014)	(.014)	(.013)	(.014)	(.014)	(.013)
Land ($/acre)						
ln(Rent)	.419***	.342***	.055	.418***	.342***	.058
	(.083)	(.086)	(.086)	(.083)	(.086)	(.086)
Year						
Year_2005	−.846***	−.912***	−.908***	−.839***	−.901***	−.900***
	(.076)	(.076)	(.074)	(.077)	(.076)	(.074)
Year_2006	−.760***	−.840***	−.719***	−.754***	−.832***	−.712***
	(.070)	(.071)	(.070)	(.070)	(.071)	(.070)
Year_2007	−.720***	−.869***	−.752***	−.715***	−.860***	−.749***
	(.080)	(.079)	(.079)	(.079)	(.078)	(.078)
Year_2008	−.206***	−.276***	−.105*	−.197***	−.266***	−.096
	(.063)	(.064)	(.062)	(.063)	(.064)	(.062)
Year_2009	−.186***	−.202***	.019	−.177***	−.192***	.026
	(.071)	(.071)	(.071)	(.071)	(.071)	(.071)
Year_2010	−.795***	−.796***	−.772***	−.777***	−.775***	−.756***
	(.071)	(.071)	(.071)	(.072)	(.071)	(.071)
Year_2011	−1.315***	−1.272***	−1.251***	−1.301***	−1.256***	−1.240***
	(.088)	(.087)	(.086)	(.088)	(.087)	(.086)
Year_2012	−1.070***	−.998***	−.966***	−1.053***	−.980***	−.953***
	(.087)	(.087)	(.084)	(.087)	(.087)	(.084)
Year_2013	−.576***	−.529***	−.555***	−.571***	−.523***	−.551***
	(.056)	(.057)	(.054)	(.057)	(.057)	(.054)
Year_2014	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Year_2015	−.352***	−.305***	−.295***	−.345***	−.297***	−.289***
	(.063)	(.062)	(.061)	(.063)	(.062)	(.061)
Trend	−.005***	−.004***	−.005***	−.005***	−.004***	−.005***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Arellano-Bond test						
Order 1	-25.554	-25.731	-25.309	-25.516	-25.686	-25.275
(p-value)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Order 2	-1.482	-1.230	-1.382	-1.457	-1.201	-1.344
(p-value)	(.138)	(.219)	(.167)	(.145)	(.230)	(.179)
Obs.	22,836	22,832	22,836	22,836	22,832	22,836
Counties	2,073	2,072	2,073	2,073	2,072	2,073

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

Table A.3: Costs Avoided in $ million by Year based on the Estimation Results in Table 12

Year	LR specification	LRsubsidy specification	LCR specification
2004	53	59	67
2005	24	28	30
2006	37	42	50
2007	104	118	121
2008	196	215	221
2009	113	128	139
2010	61	67	72
2011	153	175	208
2012	204	214	212
2013	237	258	301
2014	180	192	219
2015	77	84	93
Average	120	132	144

Figure A.1: Costs Avoided in $ million by Year based on the Estimation Results in Table 12