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An Empirical Long-Run Competitive Equilibrium Model of Subsidized Crop Insurance and Farm Industry Structure

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By

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Previous research has found a positive and significant planted acreage response to the participation in, and increases in the premium subsidization of, the federal crop insurance program. However, no research to our knowledge has evaluated what influence the response in planted acreage and crop choice to subsidized crop insurance has had on market industry in terms of farm numbers and average farm output. To address this issue, we utilize the theory of long-run competitive equilibrium with subsidized crop insurance to generate a conceptual model with econometrically testable hypotheses. Testing the econometric model in two distinct regions of the U.S, we find the premium subsidy regime change in the federal crop insurance program associated with the Agricultural Risk Protection Act of 2000 has contributed to fewer farms and larger average farm output across over 600 counties in two distinct regions in the U.S.

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Contents

CHAPTER 1

1. Introduction

Over the past four decades the federal crop insurance program (FCIP) evolved from an obscure government provided risk management program to the primary government risk management program. Expansion of FCIP occurred through a series of legislative acts, beginning in 1980 with the Federal Crop Insurance Act, followed by the Federal Insurance Reform Act in 1994, and the Agricultural Risk Protection Act (ARPA) in 2000, all aimed at encouraging producer participation through increased premium subsidies and enhanced coverage options. These acts resulted in an increase in premium subsidies from $0.20 billion in 1989 to $0.80 billion in 1995 to $6.2 billion in 2017. As a result of increased subsidies, program liability also increased from $13.5 billion in 1989 to $23 billion in 1995 to $106 billion in 2017. At the crop per acre level, the impacts of the legislative acts are even more pronounced. For corn, average per acre subsidy increased over twelvefold from $2.22 per acre in 1989 to $27.20 per acre in 2017 while average liability increased over three-fold from $171.75 per acre to $499.00 per acre (RMA 2018).

Under the United States Department of Agriculture, the Risk Management Agency (RMA) administers the program and has a statutory goal of a loss ratio equal to one. This means that FCIC premiums are set to equal the expected value of the indemnity. The federal government offers premium subsidies to all insurance participants, which for crops like corn, soybeans and wheat, are applied as a percent of premium. Premium subsidies directly lower the cost of insurance participation and indirectly provide a positive expected return to insurance participation over time. Hence, legislatively increasing premium subsidies raises expected returns to insurance participation.

It has long been suggested in the literature that to the extent that a rise in expected returns to participation in insurance induces individual participating farmers to expand planted acreage and increase crop output, and to the extent that they collectively supply a significant share of total output, participating farmers may see their benefit from insurance offset by declining market revenue and non-participating farmers make incur losses, all because the resulting increase in aggregate crop supply in the face of inelastic market crop demand results in declining market prices (Young et al. 2001).

Other literature has confirmed a significant response of planted acres to both general crop insurance participation (Wu 1999), and premium subsidization (Goodwin, Vandeveer, and Dean 2004; Goodwin and Smith 2013; Yu, Smith, and Sumner 2017). What these articles did not consider is that, by even modestly influencing planted acreage of insured crops, federal crop insurance may alter market returns and hence industry structure.

What this thesis suggests and empirically tests, is that, by affecting market returns for participating as well non-participating farmers, subsidized crop insurance may also affect farm industry structure in the long-run through entry and exit in response to the interplay between market returns and expected returns from subsidized insurance, and the co-existence of participating and non-participating farmers. Positive net returns to program participation may give a strategic financial advantage to insurance participants over non-participants. Program participants may outbid financially strapped non-participants in land purchase and rental markets. More importantly, after a rare and adverse event such as a drought, which generally triggers indemnity payments, those with insurance can better compete in the land rental and purchase market due to a substantially better off financial position. Non-participants in a poor financial position who are losing shares in the land rental and purchase market may exit the industry. These points suggest that the program may induce long-run changes in farm structure.

To empirically estimate such changes, this thesis draws on the theory of long-run competitive equilibrium to examine whether subsidized federal crop insurance has induced long-run changes in farm structure. Specifically, we formulate and empirically implement a conceptual model that incorporates returns of subsidized insurance participation into producer profit and guarantees the profit is driven to zero in the long-run. We use the comparative statics with respect to the exogenous shift in the crop insurance regime brought by ARPA to provide predictions on how changes in the regime influence the number of farms and average farm output in the long-run. We test the econometric model using two newly constructed county-level panel datasets for two multi-state U.S. regions.

2. Literature Review

Federal crop insurance has been the focus of many academic studies. These studies have ranged from asymmetric information in the form of either moral hazard or adverse selection (Horowitz and Lichtenberg 1993; Babcock and Hennessy 1996; Smith and Goodwin 1996; Atwood, Robinson-Cox, and Shaik 2006; Walters et al. 2015), to environmental concerns (Goodwin and Smith 2003; Schoengold, Ding and Headlee 2014; Walters et al. 2012) to land use changes (Wu 1999; Wu and Adams 2001; Young Vandeveer and Schnepf 2001; Goodwin, Vandeever, and Deal 2004; Walters et al. 2012; Goodwin and Smith 2013; Yu, Smith, and Sumner 2017).

Our work on the long-run structural influence of crop insurance is similar in nature with work examining the relationship between crop insurance and land use. Young, Vandeveer, and Schnepf (2001) and Goodwin, Vandeveer, and Dean (2004) both found a small and positive planted acreage response to crop insurance participation and premium subsidization. These results suggest crop insurance influences the producers' decision-making process. Key and Roberts (2006; 2007; 2008) found empirical evidence of a strong association between government payments per acre and subsequent market concentration growth rates at the zip-code level. Additionally, they found a positive and significant association between government payments per acre and farm-level survival rates. Walters et al. (2012) found a small but significant impact on planted acreage increase of insured crops. Their study used producer level data and showed the effect of crop insurance participation on planted acreage varied by region and crops. Goodwin and Smith (2013) present some preliminary empirical evidence that increased premium subsidization positively impacted crop acreage. More recently, Yu, Smith, and Sumner (2017) broke down the acreage response to increased premium subsidization into direct profit and indirect profit effects. Like others, they found a positive acreage response to increasing premium subsidies. Yu and Sumner (2018) found that premium subsides' effects varied, with larger impacts on risky crop investments.

This thesis more closely examined the relationship between crop insurance and farm entry and exit. Wang et al. (2003) have concluded, based on empirical evidence, that some farmers participate in the insurance program only to receive the premium subsidy. Cabas et. al (2008) used an expected utility framework to model the exit and entry decisions of farmers through the Ontario crop insurance program between 1988 and 2004. They found when modeling entry and exit decisions at the farm-level separately, aggregation often mutes the effect of key variables. Our analysis differs from theirs in two significant ways. First, we are directly interested in the aggregate effects of the FCIP in terms of number of farms and average farm size. Second, while they model the decision to participate in the insurance program, we model the influence of the FCIP on the decision to farm.

Burns and Prager (2018) examined the relationship between United States net farmer paid premiums, farm expansion, and farm exit between 2007 and 2012. They found no association between higher farmer paid premiums and the decision to expand their operation or exit farming. However, they only consider data between 2007 and 2012, a short time-frame with few changes to the FCIP. Additionally, they noted future research should focus on the effects of premium subsidies rather than paid premiums on farm survival.

The effects of policy on market structure in the long-run has been studied in many theoretical and empirical contexts. This literature includes effects of various policies, e.g. trade (Dixit 1984; Venables 1985; Eaton and Grossman 1986; Dasgupta and Stiglitz 1988; Belloc 2006), environmental (Markusen, Morey, and Olewiler 1991; Lahiri and Ono 2007), market transparency in the livestock industry (Azzam 2003), and government investment (Munnel 1992). The influence of environmental regulation on farm structure has been extensively examined in the livestock industry (Metcalfe 2001: Roe, Irwin, and Sharp 2002: Herath, Weersink, and Carpentier 2005; Weersink and Eveland 2006; Sneeringer and Key 2011; Azzam, Nene, and Shoengold 2014).

Conceptually, our model most resembles the framework in Azzam, Nene, and Shoengold (2014). What Azzam, Nene, and Shoengold (2014) discovered was that the effects of environmental size-based policy on hog market industry structure depends on how the policy shifts the typical large-scale hog producer's marginal cost relative to the average cost. Analogously, what we find is that subsidized crop insurance's influence on market structure at least partially depends on the marginal returns to insurance relative to average returns.

3. Review of Federal Crop Insurance

Before analyzing how subsidized crop insurance influences market structure, the basics of crop insurance are briefly reviewed. Walters et al. (2012) provides additional details not presented here. The typical producer profit in the absence of insurance is given by:

$$\pi = pq - c(q, \boldsymbol{w}) \tag{1}$$

Where p is output price, q is production quantity, $c(q, \boldsymbol{w})$ is the cost function, and $\boldsymbol{w}$ is a vector of factor prices. Purchasing insurance sets a guaranteed lower bound to the profit function through the addition of an indemnity function while reducing profit across all outcomes by the value of the premium. Total payoff from subsidized crop insurance is given by:

$$v(q, \bar{q}, z) = I(q, \bar{q}, z) - h(z) + s(z) \tag{2}$$

Where $I(q, \bar{q}, z)$ represents the indemnity (payout), $\bar{q}$, represents the production history, z represents the producer insurance contract choice, $h(z)$ represents the actuarially fair total premium *i.e.* cost, for contract choice z (e.g. coverage-level, policy type, etc.), and $s(z)$

represents the total premium subsidy available for contract z . The farmer always pays $s(z) - h(z)$ in premiums and receives an indemnity payment $I(q, \bar{q}, z)$ whenever $\bar{q} > q$.

The FCIP experienced a major change in its premium subsidy regime following ARPA in 2000. Table 1 gives the change in percent of premiums paid for by the government (i.e. subsidy levels) for yield-based policies across coverage levels on basic (and optional) units pre and post-ARPA (O'Donoghue 2014). Figure 1 presents the average national premium subsidy per acre for corn, wheat, and soybeans between 1991 and 2012. It is clear ARPA had an important influence on premium subsidies. Figure 2 shows the national buy-up premium subsidy per planted acre for corn, wheat, and soybeans. Prior to ARPA, revenue policies' premium subsidies had a stated per acre subsidy level. ARPA made revenue-based policies' premium subsidies identical to yield-based policies under which the premium subsidy is applied as a percentage of the premium (Babcock and Hart 2005). As a result, revenue-based policies became more attractive to farmers and expanded between 1997 and 2002 following its introduction in 1996 and the ARPA induced subsidy regime change (figure 3). Although we cannot say the trend toward revenue-based insurance products would not have continued without ARPA these points suggest ARPA represented a major shift in the FCIP, altering the environment in which producers manage risk.

The hypothesis in this thesis is that by inducing changes in production at the producer level, such a large and immediate shift in premium subsidization has affected market returns through a shift in supply at the market level, stimulating a change in farm structure through entry and exit. To test the hypothesis, we first incorporate the returns to subsidized insurance and the effect of the change in the ARPA regime into producer profits such that:

$$\pi = pq - c(q, \boldsymbol{w}) + I(q, \bar{q}, z^*(\theta)) - h(z^*(\theta)) + s(z^*(\theta), \theta) =$$

$$pq - c(q, \boldsymbol{w}) + v(q, \bar{q}, z^*(\theta), \theta) \tag{3}$$

For simplicity and in anticipation of empirical implementation, we assume the contract choice z^*, to have been chosen in response to θ prior to the choice output, which we assume is based on static profit maximization. Rather than additionally modeling optimal coverage selection, which is not our goal, we remain agnostic as to how the level of coverage is chosen. While the usual approach is to assume that producers maximize expected utility of profits (see Cabas, Leiva, and Weersink 2008). There is empirical evidence that such an assumption is not supported by observed farmer behavior (Du, Feng, and Hennessy 2017). Additionally, prospect theory was shown to be empirically inconsistent with observed coverage choice when insurance is viewed as a risk management tool but may be consistent when viewed as a stand-alone investment (Babcock 2015).

The variable θ represents an exogenous shift in ARPA. The shift variably affects profits increasing the premium subsidy regime across coverage levels. Since the optimal coverage level z^* is a function of θ, changing the subsidy regime across all z^* may induce producers to increase their coverage level or switch policies (*i.e.* increase z^*). This means that a change in the ARPA regime would affect the payoff from insurance directly and indirectly through the contract choice. To demonstrate, we differentiate the payoff v with respect to the change in the ARPA regime θ:

$$\frac{dv}{d\theta} = \ v_{\ \theta} + \frac{dz\,*}{d\theta}\left(\frac{\partial I}{\partial z\,*} - \frac{dh}{dz\,*} + \frac{\partial s}{\partial z\,*}\right) \tag{4}$$

Where the first term on the right-hand side $v_{\ \theta}$ is the direct effect and always positive, i.e. the government cannot decrease the returns to insurance by increasing subsidies, *ceteris paribus*. The indirect effect is captured by the second term, where $\frac{dz*}{d\theta}$ is the response of optimal contract choice, $\frac{\partial I}{\partial z*}$ the change in indemnity payments, assumed positive; $\frac{dh}{dz*}$ the change in total premium; also assumed positive, and $\frac{\partial s}{\partial z*}$ the change in the premium subsidy. The last term is generally increasing for lower coverage-levels and decreasing for higher coverage levels (see Babcock and Hart 2005 for example). Because the premium subsidy level at the dollars per acre level is a non-linear function of z*, increasing z* could increase or decrease the total returns to insurance depending on the typical producer's optimal contract choice. This implies the sign of bracketed term, $\frac{\partial I}{\partial z*} - \frac{dh}{dz*} + \frac{\partial v}{\partial z*}$, is ambiguous.

4. **Conceptual Model**

Considering the preceding discussion, the starting point of the conceptual model is a perfectly competitive crop industry consisting of n profit-maximizing identical farms, each producing output q using technology $c(q, \boldsymbol{w})$ with marginal cost increasing in q, i.e., $mc_q = c_{qq} > 0$. Inverse market demand is denoted by $p = p(n * q)$, where p is the market price with $p' < 0$, and n is the number of (equally sized) farms. Profits for the average farm are given by:

$$max_q[p(n*q)q - c(q,\boldsymbol{w}) + v(q,\bar{q},z^*(\theta),\theta)] \tag{5}$$

The long-run equilibrium of the farm and the industry are given by the optimality conditions

$$p(n*q) - mc(q,\boldsymbol{w}) + v_q(q,\bar{q},z^*(\theta),\theta) = 0 \tag{6}$$

$$p(n*q) - \frac{c(q,\boldsymbol{w})}{q} + \frac{v(q,\bar{q},z^*(\theta),\theta)}{q} = 0 \tag{7}$$

where (6) insures static profit be maximized and (7) requires each farm's profit (including returns to insurance) is driven to zero in the long-run.

The effect of a change in θ on farm structure is found by totally differentiating (6) and (7) with respect to θ and solving for the change in the average output, $\frac{dq}{d\theta}$, and the change in the number of farms $\frac{dn}{d\theta}$. The economic intuition behind this system is straight-forward. Prior to a shift in θ, the market is in long-run equilibrium such that (6) and (7) hold. When the government alters the crop insurance subsidy regime, the initial long-run equilibrium is disrupted. A new equilibrium, where (6) and (7) hold again, is attained through a change in *n*, the number of farms, and q, average output.

In matrix form, this system of equations is represented by

$$\begin{bmatrix} p'n + \pi_{qq} & p'q \\ p'n + D_1 - D_2 & p'q \end{bmatrix} \begin{bmatrix} \frac{dq}{d\theta} \\ \frac{dn}{d\theta} \end{bmatrix} = -\begin{bmatrix} A \\ M \end{bmatrix} \tag{8}$$

With $A = \frac{v_{z*}\frac{dz*}{d\theta} + v_\theta}{q} = \frac{(\frac{dv}{d\theta})}{q}$, $M = v_{qz*}\frac{dz*}{d\theta} + v_{q\theta}$, $\pi_{qq} = v_{qq} - c_{qq} < 0$, and $D_1 - D_2 = \left(\frac{ac(q)}{q} - \frac{mc(q)}{q}\right) - \left(\frac{av(\cdot)}{q} - \frac{v_q(\cdot)}{q}\right)$ where $ac(q)$ and $av(\cdot)$ denote the average production cost and average returns to insurance, respectively, and $mc(q)$ and $v_q(\cdot)$ denote the marginal production cost and marginal returns to insurance. Letting $\mathbf{\Lambda}$ denote the 2 x 2 matrix in (8), $det(\mathbf{\Lambda}) = p'n(D_1 - D_2 - \pi_{qq})$.

A represents the average marginal returns to insurance due to the shift in θ. Because it is directly proportional to $\frac{dv}{d\theta}$, the term A cannot be signed following the discussion on (4) above. The term M represents the change in the marginal returns to insurance with respect to a change in output following the shift in θ. Its sign cannot be determined without further assumptions about the relationship between $v_q(\cdot)$, the marginal returns to insurance with respect to output, and θ or $z*$. π_{qq} is signed according to the second-order sufficient condition of (5).

The term $D_1 - D_2$ denotes the difference in differences between average/marginal cost and average/marginal insurance. While traditional long-run competitive equilibrium models' marginal cost equal average cost, this is not the case here. The reason the respective cost functions differ is due to the presence of positive returns to insurance in (3). We can also interpret $D_1 - D_2$ in another way which directly demonstrates how crop insurance can influence entry or exit and average farm size. Rearranging the terms shows $D_1 - D_2 = \left(\frac{ac(q)}{q} - \frac{av(\cdot)}{q}\right) - \left(\frac{mc(q)}{q} - \frac{v_q(\cdot)}{q}\right)$. This demonstrates that the sign of $D_1 - D_2$ depends on the difference between the insurance-induced decline in average cost and marginal cost, respectively. Altering cost structure has been shown to influence market equilibrium in multiple settings (Perrin 1997; Azzam, Nene, and Schoengold. 2014). Without knowing the typical farmer's average cost relative to average returns to insurance, $D_1 - D_2$ cannot be signed (hence $det(\mathbf{\Lambda})$ remains unsigned). However, this term highlights the important effects average returns to insurance has on market structure.

Solving (8) yields

$$\frac{dq}{d\theta} = \frac{\boldsymbol{M - A}}{(\boldsymbol{D_1 - D_2 - \pi_{qq}})} \tag{9}$$

$$\frac{dn}{d\theta} = \frac{\boldsymbol{A\pi_{qq} + M(D_1 - D_2)}}{\boldsymbol{p'q(D_1 - D_2 - \pi_{qq})}} - \left(\frac{\boldsymbol{n}}{\boldsymbol{q}}\right)\left(\frac{\boldsymbol{dq}}{\boldsymbol{d\theta}}\right) \tag{10}$$

While (9) and (10) have no obvious sign, they do provide information. For example, assuming $M = 0$, $D_1 = D_2$, and $A < 0$ simplifies the expressions. The restrictions imply the marginal returns to insurance with respect to q are unchanged by θ and the change in average and marginal cost due to insurance offset one another; $A < 0$ implies the subsidy regime change lead the typical farmers to increase coverage high enough that total returns to insurance decreased relative to before the subsidy regime change. The decline in market returns leads to exit; $\frac{dn}{d\theta} = -\left(\frac{A}{\boldsymbol{\pi_{qq}}} + \frac{\mathrm{A}}{\mathrm{p'q}}\right) < 0$, and a rise in average output $\frac{dq}{d\theta} = \frac{A}{(\pi_{qq})} > 0$, implying and increase in the average size of the farms in the new industry equilibrium.

Determining other conditions under which (9) and (10) are positive, negative, or zero is complex because of the sign ambiguity of multiple parameters, and particularly because of the effect of the subsidy regime and the respective shifts in average production costs and average returns to insurance relative to the respective shifts in marginal production costs and margins returns to insurance. Instead of delineating every other condition under which each equation yields a clear sign in theory, we turn to the empirical version of the theoretical model to determine the direction of the crop insurance effect on the number and size of farms due to ARPA.

CHAPTER 2

1. Empirical Model and Estimation Procedure

Based on the above conceptual model, the relevant variables for econometric implementation are output (q), number of farms (n), output prices (p), production history $(\bar{q})$, optimal crop insurance coverage (z^{*}), the premium subsidy level, ARPA (θ), and factor prices $(\boldsymbol{w})$. Solving (6) and (7) for average output and number of firms provides the estimating equations

$$q_{ijt} = q_{ijt}\big(p_{ijt}, w_{ijt}, \bar{q}_{ijt}, z*_{ijt}\,(\theta_t), \theta_t\big) \tag{11}$$

$$n_{ijt} = n_{ijt}(p_{ijt}, w_{ijt}, \bar{q}_{ijt}, z*_{ijt}\,(\theta_t), \theta_t) \tag{12}$$

for county *i*, our unit of aggregation, in region *j* ∈ {Corn Belt, wheat}, described in the data section below, in year *t*. We augment these functions with a linear time-trend to account for the state of crop production technology (T_t). Because the premium subsidy per acre available to farmers shifted under θ_t it is reasonable to assume the effect of z^{*}_{ijt} (which helps determine the premium subsidy a farm receives) on farm industry structure also shifted. Therefore, we interact θ_t with z^{*}_{ijt} and assume (11) and (12) take the following linear forms:

$$\begin{aligned} log(q_{ijt}) = \alpha_{0j} + \alpha_{1j}log(p_{ijt}) + \alpha_{2j}log(w_{ijt}) + \alpha_{3j}log(\bar{q}_{ijt}) + \alpha_{4j}(z^{*}_{ijt}) \\ + (\alpha_{5j} + a_{5ij})\theta_t + \alpha_{6j}(z^{*}_{ijt} * \theta_t) \\ +\alpha_{7j}T_t + D^{n}_{ij} + e_{ijk} \end{aligned} \tag{13}$$

$$\begin{aligned} log(n_{ijt}) = \beta_{0j} + \beta_{1j}log(p_{ijt}) + \beta_{2j}log(w_{ijt}) + \beta_{3j}log(\bar{q}_{ijt}) + \beta_{4j}(z^{*}_{ijt}) \\ + (\beta_{5j} + b_{5ij})\theta_t + \beta_{6j}(z^{*}_{ijt} * \theta_t) \end{aligned}$$

$$+\beta_{7j}T_t + D_{ij}^n + \eta_{ijk} \tag{14}$$

Where e_{ijk} and η_{ijk} denote random error terms and D_{ij}^k is USDA state-level crop-reporting district fixed-effects to control for unobservable time invariant district effects. While we would ideally use county-level fixed effects, our implementation of the model with county fixed-effects is not feasible because of the number of parameters involved. Because each state has several crop reporting districts which are made up of around ten similar counties in each state, little information is lost by estimating the model with district rather than county-fixed effects. However, when dropping the random slope and estimating both models with county-fixed effects, we obtain nearly identical marginal results for all models.

Our data (described below) are hierarchical at the county, crop reporting district, state, and regional levels. To account for the hierarchal structure both (13) and (14) are estimated using a random effects model, allowing for a random slope on ARPA (θ_t) at the county level. This variable captures the exogenous shift in the premium subsidy regime brought about by ARPA. For econometric implementation, θ_t is measured by a dummy variable whose value is 0 in all counties for years prior to 2001 and 1 for all years after. Given the results of (9) and (10) and that returns to insurance likely differ across counties, we hypothesize ARPA's effect will also vary by county and therefore use a random-slope model to form a county-level distribution of effects which we can map across space.

This specification gives an ARPA specific effect by county, providing information on the distributional effect of ARPA across space. While α_{5j} and β_{5j} are assumed fixed means in the population, we treat a_{5ij} and b_{5ij} as normally distributed random variables.

That is to say that in (13) and (14) we allow for random slopes (effects) of ARPA at the county-level with the assumptions that both slope parameters are normally distributed. We assume the variance-covariance matrix of the random effects has no predetermined structure in order to avoid imposing additional restrictions on the data (Laired and Ware 1982). We estimate the linear mixed models in STATA using *MIXED* command with an unstructured variance-covariance random effects matrix.

We also address important econometric issues. First, our time series showed evidence of heteroscedasticity. We estimated robust cluster standard errors to account for this sampling error structure. Second, endogeneity may exist in our model because either input or output prices and either of the dependent variables may be jointly determined. We tested for endogeneity using the Durbin-Wu-Hausman test. We found evidence of endogeneity in the Corn Belt for both output price indices and input prices under both dependent variable specifications using a 5% critical level. In the wheat region, we found evidence of endogeneity in output price indices in the average output specification and in input prices in the grain farm specification using a 5% critical level.

To address the endogeneity issues, we need strong instruments. For input prices we relied upon national childhood obesity rates between 1992 and 2012 (Fryar, Carroll, and Ogden 2016). While obesity may not immediately appear a good instrument, Courtemanche (2011) found robust evidence of a link between gasoline prices (a major agricultural input) and obesity. As gas prices rise, people walk more which also accompanies fewer restaurant visits as individuals budget more. This creates a link between oil prices and obesity. We found evidence of obesity being a strong instrument using the Cragg-Donald Wald statistic in conjunction with the Stock and Yogo weak instrument test with a maximal instrumental variable critical value of 1% in both regions (minimum eigenvalue F Stats of 418 and 89 in corn and wheat regions respectively).

For the output price index, we use the 5-year moving average annual returns from the S and P 500 index. We cannot use lagged output values because the index is chained, and correlation with the error term will carry over through time (Reed 2015). Tedesse et al. (2014) have presented evidence of a strong link between increased financial speculation and food price volatility via the commodity futures market using data from the Chicago Board of Trade and USDA. Given the connection between the total market and commodity futures market through ETFs and other derivatives, the S and P 500 returns represents a valid instrument for commodity price indexes. Testing for strength, we found evidence of strong instruments using the Cragg-Donald Wald statistic in conjunction with the Stock and Yogo weak instrument test with a critical value below 1% in both regions (minimum eigenvalue F statistics of 5172 and 910 in corn and wheat regions respectively).

2. Data

As discussed above, we construct the data using counties as units of observation. The counties considered are from the top-five corn and soybeans producing states: Illinois, Indiana, Iowa, Minnesota and Nebraska and the top-five wheat producing states: Kansas, Montana, North Dakota, Oklahoma and Washington. These states generally accounted for the largest share of production (in terms of bushels) in corn/soybean and wheat production between 1992 and 2012 (NASS 2018). The ten states encapsulate a significant share of national grain markets, variation in climate, soil, production methods and crop-type.

The number of farms is obtained from the quinquennial USDA Census of Agriculture for years 1992, 1997, 2001, 2007, and 2012. Because some counties have a significant number of non-grain farms (e.g. livestock operations), rather than using the total farms estimate, we use a subset that focuses on the number of farms, as classified under the North American Industry Classification System (NAICS) available from the Census of Agriculture. Within the Census of Agriculture, the number of 'Oilseed and Grain' farms are reported for each county in each year. According to the 2017 NAICS Manual, "This industry group comprises establishments primarily engaged in (1) growing oilseed and /or grain crops and/or (2) producing oilseed and grain seeds" (NAICS 2017). Hence, the dataset covers farms primarily involved in the production of corn, soybeans, and wheat.

Crop production must be aggregated across multiple crop types to measure county-level output and prices to obtain a single output estimate for each county in each year. For each state, we first determined which crops accounted for the majority of crop insurance liability across all counties in the state across all years in the sample. Data on crop liability were obtained from the Summary of Business county-level data available from the RMA for years between 1992 and 2012 (RMA 2018). We select a combination of crops for each state that covered, on average, at least 75% of county-level insurance liability. Table 2 provides a meta-data summary of the crop types included for counties in each state. Additionally, the average percent of liability covered by the selected crops is provided. For wheat producing states, we focus on counties where wheat accounted for at least 50% of liability, on average, across all years. Table 2 also includes the number of counties in the dataset for each state.

For the county-level aggregation of prices and quantities across crops, we rely on the Tornqvist approximation to the Divisa Index (referred to as the Tornqvist Index) setting 1992 as the base year (Tornqvist 1936). Tornqvist Indices are chained and flexible, meaning the output index provides a second-order approximation to any arbitrary homogenous production function. Also, the index is exact for translog production functions. Additionally, it has been concluded the index "… can probably be used in analyzing most production situations" (Christensen 1974). In studying the effect of index choice on Canadian agricultural output and input indices, Fantino and Veeman (1997) find little difference between the Fischer Ideal Index and the Tornqvist Index. Essentially, one creates revenue shares of each commodity in the index and multiples each yearly share distribution by the individual commodities' quantity (or price) to get the relative change from one year to the next. Once a base year is set, a chained index for each year can be calculated based on the previous year and the percent change from one year to the next. Appendix A provides detailed formulation of the county-level price and quantity indices. Once total county output ($Q = n * q$) is aggregated using the Tornqvist Index, we calculate average output (q) by dividing total output by the number of grain and oilseed farms ($q = \frac{Q}{n} = \frac{n*q}{n}$).

To aggregate $z*$, the optimal producer contract choice, the total buy-up insured acres at the county-level of each respective crop is calculated from county-level data available from the RMA Summary of Business (RMA 2018). That is, for empirical implementation we take optimal contract choice as whether a given planted acre is insured with a buy-up policy or not and hence aggregate across coverage-level, policy, and unit types. We leave out Catastrophic coverage (CAT), which generally covers 50% of average production history at 55% of the projected price. Hence CAT policies represent minimal coverage at best and generally do not pay indemnities. Therefore, we do not expect CAT policies to drive changes in market structure compared to buy-up policies. While we would ideally separate the variable by coverage-level to allow varying effects, we are unable to do so because of high multicollinearity between contract choice levels.

The buy-up coverage insured acres of each commodity included in the county are then summed across the commodities to measure total county-level insured acres. To keep the panel balanced, counties with no insurance policies available in 1992 were excluded from the analysis.

Total insured acres are then divided by the sum of estimated total planted acres across commodities. These data are available from the USDA's National Agricultural Statistical Services (NASS 2018). NASS does not estimate planted acre for all crops in all counties for all years. For county-crop-year combinations that are missing, the county average (of all available years between 1992 and 2012) estimate of planted acres is used, provided there is at least one year of estimated planted acres. If no estimate in any year for a specific county-crop combination is available, that crop is dropped from the analysis within that county. The variable z^* is then an estimate of the proportion of planted acres covered under a buy-up coverage policy at the county-level. Letting l_{ikt} denote buy-up insured acreage and L_{ikt} denote the NASS acreage estimate in county *i* for commodity *k* in year *t*, $z*_{it}=\frac{\sum_k l_{ikt}}{\sum_k L_{ikt}}$.

To calculate production history ($\bar{q}$), we obtain NASS county-level estimated yields for years between 1982 and 2012. Following how the RMA calculates average production history (APH) for individual producers, we use a ten-year moving average for each county-crop combination. We then weight each moving average crop yield by the long-run proportion of estimated planted acres accounted for by each commodity described below. All available county-level crop yields across time are used to calculate an average if specific county-crop-year combinations are missing. Crops are dropped from the county analysis if no yield estimate is available in that county for any year. Because NASS either estimates both acres and yields or does not estimate either, the same crops are dropped from the same counties as with the calculation of z*. Each crop's ten year moving-average yield estimate is then weighted by the long-run proportion of estimated planted acres accounted for by that crop. The weighted yields are then summed to form an estimate of $\bar{q}$. Letting y_{ikt} denote the NASS yield estimate, in county *i* for commodity *k* in year *t*, the ten-year moving-average is $\frac{\sum_{t=t_0}^{t_0-9} y_{ikt}}{10}$. If μ_{ik} represents the estimated long-run proportion of planted acres accounted for by commodity k, then $\sum_k \frac{\sum_{t=t_0}^{t_0-9} y_{ikt}}{10} \cdot \mu_{ik} = \bar{q}_{it}$

For input prices, *w*, we would ideally use a county-level input price index. However, such an index is not readily available. Therefore, we use inflation adjusted state-level gasoline prices (in $/ btu) available from the Energy Information Administration (EIA 2018). While this does not allow us to fully capture variability of all input prices across time and space, it does allow us to capture variability of a major input used in the production process. As discussed in the empirical modeling section, we instrument input prices with yearly childhood obesity rates available from the CDC (2012).

Summary statistics for both regions can be found in table 3. The tables in Appendix C give the same summary statistics by state.

3. Results

We first present and discuss parameter estimates from equations (13) and (14) for the Corn Belt region followed by a discussion of the wheat region results and conclude with a general comparison of results between the two regions.

Corn Belt

Focusing on the number of farms as the dependent variable in table 4 we find that all independent variables are significant at the 10% or below except for the output price index, the ARPA and contract choice interaction term, and the time trend. The estimated coefficient on the input price index is negative and significant, indicating higher input prices are associated with fewer farm numbers. The estimated coefficient implies production history is positively associated with the number of farms.

Because of the presence of the interaction term we calculated the marginal effects of ARPA and contract choice on Corn Belt farm numbers, found at the bottom of table 4. These estimates are of interest because significant effects of ARPA provide evidence of a structural break in the farm industry that occurred simultaneously with ARPA. Results indicate statistically negative *ceterus paribus* impact of ARPA on the farm numbers; the estimated effect is a 36% decrease in farm numbers for the average county. While this number may seem large in magnitude, it is important to note that many counties in the data set had relatively few farms for the first two years in the data set. In the Corn Belt, nearly 10% of counties had fewer than 100 farms in 1997. This can translate into a rather large percentage change in farm numbers even if the absolute change between 1992-1997 and 2002-2012 is relatively small.

Table 4 also presents the marginal effects of the county-level contract choice. The estimate is 0.13 and significant below only the 5% level. The marginal results of the contract choice can be interpreted as follows: if a county increased its percentage of planted acres covered by a crop insurance policy ten percentage points (z* increases by 0.1), there is an approximately (0.10 * 0.13)*100% = 1.3% marginal effect on farm numbers from the increase in contract choice because the regressions are log-linear with respect to z*. This increase is modest compared to larger (in magnitude) marginal effect associated with ARPA (recall the estimated marginal effect is an approximately 36% decrease). The positive sign is consistent with the hypothesis that subsidized insurance is negatively influencing farm numbers if we assume the increase in covered acres corresponds to more farms participating in the insurance program (and hence less likely to face ruin given adverse outcomes). However, given the small magnitude of the estimate, the results indicate the effects of insurance on farm numbers in the Corn Belt has largely been a result of the structural break that occurred with ARPA rather than increases in buy-up coverage.

Through the random effect we can inspect the distributional impact of ARPA across all 426 Corn Belt counties. Figure 4 shows the distribution of ARPA's estimated effect on county-level average farm output in the Corn Belt, calculated by adding the mean estimated effect of ARPA to the random slope term for each county then added to the product of the mean county-level contract choice and the interaction term (take the partial derivative of (13) or (14) with respect to θ_t, and replace z_{ijt}^* with its county-level mean) . Results from the random effects indicate that all counties except seven experienced a decrease in farm numbers. This indicates ARPA was associated with a decrease in numbers in nearly but not all counties of the dataset, which is fully consistent with the sign ambiguity of (10).

Recall that we hypothesized based on (9) and (10) that ARPA's influence depends on, among other factors, the returns to insurance *at the county-level*. Hence, we should expect a wide distribution of estimates given the geographic variation of the counties and thus returns to insurance. Figure 4 demonstrates ARPA was indeed associated with a wide distributional effect from an estimated 64% decrease in county-level farm numbers to an increase of just over 8%.

Figure 5 demonstrates the spatial distribution of the histogram found in figure 4. We highlight a few notable points. Eastern Nebraska, central Iowa, and central Illinois counties have experienced the smallest percentage decrease in farm numbers associated with ARPA. As we move geographically farther from these areas, counties tend to experience larger changes in farm numbers. We do see clusters of counties that experienced the highest percentage decrease (greater than a 40% decrease, brick red in figure 5). Again, it is important to remember that the map generates *percentage* changes in farm numbers *at the county level*. Therefore, each county has its own base number of farms from which the percentage change is calculated, so comparisons between counties is limited because the estimated changes are not absolute.

Focusing now on the average farm output as the dependent variable in table 4, all parameter estimates except the production history and contract choice are significant at or below the 1% level. Both input and the output price index are found to positively influence average farm size with input prices having a stronger impact on average farm output than the output price index. An exact interpretation of the estimated parameters on input and the output price index is difficult because q, average farm output, is an index divided by farm numbers. We do find an increase in the county level production history is associated with an increase in average farm output, but the point estimate is insignificant. The positive and significant interaction term implies counties with a higher proportion of planted acres in 1992 and 1997 (higher levels of z*) experienced, on average, a greater change in post-ARPA average farm output.

We now turn to the bottom of table 4 to inspect the marginal impact of ARPA and contract choice on average farm output. We found a significant and positive impact of ARPA on average farm output by an approximately 47%. It is important to recall the average farm output index is chained and then divided by county-level farm numbers. Therefore, high levels of growth within the index may not translate to high levels of absolute growth of crop production because every county begins with a total production index of 100 in 1992. In essence, all we can conclude is ARPA was associated, on average, with average farm output growth based on our measurement. We do find a statistically significant and positive impact on the marginal impact of contract choice on average farm output, with an estimated parameter estimate of 17%. This implies if a county increased its percentage of planted acres insured by ten percentage points, there is an approximately (0.17 * 0.10) * 100% = 1.7% marginal effect on farm numbers from the increase in contract choice. Compared to the 47% marginal effect of ARPA, the relative estimated impact of contract choice on average farm output is negligible.

Figure 6 shows the distribution of the random effects slope like figure 4, except now for the marginal effect of ARPA on average farm output. Again, we see a wide distributional effect, but with no county estimate falling below zero, indicating ARPA was associated with expanded average farm output in all counties in our dataset. Estimates range from a 15% increase to a 91% increase. These results are consistent with previous findings that have found increases in land use in response to crop insurance participation (e.g. Young, Vandeveer, and Schnepf 2001; Walters et. al 2012; Yu, Smith, and Sumner 2017). Relating this fact back to (9), it appears the sign is identical for every county in the dataset and is positive. Without further knowledge about average farm cost structure, the role of insurance in altering production costs, the shape of the marginal insurance payoff function, and how ARPA influenced the overall payoff from insurance to the typical farmer, we cannot determine which elements of (9) contribute to its unambiguous sign.

Figure 7 maps the county-level estimated effect of ARPA across space. Again, we highlight a few key points with the caveat that comparisons between counties is difficult given each county-level index is formed with a unique set of crops and divided by the county-level number of farms. Therefore, changes in both the absolute number of farms and the output index (chained through time) are used to calculate average farm output. Figure 7 shows counties in mainly Iowa and southwestern Minnesota experienced the smallest percentage change in average farm output. Nebraska, eastern Illinois, and almost all counties in Indiana experienced a greater than 55% increase in average farm output associated with ARPA. We again see clustering of colors, potentially due to the fact that most counties in a given area grow similar crops and generally have similar farm numbers. This makes comparisons between these counties easier and likely influences the patterns we see in figure 7.

Wheat Region

Table 5 presents the wheat region regression parameter estimates. When number of farms is the dependent variable, all variables except for the interaction term, price index, and contract choice are significant below the 5% level. Parameter estimates imply higher input prices are associated with fewer farms and a higher output price index (though insignificant) are associated with more farms. Input prices are associated with an elastic negative effect on farm numbers. The bottom of table 5 presents marginal effects of ARPA and contract choice for the wheat region. We again find a significant and positive estimated marginal impact of ARPA on farm numbers (56% decrease) while average contract choice was associated with an increase in number of farms (and approximately 2.4% increase for a ten-percentage point increase in z*). As with the Corn Belt, we should not be too concerned about the large estimated average decrease. Over a quarter of counties in the wheat dataset had fewer than 200 farms in 1997. Hence, relatively small changes in absolute farm numbers can translate into large estimated percentage changes.

Figure 8 presents the estimated marginal influence of ARPA on county-level number of farms in the wheat region. All estimates are negative, implying ARPA was associated with an estimated decrease in county-level farm numbers for all counties in the Wheat region. The estimated effects vary substantially, ranging from a nearly 40% decrease to an 80% decrease. Figure 9 plots the estimated distribution in figure 8 to the corresponding county across space. We again see some patterns of clustering. The largest percentage change category of farm numbers appears in all states (over a 60% decrease, brick red, figure 9).

With average farm output as the dependent variable in the wheat region, table 5 shows all independent variables excluding the interaction term are significant below the 10% level. The output price index is associated with higher average farm output. Input prices were found to be positively associated with average farm output. Results indicate higher levels of production history are associated with lower levels of average farm output.

The bottom of table 5 presents the marginal effect of ARPA on average farm output. Results indicate on average ARPA was associated with a 40% increase in average farm output.

Figure 10 presents a histogram of the estimated slope parameters for the average farm regression in the wheat region. The estimated effects vary substantially across counties with no county experiencing an estimated negative effect, implying ARPA was associated with an increase in average farm output

Figure 11 plots the histogram in figure 10 across space. Again, we note that comparisons between counties, particularly those in different areas of the county are not useful. Rather, we again note the color clustering is consisted with counties in a small geographic area tending to have similar beginning farm industry structure. This relationship between nearby counties may contribute to the clustering. However, the variation across space with clustering is consistent with variation expected from (9) and (10) if counties in a given region grow similar crops, have similar farm numbers, and experience, on average, similar returns to insurance.

Comparisons between Corn Belt and Wheat Region

We focus now on comparing the results found in table 4 and table 5 between the two regions. Considering the number of farms regressions first, we note most independent variable parameter estimates are of similar size and significance. While the interaction term in the number of farms regression is significant in the wheat region, it is not in the Corn Belt. This implies the effect of ARPA in the wheat region was significantly more effected by insured planted acres than in the Corn Belt, potentially due to differences in average insurance payouts between the regions. Indeed, comparing the marginal effects at the bottom of table 4 and table 5, the marginal effect of ARPA was, in magnitude, greater in the wheat region than in the Corn Belt.

We see both histograms in figures 4 and 8 are skewed left. The wheat distribution is shifted farther to the left than the Corn Belt distribution, demonstrating the larger marginal effect found in the wheat region. The other main difference between the two regions is the estimated marginal effect of the contract choice, found at the bottom of tables 4 and 5. While estimates are positive in both regions, the effect of increased insured acres in the wheat region is almost twice as large as in the Corn Belt (0.13 compared to 0.24). We again note that comparisons beyond these basic highlights is difficult because the number of farms per county varies substantially both *within* a region and *between* regions.

We finally turn to the average farm output regressions, with the caveat that comparisons can only be made at the surface given the substantial variation in crop types and farm numbers (and hence average output) across the two regions. Again, most coefficient estimates are of similar size and magnitude in the average output regressions of tables 4 and 5. For the estimated marginal effect of ARPA, the coefficients are both positive and significant, with the Corn Belt region experiences a somewhat larger marginal effect from ARPA (0.47 and 0.40 respectively), although it is not clear how this translates to comparisons in absolute changes. The histograms in figures 6 and 10 indicate the estimated county-level distribution of the ARPA random slope variable are similarly dispersed in the wheat region and Corn Belt.

One key difference between the two regressions is the estimated marginal effect of the contract choice is positive and significant in the Corn Belt but negative and significant in the wheat region, with the magnitude of the wheat region estimated greater than that of the Corn Belt (0.17 and -0.23 respectively). However, when one remembers the different crop types of the proportion of liability accounted for in the wheat states versus the Corn Belt states (table 2), it is not necessarily surprising these estimates differ. Additionally, the wheat regions had around half the counties (units of observations) as the Corn Belt, and both estimates are only marginally significant. Overall, we find ARPA, at the margin, was associated with an increase in average farm output in both regions, but the effect at the county level varied substantially across counties and regions.

4. Conclusion

Government policy often has unintended consequences, and federal crop insurance may be no different. In this thesis, we draw on the theory of long-run competitive equilibrium to evaluate the association between ARPA and the industry structure of grain farms. The main goal of the thesis was to empirically measure what association, if any, there was between ARPA and subsidized crop insurance in general and county-level farm industry structure in terms of number of farms and average farm output.

Our empirical model, guided by our theoretical model, implies that the implementation of ARPA was associated with fewer farms and greater average farm output in the top corn, soybean, and wheat producing states. For policy-makers concerned with market consolidation and the survival of the family-farm, our results point to a strong relationship between crop insurance subsidization and subsequent farm concentration. While the results do not apply to any single farm, they do suggest we cannot reject the hypothesis that the typical farmer has been impacted by the large subsidies available through federal crop insurance. We recognize that the relationship may not be causal, as a different measure of subsidization or an economic experiment would need to be established to provide any direct link. However, we are unaware of any major structural changes outside of ARPA that occurred between 1997 and 2002 that would drive these results even after controlling for the general trend in farm numbers and average farm output.

These results are useful, but more work is needed to further examine the role of subsidized crop insurance on industry concentration and expansion. We aggregate our measure of crop insurance participation according to whether a planted acre in a county is insured under buy-up coverage. However, theoretically establishing and empirically testing varying effects of different coverage-levels on subsequent farm consolidation may be of interest. Also, while we do not model the selection of contract type in this paper, future work may look to do so.

Our results do not generalize to other areas of the country with other crop mixes, so expanding the data to include states would be a fruitful follow-up, Still, our work covers the largest producing states of the three most valuable (in total dollar terms) crops grown in the United States, uncovering a relationship between subsidized insurance and farm structure in the crop sector, a relationship that has so far received little attention from academics or policy-makers.

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Tables and Figures

Table 1. Subsidy level (% of premium paid by government) by coverage level for yield-based policies on basic units at 100% price coverage, pre and post-ARPA

	Coverage Level							
	50	55	60	65	70	75	80	85
Pre-ARPA	55	46	38	42	32	24	17	13
Post-ARPA	67	64	64	59	59	56	48	38
Percent Increase	22	39	68	40	84	133	182	192

Source: O'Donoghue (2014)

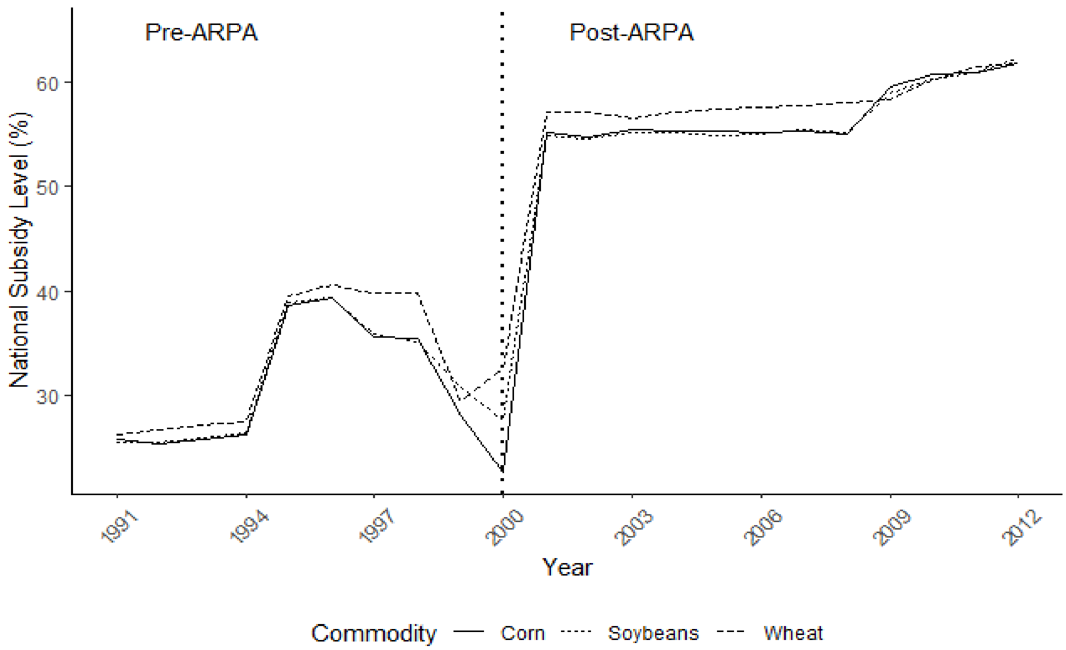

Figure 1 *Average national premium subsidy level by commodity (1991-2012)*

Source: RMA (2018)

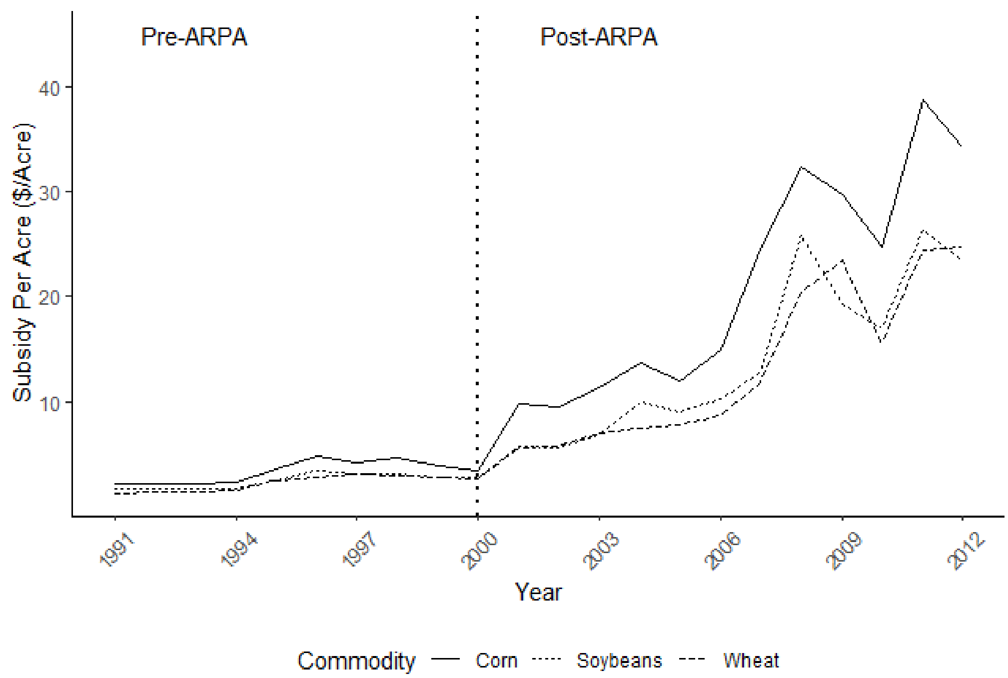

Figure 2 *Average national subsidy per planted acre by commodity (1991-2012)*

Source: RMA (2018)

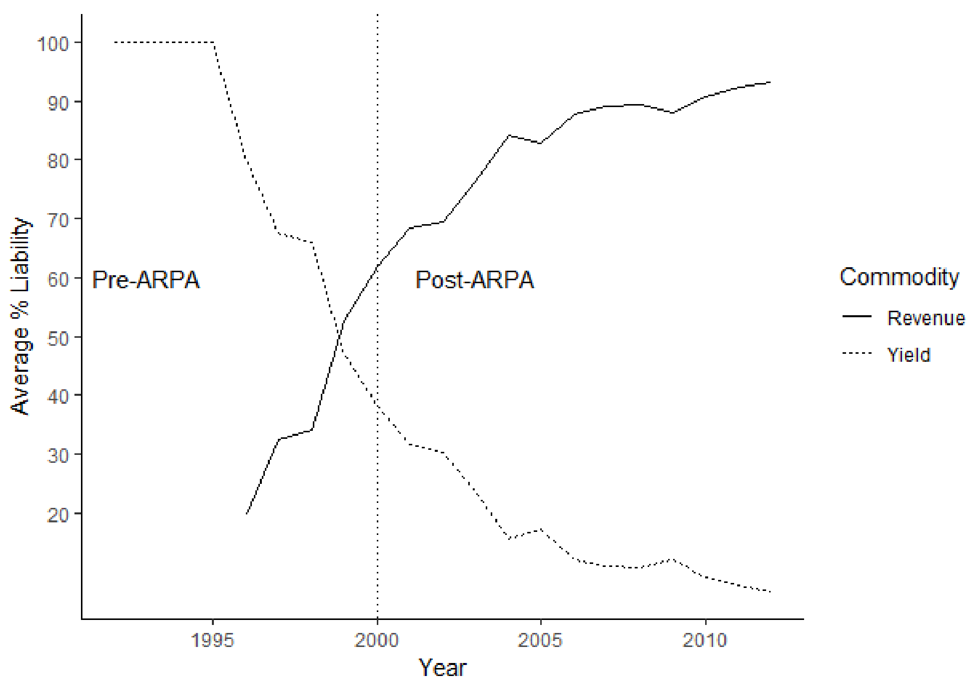

***Figure 3** National average % of liability accounted for by revenue and yield based insurance products including corn, wheat, and soybean insurance contracts (1992 – 2012)*

Source: RMA (2018)

Table 2. State level summary of crops included, number of counties per state per year, and average percent of county level liability accounted for by included crops (standard deviation in parenthesis)

State	Region	Crops Included in Analysis	# of Counties Included in Balanced Panel	Average % of County-Level Liability Accounted for by Included Crops 1992-2012
Illinois	Corn Belt	Corn, Soybeans, Wheat (Winter)	94	97.9% (3.4)
Indiana	Corn Belt	Corn, Soybeans, Wheat (Winter)	79	95.3% (9.6)
Iowa	Corn Belt	Corn, Soybeans	98	98.3% (3.5)
Minnesota	Corn Belt	Corn, Soybeans, Wheat (Spring)	74	87.3% (16.9)
Nebraska	Corn Belt	Corn, Soybeans, Wheat (Winter)	81	91.0% (13.9)
Kansas	Wheat	Wheat (Winter), Corn, Soybeans, Sorghum	104	99.1% (2.0)
Montana	Wheat	Wheat (Durum, Spring, Winter), Barley	34	74.0% (25.2)
North Dakota	Wheat	Wheat (Durum, Spring, Winter), Barley, Corn Soybeans	31	75.0% (15.0)
Oklahoma	Wheat	Wheat (Winter), Corn, Cotton, Sorghum, Soybeans	41	90.3% (18.8)
Washington	Wheat	Wheat (Spring, Winter), Barley	11	75.8 % (29.3)

Source: RMA (2018)

Table 3. Regional summary statistics of variables (average output, number of grain farms, output price index, contract choice, input prices, and production history)

Corn Belt Region (Illinois, Indiana, Iowa, Minnesota, Nebraska)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Avg.	S.d	Min.	Max.	Avg.	S.d	Min.	Max.	Avg.	S.d	Min.	Max.
q	0.3	0.7	0.1	12.5	0.5	1.2	0.1	19.1	0.5	1.6	0.1	19.1
n	530	266	8.0	154	361	182	6.0	119	428	243	6.0	154
P	107	8.0	100	122	202	80	99	331	164	77	99	331
z	39	21	2.0	92.2	75	17	11	100	60	25	2.3	100
w	9.3	0.6	8.3	10.5	21	7.8	10	30	16	8.1	8.3	30
$\bar{q}$	80	17	30	143	99	22	29	162	92	22	30	162

Wheat Region (Kansas, Montana, North Dakota, Oklahoma, Washington)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Avg	S.d	Min.	Max.	Avg	S.d	Min.	Max.	Avg	S.d	Min.	Max.
q	0.6	3.6	0.1	73	1.46	2.0	0.11	21.1	1.14	2.7	0.1	73.6
n	345	15	2.0	1011	181	125	4.0	705	246	173	2.0	1011
P	104	6.3	89	129	153	65	100	309	152	64	89	309
z	44	22	0.8	99	73	18	9.6	99	61	24	0.8	99
w	9.1	0.7	8.3	10.9	20	7.6	9.9	31.4	16	8.2	8.3	31.4
$\bar{q}$	39	13	18	105	46	16	22	109	43	15	18	109

Source: RMA (2018), NASS (2018)

Table 4. Corn Belt region regression parameter estimates and marginal effects estimates

	Dependent Variables: Number of farms	Average farm output
Independent Variables:		
Constant	9.47***	-17.24***
	(1.32)	(1.84)
Output Price Index	-0.02	0.40***
	(0.02)	(0.03)
Input Price	-1.63 ***	6.22***
	(0.54)	(0.75)
Production History	0.12**	0.03
	(0.07)	(0.09)
Contract Choice	0.09*	0.03
	(0.05)	(0.06)
ARPA	-0.40***	0.33***
	(0.04)	(0.05)
ARPA/Contract interaction	0.07	0.23***
	(0.06)	(0.08)
Time Trend	-0.01	-0.17***
	(0.01)	(0.02)
Estimated marginal effects of ARPA and contract choice		
ARPA	-0.36***	0.47***
	(0.01)	(0.02)
Contract Choice	0.13**	0.17**
	(0.06)	(0.08)

Notes: Prices are in 1992 dollars. Robust standard errors of the estimated coefficients are given in parenthesis below the estimates. Statistical significance is denoted by *, **, and *** for the 0.1, 0.05, and 0.01 levels respectively, with p-values obtained using Wald (Standard Normal) Test.

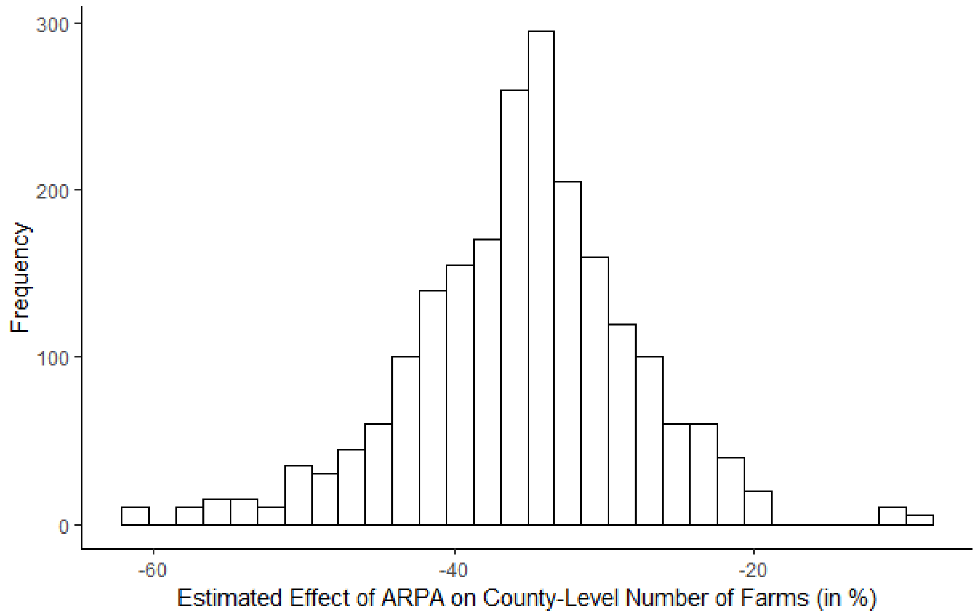

Figure 4 *Distributions of Corn Belt county-level estimated random slope coefficients, number of farms regression*

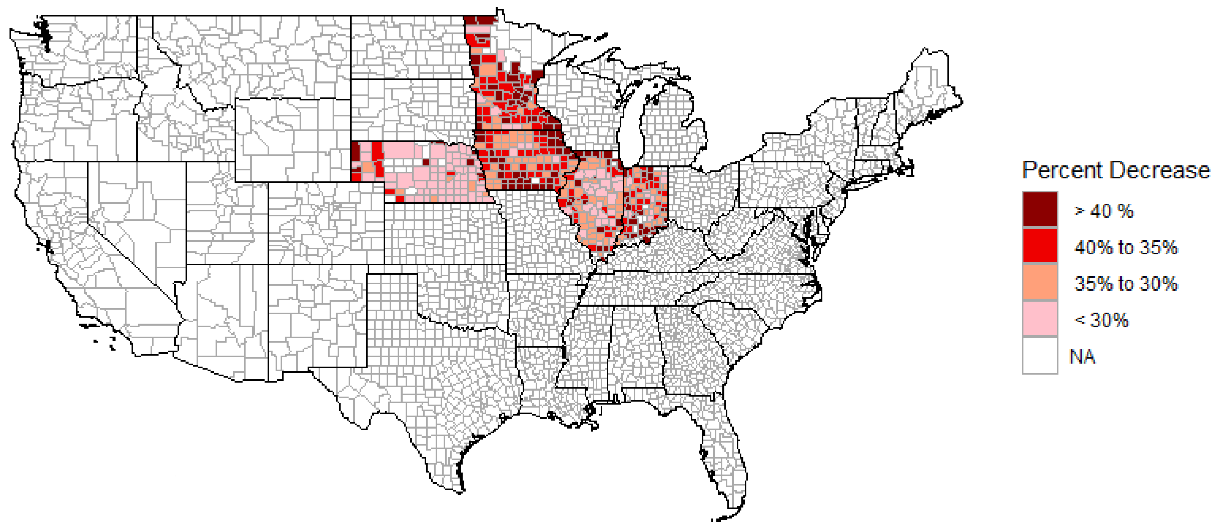

Figure 5 Corn Belt spatial distributions of county-level estimated effect of ARPA on number of farms

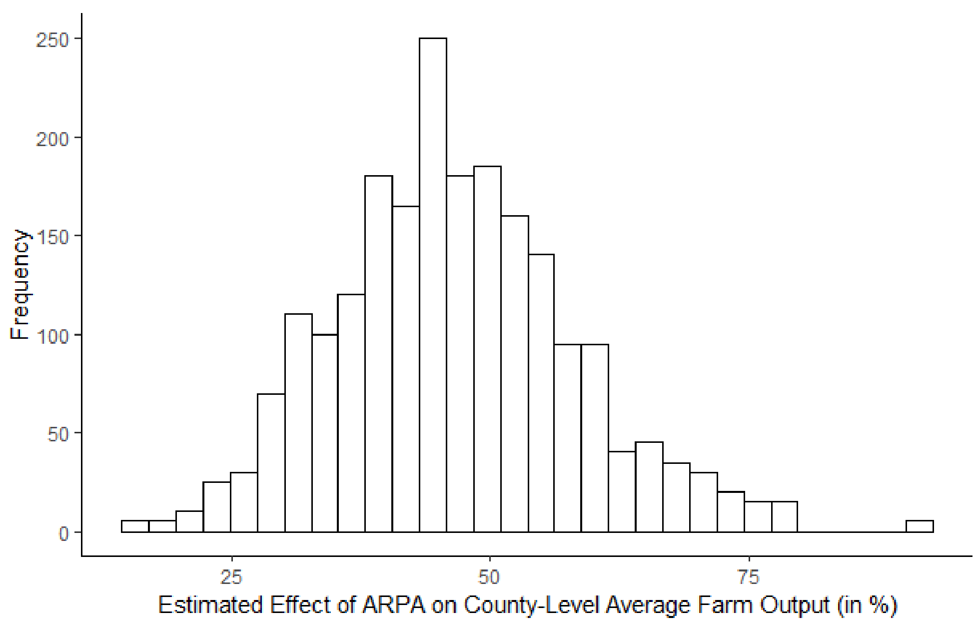

Figure 6 *Distributions of Corn Belt county-level estimated random slope coefficients, average farm output regression*

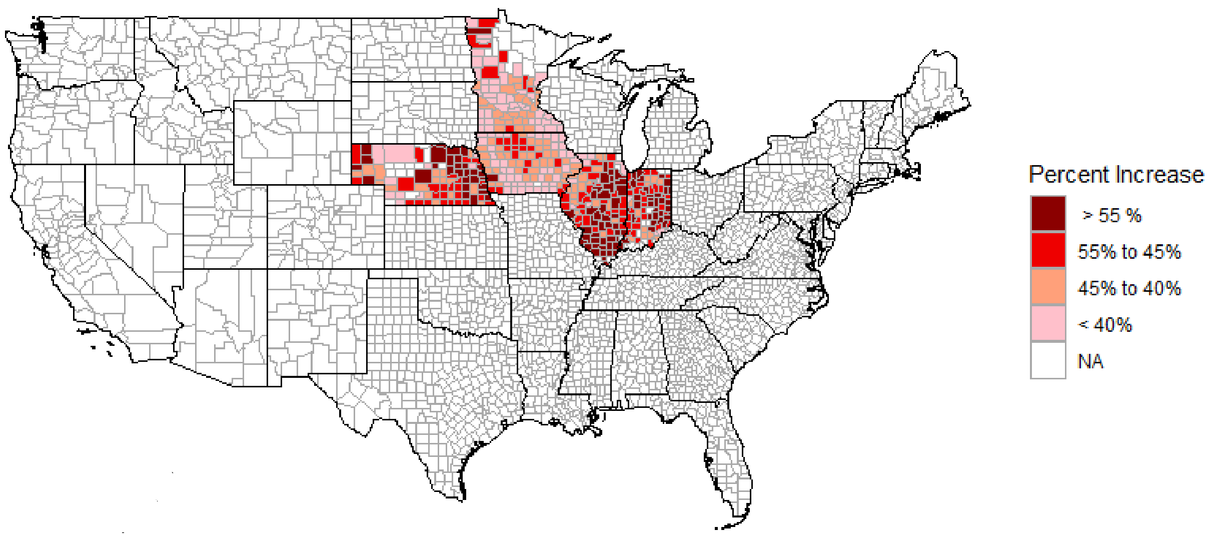

Figure 7 *Corn Belt spatial distributions of county-level estimated effect of ARPA on average farm output*

Table 5. Wheat region regression parameter estimates and marginal effects estimates

Independent Variables:	**Dependent Variables:** Number of farms	Average farm output
Constant	9.40***	-6.42***
	(2.00)	(3.43)
Output Price Index	0.06	0.63***
	(1.05)	(0.06)
Input Price	-2.56**	1.93**
	(1.27)	(0.59)
Production History	0.33**	-0.27**
	(0.14)	(0.15)
Contract Choice	0.17	-0.20*
	(0.11)	(0.13)
ARPA	-0.64***	0.43***
	(0.07)	(0.10)
ARPA/Contract interaction	0.11***	-0.06
	(0.09)	(0.13)
Time Trend	0.06***	-0.07***
	(0.01)	(0.02)
Estimated marginal effects of ARPA and contract choice		
ARPA	-0.56***	0.40***
	(0.03)	(0.05)
Contract Choice	0.24**	-0.23*
	(0.11)	(0.14)

Notes: Prices are in 1992 dollars. Robust standard errors of the estimated coefficients are given in parenthesis below the estimates. Statistical significance is denoted by *** for the 0.01 level, with p-values obtained using Wald (Standard Normal) Test.

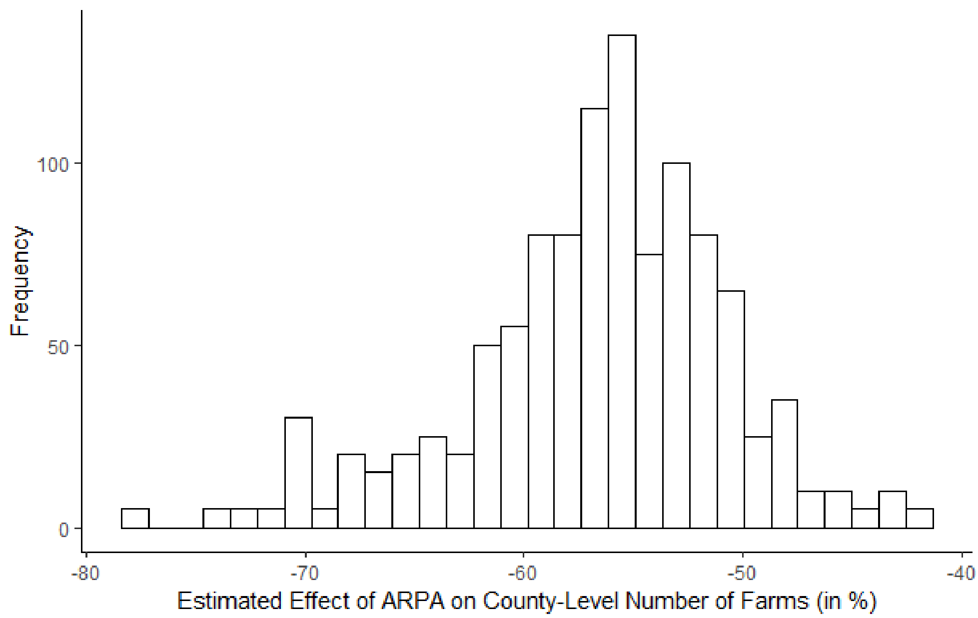

Figure 8 *Distributions of wheat region county-level estimated random slope coefficients, number of farms regression*

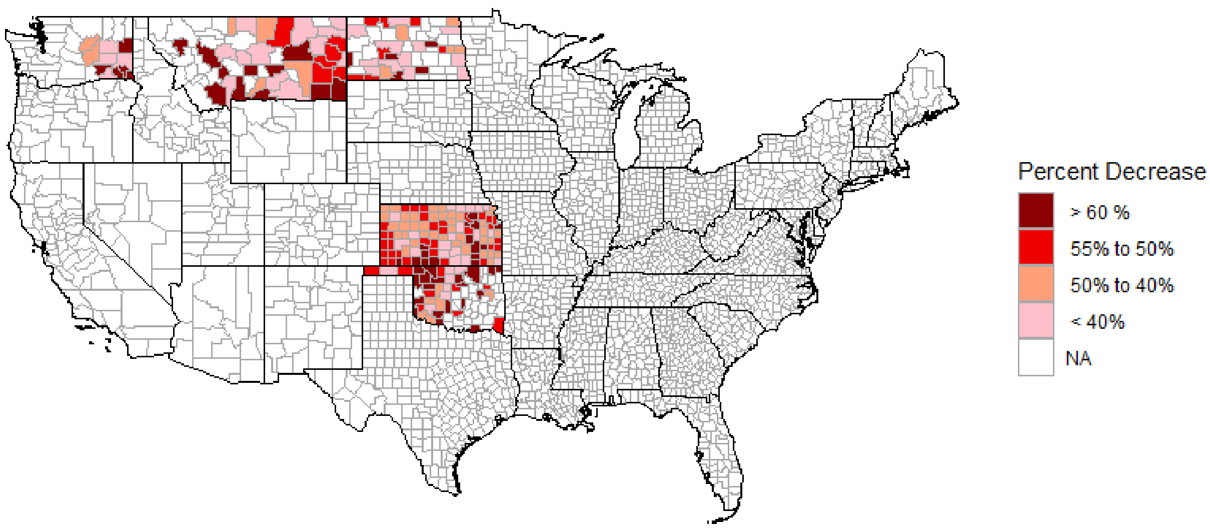

Figure 9 *Wheat region spatial distributions of county-level estimated effect of ARPA on number of farms*

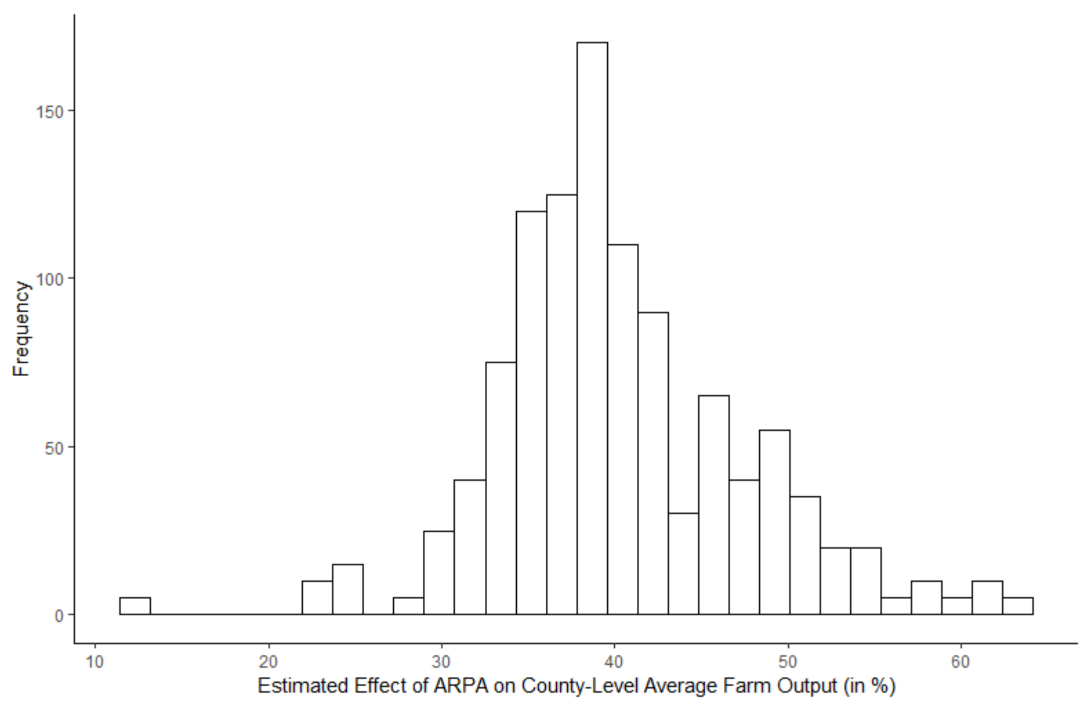

Figure 10 *Distributions of wheat region county-level estimated random slope coefficients, average farm output regression*

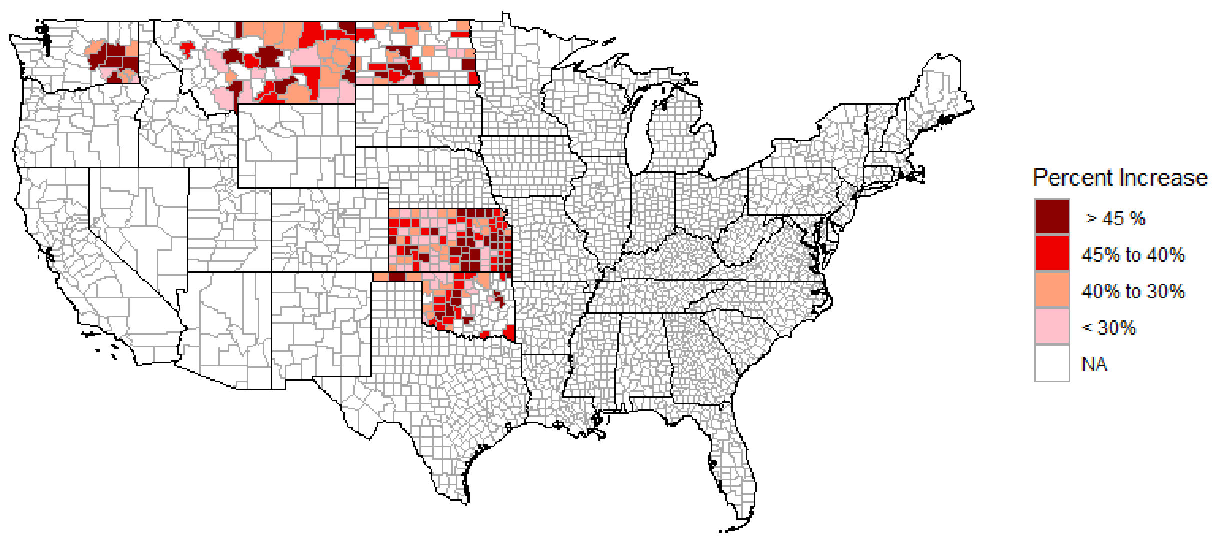

Figure 11 *Wheat region spatial distributions of county-level estimated effect of ARPA on average farm output*

Appendix I: Formation of Tornvist Price and Quantity Indices

Creating the county-level indices for both prices and quantities follow the same procedure. First suppose we have I counties, each with J crops, across T years. Focusing on prices for now, for each county I, the relative rate of change of the index is a weighted average of the J commodities' prices (weighted by the share of crop revenue accounted for by each j in county i) in the current and previous year.

Let P_{ti} denote the price index in county i and p_{it} denote the actual received price for commodity j in year t. The relative rate of change in logarithmic form is therefore given by

$$ln(\frac{P_{i,t}}{P_{i,t-1}}) = \frac{1}{2}\sum_{j=1}^{J}(\frac{p_{i,j,t}q_{i,j,t}}{\sum_{j=1}^{J} p_{i,j,t}q_{i,j,t}} + \frac{p_{i,j,t-1}q_{i,j,t-1}}{\sum_{j=1}^{J} p_{i,j,t-1}q_{i,j,t-1}})ln(\frac{p_{i,j,t}}{p_{i,j,t-1}}) = \rho_{i,t} \qquad (1a)$$

Solving for $P_{i,t}$ in terms of $P_{i,t-1}$, we have

$$P_{i,t} = exp(\rho_{i,t})P_{i,t-1} \qquad (2a)$$

By arbitrarily setting a base year (1992 in this thesis) to an arbitrary number (100 in this thesis), the relative price index in each county can be chained together using (2a).

Similarly, letting $Q_{i,t}$ denote the Tornqvist quantity index in county i in year t, we have

$$ln(\frac{Q_{i,t}}{Q_{i,t-1}}) = \frac{1}{2}\sum_{j=1}^{J}(\frac{p_{i,j,t}q_{i,j,t}}{\sum_{j=1}^{J} p_{i,j,t}q_{i,j,t}} + \frac{p_{i,j,t-1}q_{i,j,t-1}}{\sum_{j=1}^{J} p_{i,j,t-1}q_{i,j,t-1}})ln(\frac{q_{i,j,t}}{q_{i,j,t-1}}) = \varphi_{i,t} \qquad (3a)$$

As above, solving for $Q_{i,t}$ in terms of $Q_{i,t-1}$, we have

$$Q_{i,t} = exp(\varphi_{i,t})Q_{i,t-1} \qquad (4a)$$

As with prices, we set 1992 as the base year to 100 in each county and chain the future quantity index based on (4a).

For this analysis, the $q_{i,j,t}$'s are obtained from NASS production estimates (in bushels) for all county, crop, year combinations. As discussed in the data section, not all counties had all crop production estimated in each year. We use all available data at the county-level to calculate an average if specific county-crop-year combinations production estimates are missing. Crops are dropped if no bushel estimate is available in any year. Because NASS either provides an estimate for acreage, yield, and production or does not provide an estimate for any, the same commodities that are dropped for the calculation of z and $\bar{q}$.

The $p_{i,j,t}$'s are obtained from NASS state-wide average price received for commodity j in year t. Hence, every county in a given state is assumed to have received the state-wide average price. While we cannot capture price variations within a state, this measure does allow us to capture geographical variations across states and variations in prices over time.

Appendix II: State-Level Summary Statistics

State Summary Statistics for average output, number of grain farms, output price index, contract choice, input price, and production history

Kansas (104 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.41	0.29	0.10	1.90	1.19	1.34	0.19	9.30	0.88	1.13	0.10	9.30
n	377.10	170.82	54.00	1011.00	212.88	115.44	9.00	705.00	278.57	161.58	9.00	1011.00
P	104.96	5.72	100.00	117.45	196.70	70.93	107.17	309.29	160.00	71.07	100.00	309.27
z	42.04	19.12	5.96	87.94	76.25	12.96	40.06	98.94	62.57	22.94	5.96	98.94
w	8.92	0.43	8.49	9.34	20.53	7.42	10.72	28.60	15.89	8.09	8.49	28.60
$\bar{q}$	48.27	13.27	30.93	105.06	56.68	15.50	32.48	109.74	53.31	15.21	30.93	109.74

Montana (34 counties)

	Pre-ARPA 1992, 1997				Post-ARPA 2002, 2007, 2012				All Years			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.75	2.52	0.18	3.84	2.92	3.66	0.11	21.13	2.06	3.05	0.11	21.16
n	200.74	120.87	26.00	479.00	90.97	87.03	4.00	386.00	134.87	115.01	4.00	479.00
P	103.27	4.55	100.00	126.01	188.40	54.26	111.77	262.90	154.35	59.31	100.00	262.90
z	56.13	22.42	7.95	99.49	71.57	21.47	17.20	99.54	65.40	23.07	7.95	99.54
w	10.15	0.77	9.39	10.92	21.41	7.64	11.38	29.80	16.91	8.11	9.39	29.80
$\bar{q}$	31.42	9.67	18.06	57.26	34.95	10.68	23.29	65.95	33.53	10.40	18.06	65.95

North Dakota (31 counties)

	Pre-ARPA 1992, 1997				Post-ARPA 2002, 2007, 2012				All Years			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.29	0.26	0.08	1.85	0.69	0.71	0.12	4.98	0.53	0.60	0.08	4.98
n	408.71	188.36	54.00	868.00	226.20	138.98	15.00	615.00	298.41	182.93	15.00	868.00
P	107.61	8.64	100.00	129.37	208.13	68.81	109.34	306.86	167.93	72.79	100.00	306.86
z	67.16	11.08	35.17	87.70	89.86	6.57	71.78	99.96	80.78	14.10	35.17	99.96

w	9.49	0.20	9.29	9.68	21.73	7.97	11.34	30.57	16.87	8.63	9.29	30.57
$\bar{q}$	32.10	6.97	22.21	50.03	41.05	11.61	27.12	78.46	37.46	10.63	22.21	50.03

Oklahoma (41 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.56	0.67	0.12	3.70	1.56	1.85	0.27	11.76	1.16	1.57	0.12	11.77
n	337.60	199.27	27.00	777.00	134.72	105.57	7.00	463.00	215.87	179.88	7.00	777.00
P	103.09	4.97	100.00	118.75	132.24	8.54	122.26	150.77	120.58	16.07	100.00	150.77
z	24.20	17.74	0.88	77.01	57.00	21.32	9.61	92.00	44.00	25.45	0.88	92.00
w	8.69	0.31	8.37	8.99	20.00	7.52	9.99	28.01	15.47	8.05	8.37	28.01
$\bar{q}$	30.71	5.55	20.17	53.77	33.88	8.07	22.96	70.40	32.61	7.31	20.17	70.40

Washington (11 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	4.11	15.59	0.11	73.68	1.21	1.77	0.16	7.43	2.37	9.92	0.11	73.68
n	354.27	253.89	2.00	924.00	207.00	152.30	22.00	680.00	265.91	210.04	2.00	924.00
P	95.61	4.59	89.70	100.00	173.59	51.40	100.50	223.06	142.40	55.32	89.69	223.06

z	39.09	16.62	3.54	76.77	66.71	17.30	16.80	95.61	55.66	21.73	3.54	95.61
w	9.97	0.51	9.47	10.46	22.20	8.56	11.08	31.47	17.31	8.95	9.47	31.47
$\bar{q}$	37.02	6.41	24.06	46.77	39.97	5.42	26.18	48.52	38.79	5.96	24.06	48.51

Illinois (94 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.24	0.23	0.07	2.18	0.33	040	0.07	5.20	0.29	0.34	0.07	5.20
n	587.31	297.11	55.00	1482.00	416.33	223.62	17.00	1169.00	484.72	268.68	17.00	1482.00
P	108.66	8.79	100.00	121.02	195.68	77.26	99.45	312.88	160.88	73.68	99.45	312.88
z	26.05	15.09	2.34	71.27	64.42	15.46	22.47	97.71	49.07	24.25	2.34	97.71
w	9.37	0.58	8.79	9.95	20.92	7.53	11.03	29.3	16.30	8.14	8.79	29.30
$\bar{q}$	78.10	14.93	45.82	110.65	99.88	22.63	47.94	155.90	91.17	22.58	45.82	156.90

Indiana (79 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.24	0.23	0.07	2.18	0.33	040	0.07		0.29	0.34	0.07	5.20

n	587.31	297.11	55.00	1482.00	416.33	223.62	17.00		484.72	268.68	17.00	1482.00
P	108.66	8.79	100.00	121.02	195.68	77.26	99.45		160.88	73.68	99.45	312.88
z	26.05	15.09	2.34	71.27	64.42	15.46	22.47		49.07	24.25	2.34	97.71
w	9.37	0.58	8.79	9.95	20.92	7.53	11.03		16.30	8.14	8.79	29.30
$\bar{q}$	78.10	14.93	45.82	110.65	99.88	22.63	47.94		91.17	22.58	45.82	156.90

Iowa (98 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.16	0.05	0.07	0.35	0.31	0.16	0.11	1.01	0.25	0.14	0.07	1.01
n	680.04	208.83	293.00	1445.00	436.78	147.07	120.00	900.00	534.08	211.14	120.00	1445.00
P	108.06	8.10	100.00	119.29	206.53	83.11	105.50	331.61	167.14	80.60	100.00	331.61
z	51.84	16.08	6.80	83.12	82.97	10.72	41.55	99.09	70.52	20.12	6.80	99.10
w	9.11	0.39	8.72	9.49	20.55	7.60	10.49	28.80	15.97	8.13	8.72	28.80
$\bar{q}$	84.65	10.14	59.17	120.96	108.14	17.02	67.96	151.00	98.75	18.63	59.17	151.00

Minnesota (74 counties)

Pre-ARPA 1992, 1997	**Post-ARPA 2002, 2007, 2012**	**All Years**

	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.31	2.51	0.07	4.65	0.62	0.64	0.13	5.20	0.50	0.59	0.07	5.20
n	588.90	287.92	47.00	1548.00	380.56	187.58	30.00	1198.00	463.89	254.05	30.00	1548.00
P	105.81	5.97	100.00	114.37	205.17	81.41	103.13	327.41	165.42	79.75	100.00	327.41
z	44.23	23.48	2.91	92.21	79.60	18.86	10.90	99.50	65.50	27.07	2.91	99.50
w	9.78	0.67	9.11	10.45	21.05	7.51	11.24	29.42	16.45	8.03	9.11	29.42
$\bar{q}$	71.43	17.90	32.98	117.14	92.93	25.55	29.83	144.91	84.33	25.10	29.83	144.91

Nebraska (81 counties)

	Pre-ARPA 1992, 1997				**Post-ARPA 2002, 2007, 2012**				**All Years**			
	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.	Mean	S.d	Min.	Max.
q	0.76	1.56	0.11	12.5	1.17	2.57	0.12	19.04	1.00	2.23	0.11	19.04
n	315.82	167.67	8.00	842.00	253.54	139.02	6.00	700.00	278.45	153.99	6.00	842.00
P	105.75	6.04	100.00	114.61	200.91	79.10	105.54	323.79	162.85	77.08	100.00	323.79
z	50.57	18.75	8.47	89.70	85.49	8.11	49.81	98.51	71.52	21.75	8.47	98.51
w	9.36	0.27	9.09	9.62	21.14	7.76	10.86	29.59	16.42	8.34	9.09	29.59

$\bar{q}$	88.04	25.67	30.95	143.45	101.95	26.62	35.70	162.75	96.39	27.08	30.95	162.75