Supply of Insurance for Specialty Crops and its Effect on Yield and Acreage

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We exploit variation in the timing of specialty crop insurance supply to different crops and counties in California to assess its effect on output as decomposed into yield and harvested acreage. Four woody-perennial crops and one field-annual crop are used to represent this effect. We find that the supply of crop insurance has a significant positive effect on output for several perennial crops and the field crop, but it only has a significant positive effect on yield for certain perennial crops. These findings suggest that even for disparate crops the supply of insurance reduces production risks for the insured crops and causes harvested acreage to expand. The positive significant effect of insurance supply on yield for several of the woody-perennial crops suggests that, regardless of the effect on acreage, it accelerates growers' adoption of improved tree/vine varieties and rootstocks, which are likely to be risk-increasing inputs due to the their relatively high cost of investment.

Keywords: federal crop insurance program, specialty crops, yield, acreage, input-risk relationship

Recent fiscal distress has prompted the United States government to propose a shift in paradigm that would make the federal crop insurance program (FCIP) the primary risk management tool for domestic agriculture. For the next farm bill both the Senate and House propose to reduce funding to commodity programs (Title I), while expanding funding to crop insurance (Title XI).[2] Both of the proposed bills eliminate the direct payment program, which would provide an annual saving to taxpayers of about $5 billion (Chite 2012). Both bills propose a requirement for the United States Department of Agriculture (USDA) to conduct more research on whole-farm revenue insurance to help obviate contractual complexities for diverse farms growing specialty crops. Both bills propose to introduce Agricultural Risk Coverage, a new crop revenue insurance

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[2] These policy changes are consistent with Goodwin's (1993) observation that the reason for expanding the FCIP is to "[…] create an insurance program that would replace [other] disaster relief measures while operating on an actuarially sound basis […]".

program offered to Title I crops.[3] Furthermore, both bills reauthorize funding from the 2008 Farm Bill to develop and improve the FCIP for organic producers. Beginning in fiscal year 2013 the FCIP is expected to cost taxpayers $9 billion annually and will be the primary subsidy program for domestic agriculture.

The importance of the FCIP to farm income protection and regional economies is evident given events like the 2012 mid-western drought.[4] However, the recent farm bill discussion has raised questions about the fiscal prudence of the FCIP. This year federal investigators unraveled the largest crop insurance fraud to date. The fraud occurred in North Carolina where from 1996 through 2007 tobacco producers paid an insurance adjuster to falsify claims regarding the scope of damage or the producer's true output on a particular acreage, with the hidden tobacco output being sold to a co-conspiring broker. In addition to other charges, restitution exceeding $21,000,000 and $13,000,000 was imposed on the adjuster and the broker, respectively.[5]

Improved monitoring protocols are a primary means to encourage compliance and reduce fraud in the FCIP. An understanding of the relationship between the federal supply of crop insurance and output, as decomposed into yield and harvested acreage, provides insights about the unintended consequences of the FCIP. This information can be used to improve monitoring protocols and the actuarial soundness of the FCIP. Given the proposed increase in funding for the FCIP and the focus on expanding the types of specialty crop insurance policies, this article makes a critical contribution to the current policy debate.

This article uses crop insurance supply data (1981-2011) collected by the Risk Management Agency (RMA) and highly disaggregated agricultural production data (1980-2011)

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[3] "Title I crops" refers to crops such as wheat, corn, cotton, rice, feed grains, and oilseeds that have had access to support programs through Title I of the farm bill (e.g., direct payments, counter-cyclical payments, and non-recourse loans).

[4] According to Vince Smith at Montana State University, taxpayers will pay about $15 billion for the 2012 FCIP, including $7 billion in premium subsidies, $1.3 billion in overhead costs for insurers, and about $7 billion from underwriting losses.

[5] News releases for these court cases can be found at the Risk Management Agency website: rma.usda.gov/.

collected by California's Agricultural Commissioners and reported by the USDA to estimate the supply of insurance to counties in California for five specialty crops (apples; wine grapes; prunes; English walnuts; and dry beans). We use the estimated supply relationships to model the effects of crop insurance supply on the yields and harvested acreage of the insurable crops. The yield and acreage response models are used to assess the unintended consequences of the FCIP on output. The results provide valuable insights for improving monitoring protocols and the actuarial soundness of the FCIP in relation to specialty crops.

This study builds upon previous analysis of the unintended consequences of the FCIP on production, which typically is described as examples of moral hazard and adverse selection (Knight and Coble 1997; Glauber 2004).[6] Several studies analyze the effect of participation in crop insurance programs on the intensive-margin effect. Horowitz and Lichtenberg (1993) found that producers who purchased crop insurance increased fertilizer use by 19 percent and pesticide expenditure by 21 percent. They argue that these inputs are often strongly risk increasing and that yield insurance may increase input use. In contrast, Babcock and Hennessy (1996) argue that the effect of increased fertilizer use on the probability of low yields primarily determines whether insurance purchases will cause insured producers to alter their fertilizer expenditures. They conclude that increased fertilizer use sharply decreases the probability of low yields, suggesting that insurance purchases and fertilizer are substitutes. This result is consistent with Smith and Goodwin (1996), who argue that moral hazard probably decreases chemical input use for two reasons. First, inputs increase production costs and lower (increase) the expected profits (losses) when indemnity payments are made. Second, the critical yield that triggers an indemnity payment is determined by the producer's yield history.

[6] Arrow (1984) provides simple and compelling definitions of moral hazard as "hidden action" on the part of an insured agent, and of adverse selection as "hidden knowledge" possessed by the insured as to his probability of loss.

Several studies investigate the effect of premium rate subsidies on the intensive- and extensive-margin effects[7]. Goodwin et al. (2004) find that a 30 percent decrease in premium costs were likely to decrease total input use (fertilizer and chemical expenditure), but were associated with an increase in barley acreage of about 1.1 percent and corn acreage by less than 0.5 percent. Young et al. (2001) find that planted acreage for major field crops was only 0.4 percent higher due to subsidized crop insurance. Several other studies find that the extensive-margin effect of subsidized crop insurance for field crops is small, also at less than 2 percent (Walters et al. 2012; Miao et al. 2011; Classen et al. 2011; O'Donoghue et al. 2009; Lubowski et al. 2006).

Fewer studies address issues relating to specialty crop insurance, mainly due to data limitations. Most studies of specialty crop insurance markets focus on the factors affecting the demand for crop insurance (e.g., Miller et al. 2000; Richards 2000; Richards and Mischen 1998). On the other hand, one recent study estimated the effects of the supply of specialty crop insurance on the supply of and the demand for the insurable crops (Ligon 2011). He found a positive significant effect of crop insurance supply on the output of woody-perennial crops, but no significant effect for other crops. The author concludes that this finding is perhaps "a consequence of the much larger investments at risk" with woody-perennial crops. He also finds a significant negative effect of crop insurance supply on the prices of insurable crops.

Ligon's (2011) study has two major shortcomings. First, it measures output as harvested acreage, production, or production value, depending upon the crop. As such, the author notes that their results do not provide any information about whether the positive effect of insurance supply on the output of woody-perennial crops is due to intensive- or extensive margin effects, or, both.

[7] Following the Crop Insurance Reform Act of 1994 producers can receive a basic level of coverage, catastrophic risk protection (CAT), with fully subsidized premiums and only a small sign-up fee per crop per county. Premium subsidies were also provided in the 1999 and 2000 crop years and in 2000 the Agricultural Risk Protection Act was passed, increasing subsidy levels for most buy-up levels (Glauber 2004).

Second, because crops are aggregated into categories he cannot distinguish whether the positive effect of insurance supply on the output of woody-perennial crops is due to increases in output across all crops in the category or substitution between them.

This article intends to provide a more thorough understanding of the unintended consequences of the FCIP on the output of specialty crops. To do so, we will address the output measurement and aggregation issues present in Ligon (2011). Specifically, we estimate the effects of crop insurance supply for highly disaggregated specialty crops on the yields and harvested acreage of the insurable crops. This information can be used to improve monitoring protocols and the actuarial soundness of the FCIP in relation to specialty crops.

Empirical Models

We use five crops (apple; wine grapes; prunes; English walnuts; and dry beans) to represent the diversity of specialty crops that the RMA chooses to insure.[8] We feel that this is a reasonable representation of the alternatives encountered by the RMA given that this crop portfolio includes several fruits, a tree nut, and a field crop. Similarly, these crops provide an important distinction between woody-perennial crops (apple; wine grape; prune; and English walnut) and field-annual crops (dry bean). Furthermore, the RMA rarely introduces more than one new crop insurance policy in California in any given year (Ligon 2011), which provides some support for using crop-specific models as we do. Crop insurance policies are supplied by the RMA on a county-by-county and crop-by-crop basis. New programs are offered for different crops at different times (table 1). Taking walnut as an example, we see in table 1 that no counties were provided with

[8] The RMA was created in 1996 to administer the Federal Crop Insurance Corporation and operate the FCIP. The FCIC was founded in 1938 when it began supplying insurance to wheat, followed by other Title 1 crops. The RMA began to supply crop insurance to fruits, tree nuts, vegetables, nursery crops, and floriculture in 1981. These crops are typically referred to as "specialty" or "horticultural" crops.

Table 1. Number of Counties in California Supplied with Insurance, Selected Years & Crops							
	1981	1985	1990	1996	2002	2008	2012
Crops We Analyze							
Apple	0	0	3	11	14	25	25
Grape	8	15	16	26	28	31	31
Prune	0	0	10	15	14	14	14
Walnut	0	10	15	25	26	26	26
Dry Bean	0	16	15	17	18	18	17
Some Other Crops							
Almond	4	15	16	16	16	16	16
Raisin[a]	7	7	7	7	7	7	7

Note: This table is generated from the RMA's Summary of Business Reports: rma.usda.gov/data/sob/scc/index.html. The table includes years when new Farm Bills were introduced and 2012. In California there are 58 counties.

[a]Raisins are grapes that are dried pre-harvest on the vine.

federal crop insurance policies for walnut in California during 1981. By 1985 there were 10 counties in California were walnuts were insurable and by 2002 that number stabilized at 26. The RMA has offered crop insurance differently for specialty and has developed a decision rule for determining whether to offer insurance to a particular specialty crop in a particular county (General Accounting Office 1999, Appendix III). There are three basic criteria which must all be satisfied for an insurance policy to be developed. First, the crop must be “economically significant"; second, there must be “producer interest"; and third, offering the policy must be “feasible".

The Federal Crop Insurance Corporation (FCIC) regards a particular crop economically significant in a particular area only if the total market value of the crop is at least *one* of the following: (1) \$3 million in the agricultural statistics district where it will be covered (8 in California); (2) \$9 million in the state where it will be covered; (3) \$15 million in the RMA administrative region (10 nationally); or (4) \$30 million nationally.

Producer interest in insurance is considered to be indicated by high levels of noninsured disaster payments as well as recommendations by RMA regional offices. For a pilot program to be initiated projected producer participation in the program must be at least 10 percent. Offering an insurance product may be infeasible if, for example, there are inadequate data to evaluate the actuarial soundness of the product; if mechanisms to market the product are lacking; or if the proposed product itself is too complicated (General Accounting Office 1999). Once the RMA has decided to try to develop a new insurance product, the process of development takes about five years to complete, including two years of feasibility studies and three years to carry out a pilot program.

To investigate the factors affecting the supply of specialty crop insurance we estimate supply relationships for a diverse portfolio of crops: apple; wine grape; prune; English walnut; and dry bean. We use $\mathbf{S}_{ijt}$ to denote the supply of insurance to crop i in county j in year t. The vector of policy variables affecting the supply of crop insurance is represented by $\mathbf{P}_{ijt}$. It is comprised of two variables, the lagged supply of insurance to crop i in county j and another binary variable indicating whether the USDA's Tree Assistance Program (TAP) is available in year t.[9] The lagged supply of insurance is expected to reflect producer interest in crop insurance policies. The variable for the Tree Assistance Program is intended to capture the effect of policies that compete for funding with the FCIP.

A vector of regional own-crop values $\mathbf{V}_{ijt}$ is used to capture the economic significance of the crop and the feasibility of providing it with insurance. Lagged own-crop values at the county, state and national levels are used as variables to represent the economic significance of the crop at different spatial scales. The variance of own-crop unit revenue prior to the supply of insurance (henceforth, "pre-supply") is used to represent the feasibility of providing insurance. When pre-supply unit revenue is more variable we expect that evaluating the actuarial soundness of the policy would be more difficult; there would be fewer mechanisms to market the product; and

[9] TAP provides ad-hoc financial assistance to qualifying orchardists to replant or rehabilitate eligible trees, bushes, and vines damaged by natural disasters. TAP was authorized in the 2002 Farm Bill and was reauthorized in the 2008 Farm Bill. TAP is not offered to growers of trees used for pulp, timber, Christmas trees, and nursery tree stock.

insurance policies would need to be more complicated. Lastly, to represent the steady growth in federal crop insurance funding over time (Glauber 2004) we include a time trend represented by the vector $\mathbf{T}_t$. The supply of insurance to crop *i* in county *j* in year *t* is represented by this equation

$$\mathbf{S}_{ijt} = f(\mathbf{P}_{ijt}, \mathbf{V}_{ijt}, \mathbf{T}_t), \tag{1}$$

where i = apple, wine grape, prune, English walnut, and dry bean; $j = 1,\ldots J$; and $t =$ 1980,…,2011. Note that the counties are different for each crop.

Producers in each county are assumed to make management decisions that affect the yield and harvested acreage of each commodity to maximize the expected crop-specific profit, conditional on agricultural policies, lagged production and prices, climate and land quality, and time. To assess how the supply of insurance for specialty crops affects the acreage and yield of the insurable crop we develop response equations for each crop. We use $\mathbf{Y}_{ijt}$ and $\mathbf{A}_{ijt}$ to represent, respectively, the yield and acreage of crop *i* in county *j* in year *t*.

The vector of policy variables affecting yield and acreage $\mathbf{L}_{ijt}$ is comprised of three variables: the predicted probability of supply for crop *i* in county *j* in year *t*; a binary variable indicating whether TAP is available in year *t*; and the Acreage Reduction Program (ARP) rate for wheat in year *t*.[10] The predicted probability of supply from equation 1 will be used to assess the effect of the supply of specialty crop insurance on yield and harvested acreage of the insurable crops. Prior studies suggest that the supply of crop insurance will have a positive effect on acreage (Walters et al. 2012; Miao et al. 2011; Classen et al. 2011; O'Donoghue et al. 2009; Lubowski et al. 2006; Goodwin et al. 2004; Young et al. 2001).

[10] The ARP was an annual land retirement program for wheat, feed grains, cotton, and rice in which producers participating in Title 1 programs reduced a crop-specific, nationally set portion of that crop acreage base in order to be eligible for Title 1 benefits. The ARP was not reauthorized in the 1996 Farm Bill or subsequently.

The hypothesized effect on yield for the crops we investigate is less clear. Following previous work (Babcock and Hennessy 1996; Smith and Goodwin 1996; Horowitz and Lichtenberg 1993) we expect that the effect of the supply of crop insurance on yield is dependent on the *input-risk relation*, the relative importance of risk-increasing and risk-decreasing inputs in the production of that crop. For woody-perennial crops, producers' yields and acreage may respond similarly to the supply of crop insurance and TAP because both policies tend to reduce production risk for these crops. Ligon (2011) showed that from 1980-2007 the market shares of California agricultural production declined for grains and increased for fruits and vegetables. This suggests that wheat and the crops we analyze are competing crops, and that the ARP rate for wheat may affect the yields and land allocation of both.

The crop-specific expected profit is also affected by a vector of lagged production and price variables $\mathbf{Q}_{ijt}$, including own-crop unit revenue and harvested acreage; unit revenue and harvested acreage of a competing crop (wheat); and input price indices for fertilizer and labor. The variables for unit revenue capture the effects of relative output prices on yield and acreage. The variables for harvested acreage allow for adjustment costs and partial adjustment (Goodwin et al. 2004). Such lagged effects may represent costly adjustment and may also reflect the importance of output storage and crop rotational patterns (for dry beans and wheat) on yield and acreage decisions. The input price indices control for the differing input intensities of each crop.

We account for the effect of cross-sectional variation in climate and land quality on output with a vector $\mathbf{R}_j$ in the yield and acreage response equations. Growing season maximum temperature (April through September) and its squared value are included in $\mathbf{R}_j$ for the acreage response equations. For the yield response equations, $\mathbf{R}_j$ also includes minimum temperatures and precipitation during the growing season and their squared values. The land quality variables are identical in the yield and acreage response equations and include the average land capability class, soil permeability and land slope. An interaction term between soil permeability and land slope is also included. These climate and soil variables control for the optimal growing conditions of each crop. Lastly, we include a time trend vector $\mathbf{T}_t$, as in equation 1, to reflect the improvement in crop varieties over time. The yield and acreage of crop *i* in county *j* in year *t* are, respectively, represented by the following equations:

$$\mathbf{Y}_{ijt} = g(\mathbf{L}_{ijt}, \mathbf{Q}_{ijt}, \mathbf{R}_j, \mathbf{T}_t), \tag{2}$$

$$\mathbf{A}_{ijt} = g(\mathbf{L}_{ijt}, \mathbf{Q}_{ijt}, \mathbf{R}_j, \mathbf{T}_t), \tag{3}$$

where i = apple, wine grape, prune, English walnut, and dry bean; $j = 1,\ldots J$; and t = 1980,…,2011. Note that the counties are different for each crop. Equations 1, 2 and 3 are estimated using crop insurance supply data (1981-2011) collected by the RMA and highly disaggregated agricultural production data (1980-2011) collected by California's Agricultural Commissioners and reported by the USDA, among other data sources.

Econometric Estimation

We estimate the supply of insurance to counties in California for five specialty crops (apples; wine grapes; prunes; English walnuts; and dry beans). We use the estimated supply relationships to model the effects of crop insurance supply on the yields and harvested acreage of the insurable crops. The dependent variable of equation 1 is binary and it indicates whether crop *i* had federal insurance policies available in county *j* and year *t* (henceforth, "county-year"). The variable indicates whether crop *i* in county *j* in year *t* was insurable. As indicated in table 2, just because a crop is insurable does not mean that its total acreage is insured. We use a logit regression to

Table 2. Percentage of Acreage Insured in California, Selected Years & Crops[a]													
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Mean
Crops We Analyze													
Apple	66	62	15	56	48	—	36	37	39	35	39	35	43.1
Grape	97	98	97	98	74	—	75	74	97	98	90	94	90.4
Prune	87	87	78	88	89	—	96	95	93	91	93	88	89.2
Walnut	43	40	49	37	43	—	35	43	55	54	56	60	46.5
Dry Bean	17	46	31	27	49	—	48	44	50	43	39	39	38.9
Some Other Crops						—							
Almond	61	58	74	65	77	—	77	78	77	79	83	84	73.3
Raisin[b]	76	77	62	80	85	—	69	94	94	—	—	—	80.8

[a]This table is generated from the RMA's State Profiles: rma.usda.gov/pubs/state-profiles.html
[b]Data not available for 2006 and for raisins from 2010-2012.

estimate equation 1. The logit regressions relate the probabilities of supplying insurance to crop *i* in county *j* in year *t* to the independent variables. To remove indeterminacy in the models represented by equation 1, the benchmark alternative ($\mathbf{S}_{ijt}$=0) represents the pre-supply years *t* for crop *i* in county *j*.

We acknowledge that, for example, 2-stage probit, heckman, and endogenous switching regressions could also be used to estimate supply relationships as in equation 1 that could be linked to models for continuous variables to estimate the effect of crop insurance supply on the yield and acreage of the insurable crops (Miranda and Rabe-Hesketh 2006). In the future we will use to use an endogenous switching regression model for the purposes of this article.[11]

The dependent variables of equations 2 and 3 measure harvested yield and acreage for crop *i* in county *j* in year *t*, which are continuous variables without truncation or censoring issues. As such, we use OLS regressions to estimate equations 2 and 3 and remind the reader that in the future we will use endogenous switching regressions to simultaneously fit the binary and continuous parts of the models. Before we estimate equations 2 and 3 we use the logit regressions to estimate equation 1 and obtain the linear predictor $\widehat{\mathbf{x}\boldsymbol{\beta}}$. We use the linear prediction

[11] In an endogenous switching regression model, a switching equation sorts individuals over two different states (with one regime observed).The full information maximum likelihood method (FIML) simultaneously fits binary and continuous parts of the model to yield consistent standard errors (Lokshin and Sajaia 2004).

to calculate the predicted probability of insurance supply for crop i in county j in year t. This requires a linear transformation of the linear predictor to obtain this equation

(4) $$\widehat{Pr(\mathbf{S}_{ijt})} = \frac{e^{\widehat{\mathbf{x}\boldsymbol{\beta}}}}{1 + e^{\widehat{\mathbf{x}\boldsymbol{\beta}}}}\,.$$

The predicted probabilities of insurance supply for crop i in county j in year t from equation 4 are the main policy variables of interest in $\mathbf{L}_{ijt}$ used in the second stage models of yield and acreage response.

Data

We pool time-series and cross-sectional data to construct our research database. The time-series data comes from two sources.[12] The first source is crop insurance supply data (1981-2011) collected by the Risk Management Agency (RMA). The insurance data includes detailed crop-specific information at the county-level such as the number of policies sold, insured acreage, total liability, total premiums, total indemnities and the total premium subsidy. However, several of these variables are dependent on the type of insurance policy (e.g., Actual Production History and Actual Revenue History), coverage level and price election, for which we do not currently have data. So these variables were not integrated into the research database. Instead we use these data to generate a binary variable that is equal to one, zero else, if some insurance policy is offered to crop i in county j in year t. This is the dependent variable in equation 1(table 3), which is used to create a lagged independent variable in the same equation. The data shows that whenever an insurance policy is offered a positive number of insurance policies were sold, so we can refer to the RMA as "offering" and "supplying" insurance to crop i in county j in year t interchangeably. We exclude insurance data from the research database if the data for that crop

[12] These are the only two data sources used in Ligon (2011).

exhibited any of the following features: (1) it is not a specialty crop; (2) it is never supplied with insurance; (3) it has insufficient variation in the supply of insurance (see almonds and raisins in table 1); or (4) if there are ambiguous crop categories. For example, at points in time various citrus crops were supplied with insurance for “citrus”; “citrus” or “special citrus”, and finally by a wide variety of policies for more specific citrus crops. This ambiguity presents identification issues for determining which crops are supplied with insurance across time.

The second source is highly disaggregated agricultural production data (1980-2011) collected by California’s Agricultural Commissioners and reported by the USDA.[13] The production data includes prices, yields, and harvested acreage at the county-level. The yield and acreage data are used for the dependent variables in equations 2 and 3 (table 3). These data are also used to generate the independent variables of county and state own-crop output value; own-crop unit revenue and harvested acreage; unit revenue and harvested acreage for wheat; and the variance of own-crop unit revenue. The variance of own-crop unit revenue is equal to the variance of unit revenue (price times yield) across time and is calculated using the data from pre-supply years only (if $\mathbf{S}_{ijt}$=0). Several features of the production data caused us to restrict the research database further.

We exclude data from the research database if the data for that crop exhibited any of the following features: (1) there is data for insurance but not production; (2) a county was never supplied with insurance; or (3) there is insufficient data for pre-supply years to calculate the variance of own-crop unit revenue. Lastly, data for several crops were dropped from the research database because there were few observations. These procedures resulted in the insurance and

[13] California’s Agricultural Commissioners are elected officials and according to Chris Mertz, the Director of the National Agricultural Statistic Services’ Pacific Northwest Field Office, other states do not have agricultural commissioners. Hence, analogous data is not available for other states.

production data used for the five crops analyzed in this article.

Table 3. Descriptive Information for Dependent Variables					
Variable$_{i,j,t}$ (units)	Obsv.	Mean	Std. Dev.	Min.	Max.
Supply of Federal Crop Insurance$_{i,j,t}$ (0/1)					
Apple	492	0.45	0.50	0	1
Grape[a]	556	0.60	0.49	0	1
Prune[b]	405	0.73	0.45	0	1
Walnut[c]	796	0.68	0.47	0	1
Dry Bean[d]	544	0.65	0.48	0	1
Harvested Land$_{i,j,t}$ (acres)					
Apple	492	1,515.06	1,693.77	35.00	7,747.00
Grape	556	8,653.38	12,959.47	50.00	58,100.00
Prune	405	5,958.26	5,484.28	8.00	27,326.00
Walnut	796	7,226.24	8,996.12	140.00	55,400.00
Dry Bean	544	7,068.04	8,216.99	200.00	50,200.00
Harvest Yield$_{i,j,t}$ (tons/acre)					
Apple	492	11.84	4.89	0.20	28.70
Grape	556	3.88	1.56	0.80	10.40
Prune	405	2.15	0.82	0.00	5.10
Walnut	796	1.24	0.78	0.10	17.40
Dry Bean	544	1.13	0.47	0.20	6.50

Note: Statistics are at the county-level.
[a]Refers to grapes used to produce wine.
[b]Prunes are plums that are dried post-harvest; producers typically prefer to market them as "dried plums".
[c]Refers to English Walnuts.
[d]Includes the following types of dry edible beans: large lima, baby lima, green lima, unspecified lima, blackeye, red kidney, garbanzo, pink, small white, fava, small red, pinto, and unspecified others. One type is excluded due to insufficent data, small white flat. We exclude all beans denoted as "fresh", "fresh for market", "snap", and "seed".

Variables that complement the insurance and production data are obtained from other sources. The TAP variable is a binary variable equal to one if TAP is offered in year *t*, zero else. TAP was first offered in 2002 and has been offered in all subsequent years (see footnote 8). The ARP rate for wheat was taken from Greene (1990) and Anderson and Magleby (1997). We obtain own-crop output values in the United States for several crops from the USDA's Crop Values Annual Summary. However to develop this variable for wine grape, we used national output levels from the USDA's Agricultural Statistics and wine grape prices in California from the Agricultural Prices Summary. For prune and walnut we do not have output values for the United States because more than 99 percent of national output for these crops is produced in

California (California Department of Food and Agriculture 2010). Input price indices for fertilizer and labor are obtained from the USDA's Agricultural Prices Summary. All prices are adjusted (1990-1992=1) by the index of prices paid by farmers for all inputs including interest, taxes, and wages, which is also obtained from the Agricultural Prices Summary.

Long term data (1971-2000) for maximum and minimum temperature (°F) and precipitation (inches) during the growing season (April through September) from weather stations across the study region were obtained from the Western Regional Climate Center. Climate in a particular county is measured as the average across all weather stations in the county. The growing season measures we use are the average values across the months in the growing season. The land quality variables are obtained from the Natural Resource Conservation Service's1997 Natural Resources Inventory. Land capability class is designated by the numbers 1 through 8, but because our variable is a county level average, our measure of land capability class is a continuous variable between 1 and 8, inclusive. The land slope variable is measured in degrees and bounded between 0 and 90, inclusive.

Estimation Results

Federal Supply of Insurance to Specialty Crops

Estimated marginal effects for the binomial logit models of the federal supply of insurance to specialty crops are presented in table 4. By comparing the observed supply of crop insurance in table 3 to the predicted probability of supply in table 4 we find that we over-predict the probability of supply for all crops, except apple. This may be a result of using the lagged insurance supply variable as an independent variable in the estimation (Brandow 1958).

Nonetheless, our crop insurance supply models explain most of the variation in supply and correctly predict supply at least 92 percent for all crops.

Table 4. Elasticities, Probabilities, and Estimation Statistics for Binomial Logit Models of Federal Crop Insurance Supply

	Apple	Grape	Prune	Walnut	Dry Bean
Variable$_{i,j,t}$ (units)	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Policy Variables					
Own-Crop Insurance Supply$_{i,j,t-1}$ (0/1)	[0.700]***	[0.723]***	[0.422]***	[0.601]***	[0.758]***
	(9.48)	(13.80)	(3.50)	(8.85)	(19.44)
TAP$_t$ (0/1)	[−0.272]	[−0.245]*	[−0.682]***	[−0.122]	—
	(−1.34)	(−1.84)	(−2.94)	(−0.93)	
Crop Value Variables					
County Own-Crop Value$_{i,j,t-1}$ ($)	2.93E−5***	3.52E−6***	3.00E−6**	5.57E−6***	8.57E−6***
	(3.68)	(4.12)	(2.16)	(3.45)	(2.64)
California Own-Crop Value$_{i,t-1}$ ($)	2.22E−6	5.97E−8	−8.49E−7***	−1.10E−6***	4.58E−6*
	(1.34)	(0.19)	(−2.79)	(−5.58)	(1.71)
U.S. Own-Crop Value$_{i,t-1}$ ($)	−3.64E−7	−4.46E−8	—	—	−9.55E−7***
	(−1.51)	(−0.18)			(−2.95)
Variance of Own-Crop Unit Revenue$_{ij}$	2.18E−5	4.00E−6	6.20E−5	1.02E−4	−0.001**
	(0.88)	(0.12)	(1.52)	(0.84)	(−2.37)
Other Variables					
Trend$_t$ (year)	0.080***	0.022*	0.014***	0.022***	0.022*
	(4.93)	(1.74)	(2.85)	(3.62)	(1.95)
Probability of supply	37%	83%	96%	93%	80%
Estimation statistics					
Observations	473	537	392	771	525
McFadden R^2	0.73	0.69	0.76	0.75	0.60
Correct Prediction	93%	93%	95%	95%	92%

Note: The benchmark alternative for each dependent variable is pre-supply years *t* for crop *i* in county *j*.
Note: In brackets are the percent change in the probability of insurance supply as the discrete variable changes from 0 to 1.
Note: All models estimated with robust standard errors. In parenthesis are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

We find the expected effect that the lagged dependent variable has a positive significant effect on supply for all crops. The marginal effects suggest that if crop *i* in county *j* is supplied with insurance in the prior year, it increase the probability that supply will occur in the following period by 42 to 76 percent, depending on the crop. The estimated marginal effect for TAP is negative for all (woody-perennial) crops, but is only significant in the grape and prune equations. These estimated effects support our expectation that other disaster relief policies for specialty crops compete for funding with crop insurance programs. The marginal effects suggest that supply of TAP reduced the probability of supplying insurance for grape and prune by 25 and 68 percent, respectively.

As expected own-crop output value in the county has a positive effect on supply for all crops. The marginal effect for own crop output value in California is significant and negative for prune and walnut, while it is significant and positive for dry bean. Because prune and walnut are only produced in California (>99 percent of national output) the marginal effects suggest that when there output value is more dispersed there is a lower probability that a given county will be supplied with insurance. On the other hand, the marginal effect for dry bean suggests that because its production is dispersed nationally, higher output values in California will tend to increase the supply of insurance to counties within the state. Similarly, we find a negative significant effect of the output value for dry bean in the United States on the probability of insurance supply. Again, suggesting that when output values are more dispersed there is a lower probability that a particular county will be supplied with crop insurance. For dry bean, we find that the variance of unit revenue has a negative significant effect on insurance supply. We used this variable to represent the feasibility of supplying crop insurance and so we find the expected effect. This result may be related to the fact that we aggregate several types of bean in this crop category. If the variance of dry bean unit revenue is more variable because producers often switch between the production of various types of bean in response to market conditions this would indeed complicate the supply of crop insurance.

Lastly, we find significant positive marginal effects for the time trend variable, suggesting that the steady growth in crop insurance funding over the last three decades has increased the probability of the supply of insurance for these crops. Specifically, the marginal effects suggest that the probability of insurance supply increases by 1 to 8 percent each year, depending on the crop. Complete coefficient estimation results for the binomial logit models of the federal supply of crop insurance are presented in table A.1in the appendix

Acreage Response

The estimation results for the OLS models of acreage response are presented in table 5. The acreage response equations explain nearly all of the variation in acreage, with the R^2 in each model ranging from 92 to 99 percent. We estimate a significant positive effect of the supply of insurance on the acreage of prune and dry bean, suggesting that the supply of crop insurance reduces production risks and encourages a positive acreage response for these crops. If crop insurance reduces production risks it is likely to cause producers to engage in riskier behavior such as expanding production onto marginal land. We find unexpected effects which suggest that TAP reduces acreage of prune and that the ARP rate for wheat reduces the acreage for apple.

We find significant positive effects for lagged own-crop unit revenue on acreage for all crops except prune, suggesting that the unit value of the crop is an important determinant of acreage response. We find a significant positive effect of lagged own-crop acreage on current own-crop acreage, suggesting that adjustment costs and partial adjustment are critical factors determining acreage response. We find a significant negative effect of lagged wheat acreage on the acreage of grape and prune, but a significant positive effect for walnut. This suggests that grape and prune compete with wheat for land, but walnut does not.

Table 5. Estimation Results for OLS Models of Acreage Response					
	Apple	Grape	Prune	Walnut	Dry Bean
Variable$_{i,j,t}$ (units)	Coef.	Coef.	Coef.	Coef.	Coef.
Constant	−79232.440**	−123491.000	166150.200	−100694.400	−190138.200
	(−2.17)	(−0.83)	(1.08)	(−1.59)	(−0.58)
Policy Variables					
Predicted Probability of Supply$_{i,j,t}$ (0-1)	25.774	442.008	2251.551***	−244.688	4214.755***
	(0.09)	(0.93)	(2.67)	(−0.62)	(2.78)
TAP$_t$ (0/1)	35.650	−60.200	−564.530**	134.212	—
	(0.49)	(−0.18)	(−1.97)	(0.93)	
ARP Rate for Wheat$_t$ (%)	−3.0560*	0.379	3.777	3.289	−5.923
	(−1.95)	(0.06)	(0.63)	(0.89)	(−0.41)
Production and Price Variables					
Own-Crop Unit Revenue$_{i,j,t-1}$ ($/acre)	0.0234***	0.232***	0.024	0.108**	1.836***
	(3.55)	(3.79)	(0.58)	(2.44)	(3.82)
Own-Crop Harvest$_{i,j,t-1}$ (acres)	0.954***	1.014***	0.967***	1.027***	0.902***
	(84.38)	(120.30)	(51.40)	(116.25)	(32.81)
Wheat Unit Revenue$_{i,j,t-1}$ ($/acre)	0.0292	−0.053	−0.475	−0.094	−0.043
	(0.20)	(−0.71)	(−0.88)	(−0.41)	(−0.40)
Wheat Harvest$_{i,j,t-1}$ (acres)	−0.001	−0.008*	−0.005*	0.003**	0.001
	(−1.38)	(−1.69)	(−1.76)	(1.96)	(0.16)
Fertilizer Price$_{t-1}$ ($)	0.794**	−0.224	0.979	0.838	7.736**
	(2.10)	(−0.20)	(0.81)	(1.10)	(2.51)
Labor Price$_{t-1}$ ($)	−12.675**	−11.147	26.286	−8.736	−39.535
	(−2.42)	(−0.52)	(1.30)	(−1.03)	(−1.28)
Climate and Land Quality Variables					
Growing Season Max. Temp.$_j$ (°F)	−66.337	416.906**	1889.504*	428.336	−811.149
	(−0.48)	(2.34)	(2.07)	(1.34)	(−0.34)
Growing Season Max. Temp. Squared$_j$ (°F)	0.429	−2.555**	−11.3115*	−2.668	4.848
	(0.50)	(−2.32)	(−2.08)	(−1.36)	(0.34)
Land Capability Class$_j$ (1-8)	−4.650	−301.751*	143.111	41.464	−400.748
	(−0.15)	(−2.51)	(1.21)	(0.88)	(−0.98)
Permeability of Soil$_j$	97.623**	−30.621	−713.621**	−107.180	1290.339
	(2.31)	(−0.15)	(−2.43)	(−0.83)	(1.60)
Slope of Land$_j$ (degrees, 0-90)	48.652*	−106.208	−620.072**	−75.437	547.837
	(1.86)	(−0.79)	(−2.57)	(−0.86)	(0.99)
Permeability of Soil$_j$	−27.297**	54.045	350.931**	39.471	−367.171
× Slope of Land$_j$	(−2.21)	(0.85)	(2.56)	(0.93)	(−1.27)
Other Variables					
Trend$_t$ (year)	41.588**	54.509	−124.522	42.279	112.250
	(2.36)	(0.71)	(−1.52)	(1.38)	(0.80)
Observations	473	537	392	771	525
R^2	0.98	0.99	0.98	0.99	0.92

Note: All models estimated with robust standard errors. In parenthesis are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Yield Response

The estimation results for the OLS models of Yield Response are presented in table 6. We find a significant positive effect of the supply of insurance on the yield of prune and grape. One reason why we find that the supply of crop insurance only has a significant positive effect on output (acreage or yield) for grape and prune may relate to the insurance participation rates for these crops. Table 2 shows that the percentage of insured acreage in California for the crops we investigate is greatest for grape and prune. We should expect that the crops that insure a greater proportion of acreage will be most responsive to the supply of crop insurance. We estimate that the TAP program also has a positive significant effect on yield for grape. This suggests that the ad-hoc financial assistance provided by TAP to replant or rehabilitate trees, bushes, and vines damaged by natural disasters has been a more important policy for wine grape producers than the other crops investigated here. We also estimate that the ARP rate for wheat has a positive effect on the yield for walnut and dry bean.

We find that lagged own-crop unit revenue has a positive effect on yields for all crops, suggesting that producers increase the intensity of input use to increase yields in response to high prices. We find mixed results for lagged own-crop acreage on yields. This is not unexpected because costly adjustment and partial adjustment can have mixed effects on yield. We also find mixed results among crops for wheat unit revenue and wheat acreage. This suggests that wheat may only compete for inputs with some of the crops we analyze.

Table 6. Estimation Results for OLS Models of Yield Response					
	Apple	Grape	Prune	Walnut	Dry Bean
Variable$_{i,j,t}$ (units)	Coef.	Coef.	Coef.	Coef.	Coef.
Constant	133.235	−315.246***	−76.026	76.414**	−118.491***
	(0.23)	(−3.13)	(−0.66)	(2.02)	(−2.89)
Policy Variables					
Predicted Probability of Supply$_{i,j,t}$ (0-1)	−2.627	3.400***	1.425*	0.303	−0.477
	(−0.75)	(4.43)	(1.79)	(1.55)	(−1.39)
TAP$_t$ (0/1)	−0.443	0.505**	0.236	−0.041	—
	(−0.46)	(2.14)	(1.26)	(−0.54)	
ARP Rate for Wheat$_t$ (%)	0.016	0.003	0.001	0.006**	0.008*
	(0.49)	(0.54)	(0.21)	(2.35)	(1.84)
Production and Price Variables					
Own-Crop Unit Revenue$_{i,j,t-1}$ ($/acre)	6.80E−4***	2.04E−4***	1.85E−4***	0.001***	3.71E−4***
	(5.33)	(4.19)	(3.58)	(6.93)	(2.63)
Own-Crop Harvest$_{i,j,t-1}$ (acres)	1.18E−4	1.99E−5***	−5.33E−5***	6.23E−6*	3.32E−7
	(0.87)	(4.62)	(−3.57)	(1.79)	(0.21)
Wheat Unit Revenue$_{i,j,t-1}$ ($/acre)	0.003	−3.42E−4***	−3.19E−4	3.54E−4*	1.66E−4***
	(1.13)	(−3.16)	(−0.69)	(1.78)	(7.86)
Wheat Harvest$_{i,j,t-1}$ (acres)	−1.65E−5	1.77E−5***	−8.37E−6**	−2.01E−6**	−5.77E−7
	(−1.18)	(3.51)	(−2.63)	(−2.50)	(−0.58)
Fertilizer Price$_{t-1}$ ($)	0.003	0.006***	0.006***	−0.001*	−2.75E-4
	(0.47)	(3.86)	(5.69)	(−1.85)	(−0.71)
Labor Price$_{t-1}$ ($)	0.028	−0.059***	−0.035**	0.013*	−0.007
	(0.36)	(−4.10)	(−2.60)	(1.73)	(−1.43)
Climate and Land Quality Variables					
Growing Season Max. Temp.$_j$ (°F)	16.179***	−1.314*	1.154	−0.234	0.704
	(3.90)	(−1.84)	(0.77)	(−0.38)	(1.47)
Growing Season Max. Temp. Squared$_j$ (°F)	−0.103***	0.009*	−0.007	0.001	−0.004
	(−3.98)	(1.94)	(−0.76)	(0.37)	(−1.46)
Growing Season Min. Temp.$_j$ (°F)	−31.900***	1.259**	−5.238***	−0.217	−0.754***
	(−7.97)	(2.22)	(−3.70)	(−0.51)	(−3.76)
Growing Season Min. Temp. Squared$_j$ (°F)	0.312***	−0.014**	0.052***	0.002	0.007***
	(7.80)	(−2.41)	(3.72)	(0.57)	(3.73)
Growing Season Precipitation$_j$ (inches)	4.339***	−2.149***	−0.013	−0.132	−0.124
	(3.99)	(−10.53)	(−0.08)	(−1.18)	(−1.52)
Growing Season Precipitation Squared$_j$ (inches)	−0.528***	0.210***	0.017	0.014	0.010
	(−4.38)	(9.88)	(1.14)	(1.48)	(1.14)
Land Capability Class$_j$ (1-8)	−0.050	−1.776***	0.183	−0.196***	−0.142***
	(−0.08)	(−12.41)	(0.92)	(−5.59)	(−3.54)
Permeability of Soil$_j$	2.427***	1.661***	−2.629***	−0.136*	0.275*
	(3.59)	(5.63)	(−3.54)	(−1.74)	(1.78)
Slope of Land$_j$ (degrees, 0-90)	−0.987**	1.030***	−2.127***	0.0558	0.164**
	(−2.15)	(4.97)	(−3.95)	(1.26)	(2.06)
Permeability of Soil$_j$	0.230	−0.368***	1.325***	0.009	−0.065
× Slope of Land$_j$	(1.22)	(−4.19)	(4.25)	(0.40)	(−1.26)
Other Variables					
Trend$_t$ (year)	0.022	0.176***	0.084	−0.031	0.056***
	(0.08)	(3.39)	(1.54)	(−1.30)	(2.67)
Observations	473	537	392	771	525
R^2	0.43	0.62	0.47	0.35	0.47

Note: All models estimated with robust standard errors. In parenthesis are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Conclusion

We exploit variation in the timing of specialty crop insurance supply to different crops and counties in California to assess its effect on output as decomposed into yield and harvested acreage. Four woody-perennial crops and one field-annual crop are used to represent this effect. We find that the supply of crop insurance has a significant positive effect on output for several perennial crops and the field crop, but it only has a significant positive effect on yield for certain perennial crops. These findings suggest that even for disparate crops the supply of insurance reduces production risks for the insured crops and causes harvested acreage to expand. The positive significant effect of insurance supply on yield for several of the woody-perennial crops suggests that, regardless of the effect on acreage, it accelerates growers' adoption of improved tree/vine varieties and rootstocks, which are likely to be risk-increasing inputs due to the their relatively high cost of investment. The results suggest that woody-perennial crops deserve added attention when designing monitoring protocols so as to reduce the unintended acreage expansion and premature adoption of improved tree/vine varieties and root stocks that are likely to result from the supply of insurance to these crops.

References

Anderson, M., and R. Magleby. 1997. ''Agricultural and Environmental Indicators, 1996–97.'' Economic Research Service, U.S. Department of Agriculture. Agricultural Handbook No. 712.

Arrow, K. 1984. "The Economics of Agency." *Principals and Agents: The Structure of Business*. In J. Pratt and R. Zeckhauser (eds.), pp. 37-51. Boston: Harvard Business School Press.

Babcock, B.A., and D.A. Hennessy. 1996. "Input Demand Under Yield and Revenue Insurance." *American Journal of Agricultural Economics* 78:416–27.

Brandow, G.E. 1958. "A Note on the Nerlove Estimate of Supply Elasticity." *Journal of Farm Economics* 40:719-22.

California Department of Food and Agriculture. 2010. "California Agricultural Resource Directory 2010-2011." California Department of Food and Agriculture.

Chite, R.M. 2012. " The 2012 Farm Bill: A Comparison of Senate-Passed S. 3240 and the House Agriculture Committee's H.R. 6083 with Current Law." Congressional Research Service, 7-5700, R42552.

Claassen, R., F. Carriazo, J.C. Cooper, D. Hellerstein, and K. Ueda. 2011. "Grassland to Cropland Conversion in the Northern Plains: The Role of Crop Insurance, Commodity, and Disaster Programs." USDA, Economic Research Service, Economic Research Report 120.

General Accounting Office. 1999. "Crop insurance: USDA's progress in expanding insurance for specialty crops." GAO/RCED 99-67, General Accounting Office. Report to the Ranking Minority Member, Subcommittee on Risk Management, Research, and Specialty Crops, Committee on Agriculture, House of Representatives.

Glauber, J.W. 2004. "Crop Insurance Reconsidered." *American Journal of Agricultural Economics* 86:1179–95.

Goodwin, B.K. 1993. "An Empirical Analysis of the Demand for Crop Insurance." *American Journal of Agricultural Economics* 75:425-34.

Goodwin, B.K., M.L. Vandeveer, and J. Deal. 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86:1058–77.

Green, R.C. 1990. "Program Provisions for Program Crops: A Database for 1961-90." Agriculture and Trade Analysis Division, Economic Research Service, U.S. Department of Agriculture. Staff Report No. AGES 9010.

Horowitz, J.K., and E. Lichtenburg. 1993. "Insurance, Moral Hazard, and Chemical Use in Agriculture." *American Journal of Agricultural Economics* 75: 926–35.

Knight, T.O., and K.H. Coble. 1997. "Survey of U.S. Multiple Peril Crop Insurance Literature Since 1980." *Review of Agricultural Economics*. 19(1):128-56.

Ligon, E. 2011. "Supply and Effects of Specialty Crop Insurance" National Bureau of Economic Research, Working Paper 16709.

Lubowski, R.N., S. Bucholtz, R. Claassen, M.J. Roberts, J.C. Cooper, A. Gueorguieva, and R. Johansson. 2006. "Environmental Effects of Agricultural Land-Use Change: The Role of Economics and Policy." USDA Economic Research Service, Economic Research Report 25.

Miao, R., H. Feng, and D.A. Hennessy. 2011. "Land Use Consequences of Crop Insurance Subsidies." Paper Presented at the Annual Meeting of the Agricultural and Applied Economics Association, Pittsburgh, PA, July 24-26.

Miller, S.E., K.H. Kahl, and P.J. Rathwell. 2000. "Revenue Insurance for Georgia and South Carolina Peaches." *Journal of Agricultural and Applied Economics* 32(1):123-32.

Miranda, A., and S. Rabe-Hesketh. 2006. "Maximum likelihood estimation of endogenous switching and sample selection models for binary, ordinal, and count variables" *The Stata Journal* 6(3):285-308.

O'Donoghue, E.J., M.J. Roberts, and N. Key. 2009. "Did the Federal Crop Insurance Reform Act Alter Farm Enterprise Diversification?" *Journal of Agricultural Economics* 60(1):80-104.

Richards, T.J. 2000. "A Two-Stage Model of the Demand for Specialty Crop Insurance." *Journal of Agricultural and Resource Economics* 25(1):177-94.

Richards, T.J., and P. Mischen. 1998. ''The Demand for Specialty-Crop Insurance: Adverse Selection and Inefficiency.'' *Journal of Agribusiness* 16:53–77.

Smith, V.H., and B.K. Goodwin. 1996. "Crop Insurance, Moral Hazard, and Agricultural Chemical Use." *American Journal of Agricultural Economics* 78:428–38.

Walters, C.G., C.R. Shumway, H.H. Chouinard, and P.R. Wandschneider. 2012. "Crop Insurance, Land Allocation, and the Environment." *Journal of Agricultural and Resource Economics* 37(2):301-20.

Young, C.E., M.L. Vandeveer, and R.D. Schnepf. 2001. "Production and Price Impacts of U.S. Crop Insurance Programs." *American Journal of Agricultural Economics* 83:1194–201.

Appendix

Complete Coefficient Estimation Results

Table A1. Estimation Results for Binomial Logit Models of Federal Crop Insurance Supply

	Apple	Grape	Prune	Walnut	Dry Bean
Variable$_{i,j,t}$ (units)	Coef.	Coef.	Coef.	Coef.	Coef.
Constant	–689.373***	–313.915*	–786.213***	–659.401***	–278.183*
	–4.76	–1.73	–4.98	–6.04	–1.95
Policy Variables					
Own-Crop Insurance Supply$_{i,j,t-1}$ (0/1)	3.534***	4.658***	4.135***	4.562***	4.415***
	6.74	10.22	5.10	8.85	11.22
TAP$_t$ (0/1)	–1.312	–1.536**	–5.791***	–1.431	—
	–1.20	–1.98	–3.27	–1.28	
Crop Value Variables					
County Own-Crop Value$_{i,j,t-1}$ ($)	1.26E–4***	2.55E–5***	8.28E–5***	8.46E–5***	5.49E–5***
	4.08	2.79	3.24	5.17	2.81
California Own-Crop Value$_{i,t-1}$ ($)	9.56E–6	4.33E–7	–2.34E–5**	–1.66E–5***	2.93E–5*
	1.28	0.20	–2.04	–5.46***	1.68
U.S. Own-Crop Value$_{i,t-1}$ ($)	–1.57E–6	–3.23E–7	—	—	–6.12E–6***
	–1.61	–0.18			–2.96
Variance of Own-Crop Unit Revenue$_{ij}$	9.40E–5	2.90E–5	0.002*	0.002	–8.69E–3**
	0.89	0.12	1.84	0.82	–2.35
Other Variables					
Trend$_t$ (year)	0.344***	0.156*	0.400***	0.332***	0.139*
	4.74	1.71	4.98	6.05	1.95
Observations	473	537	392	771	525
McFadden R^2	0.73	0.69	0.76	0.75	0.60

Note: The benchmark alternative for each dependent variable is pre-supply years t for crop i in county j.

Note: All models estimated with robust standard errors. In parenthesis are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.