Chemical and Fertilizer Applications in Response to Crop Insurance: Evidence from Census Micro Data

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Abstract
This paper presents preliminary evidence on the effect of crop insurance on fertilizer and chemical inputs in agriculture. Our estimates are based on two sources of identification that emerge from a policy change concerning insurance subsidies that approximately doubled total premiums and the share of acres insured. First, we compare per-acre applications on these inputs from the same farms before and after the policy change. Second, we compare farm-level changes in input applications to differential changes in coverage growth induced by the policy change. We are able to make this second comparison because farms in some regions were more heavily insured than others before the policy change so they were not required to increase coverage in order to obtain the subsidy. Thus, the policy change caused some farms to increase coverage more than others. We find that the insurance subsidies induced modest reductions in fertilizer and chemical applications on tobacco and cotton crops and a modest increase in chemical applications on corn.

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Introduction

Certain agricultural production decisions affect not only expected returns to farming, but also the random variability of profits and environmental quality. Several researchers have pointed to pesticide and fertilizer applications as decisions with implications for risk and the environment (Leathers and Quiggen; Horowitz and Lichtenberg; Babcock and Hennessey; Smith and Goodwin). If market imperfections preclude full insurance, risk-averse farmers might apply more or less of these inputs in order to mitigate profit risk. All else the same, greater risk causes risk-averse farmers to reduce applications of risk-increasing inputs and to increase applications of risk-decreasing inputs (Pope and Kramer).

Crop insurance subsidies, through risk mitigation, should cause risk-averse farmers to increase applications of risk-increasing inputs and reduce applications of risk-reducing inputs. Thus, depending on farmers’ risk aversion, the availability of other risk coping mechanisms, and how pesticide and fertilizer inputs influence profit risk, crop insurance subsidies may affect farmers’ production decisions and, in turn, have unintended consequences for the environment. Evidence on the relationship between insurance and agrochemical use, however, is mixed.

The empirical ambiguity that surrounds the relationship between risk and chemical and fertilizer use appears to stem from three challenging identification problems: (1) risk is difficult to quantify; (2) differences in risk measures over time and across farms are highly correlated with other factors that drive the use of these inputs; and (3) risk (like insurance adoption) is partly endogenous.¹ For example, researchers have typically measured risk using historical variance of reported profits, sales, or yields, and have identified risk effects from cross-sectional differences in these measures across farms and regions. These variance measures may or may

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¹ Census of Agriculture data only allows us to measure chemical purchases, which consist of insecticides, herbicides, fungicides, other pesticides, and defoliants. This measure does not include purchases of either fertilizers or lime. Therefore, our discussion on chemicals should complement the discussion in the literature concerning pesticides, since “chemical purchases” mainly reflect pesticide purchases.
not provide adequate risk measures because the measures are imprecise and one cannot cleanly
disentangle anticipated profit variability from unanticipated profit variability. Also, cross-
sectional differences in these measures are almost surely associated with confounding factors,
such as climatic conditions, soil types, and perhaps even farmers’ risk preferences (Ackerberg
and Botticini). Furthermore, observed profit variances, even if they do provide appropriate risk
measures, are endogenous.

To estimate the importance of risk for production decisions requires exogenous
differences in risk over time and/or across farm operations together with suitable controls for
factors associated with, but not caused by, differences in risk. A source of identification that
possesses these properties is difficult to find.

The Federal Crop Insurance Reform Act (FCIRA) of 1994 provides a unique opportunity
to measure the importance of risk for agricultural production. The FCIRA significantly
increased federal subsidies associated with crop insurance. For $50 per county and crop, farmers
received, free of any additional charge, ‘Catastrophic Coverage’ for 50 percent of average yield
at 60 percent of expected price. In addition, Congress markedly increased subsidies for
premiums at higher coverage levels relative to pre-1994 levels. Following the subsidy increase,
the number of insurance policies and total insured acreage more than doubled (Glauber and
Collins). Between 1992 and 1997, the years our data were collected, total premiums increased
(nominally) from $758.7 million to $1,773.8 million. This policy change constitutes a large and
exogenous reduction in the cost of risk bearing—a source of identification that overcomes the
above challenges associated with measuring the consequences of risk and insurance.

Our primary data include a panel consisting of micro data from the 1992 and 1997
Censuses of Agriculture. Each Census file includes an observation from nearly every farm
business operation in the US. The final data set merges these two Census files by farm operation
together with county-level crop insurance data obtained from the Risk Management Agency (RMA). Armed with two observations for each farm operation, we first estimate per-acre applications of fertilizers and chemicals before and after the policy change, controlling for commodity price changes and other policy changes that took place around the same time. We then construct a second set of estimates by comparing farm-level changes in chemical and fertilizer use to changes in county-level insurance adoption. We are able to make this second comparison because there is variation across counties in the level of change in insurance coverage – that is, farms that held less insurance before the policy change increased their coverage the most (and vice versa).

This approach provides us with a source of identification that overcomes the challenges normally involved with measuring the consequences of risk. First, the policy change provides a quantifiable change in farmers’ exposure to risk. Second, the rich data set we use enables us to control for unobserved factors that affect the use of chemicals and fertilizers and might be highly correlated with the risk measures we use. Finally, the policy change represents an exogenous reduction in the price of risk management available to farmers. This approach should therefore allow us to attribute changes in input use to changes in risk exposure.

Conceptual Background

The relationship among risk, crop insurance, and farmers’ agrochemical applications remains unclear for two reasons. First, the empirical evidence remains unclear as to whether chemical and fertilizer applications increase, decrease, or have no effect on yield or profit variance. The ‘conventional wisdom’ states that chemical applications reduce risk while fertilizer applications increase risk, as measured by profit variance (Leathers and Quiggen). Alternatively, Horowitz and Lichtenberg provided some reasoning and empirical evidence to
suggest that pesticide applications increase risk. Other authors question Horowitz and Lichtenberg’s argument and suggest that improper model specification biased their empirical results (Babcock and Hennessy; Smith and Goodwin). Roosen and Hennessy recently analyzed data from experimental field plots and found that fertilizer inputs increased corn yield risk on experimental Iowa research farms. In sum, no consensus exists concerning the relationship between profit risk and farmers’ agrochemical applications.

Second, it remains unclear whether risk even affects production decisions. The above predictions regarding the relationship between applications and their marginal effect on profit risk assume that farmers have risk-averse (concave) objectives: they choose crops, production practices, and input levels in order to maximize the expected value of a smooth, “utility” function of current profits. However, institutional and contractual constraints may arise in a world of imperfect markets with asymmetric information and give rise to highly non-linear or even discontinuous incentives, despite farmers’ preferences. These incentive schemes will alter risk-related incentives, even if one can characterize preferences using a smooth and concave utility function. Ghatak and Pandey, for example, show that in limited liability environments the optimal combination of share-contract and debt financing induces risk-loving production choices, despite the agents having risk-neutral preferences. The next section discusses how insurance can influence production decisions through two channels that may or may not interact with each other: moral hazard and risk response.

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2 We put the term “utility” in quotes because we do not regard it as a literal representation of preferences. Curvature of the current objective depends on many constraints and dynamic risk-coping mechanisms in addition to preferences. Risk-averse producers have various means to smooth consumption including the accumulation and depletion of liquid assets, formal and informal insurance arrangements, or borrowing. Thus, in this context, one should interpret the “utility” function as complicated amalgamation of preferences and constraints on risk sharing.
Moral hazard

According to the standard moral hazard argument, insurance gives farmers an incentive to reduce efforts to maintain high yields, which include applications of fertilizer and chemical inputs. The structure of insurance contracts, which include deductibles and premiums that depend on farm-specific yield histories, may attenuate moral hazard. Most federal crop insurance contracts provide coverage for less than half of expected profits, so the deductible is large. A farm’s premium also depends on its 10 year yield history, so a claim in one year increases the premium paid in the next, and reduces the yield at which insurance pays, effectively increasing the deductible. In light of the contract structure, it is unclear how insurance affects farmers’ incentives to apply inputs. However, because the premiums are subsidized, the effectiveness of insurance contracts in mitigating moral hazard may be reduced. Catastrophic coverage, for example, is fully subsidized, so a claim in the current year does not translate into higher premium payments made by the farmer. A claim in the current year does, however, reduce future coverage.

Risk response

The standard theoretical relationships between risk and input use can be derived mathematically in the following way. Define the value of a current-year farming opportunity as

\[
V = \max_x E[u(\pi(x,s))],
\]

where \(u()\) is a concave “utility” function, \(\pi\) is profit, \(x\) is a vector of production decisions (including chemical and fertilizer applications), \(s\) is vector of random uncertainties (including weather and prices), and \(E\) is an expectations operator. Embedded within the profit function is a stochastic production function that maps inputs and weather to outputs. Inputs and outputs may depend on the weather and prices, some of which are stochastic. Profits, in turn, depend on
inputs, outputs, and prices. The “utility” function, \( u() \), maps profits to the farm operator’s value of profits.

Within the agricultural economics literature it is common to interpret \( u() \) as a smooth and concave function that reflects diminishing marginal value of returns, identical to the contemporaneous utility functions often used in the consumption literature, with profits substituted for consumption. Below, we describe how this function may have a more general interpretation and may be neither smooth nor concave.

This optimization problem, the solution of which characterizes the way risk influences production choices, is complicated. We can characterize a simpler approximate solution to the general problem by assuming a smooth utility function, that \( s \) has a well-behaved probability distribution function, and take a second-order Taylor expansion around the average (or expected) level of profits. Specifically, we can approximate \( V \) by

\[
V = \max_x u(E[\pi(x,s)]) + \frac{1}{2} u''(E[\pi(x,s)])VAR(\pi(x,s)).
\]

If risk aversion implies negative \( u'' \), production decisions that increase profit variance, all else the same, are under-utilized in comparison to those in a perfect-markets world; while those that decrease profit variance, all else the same, are over-utilized in comparison to those in a world with full risk sharing. The larger the variance of profits, the larger this effect. Production decisions that could influence the variance of profits include applications of specific inputs, such as fertilizer and chemicals, the allocations of acreage between crops, and perhaps other decisions.

Maximization of this approximate objective gives the following first-order condition (assuming an interior solution) for each input \( x_i \) contained in the vector \( x \):

\[
\left\{ u'(E[\pi(x,s)]) + \frac{1}{2} u''(E[\pi(x,s)])VAR(\pi(x,s)) \right\} \frac{\partial E[\pi]}{\partial x_i} + \frac{1}{2} u''(E[\pi(x,s)]) \frac{\partial VAR[\pi]}{\partial x_i} = 0
\]
The second term in the bracket includes only second- and third-order elements and normally will be dominated by the first term. For this reason, and because we ignore higher-order elements in the approximate objective, we drop this term. This second-order approximation is equivalent to the assumption that utility is a quadratic. By defining $A$ as the coefficient of absolute risk aversion, the condition implies

$$\frac{\partial E[\pi]}{\partial x_i} = \frac{A}{2} \frac{\partial VAR[\pi]}{\partial x_i} \text{ for all inputs } x_i.$$

By contrast, the first order condition of a risk-neutral (or fully-insured) expected profit maximizing farmer is:

$$\frac{\partial E[\pi]}{\partial x_i} = 0 \text{ for all inputs } x_i.$$

Relative to the expected profit maximizing farmer, these expressions imply that a risk-averse farmer will (at the margin) apply greater amounts of inputs that reduce profit risk ($dVAR(\pi)/dx_i < 0$) and lower amounts of inputs that increase profit risk ($dVAR(\pi)/dx_i > 0$), as compared to the risk-neutral objective. An exogenous reduction in risk (or increased insurance availability) would therefore cause farmers to increase applications of risk-increasing inputs and reduce applications of risk-decreasing inputs. More thorough theoretical treatments of input demand under risk for specific families of utility and profit functions can be found in Pope and Kramer, Loehman and Nelson, and Leathers and Quiggin.

The above input use predictions, as well as those in the cited references, are based on rather strong assumptions regarding the smooth concavity of the “utility” function $u(\pi)$. More generally, one might view this function as $v(w(\pi))$, where $v()$ is a true reflection of preferences and $w()$ is an explicit or implicit incentive contract available to the farmer in a world of imperfect risk sharing. This contract can be viewed as an optimal incentive scheme arising from a principal-agent problem, which may include risk-sharing motives. It may contain the explicit
insurance contract written with the government under FCIRA, relationships with lenders, positions in futures markets, formal and informal arrangements input suppliers, landlords, integrators, and so on. It may also reflect the ongoing value of the farm in a dynamic context. Because the incentive contract may be concave, convex, or even discontinuous, the function \( u(\pi) = v(w(\pi)) \) may take on almost any conceivable shape, even if farm operators have preferences that can be characterized by diminishing marginal utility of consumption. From this more general point of view, it is more difficult to make predictions about the relationship between risk and input use.

Further ambiguity regarding input demand under risk arises from the psychology literature. Inquiries that have attempted to measure the shape of preferences in response to risk reject the notion that risk preferences can be encapsulated by a smooth, increasing, and concave cardinal utility function (Kahneman and Tversky, Rabin). Indeed, considerable experimental evidence refutes the expected utility model altogether. In the end, we have little theoretical reasoning or empirical evidence to suggest whether risk or insurance (an exogenous reduction in the \( \text{VAR}(\pi) \)) should increase or decrease the use of chemical and fertilizer inputs. It is empirically ambiguous whether or not these inputs increase or decrease risk. Furthermore, we do not know how preferences and constraints on risk sharing congeal to shape marginal application incentives \textit{given} the marginal influence of these inputs on profit risk.

In this paper, we therefore attempt to estimate the reduced form relationship between crop insurance and input use, rather than attempt to measure the structure of preferences or the marginal effect of chemical and fertilizer inputs on yield and profit risk. This relationship provides insight into the unintended environmental consequences of crop insurance subsidies. It
may also provide clues about the structure of preferences and constraints that underlie observed responses to insurance subsidies.

**Methods**

To measure the reduced form relationship between insurance and input use we examine how input use actually changed following a large 1995 increase in crop insurance subsidies. These subsidies caused a large increase in insurance adoption that reduced the amount of risk faced by many farmers. Our primary goal is to estimate the effect of this policy change on per-acre applications of chemical and fertilizer. Specifically, define $x_{it}$ as applications per acre of cropland for farm $i$ in period $t$, $A$ as a vector of average application rates for all crops (indexed by $j$) in the absence of insurance coverage, $S_{it}$ as a vector of shares of cropland allocated to each crop for farm $i$ in time $t$, $B$ as a vector of average marginal effects of insurance coverage on application rates, and $C_{it}$ as a vector of insurance coverage levels for farm $i$’s crops in time $t$. Our goal is to obtain an estimate for $B^T$. Using this notation, per-acre applications can be decomposed as

$$x_{it} = A^TS_{it} + B^T(S_{it}^TC_{it}) + \varepsilon_{it}$$

where the “error” $\varepsilon_{it} = \sum_j \varepsilon_{ijit}$ encapsulates the differences between farm $i$ and the average farm; that is, the error components, $\varepsilon_{ijit}$, are the elements of the vector

$$\varepsilon_{it} = (A_n - A)^TS_{it} + (B_n - B)^T(S_{it}^TC_{it}),$$

where $A_{it}$ is a vector of farm-specific base (non-insured) application rates for farm $i$ in time $t$ and $B_{it}$ is a vector of farm-specific marginal effects of insurance coverage on application rates.
Equation 6 contains no behavioral structure—it is a simple decomposition of each farm’s per-acre applications of a particular input. Armed with data on $x_{it}$, $S_{it}$, and $C_{it}$, one may regress $x_{it}$ against $S_{it}$, and $S_{it}^TC_{it}$ and obtain coefficients $\hat{A}$ and $\hat{B}$. These regression coefficients represent unbiased estimates of $A$ and $B$ only if $S_{it}$ and $S_{it}^TC_{it}$ are uncorrelated with $\sum_j e_{ijt}$ or, equivalently, with $\sum_j a_{ijt}$ and $\sum_j b_{ijt}$.

Strictly speaking, $x_{it}$, $S_{it}$, $A_{it}$, $B_{it}$ and $C_{it}$ are all endogenous—choices made by specific farm operations. Furthermore, these decisions are likely based on the same set of exogenous variables, which include prices of inputs and outputs, specific features and locations of the land on which the farms are situated, such as soil types and climate, and characteristics and preferences of the farm operators, such as age, risk attitudes, and so on. Because these variables have the same determinants, they are likely correlated with each other, $\hat{A}$ and $\hat{B}$ are likely biased. For example, in areas more prone to pest infestations, farmers may choose to apply higher-than-average levels of chemicals and purchase higher-than-average insurance coverage. This positive correlation between $A_{it}$ and $S_{it}^TC_{it}$ would cause an attenuation bias in $\hat{B}$, all else the same. Alternatively, in areas where the price of fertilizer is higher than average, farmers may apply less fertilizer and purchase more insurance as a substitute, causing negative correlation between $A_{it}$ and $S_{it}^TC_{it}$, which would cause $\hat{A}$ to be biased upward in magnitude.

To obtain unbiased estimates of $\hat{A}$, one needs an exogenous source of variation in insurance coverage ($S_{it}^TC_{it}$) that is uncorrelated with $A_{it}$ and $B_{it}$. For this study, we attempt to estimate $B$ by isolating the variation in $S_{it}^TC_{it}$ caused by the FCIRA of 1994. This large change in insurance subsidies caused many farms to purchase insurance for the first time and likely caused many other farms to increase their level of insurance coverage (see Figure 1). Because many farms had already adopted substantial insurance coverage prior to the FCIRA, the Act

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3 The candidate source of variation also must be uncorrelated with $S_{it}$, if $S_{it}^TC_{it}$ is correlated with $S_{it}$ and $S_{it}$ is correlated with $\sum_j e_{ijt}$. 
likely caused some farms to increase their coverage by greater amounts as compared to others. Thus, we expect that most of the variation in insurance growth was caused by the exogenous policy change, not unobserved determinants of $A_{it}$ and $B_{it}$. By comparing input applications before and after FCIRA, and by comparing how the growth in farmers’ applications relates to the different coverage growths likely induced by the FCIRA, we obtain two alternative estimates of $B$.

**Identification based on the time difference**

Using data on farm-level applications from two time periods, one before $(t = 0)$ and one after $(t = 1)$ the policy change, we estimate average applications per acre, per crop by regressing total applications per acre against crop shares, a year dummy variable interacted with each crop share, and a fixed effect for each farm. The dummy variable interaction terms estimate the differences in application rates before and after the policy change. That is, these interaction terms provide estimates for the average value of $B^T \Delta(S_i^T C_i)$ across farms. Specifically, the equation we estimate is

$$x_{it} = d_i + A^T S_{it} + B^* t_i S_{it} + D^T Z_{it} + \eta_{it},$$

where $t_i$ is an indicator variable for time period 1 (post policy change), $B^*$ equals the effect stemming from the policy change, $d_i$ is a farm fixed effect, $Z_{it}$ is a vector of control variables, $D^T$ a vector of coefficients on the controls, and $\eta_{it}$ an error.

The endogeneity problems discussed above stemmed from a correlation of individual application rates with individual coverage levels. In equation 8, however, the farm fixed effect ($d_i$) captures all time-invariant heterogeneity across farms. Furthermore, because the variable $t_i$ in this balanced panel equals one for all time 1 observations and zero for all time 0 observations, it is uncorrelated with the error if the average value of the error in time 1 equals the average value of the error in time zero—i.e., the average unobserved effect is the same in both periods.
Thus, estimation of this model will provide an unbiased estimate of the effect of the subsidy increase if unobserved variables did not cause *average* applications per acre to change between our sample periods. We therefore attempt to control for aggregate changes as well as possible.

To control for aggregate changes in commodity prices we include the previous year’s prices of each commodity in each state. We use the previous year’s prices because commodity prices are well-known to show a large degree of autocorrelation—prices follow a random walk or near random walk. In other words, the previous year’s price is a good forecast for next year’s price. We also include interactions of these prices with crop shares.

Around the same time as FCIRA, another policy change occurred, which may also have influenced average application rates. In 1996 the Federal Agricultural Improvement Reform Act (FAIR) dramatically altered the structure of agricultural income support payments. This Act, sometimes called the “freedom to farm bill,” decoupled most payments from farmers’ current planting decisions. Prior to this Act, government commodity program payments to farmers were tied to commodity prices, and to qualify for payments, farmers were required to limit current plantings to a share of historical plantings. The FAIR Act lifted nearly all planting restrictions and divorced payments from price levels. In effect, the Act scheduled lump-sum payments to land units based on pre-Act participation in government farm programs.

To control for the effects of the FAIR Act, we include each farm’s level of 1997 government farm payments per acre as an explanatory variable in the vector $Z_t$.\(^4\) The level of these payments was determined in advance according to parameters laid out in the FAIR Act. The larger these payments, the more engaged a farm was in pre-1996 farm programs, and the greater the effect of the policy change on input applications, all else the same.

\(^4\) We subtract conservation payments. In 1997, nearly all payments to farmers (net of conservation payments) were payments scheduled by the 1996 Act.
**Identification based on differences in differences**

It could be that unobserved aggregate factors, not captured by commodity price changes and the FAIR Act payments, caused application rates to change between our sample years. To address this issue, we make use of a second source of identification: different growths in insurance coverage across crops and farms induced by FCIRA. Some crops in some regions were more heavily insured than others prior to FCIRA. For some crops (such as tobacco), no federal insurance was available before FCIRA. In general, we find a negative correlation between the level of coverage before FCIRA and the growth in coverage following FCIRA. This relationship makes sense: farmers who were already insured did not have to change their behavior to obtain the newly increased insurance subsidies. Those who were not previously insured, however, had to adopt insurance in order to obtain them.

Specifically, we estimate the following model

$$\Delta x_t = A^T \Delta S_{it} + B^T \Delta (C_{it}^T S_{it}) + D^T Z_{it} + \eta_{it},$$  

Estimation of this difference equation has several benefits as compared to estimation of equations 6 and 8. First, we have an identifiable, exogenous source of variation in $\Delta(C_{it}^T S_{it})$—the FCIRA which likely caused insurance coverage to increase more for some crops and regions than for other crops and regions. Second, by differencing we have removed time-invariant heterogeneity of farms (equivalent to the fixed effects $(d_{it})$ in equation 8). A farm prone to pest infestations that applies chemicals at a higher-than-average rate will have higher-than-average applications in both periods. By differencing, we have removed differences between an individual farm’s application rate and the average application rate. Thirdly, change in crop shares ($\Delta S_{it}$) and regional fixed effects captures all unobserved aggregate and regional changes that are not accounted for in estimation of equation 8.
Still, changes in crop insurance coverage may be partly influenced by changing prices, technology, or other factors that affect some farms more than others. These factors that influence idiosyncratic variation in coverage growth may be correlated with idiosyncratic variation in application growth. To eliminate biases that may be caused by these factors we include a series of controls, including price changes interacted with time-zero crop shares, and 1997 government payments interacted with time-zero crop shares (to control for changes induced by the FAIR Act). These estimates are “differences in differences” estimates that have been widely used in the quasi-experimental empirical literature in recent years. In this case, our treatment is differential premium growths across regions caused by the FCIRA.

Data

Figure 1 presents data constructed from county-level data obtained from the Risk Management Agency (RMA) of the U.S. Department of Agriculture. The figure shows total subsidies, total premiums, and total acres enrolled in the crop insurance program from 1990 to 1998. The figure shows a marked increase in crop insurance subsidies beginning in 1995, the season following the FCIRA of 1994. We present separate plots for all crops and for the three largest individual crops (in acreage): corn, soybeans, and wheat. In 1997, these three crops made up 78.9% of the acreage insured, 55.5% of the subsidies, and 51.7% of the total premiums paid. As of 1997, these three crops also made up 53.8% of cultivated cropland in the U.S. (excluding hay).

For the ten crops that account for the most total premiums, table 1 reports 1992 and 1997 levels of premiums, acres harvested, share of acres insured, premiums per acre harvested, premiums per insured acre, and subsidies per insured acre. These ten crops make up 85% of all premiums paid in 1997. The table illustrates the dramatic increase in premiums across most crops. Premiums, however, increased more for some crops than other crops. For barley,
potatoes, and dry beans, premiums per acre harvested increased by about 1/3, whereas for wheat and sorghum the ratio increased by about ½, and for cotton, corn, soybeans the increase was almost 2/3. The most extreme cases were peanuts, which showed little increase (the crop was heavily insured before the policy change), and tobacco, for which no federal crop insurance was available in 1992. Within each crop, there is also large variation across regions in premium growth.

The data obtained from RMA are county population values for crop insurance enrollment. These data, however, do not include information on production practices. We obtained data on individual farm operations from the micro files of the 1992 and 1997 Agricultural Censuses. The Census micro files contain limited information about almost every farm operation in the U.S. and somewhat more detailed information, elicited in the “long form,” for about one third of farm operations. Large farm operations are more likely than small operations to receive the long form. We then merged all Census records from 1992 and 1997 by farm operation to obtain a panel.\footnote{We linked farm operations from the 1992 Census file with those in the 1997 Census file using a longitudinal Census file. The longitudinal file links farm operations in the 1978, 1982, 1987, 1992 and 1997 Census but contains only a few variables. This file, however, includes an indicator that allowed us to link the longitudinal file with all the available data from the files for each census years. We were thus able to use the longitudinal file to merge all Census records from 1992 and 1997 by farm operation and obtain a panel data set that included the more detailed production data.} We restricted this data set to include all farms that received and returned the long form in both 1992 and 1997 and received more than $100,000 in sales in both 1992 and 1997. Because large farms are more likely than small farms to receive the long form, these farms also are more likely to receive the long form in two consecutive censuses. We then restricted this data set to farms in which 95% or more of the total harvested cropland in both 1992 and 1997 was comprised of the ten crops listed in Table 1 plus hay.

Our measures of chemical and fertilizer applications are constructed from Census long-form responses on expenditures. Each farm reports the dollar value spent of all forms of
commercial fertilizer purchased, including rock phosphate and gypsum, and the dollar value of all agricultural chemicals purchased, including insecticides, herbicides, fungicides, defoliants, and other pesticides. We then converted the dollar values into proxies for applications using price indices for these respective classes of inputs. In our regressions, applications are measured in 1997 dollars.

To link the Census data and the insurance data from RMA, we constructed a measure of the average insurance premium per harvested acre for each county, crop, and year. Total harvested cropland was obtained from the Agricultural Census. If the total harvested cropland reported in the Census was less than the amount of land insured by RMA, we substituted total insured acreage for total acreage. The average of these ratios, weighted by the number of acres in each county, is reported in column 4 of table 1. We use this variable as a proxy for $C_{ijt}$ in equations 6 through 9. We then merged these data with the individual operations according to the county in which each farm resides. The appendix spells out these steps in more detail.

Although it may seem that farm-level insurance data would be preferred over merging county-level data with individual farms as described above, there are certain benefits. Idiosyncratic variability of individual farm coverage changes that is correlated with idiosyncratic variability of changes in crop shares and or input applications could bias our regression estimates. In using county-level coverage levels, proxied by the average premium per acre harvested, we limit our source of identification to between-county variation in coverage growth, which should reduce biases of this kind. It is as if we use county-level coverage changes as an instrument for farm-level changes.
Results

Tables 3 through 5 summarize our findings. Table 3 reports estimates of the average per-acre application rates ($\hat{A}$) associated with OLS estimation of applications against crop shares (equation 6). These coefficients provide estimates for the average application rates across all regions and both years (1992 and 1997). Tables 4 and 5 report five estimates each for the effect of insurance on chemical and fertilizer applications ($\hat{B}$). The first column of each table reports estimates of equation 6; the second column reports estimates of equation 8 without controls; the third column reports estimates of equation 8 with controls; the fourth column reports estimates of equation 9 without controls; and the fifth column reports estimates of equation 9 with controls. All of the estimates in tables 4 and 5 predict changes in applications per acre induced by the FCIRA as measured in 1997 dollars per acre. The estimates and standard errors in columns one, four, and five have been adjusted by the average growth in premiums per harvested acre in order to make all the estimates comparable. Statistically significant values are in boldface. The estimated application rates reported in table 3 provide a rough basis for comparison.

The estimates in column 1 are most susceptible to missing variable and endogeneity biases. The estimates in columns 2 and 3 are reliable if large aggregate changes have not influenced application rates between 1992 and 1997. Estimates in columns 4 and 5 are the most robust to missing-variable and endogeneity biases.

The results imply that FCIRA induced modest reductions in chemical and fertilizer applications for cotton and tobacco and a small increase in chemical applications of chemicals for corn. The estimates imply reductions in chemical use of approximately 7.5% and 4.5% for cotton and tobacco, respectively, and reductions in fertilizer use of 1.2% and 5.6%. Chemical applications on corn increased by an estimated 2.5% as a result of the subsidy increase. Peanuts displayed a large reduction in applications between 1992 and 1997. The size of the reduction, however, is not
associated with the size of the coverage change, which suggests that unobserved aggregate factors were driving it. Cotton, tobacco, and potatoes also display relatively large aggregate changes, some of which were not associated with changes in insurance coverages. Estimates for other crops, such as dry beans, sorghum, and barley, have large standard errors relative to their application rates. FCIRA may have affected application levels on these crops but our data cannot detect it statistically. The relatively low power for these estimates is likely due to the relatively small number of acres in these crops within our sample of farms.

Conclusion

Our results for cotton and tobacco, which are our most consistent and thus reliable, appear to be in line with the standard view of moral hazard: insurance reduces farmers’ incentives to generate efforts to maintain high yields. Alternatively, some researchers may interpret our results as evidence that chemical and fertilizer inputs are risk-decreasing for tobacco and cotton and mildly risk-increasing for corn.

Overall, however, crop insurance subsidies appear to have had little effect on input use. The mixed findings from previous research are probably due to the small sizes of these effects and the fact that they are easily confounded by other factors that are correlated with risk. It could be that these inputs do little to affect the random variability of profits. Alternatively, the availability of other risk management tools may obviate the need for farmers to mitigate risk through altered production practices. Finally, because our estimates pertain to the average change in input use induced across all insured cropland, they obscure the distribution of these effects. If crop insurance subsidies induce little or no change in input use on most lands, but cause larger changes on certain lands, then our analysis obscures these effects. Acute changes in input use in certain locations could
affect environmental quality, especially if the lands on which these changes occur are particularly sensitive environmentally. In future work, it may be interesting to examine whether insurance subsidies have caused greater changes in input use in certain locations.
References


Appendix
From the county-level RMA data, define:

\[ P_{jkt} = \text{total premiums paid for crop } j \text{ in county } k \text{ at time } t \]

From the Census micro files, define:

\[ l_{ijkt} = \text{farm i’s area planted in crop } j \text{ in county } k \text{ at time } t \]

\[ A_{jkt} = \sum_k l_{ijkt} = \text{total area planted in crop } j \text{ in county } k \text{ at time } t \]

\[ c_{jkt} = \frac{P_{jkt}}{A_{jkt}} \] This variable is used as a proxy for all \( c_{ijt} \) for all farms in county \( k \) at time \( t \)

**Constructed Variables:**

\[ L_{it} = \text{farm i’s total cropland} \]

\[ s_{ijt} = \frac{l_{ijkt}}{L_{it}} \] is farm I’s share of total cropland in crop \( j \)

\[ c_{jkt} s_{ijt} = \text{proxy for coverage of farm i’s insurance coverage of crop } j \]

**Crops (j):**

Used construction of crop shares (\( s_{ij} \)): corn, soybeans, wheat, tobacco, sorghum, barley, cotton, peanuts, dry beans, potatoes, hay, all other cropland.

For construction of insurance coverage rates (\( c_{ij} \)): corn, soybeans, wheat, tobacco, sorghum, barley, cotton, peanuts, dry beans, potatoes.
### Table 1

Insurance coverage before and after FCIRA of 1994

<table>
<thead>
<tr>
<th>Crop</th>
<th>(1) Total premiums ($ x 1,000)</th>
<th>(2) Total Acres Harvested ( x 1,000)</th>
<th>(3) Share of Acres Covered</th>
<th>(4) Average Premium per Acre Harvested</th>
<th>(5) Average Subsidy per Insured Acre</th>
<th>(6) Average Premium per Insured Acre</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td>146,118</td>
<td>313,933</td>
<td>59,003</td>
<td>60,953</td>
<td>0.497</td>
<td>0.833</td>
</tr>
<tr>
<td>Cotton</td>
<td>90,657</td>
<td>252,676</td>
<td>11,742</td>
<td>13,787</td>
<td>0.371</td>
<td>0.835</td>
</tr>
<tr>
<td>Corn</td>
<td>196,412</td>
<td>460,662</td>
<td>68,905</td>
<td>70,371</td>
<td>0.327</td>
<td>0.702</td>
</tr>
<tr>
<td>Dry Beans</td>
<td>13,326</td>
<td>25,136</td>
<td>1,159</td>
<td>1,530</td>
<td>0.628</td>
<td>0.848</td>
</tr>
<tr>
<td>Sorghum</td>
<td>24,974</td>
<td>44,788</td>
<td>10,336</td>
<td>8,351</td>
<td>0.351</td>
<td>0.755</td>
</tr>
<tr>
<td>Peanuts</td>
<td>39,840</td>
<td>36,153</td>
<td>1,354</td>
<td>1,292</td>
<td>0.78</td>
<td>0.914</td>
</tr>
<tr>
<td>Soybeans</td>
<td>93,715</td>
<td>288,374</td>
<td>54,672</td>
<td>66,135</td>
<td>0.262</td>
<td>0.659</td>
</tr>
<tr>
<td>Potatoes</td>
<td>12,497</td>
<td>28,857</td>
<td>905</td>
<td>1,107</td>
<td>0.326</td>
<td>0.626</td>
</tr>
<tr>
<td>Barley</td>
<td>17,486</td>
<td>23,708</td>
<td>6,463</td>
<td>5,893</td>
<td>0.474</td>
<td>0.763</td>
</tr>
<tr>
<td>Tobacco</td>
<td>0</td>
<td>31,768</td>
<td>783</td>
<td>806</td>
<td>0</td>
<td>0.826</td>
</tr>
</tbody>
</table>

Source: Risk Management Agency at http://www.rma.usda.gov/data/
Figure 1

Insurance coverage of all crops and largest individual crops in years preceding and following the FCIRA of 1994

## Table 2

Crop Shares and Agrochemical Applications

<table>
<thead>
<tr>
<th>Variable</th>
<th>Year 1992</th>
<th>Year 1997</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Share of Total Cropland</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corn</td>
<td>0.367</td>
<td>0.346</td>
</tr>
<tr>
<td>Tobacco</td>
<td>0.015</td>
<td>0.016</td>
</tr>
<tr>
<td>Soybean</td>
<td>0.308</td>
<td>0.332</td>
</tr>
<tr>
<td>Barley</td>
<td>0.010</td>
<td>0.009</td>
</tr>
<tr>
<td>Potato</td>
<td>0.011</td>
<td>0.010</td>
</tr>
<tr>
<td>Cotton</td>
<td>0.098</td>
<td>0.115</td>
</tr>
<tr>
<td>Sorghum</td>
<td>0.037</td>
<td>0.025</td>
</tr>
<tr>
<td>Dry Beans</td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td>Peanut</td>
<td>0.019</td>
<td>0.015</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.125</td>
<td>0.123</td>
</tr>
<tr>
<td>“Other Crops”</td>
<td>0.006</td>
<td>0.005</td>
</tr>
<tr>
<td>Chemical Applications per Acre</td>
<td>34.286</td>
<td>36.426</td>
</tr>
<tr>
<td>Fertilizer Applications per Acre</td>
<td>42.544</td>
<td>39.085</td>
</tr>
<tr>
<td>Total Cropland Acres (Millions)</td>
<td>29.76</td>
<td>34.01</td>
</tr>
<tr>
<td>Number of Farms</td>
<td>25182</td>
<td>25182</td>
</tr>
</tbody>
</table>

Chemical and Fertilizer Applications are in 1997 dollars. The variable was constructed by dividing Census-year expenditures by an input price index derived by NASS. See [http://usda.mannlib.cornell.edu/reports/nassr/price/zap-bb/agpran02.pdf](http://usda.mannlib.cornell.edu/reports/nassr/price/zap-bb/agpran02.pdf)
### Table 3

Estimated Application Rates from Pooled Regression

<table>
<thead>
<tr>
<th>Crop</th>
<th>Fertilizer</th>
<th>Chemicals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>30.77</td>
<td>53.93</td>
</tr>
<tr>
<td>Tobacco</td>
<td>184.12</td>
<td>296.60</td>
</tr>
<tr>
<td>Soybean</td>
<td>23.908</td>
<td>24.36</td>
</tr>
<tr>
<td>Barley</td>
<td>2.049</td>
<td>32.490</td>
</tr>
<tr>
<td>Potatoes</td>
<td>151.33</td>
<td>182.48</td>
</tr>
<tr>
<td>Cotton</td>
<td>100.20</td>
<td>51.25</td>
</tr>
<tr>
<td>Sorghum</td>
<td>5.620</td>
<td>15.26</td>
</tr>
<tr>
<td>Bean</td>
<td>21.10</td>
<td>26.709</td>
</tr>
<tr>
<td>Peanut</td>
<td>85.91</td>
<td>89.46</td>
</tr>
<tr>
<td>Wheat</td>
<td>10.00</td>
<td>30.21</td>
</tr>
</tbody>
</table>

Notes:
(1) Chemical and Fertilizer Applications are in 1997 dollars. The variable was constructed by dividing Census-year expenditures by an input price index derived by NASS. See [http://usda.mannlib.cornell.edu/reports/nassr/price/zap-bb/agpran02.pdf](http://usda.mannlib.cornell.edu/reports/nassr/price/zap-bb/agpran02.pdf).
### Table 4

**Summary of Estimates: Chemicals**

<table>
<thead>
<tr>
<th>Crop</th>
<th>(1) Pooled time-series cross-section</th>
<th>(2) Time difference Individual fixed effects: No controls</th>
<th>(3) Time difference Individual fixed effects: w/ controls</th>
<th>(4) Difference in differences No controls</th>
<th>(5) Difference in differences With controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate  SE</td>
<td>Estimate  SE</td>
<td>Estimate  SE</td>
<td>Estimate  SE</td>
<td>Estimate  SE</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.47  0.53</td>
<td>0.95  0.73</td>
<td>1.31  1.30</td>
<td>0.98  0.47</td>
<td>0.79  0.50</td>
</tr>
<tr>
<td>Cotton</td>
<td>-17.27  0.52</td>
<td>-8.32  0.79</td>
<td>-6.99  1.43</td>
<td>-3.70  0.55</td>
<td>-3.83  0.57</td>
</tr>
<tr>
<td>Corn</td>
<td>-1.34  0.49</td>
<td>4.24  0.65</td>
<td>4.27  0.67</td>
<td>1.79  0.57</td>
<td>1.36  0.60</td>
</tr>
<tr>
<td>Dry Beans</td>
<td>-1.75  4.94</td>
<td>4.90  6.50</td>
<td>4.10  7.27</td>
<td>-2.95  6.64</td>
<td>-3.99  6.75</td>
</tr>
<tr>
<td>Sorghum</td>
<td>2.91  1.60</td>
<td>-0.29  1.98</td>
<td>10.06  12.52</td>
<td>0.07  1.34</td>
<td>-0.12  1.57</td>
</tr>
<tr>
<td>Peanuts</td>
<td>-1.27  -0.18</td>
<td>-13.18  2.67</td>
<td>-34.67  6.72</td>
<td>0.08  0.31</td>
<td>0.05  0.32</td>
</tr>
<tr>
<td>Soybeans</td>
<td>3.67  0.58</td>
<td>4.02  0.78</td>
<td>7.04  3.34</td>
<td>0.89  0.63</td>
<td>1.00  0.67</td>
</tr>
<tr>
<td>Potatoes</td>
<td>-1.60  1.80</td>
<td>23.87  2.03</td>
<td>19.37  2.52</td>
<td>1.82  2.55</td>
<td>2.07  2.55</td>
</tr>
<tr>
<td>Barley</td>
<td>3.39  1.21</td>
<td>3.97  2.81</td>
<td>0.88  3.09</td>
<td>1.81  1.36</td>
<td>2.27  1.42</td>
</tr>
<tr>
<td>Tobacco</td>
<td>-9.14  2.76</td>
<td>-3.93  1.75</td>
<td>-5.35  1.75</td>
<td>-12.73  2.52</td>
<td>-13.71  2.56</td>
</tr>
</tbody>
</table>

**Notes:**

(2) Each coefficients in columns 2 and 3 represents an element in an estimate of the vector B* in equation 8—the interaction of the crop share and the year fixed effect. The coefficients in columns 1, 2, and 3 represent estimates of the vector B multiplied by the average 1992-1997 change in premiums per acre (reported column 4 of table 1). This adjustment makes the estimates in all columns comparable.

(3) Controls include farm fixed effects, price changes for all commodities, price shares interacted with the commodities, and total 1997 government payments (less conservation payments) to control for effects stemming from the 1996 farm bill.
### Table 5

Summary of Estimates: Fertilizer

<table>
<thead>
<tr>
<th>Crop</th>
<th>(1) Pooled time-series cross-section</th>
<th>(2) Time difference Individual fixed effects: No controls</th>
<th>(3) Time difference Individual fixed effects: w/ controls</th>
<th>(4) Difference in differences No controls</th>
<th>(5) Difference in differences With controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SE</td>
<td>Estimate</td>
<td>SE</td>
<td>Estimate</td>
</tr>
<tr>
<td>Wheat</td>
<td>-4.29</td>
<td>0.98</td>
<td>-0.85</td>
<td>1.42</td>
<td>3.60</td>
</tr>
<tr>
<td>Cotton</td>
<td>-5.68</td>
<td>0.97</td>
<td>-5.62</td>
<td>1.54</td>
<td>-11.98</td>
</tr>
<tr>
<td>Corn</td>
<td>-4.18</td>
<td>0.92</td>
<td>-2.65</td>
<td>1.27</td>
<td>-3.17</td>
</tr>
<tr>
<td>Dry Beans</td>
<td>6.43</td>
<td>9.24</td>
<td>-10.61</td>
<td>12.69</td>
<td>-21.35</td>
</tr>
<tr>
<td>Sorghum</td>
<td>0.13</td>
<td>3.00</td>
<td>2.25</td>
<td>3.87</td>
<td>-12.29</td>
</tr>
<tr>
<td>Peanuts</td>
<td>-0.73</td>
<td>0.34</td>
<td>-18.42</td>
<td>5.21</td>
<td>-29.11</td>
</tr>
<tr>
<td>Soybeans</td>
<td>-3.10</td>
<td>1.09</td>
<td>-0.33</td>
<td>1.53</td>
<td>-12.88</td>
</tr>
<tr>
<td>Potatoes</td>
<td>-4.17</td>
<td>3.38</td>
<td>-37.74</td>
<td>3.97</td>
<td>-49.56</td>
</tr>
<tr>
<td>Barley</td>
<td>-1.42</td>
<td>2.26</td>
<td>6.24</td>
<td>5.48</td>
<td>6.05</td>
</tr>
<tr>
<td>Tobacco</td>
<td>-52.28</td>
<td>5.17</td>
<td>-42.99</td>
<td>3.41</td>
<td>-44.58</td>
</tr>
</tbody>
</table>

Notes:

(4) Each coefficient in columns 2 and 3 represents an element in an estimate of the vector B* in equation 8—the interaction of the crop share and the year fixed effect. The coefficients in columns 1, 2, and 3 represent estimates of the vector B multiplied by the average 1992-1997 change in premiums per acre (reported column 4 of table 1). This adjustment makes the estimates in all columns comparable.

(5) Controls include farm fixed effects, price changes for all commodities, price shares interacted with the commodities, and total 1997 government payments (less conservation payments) to control for effects stemming from the 1996 farm bill.