Title: The Impact of Farm Level Variables on Federal Crop Insurance Coverage Selections

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Introduction

The federal crop insurance (henceforth, FCI) program has become the mainstay of U.S. agricultural support and is the single largest agricultural insurance program globally (Woodard and Yi, 2019). In 2019, the FCI program serviced 2.2 million policies, collected 3.8 billion in farmer paid premiums, and covered a total of 109.9 billion in crop liability.[1] While FCI as a percentage of the total USDA budget remains a relatively small portion (around 6.2% in 2019) of the total USDA budget, the Risk Management Agency (RMA) still accounts for a significant total budget of $8.7 billion.[2] With participation rates in major crop states estimated to be well over 90% based on National Agricultural Statistic Service (NASS) data, crop insurance is an important economic topic in rural America as well as to taxpayers.[3] Past crop insurance studies have evaluated insurance premium rate design, FCI demand elasticities, moral hazard, participation decisions, and the effects of crop insurance on other producer decisions (Sherrick et al. 2004; Just et al. 1999; Goodwin et al. 2004; Woodard and Yi, 2019). Existing research however, appears to lack a clear explanation for why producers choose to insure at widely differing coverage levels. The finding that many producers select coverage levels below the maximum level remains counter to any reasonable utility model predictions given the subsidized nature and significantly positive expected return on farmer-paid premiums.

This study hypothesizes that producers choose to insure under different coverage levels based on expected or perceived cash flow constraints, while controlling for a number of other

[1] https://www3.rma.usda.gov/apps/sob/current_week/crop2019.pdf

[2] https://www.usda.gov/sites/default/files/documents/fy19-budget-summary.pdf

[3] (http://www.rma.usda.gov/data/sob.html) The Summary of Business provides regularly updated federal crop insurance data for the entire RMA book of business down to the county and unit level back to 1989.

factors such as net worth, primary crop grown, and farm size. For example, higher expected revenue per acre areas in the corn belt (e.g., Indiana) appear to insure at relatively high coverage levels, while lower expected revenue areas such as states in the high plains (e.g., North Dakota) insure at relatively lower average coverage levels (figure 1). We postulate that previous approaches employing utility theory to predict farmer choices have failed to accurately explain farmer choices in the past, due to failure to account for short-term liquidity constraints. This study attempts to evaluate whether the net of annual expected costs and revenues (i.e. cash flow) influences different coverage level selections.

Variables such as higher revenue and higher costs are expected to be positively associated with coverage level selections. Producers are assumed to make expected profit maximizing decisions with risk neutral preferences regarding crop coverage selections. Given that crop insurance is legally required to be actuarially fair (Coble et al., 2010) and that subsidies lower farmer-paid crop insurance premiums, crop insurance can both minimize risk and maximize expected profits when coverage levels are maximized under both risk aversion or risk neutrality assumptions of expected utility maximization. However, despite this assertion, farmers regularly choose lower than maximum coverage levels (Ginder et al., 2009)

Understanding the associations between coverage level selection and farm-specific variables has value in regard to agriculture sector policy, as well as determining total FCI program liability levels. In addition, understanding these associations has industry relevance, as it is in the interest of the companies and agents approved to sell FCI to maximize coverage levels and participation rates, thereby maximizing premium and commission collection. Further, the literature suggests FCI decisions have a wide range of effects, including influencing land values,

farmer crop type choices, farm debt levels, environmental health, and input level choices (Goodwin et al. 2004; Young et al. 2001; Atwood et al. 1996; Walters et al. 2012; Mishra et al. 2005).

Past efforts to understand these attempts have determined that farmers' choices do not appear to coincide with standard expected utility maximization framework (Du, Feng, and Hennesy, 2016). The standard methodology assumes farmers maximize end of period wealth by choosing input levels, including crop insurance coverage level, subject to a constraint (Sherrick et al. 2004; Smith & Baquet, 1996). A higher return on investment is assumed to increase a farmer's utility depending on the risk level and the farmer's preferences. Some studies have pointed out the rationale behind selecting the maximum coverage level or subsidy rate in order to maximize subsidy dollar extraction, thereby maximizing utility (Babcock, 2011; Barnett & Coble, 2011). Several studies using a variety of methodologies have attempted to explain the anomaly of apparent under-insurance through the selection of low coverage levels (Du, Hennesy, & Feng 2013; Du et al. 2016; Babcock, 2015). This is the first study to utilize a national farm level dataset to more comprehensively examine the associations between farm specific factors including input costs, revenues, assets, and liabilities and coverage

Theoretical Methodology

Under a profit maximization framework, the utilization of a higher coverage level involves exchanging a costlier fixed premium expense for a higher yet indeterminate conditional indemnity. The balance of real or self-imposed liquidity constraints and debt obligations are accounted for in this model, as it may constrain the farm from increasing its coverage level even

if the expected return from doing so would be positive. The payment of a higher premium due to a higher coverage level selection is a downward shift of the revenue distribution by the amount of the premium minus subsidy; the upward shift due to an indemnity receipt is based on a producer's given yield probability distribution for a given crop.

While a profit maximization model is utilized here, characteristics from Agricultural Resource Management Survey (ARMS) such as education and operator age are also considered, as well as other household and demographic characteristics that may impact insurance decisions. In addition, alternative income sources are considered as these are likely to affect the cash constraint and perceived revenue risk of the producer, thus off-farm income earned by both the producer and other household members is considered. The degree and type of farm indebtedness in addition to other potential determinants would also likely affect the producers' perceived risk.

Now consider a profit maximization framework subject to a liquidity constraint, as shown in equation (1). Producers are assumed to maximize the expected profit at year end by choosing the number of acres of each crop type and input levels including the coverage level of their crop insurance policy. Expected profit is equal to the discounted value of the difference between revenue and costs from period t to the terminal time T, which can be written as

(1)

$$\text{Max } E[\pi] =$$

$$E\left[\sum_{t=1}^{T} a_{it}\left(\sum_{i=1}^{I} P_{it}Y_{it} + I_{it}\left[Y_{it}^{b}, Y_{it}, P_{it}^{b}, P_{it}, L_{it}\right] - \theta_{it}\left[Y_{it}, P_{it}, L_{it}, s_{C_{it}}, F_{it}\right] - \sum_{j=1}^{J} w_{it}X_{it} - C_i\right)\right.$$

$$\left. - \lambda_1\left[\theta_{ij}\left[Y_{it}, P_{it}, L_{it}, s_{C_{it}}, F_{it}\right] + \sum_{j=1}^{J} w_{it}X_{it} + C_i - M_t(\pi_{t-1}, B_t(E_t))\right] + GOVT_{it}\right]$$

where the subscript *t* denotes year and the subscript *i* denotes the crop j indicates the input, and E is the expectation operator. The harvest price of the *i*-th crop at time *t* (P^b_{it}) reflects the market price for crop *i* during harvest. The projected (expected) price is denoted by P_{it}. Since the projected price is denoted from the futures price, the farmer's expectation and the RMA projected price are assumed to be the same. Yields are denoted by (i.e. the harvest yield) Y_{it}^b, planted acres by $a_{it,}$ the expected indemnity to be received from crop insurance by *I*, and crop insurance premium by θ_{it}. Crop insurance indemnity I_{it} is a function of a producer's actual production history (APH) yield (expected yield based on the ten year history of production for a particular crop and unit on a producers farm) for individual crop insurance *Y*, the projected price P_{it}, the harvest price P_{it}^b (which is assumed to be the same for both the insurance price and the price actually received by the producer), and the coverage level L_{it} the producer selects, which is our choice variable of interest.

Crop insurance premium expense θ_{it} is a function of APH/expected yield Y_{it}, price P_{it}, coverage level L_{it}, subsidy rate $s_{C_{it}}$(which is a function of coverage level and unit selection), and F_{it}, a vector of county, farm, and unit specific coefficients. X_{it} is the quantity of inputs and the w_{it} is the associated cost. C_i is the respective summed fixed cost associated with each crop type, we assume fixed cost are fixed over a number of years, hence the single subscript *i*. Other revenue may be received in the form of additional supplemental options through the farm service agency ($GOVT$), which includes Area Revenue Coverage and Price Loss Coverage. These payments enter the profit maximization model as additional income in each period.

The liquidity constraint is included in the λ term. In the constraint, the profit maximization equation is subject to an available cash constraint where premium costs, other

variable input costs, and fixed costs must be covered by the available liquid capital the farm has at its disposal; $M_t(\pi_{t-1}, B_t(E_t))$, where M_t is liquid assets as a function of the previous year's profit and the amount the farmer is willing or able to borrow against their equity $B_t(E_t)$. B_t is assumed to be a potentially binding constraint based on the financial position of some producers, such as those that have insufficient collateral to borrow sufficient funds to purchase optimal input quantities. It should be noted that it may be the case that the credit constraint faced by a farmer might be better considered a maximum willingness-to-borrow or an unwillingness to increase their debt-to-asset ratio due to risk aversion (see Atwood et al., 1996). After all it is reasonable to assume some producers insuring at lower coverage levels may nonetheless have sufficient equity in their operation to borrow additional working capital to maintain the optimal quantity of inputs.

In this model, choice variables include; coverage level L_{it}, planted acres a_{it}, and the quantity of inputs X_{it}, of which coverage level is our variable of interest. All other variables are considered exogenous parameters for the purpose of this study.

Solving equation (1) for crop insurance coverage level leads to the optimal insurance coverage level, expressed as exogenous variables. Where L_{it} is a function of (P, Y, s_c, Y^b, F, w, C) and a_{it} is a function of (P, Y, s_c, F, w, C). How producers respond to changing subsidy rates depends on the functional form of each equation, which is dependent on farm specific traits and characteristics and on their expectation of the first and the higher instances of prices and yields or their amalgamation in the form of revenues and costs, hence the inclusion of the other variables.

Our variable of interest, the coverage level selection, enters into the model as a function of indemnity and premium. The first order condition for our variable of interest is $\frac{\partial \pi}{\partial L} = E[a\left[\frac{\partial I}{\partial L} - \frac{\partial \theta}{\partial L} + \frac{\lambda \partial \theta}{\partial L}\right]] = 0$, where the sign is dependent on the functional form of the premium and indemnity calculation. We interpret this to mean a producer will, on the margin, increase their coverage level subject to the liquidity constraint. Thus, $\frac{\partial \theta}{\partial s} < 0$. In addition, while not a direct derivation from the model, considerable aggregated evidence in the literature indicates $\frac{\partial L}{\partial s}$ >0, meaning increased subsidy rates result in higher coverage level selection (O'Donoghue, 2014).

As shown in the model, coverage level decisions enter the model as functions of expected indemnity payments and known premium cost. It should be noted L_{it} is technically a discrete choice variable, which for individual level plans (RP and YP) has eight options, $L_{it} = (.50, .55, .60, .65, .70, .75, .80, .85)$. However, the ARMS data requests that producers take the average of their coverage levels, in the case they are insuring under more than one policy, this means that many observations are averages between these discrete choices. The producer is likely presented with the options of different premium costs at different coverage levels by their agent, in addition to having the option to estimate their premium at each coverage level using online calculator available from the AIPs and RMA. The profit maximizing producer would choose the coverage level based on the likelihood of indemnity, while accounting for premium expense and cash flow constraints.

The first order conditions for both the input quantity and coverage level choices indicate that farmers will increase both subject to the liquidity constraint, with coverage level being

maximized subject to the liquidity constraint and inputs being optimized. However, the results are ambiguous in regard to how producers will choose between the two options in the presence of a constraint. If the price of variable cost inputs rise, will a producer choose to decrease their coverage level and retain their current fertilizer and chemical application levels or vice versa? The return on both are assumed to be positive, with the difference being long term (multiple years) versus short term (1 growing season) payoffs. Our empirical model and variables of interest provide some insight into these decisions and farmers' choices between substitutes.

Data

We utilize three separate data sources in order to examine the relationship between farm-level coverage level choices with farm-level and regional characteristics. First, The Summary of Business (SOB)[4] data from the Risk Management Agency includes county-level farm premium, subsidy, indemnity payments, which are used as a proxy for production risks and to calculate historical loss ratios. Data from the SOB are nationally available and aggregated by policy sold in each county back to 1989. Second, the RMA Actuarial Data Master Files (ADM) data include premium base rates for particular crops, policies, practices, and types, in addition to policy and crop specific differences. These are the base insurance rates used to price insurance policies by multiplying the rate by total dollars of liability before any loading factors are added. This research utilizes this data as a proxy for premium costs for crop insurance.[5] Finally, the ARMS data are a nationally representative farm level survey conducted annually by NASS and the USDA Economic Research Service (ERS). The ARMS is the primary source of information in

[4] https://www.rma.usda.gov/SummaryOfBusiness
[5] https://legacy.rma.usda.gov/FTP/References/

this study and is used to estimate associations between farm-level financial and production variables related to coverage level selection decisions.[6]

Federal Crop Insurance Rating Data

Crop insurance premium calculations involve numerous input variables with the rating of individual plans based upon a producer's unique APH, the county of the farm, the loss history and amount of data available in that county, the coverage level selected, RMA's detrended yield estimate, the projected price, price volatility factor for revenue insurance, and heteroskedasticity adjustments.[7] Area-based insurance policies are also affected by these factors with the exception of the use of APH, which utilize county yields in the place of a producer's individual yield history. This research utilizes Area Yield Protection (AYP) base rates for individual coverage levels as a proxy for the cost of insurance in a particular county as well as a measure of risk with higher base rates being associated with higher likelihood of crop loss. Individual farm-level yields are more variable than county yields, thus rates are higher for individual plans. However, the county level base rates provide a useful approximation of the relative variance in premium rates across counties.[8]

The RMA ADM data includes base rates for insurance plans by coverage level, county, and year for the variety of crop insurance plans available from the RMA. Area Risk Protection (ARP) base rates are from the RMA online database for 2014 and 2016 for corn. Base rates differ for the respective crops depending on type and practice.

[6] https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices.aspx
[7] Note: volatility factors and heteroskedasticity adjustments are only utilized in pricing revenue plans
[8] An online premium estimator is available on the RMA's website, which allows users to examine premium differences across policies

While base rates differ across coverage levels, the shape and slope of which differ by county and crop. Some counties exhibit more of an exponential shape in their coverage levels, as opposed to a linear shape. Counties that exhibit an exponential shape will reduce the benefits of higher coverage levels and may encourage lower coverage level selections since the rates increase faster for higher coverage levels. For example, figure 2 shows two representative counties that exhibit different relationships between coverage level and base rates. Washburn County WI is shown to have a linear slope and Harrison County, IA increases at an exponential rate. Regional differences between linear and exponential changes are illustrated in figure 3 where the number 0 indicating a county where rates increase in an exponential shape as coverage level increase and 1 indicating counties where rates increase linearly.

As can be seen, the rates for counties outside of the heart of the corn belt are more likely to increase in a linear shape, particularly for soybean. We hypothesize this is due to low risk counties having a higher probability of shallow losses, thus making the higher coverage levels more expensive relative to lower coverage levels. As opposed to counties outside of the most productive and low risk areas, where a more signifcant loss is more likely relative to the liklihood of a shallow one, thus the base rates for the lower coverage levels are higher relative to counties with base rates exhibiting an exponential shape. In order to account for this difference, which has the effect of making the higher coverage levels relatively more expensive compared with midrange lower coverage levels in counties with an exponential function curve shape, a binary indicator variable was constructed representing whether a producer's farm is located in an exponential or linear shaped base rate county.

This shape was determined by defining whether the average of the .90 and .70 coverage level base rates (plus .0075 to account for slight nonlinearities[9]) is greater than or less than the .80 coverage level base rate. Indicating whether a county's base rates increase in a linear or exponential fashion as coverage level rises.

Federal Crop Insurance Experience Data

The RMA summary of business contains regularly updated data on all federal crop insurance policies sold. This data includes premium rates, indemnities, subsidies, liabilities, and acres insured, broken down by units and coverage levels down to the county level.

There are three ratios typically used in the evaluation of a policies insurance experience. First the loss ratio is the relationship between indemnities and premiums under a policy. Second, loss cost ratios (LCR) reflect the recent actual realized risk in an insurance program, i.e., the percentage of the potential total loss which was actually realized in a given year. Third, earned premium rates (EPR) were derived by taking total premium paid over total liability. This ratio provides a recent return on total risk from the perspective of the insurance company, while providing the average premium rate paid per dollar of liability from the perspective of the producer.

Loss ratios were calculated by dividing indemnities paid by earned premiums in each individual year for each county. Areas with higher relative production risks tend to correlate with higher relative loss ratios. Premiums and indemnities were aggregated to the county level for a given year and crop and then the ratio of indemnity to premium payments in a given year gives

[9] This number was chosen to account for slight nonlinear variations, which were imperceptible based on visual appraisal.

us the loss ratio. As EPR and LCR both have total liability as their denominator, when the LR is 1.00, which means total indemnity and total premium are the same, LCR and the EPR must equal one another. Because of this, given that RMA's all crop long term target loss ratio is 1.00, as mandated by the Food, Conservation, and Energy Act of 2008 (Coble et al., 2010), over time LCR and EPR should equal one another. EPR is typically a low volatility measurement temporally, as it is a function of the relatively stable measures of total liability and total premium.

For this research, five-year county level loss ratios were utilized to represent the expected return on premium to producers in that county that is based on recent experience. It should also be noted that the 2014 5-year loss ratios contain loss data for 2012, which was a record loss year. However, given that the yield losses of 2012 were likely still fresh in operator's memories when making their insurance decisions in 2014 and would be somewhat "watered down" when they made their 2016 coverage decisions, we do not believe this to be problematic.

Farm Level Data

The ERS and NASS have conducted ARMS each year since 1996. The ARMS is one of the main sources of information to the USDA for a variety of topics including agricultural resource use, costs, and farm sector financial conditions. The ARMS serves as a valuable source of farm-level data, in part because it asks producers for sensitive information such as debt to asset ratios, income, and ethnicity in addition to being relatively comprehensive. It is conducted in three phases and is the largest nationally representative farm-level survey that is conducted annually.

The ARMS samples are designed to provide representative coverage for all farms in the 48 contiguous states. The population samples included all businesses that have sold at least $1,000 of agricultural products in the previous year. The ARMS dataset provides weights to correct for sample selection bias that are based on the probability of being selected and producer response from the national population of farm businesses. This study focuses on corn production, which accounted for $64.3 billion in sales, according to the 2012 NASS Census of Agriculture. Analysis was also conducted on soybeans and wheat, which accounted for $35.9 billion and $14.2 billion in sales respectively, but is not included in this paper for a couple of reasons. First, coverage level decisions regarding corn insurance policies provide the widest regional and coverage level variation. Second, many of the key findings with corn are also consistent with the analysis with soybeans and wheat. The results from those regressions are provided in the appendix (tables A1 and A2).

The ARMS is considered representative of producer decisions regarding crop insurance and coverage level at the national level. Weber and Clay (2013) evaluated the significance of the effect of nonresponse bias in ARMS. Using a Probit model, Weber's findings suggested the nonresponse bias in coefficient estimates have a low magnitude and frequency. Meaning nonresponse bias is predicted to have a minimal effect on econometric models using ARMS. There were no results in which a coefficient estimated from the respondent subsample was outside of a 95% confidence interval. This result was despite data from ARMS and the Census of Agriculture showing non-respondents tend to operate larger farms than producers choosing to respond, even when region, commodity, and household were controlled for. It should be noted that there are obvious input cost and production differences between states, which is partially

addressed through the use of a fixed effects model. Since coverage level selection differs significantly in different growing regions, correlation between production factors and coverage level selection would lend evidence toward solving the geographic heterogeneity puzzle.

In 2014 and 2016, the ARMS included (for the first time) additional questions regarding crop insurance choices including coverage levels specific crops and plans. Since the ARMS data are a stratified pooled cross section, i.e. a different random sample of farms is surveyed each year; we cannot observe how an individual farm's coverage decisions change over a period of years.

This study uses a number of observational variables available through the ARMS including, farm household and operator characteristics, household and farm financial variables, crop and farm inputs, crop insurance selections, farm and household liabilities, asset totals, and financial ratios. These are included to examine the association between these variables and coverage level selection. Table 1 contains a summary of these variables and their definitions.

Household and operator characteristics are included in order to help explain the variation in coverage level selection across farms. These characteristics include operator age, number of owners, and operator education. Operator age is the age of the primary operator. Number of owners is a numerical variable designating the number of owners an operation has. The ARMS classify education under four indicator categories; (1) Less than a High School diploma, (2) a High School diploma, (3) some College including an Associate's Degree, and (4) at least a four-year college degree. The potential effects of these variables are discussed in later sections.

Farm financial variables related to revenue and expenses are included to help explain a producer's ability to purchase higher coverage crop insurance as well as cover their costs in the

event of a loss. On the revenue side, Off-Farm Income is the amount of income earned off of the farm by the household. Gross Farm Income is the total amount of income earned by the farm.

On the expense side, variables for both fixed and variable costs are included. These are the sum of variable and fixed costs as determined by the ARMS. A number of variables are used to account for a farm's debt and equity. These include the debt to asset ratio, net worth, and total debt (farm and non-farm). Additional variables are used to account for farm size, including total crop acres, as well as the amount of land owned, rented at a fixed rate, flexible rate, and on shares. The number of acres insured is also included. Table 2 contains descriptive statistics permitted by the ARMS for the data utilized by this study. Each observation of the ARMS variables discussed above was individually evaluated for outliers and declined responses (shown as -1s in the ARMS data). Observations with declinations to respond for explanatory variables were removed.

Empirical Methodology

This study empirically identifies the associations between cash constraint related farm level variables and coverage level selection. In particular, the differences in size and effects of the associations between different types of costs and revenue on coverage choices are of interest. The following equation characterizes the linear relationship between coverage level selected ($CovL_{icp}$) by entity *i*, for crop *c*, under policy *p*, in year *t,* and the effect of revenue, costs, crop, and farm acreage totals, insurance units, rating, insurance experience, and farmer/household characteristics. As this model utilizes an independently pooled cross section of the 2014 and 2016 ARMS data, the observations are weighted based on the weights provided by the ARMS,

which are based on the probability of an operation being selected from the national farm population.

$$CovL_{icpt} = \beta_0 + \beta_1 \mathrm{OFI}_{icpt} + \beta_2 \mathrm{GFIacre}_{icpt} + \beta_3 VCacre_{icpt} + \beta_4 FCacre_{icpt} + \beta_5 LR_{cpt} + \beta_6 EPR_{cpt} + \beta_7 BaseRate70_{cpt} + \beta_8 BRslope_{cpt} + \beta_9 DAR_{icpt} + \beta_{10} NetwAcre_{icpt} + \beta_{11} TotAcres_{icpt} + \beta_{12} Y2016_{icpt} + \beta_{13} NofOwns_{icpt} + \beta_{14} Oeduc_{icpt} + \beta_{15} Age_{icpt} + \sum_{i=1}^{c-1} \beta_{16} CF_i + u_{icpt} \quad (2)$$

The explanatory variables in the above equation are off-farm income earned by household (OFI_{icpt}), gross farm income per acre ($GFIacre_{icp}$), total variable expenses per acre ($VCacre_{icpt}$), total fixed expenses per acre ($FCacre_{icpt}$), county average 5-year loss ratio (LR_{cpt}), farm's county earned premium rate (EPR_{cpt}), each farm's county base rate (*BaseRate70*), a dummy variable of whether the county base rates associated with each coverage level increase with an exponential or linear slope ($BRslope_{cpt}$), farm business debt to asset ratio (DAR_{icpt}), net worth per acre ($NetwAcre_{icpt}$), the farm's total crop acres ($TotAcres_{icpt}$), number of owner's ($NofOwns_{icpt}$), indicator of operator's education ($Oeduc_{icpt}$), and operator's age (Age_{icpt}). In order to control for the upward trend in coverage level, a dummy variable for the year 2016 (*Y2016*) is included. This controls for the effect that programs such as the Supplemental Coverage Option (SCO), which took effect in 2015, may have had.

The end term u_{icpt} represents the random error term that includes unobservable traits and characteristics influencing a farmer's coverage level selection choice. Variables that were

initially considered and found to be insignificant to coverage level decisions and highly correlated with other variables were removed and include; ratio of farm household income to total household income, interest and principal payments per acre, total farm operator debt per acre (farm and non-farm), total acre leased variables, crop specific acres insured, alternative or competing crop acres insured, and Current Ratio.

The ratio of off-farm income to total farm income was considered but removed due to collinearity with the off-farm income earned by household and gross farm income per acre variables. Since the focus is on cash flow constraints, we believed these two variables more accurately measure the effects of revenue on coverage decision making when evaluated separately. Other potential acreage control variables were not included due to correlation with the farm's total crop acres variable. Current Ratio was not included due to a low response rate, decreasing the number of observations.

Fixed Effects Model

A fixed effects model is included additionally with the linear model to eliminate the potential of unobserved potential bias due to unobserved confounding county-level differences, such as insurance agent density, which might affect coverage level selection, but are not controlled for directly in the model. As discussed previously, the differences in coverage level selection between states are significant, which means the FE model is eliminating a substantial amount of variation if that variation is not accounted for by the explanatory variables. When the fixed effects model is utilized, the parameter estimates are identifying variation between farms within a state. County variables are represented by $\sum_{i=1}^{c-1} \beta_{16} CF_i$ in equation (2), where c is the number

of counties included in the model. Both state and county level fixed effects were considered. Since many counties might have only two or three observations, there was some concern that the majority of the variance would be removed, however when the model is run using either specification, the results stay remarkably consistent. Thus, in order to account for differences in growing conditions, premium rates, and agent density, with the greatest precision, county level fixed effects were used. The inclusion of county fixed effects eliminates variation between counties so that the variation in the dependent variables used to identify the parameter estimates is the variation between producers within an individual county.

Results and Implications

The results in Table 3 include six regression specifications. From left to right, the results in column (1) use Ordinary Least Squares with all variables included, while column (2), includes the same variables with the addition of county-level fixed effects. The results in columns (2), (4), and (6) are based on county-level fixed effects, while the remaining columns are simple ordinary least squares estimates without county fixed effects. The results reported in columns (3) and (4) exclude the 5 year average earned premium rate (*Yr5EPR*). Finally, the results reported in columns (5) and (6) exclude the two base rate variables (*BaseRate70*, *BRslope*), which allows for additional observations, since base rates are only available counties and states where the Area Yield Protection plan of insurance is offered. Though the AYP counties do account for the majority of the production and thus most of the corn belt, the observations outside of the AYP offer area are not included except in columns (5) and (6) due to the unavailability of the base rate

data. Results are attained across all farms in the annual ARMS sample across the United States for all corn growing states.

Standardized Coefficients

To allow for ease of interpretation, models with standardized regression coefficients are included. This removes the potential confusion caused by unit size in the interpretation of the magnitude and importance of a variable's effect on coverage level. The standardization method utilized allows for comparison of the size of the association of the dependent variable to coverage level selection and thus for comparison of the relative strength of each variable. Put differently, the greater the absolute value of the coefficient, the more significant is the association with coverage level. The dependent variables in these models were standardized and thus utilize standard deviations as units. This standardization is achieved by subtracting the mean from the variable outcome and dividing by two times it's standard deviation. The resulting variables have a mean of zero and a standard deviation of 1 and thus measure the change in coverage level selection given a two standard deviation increase in an independent variable.

The coefficients reported in table 3 are standardized using the methodology discussed in Gelman (2008), in which he recommends standardizing each input variable by dividing by two times it's standard deviation. Note that linear rescaling of independent variables does not change the t-statistics or p-values, but can aid the coefficient interpretations. Dividing by two standard deviations allows for coefficients to be interpreted in the same way as binary inputs. The procedure scales inputs to be comparable with binary variables and be somewhat symmetric with probabilities that fall between 0.3 and 0.7. For further discussion, see Gelman (2008).

The following models are fit to transformed inputs: the binary independent variables have been centered by subtracting their specific mean in the data, while the continuous variables have been rescaled by subtracting the mean and dividing by two standard deviations. Thus, the standard z-score formula is applied with the standard deviation multiplied by two as below

$$z = \frac{x - \bar{x}}{2s}$$

The dependent variable (coverage level percentage) is not standardized in table 3, which allows for easy interpretation of the coefficients as coverage level percentages. The independent variables of interest are the first seven (cash flow related) variables included in the model, followed by the controls. Note that the dependent variable, coverage level, is technically a discrete choice set. Though producers were asked to average their coverage level across policies resulting in observations that were not in the discrete set. This means that the interpretations of the coefficients should be considered more as average associative effects on coverage level rather than changes in producers' discrete coverage choices.

Explanatory Variable Results Discussion

Comparing the results across the six columns in Table 3, the majority of explanatory variables of interest that are significant for any model are also significant in the other models. Off-Farm income is significant at the 1 percent level in all six columns, with a two standard deviation increase being associated with a 0.44 to 0.82 increase in coverage level. This may indicate off-farm income reduces the cash flow constraint as perceived by farmers, allowing them to increase their coverage selection. The reader might note the standard deviation for off-farm income is particularly large and is also highly positively skewed. Interestingly, if off-farm income

observations of over $400,000 are removed, the magnitude of the positive association between off-farm income and coverage level actually increases, indicating that off-farm income increases coverage level up to a certain level of off-farm income, at which point the marginal incentives facing a producer might change. One postulate that might partially explain this is that outliers in terms of off-farm income ($400k+), might have an entirely different set of incentives regarding risk and personal attention than an average representative producer with the median off-farm income level for the entire dataset being $27,500. For example, the positive sign of the coefficient indicates that producers who likely less liquidity constrained, due to additional off-farm income, are associated with an increase their coverage level regardless of whether outliers or higher levels of outside income are included. However, producers with extremely high off-farm incomes near the outlier zone, while not cash constrained, also are likely not at significant financial risk in the event of a crop loss, in addition to likely having significant personal and financial interests outside of farming, thus potentially warping their insurance incentives.

Gross Farm Income/Acre is significant at the 10 percent level in column (3) and the 1 percent level in columns (5) and (6). When county fixed effects are added into the model in Column 3, the coefficient loses significance as shown in Column (4). Columns (5) and (6) do not include the yield risk (BR) controls and include observations from a much larger area. Unsurprisingly, the coefficients on this explanatory variable are positive in all models for which they are significant, meaning higher gross income per acre is associated with higher coverage level selection, which is consistent with our prediction of a less binding liquidity constraint being associated with higher coverage level selection. The magnitude of this association is significantly larger in columns (5) and (6), with a 2 standard deviation increase in Gross Farm Income per

Acre being associated with a 5.38 increase in coverage level in column (5) and a (3.45) increase in column (6) when fixed effects are added in, compared with an increase of 1.84 and 0.56 in columns (3) and (4) respectively.

The estimated association between variable costs per acre and coverage level selection is consistently negative and significant at either the .05 or .01 level across the six columns when state fixed effects are used. Columns 2 and 4 lose significance as shown in table 3 when county fixed effects are added, however Column 6 is still significant at the .01 level, when county fixed effects are added. Reviewing column (1), the coefficient suggests that at the mean a two standard deviation increase in variable costs per acre is associated with a decrease in coverage level selection from 1.72 to 2.06 in columns (1) and (3), 5.94 in column (5), and 4.47 in column (6). Once again this appears consistent with our cash flow constraint predictions as it may indicate that farmers adjust their coverage levels downward to make up for a more constrained cash flow budget that would be associated with higher variable costs per acre.

While first order conditions provide ambiguous predictions regarding producer choices between inputs and coverage level selections, the presence of a liquidity constraint means that producers will on the margin choose to increase their coverage level and thereby their premium expense or if they will increase their inputs to be closer to the optimum quantities. Empirical results from this paper suggests that producers choose inputs (variable costs) over higher coverage levels (premium costs). This is in spite of the long run positive return to crop insurance premium, indicating that farmers may be focusing on remaining financially viable in the short term, particularly if they're liquidity constrained.

An increase of two standard deviations in fixed costs per acre is associated with an increase in coverage level that is significant in all six columns at the .01 level. The magnitude is also relatively consistent ranging from 2.35 in column 1 to 3.10 in column 3. The difference in sign for associated effects between fixed costs and variable costs is likely driven by a combination of cash flow constraints and risk aversion. Since fixed costs are payments that must be made regardless of revenue, profit, or cash flow, it appears that farmers may adjust their coverage level upward in order to ensure their ability to make those fixed expense payments. While farmers have very little control over fixed costs in the short run, there is greater control over adjusting variable. If variable costs are increased, it appears that farmers may respond by reducing their premium expense in order to stay within their cash flow constraint. These results support the hypothesis that differences in expected revenue and costs are likely driving some of the geographical differences in coverage level selection. Revenue per acre also appears to be positively associated with coverage level selections.

When the fixed cost variables are removed from the models and replaced with the amount of loan payments, the sign and magnitude of the two variables are similar. Note they are not included in the same models due to a high degree of collinearity, resulting in a lack of significance in the total loan payments per acre variable. Also note there is also a high degree of collinearity between variable costs per acre and gross revenue per acre, however the signs of these variables stay consistent when either of the correlated variables are removed from the models.

Reviewing the insurance cost and risk proxy variables, the 5-year loss ratio and earned premium variable signs are consistent with predictions, with each coefficient being significant at

the .01 level for both variables. A two standard deviation increase in the average five-year loss ratio is associated an increase from .92 to 1.60 across the 6 models. When premium rate and cash expenses are controlled for, farmers appear to increase their coverage levels in the presence of higher loss ratios, consistent with theoretical predictions in standard economic models.

Coverage level selection appears to be the most responsive to changes in premium rate, regardless of the model specification used. In the presence of controls, farmers reduce their coverage levels by significant magnitudes when premiums are higher per dollar of liability with a 2 standard deviation increase associated with a 3.76 decrease in coverage level in Column 6 and a 4.35 decrease in Column 2. Higher earned premium rates are associated with lower coverage levels despite the theoretically greater probability of payout and therefore higher expected total absolute return under actuarially fair rates. As a higher premium rate results in a greater burden on cash flow at higher coverage levels, this association is also consistent with liquidity constraints playing a role on insurance selections.

Farms located in counties with higher base rates are also associated with a lower coverage level. County base rates were included as a proxy representative of yield risk in a county and are theoretically disassociated with any other rating or loading factors, thus the result is to some extent unanticipated. However, higher yield risk does imply higher yield variability which would allow farms to insure at a lower coverage level and still have a similar probability of an indemnity payout to a low yield risk area.

The base rate associations appear to be consistent regardless of whether county fixed effects are included in either model, although when fixed effects are included there appears to be a slight decrease in the coefficients due to the decrease in variance. A two standard deviation

increase in the Revenue Protection (RP) corn base rate is estimated to decrease coverage level by 1.99 based on the Column (2) coefficient and 3.12 in Column 4. These results do not support suggested hypotheses that farmers insure at higher coverage levels in order to harvest subsidy through the positive return on each dollar paid in premium.

Control Variable Discussion

Debt-to-asset ratio is found to be statistically significant with a negative sign for the first four columns for which base rates are included. An increase in a farmer's debt-to-asset ratio is typically indicative of decreased solvency. However, it should be noted that such an increase may or may not be indicative of worsened financial condition. The magnitude of the estimated coefficients in both cases means that a two standard deviation increase in the debt-to-asset ratio is associated with a 1.66 to 2.34 decrease in coverage level selection in the columns for which the control variable is significant. The negative sign on the coefficients indicates that despite the requirement of crop insurance by many agricultural lenders in order to provide operating and real estate loans, it does not appear that higher debt levels are associated with higher coverage level selections.

Higher net worth per acre is consistently associated with lower coverage levels and is significant at the .01 level in all six columns. This may be mean that higher net worth farms prefer to self-insure. Note that higher net worth per acre farms are typically associated with higher coverage levels due to the noted tendency of farms located in the high value per acre corn belt to insure at higher levels, which indicates that farms in the corn belt are insuring at higher coverage levels in order to cover their revenue and costs despite their higher net worth per acre.

This is consistent with the result of (Sherrick et al. 2004), who found that producers who owned more acres were associated with greater nonuse of insurance and when they did insure, chose to insure specific risks, such as purchasing hail insurance, more commonly than lower net worth farmers whom more insured under multi-peril options.

Cropland acres is positively and statistically significant in equations (1), (2), and (4), but mixed in the remaining regressions. The number of owners is negatively and statistically significant in all regressions, indicating that an increase in the number of owners increases by 2.26 people, the expected coverage level decreases between 1.1 to 1.7 percentage points in columns (1)-(4). This impact is reduced to 0.6 percentage points in columns (5) and (6).

Operator's education is statistically significant at the .01 level in Columns (1) through (4), indicating education is positively associated with coverage level selection. The magnitude of the association is relatively insignificant however with a two standard deviation increase in education being associated with a 0.63 to 0.76 increase. Note additionally that there are only four levels of education available to select in the ARMS, and in non-standardized terms, an additional four years of education adds between 0.24 and 0.39 to coverage level.

Operator age is significant in Columns (1) through (4). An increase in age is associated with a positive effect on coverage level selection. A two standard deviation increase in operator age is associated with an increase of 0.51 to 0.82 in coverage level. In the non-standardized model, the association is more relatable where an additional 20 years of age is associated with an estimated increase in coverage level of 0.60. This result is consistent with other studies that have found individuals tend to become more risk averse as they age. It could also suggest that older

producers have a less binding liquidity constraint through a greater ability to pay the higher insurance premiums accompanying higher coverage levels.

The interpretations in the previous results discussions are mostly based on the assumption that farmers are either liquidity constrained or unwilling to increase their debt-to-asset ratio by borrowing more in order to pay their premium expense in the fall. We maintain the assumption made for the theoretical model that farmers are profit maximizers, despite not consistently buying up on their coverage in the presence of what appears to be a significant expected return on each dollar of premium paid. These results do not negate the postulate put forward in recent literature (Du. et al., 2016) that farmers are minimizing expenditures. They do however provide some insight into which types of expenditures farmers are minimizing, in particular crop insurance premium.

Conclusion and Implications

This study provides evidence that partially explains the behavioral anomaly exhibited in farmer coverage choices across differing geographic locations. Of particular interest, the results provide insight in an area where theoretical model predictions are ambiguous; do farmers substitute away from premium expense and toward direct variable input expenses in the presence of a liquidity constrain, thereby decreasing their coverage level? In addition, it allows us to identify the existence of other significant associations between coverage level and farm level characteristics, while accounting for fixed county and year factors.

In this analysis, we find empirical evidence to suggest a few notable findings. First, higher short term/variable costs are associated with lower crop insurance coverage levels.

Second, long term/fixed costs are associated with higher coverage levels. Third, higher revenue per acre and larger farms in terms of acreage tend to insure at higher coverage levels. Finally, that farmers insuring under RP policy plans, regardless of which of the three crops evaluated are grown, are price sensitive to increases in premium rates, despite strong subsidy incentives and positive long-term return expectations that accompany higher coverage levels. Taken together, these results suggest the importance of liquidity constraints when making crop insurance selections.

As to the question posed in the literature of why farmer's do not insure at the maximum coverage level given the positive long run expected return; we find that liquidity concerns may be creating what is effectively a constraint on their spending, either affecting farmers' ability to afford the premium cost of the higher coverage levels or reducing their willingness make the expenditure at least in the short term. This appears to be particularly true in areas outside of the corn belt, where revenues are lower. Thus, while a utility maximizing farmer would choose to either maximize their total dollars of subsidy received or the percentage of premium subsidized, they may not choose do so in the presence of an expected or perceived cash flow or liquidity constraint. This phenomenon is shown in our results where higher expenses or lower revenue was associated with a decrease in coverage level, across a range of modeling assumptions.

It might well be the case that the suggested credit constraint faced by farmers may be better considered a perceived constraint or a maximum willingness-to-borrow. After all, it is not unreasonable to assume some producers choosing to insure at lower coverage levels may nonetheless have sufficient equity in their operation to borrow additional working capital to maintain the optimal quantity of inputs including a higher coverage level on their crop insurance

coverage. Evidence of this occurring is limited however. If anything, producers who borrow additionally to increase their coverage levels are those with higher fixed costs who likely want to ensure a sufficient amount of revenues to pay for the higher debt levels. Thus, we postulate that in the presence of increasing input costs, producers will decrease their input quantities (including insurance premium) to a certain point, rather than borrow the additional working capital required to maintain an optimal yield and or profit maximizing input mix.

This theory is supported by the results found in Atwood et al. (1996), in which they found the high yield risk wheat farms of Montana maintained low debt-to-asset ratios, even in the presence of subsidized insurance. Hence, we suggest here that farmers likely have a minimum debt-to-asset ratio they prefer to maintain at all times, thus reducing their willingness to pay high premium costs in the short term that will likely increase their debt-to-asset ratios over the long run. Thus, in such a case as supported by our results, we believe farmers choosing to insure at lower coverage levels are attempting to ensure they remain viable over the short term (one to five years) via either a real or self-imposed budget constraint.

The findings from this empirical analysis also allow for some insight regarding policy implications, in addition to being intended to improve our understanding of the drivers or at least variables associated with different levels of coverage level selection in the event of financial changes at the farm level. The potential implications of these results have several applications and repercussions relevant to farm and FCI policy, particularly as coverage level selection is a major determinant of the total liability outstanding during any given crop year.

More specifically the results indicate that farmers might adjust coverage level selections based on changes to costs depending on the types of cost. Based on these results, long term

increases in variable costs, such as fuel and energy prices might lead to a decrease in coverage levels. While farms with higher fixed costs, such as machinery payments, will insure at higher coverage levels. A major change in the farm economy affecting input costs could thus affect coverage levels depending on whether the effect resulted in changes to fixed or variable costs. Changes in revenue could also affect coverage level selection, along with changes in the relative net worth of farms. These associations should be of interest to agricultural lenders, crop insurance industry participants, as well as the RMA due to the implications that changes in the agricultural economy may have on coverage level and thus the total insurance liability in any given area.

As the public spotlight has shifted to the cost of the FCI program and the effect of premium subsidy on farm decision making (Smith and Goodwin, 1996), a debate has emerged on whether farmers are utilizing crop insurance to manage risk or maximize return on investment. Given discussion during the 2018 farm bill negotiations, which noted suggestions to reduce costs through a variety of mechanisms, such as the removal of the harvest price option and the capping of subsidy levels (Bekkerman et al. 2019), a future reduction in subsidy rates may occur. Such a change would result in effectively higher farmer paid premium rates. When premium rates are adjusted upward, the results of this research suggest that farmers' coverage levels will be adjusted downward to account for the increased cost. Thus, this research indicates that despite premium subsidies (Goodwin & Smith 2013), farmers are highly price sensitive, indicating they view crop insurance less as an investment, but rather as a risk management tool for which annual cash flow constraints must be considered.

As a caveat to these suggestions, it should be acknowledged that based on discussion with crop insurance industry participants and agents, farmers are typically slow to respond or adjust their insurance choices. It is unknown whether this slow response is due to the potentially daunting complexity of the modern federal crop insurance program or some other factor.

References

Atwood, J. A., Watts, M. J., & Baquet, A. E. (1996). An examination of the effects of price supports and federal crop insurance upon the economic growth, capital structure, and financial survival of wheat growers in the northern High Plains. *American Journal of Agricultural Economics*, 78(1), 212-224.

Babcock, B.A. (2011). Time to revisit crop insurance premium subsidies? CARD Policy Brief 11-PB 4. Center for Agricultural and Rural Development, Iowa State University

Babcock, B. A. (2015). Using cumulative prospect theory to explain anomalous crop insurance coverage choice. *American Journal of Agricultural Economics*, 97(5), 1371-1384.

Barnett, B. J., & Coble, K. H. (2011). Understanding regional differences in farm policy preferences. *American Journal of Agricultural Economics*, aar061.

Bekkerman, A., Belasco, E., & Smith, V. H. (2019). Does Farm Size Matter? Distribution of Crop Insurance Subsidies and Government Program Payments Across U.S. Farms. *Applied Economic Perspectives and Policy*, 41(3), 498-518.

Coble, K.H., Knight, T.O., Goodwin, B.K., Miller, M.F., Rejesus, R.M. (2010). A comprehensive review of the rma aph and combo rating methodology final report. Retrieved from http://www.rma.usda.gov/pubs/2009/comprehensivereview.pdf

Du, X., Feng, H., & Hennessy, D. A. (2016). Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics*, aaw035.

Du, X., Hennessy, D. A., & Feng, H. (2013). A natural resource theory of US crop insurance contract choice. *American Journal of Agricultural Economics*, aat057.

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in medicine*, *27*(15), 2865-2873.

Ginder, M., A.D. Spaulding, K.W. Tudor, and J.R. Winter. (2009). Factors affecting crop insurance purchase decisions by farmers in northern Illinois. *Agricultural Finance Review* Vol. 69, No. 1, pp. 113-125.

Goodwin, B. K., M. Vandeveer, & J. L. Deal. (2004). An empirical analysis of acreage effects of participation in the federal crop insurance program. *American Journal of Agricultural Economics* Vol. 86, No. 4, pp. 1058-1077.

Goodwin, B.K., & Smith, V.K. (2013). What harm is done by subsidized crop insurance? *American Journal of Agricultural Economics* 95(2), 489-497.

Just, R. E., Calvin L., & Quiggin J. (1999). Adverse selection in crop insurance: actuarial and asymmetric information incentives. *American Journal of Agricultural Economics* 81 4: 834–49.

Mishra, A. K., Nimon, R. W., & El-Osta, H. S. (2005). Is moral hazard good for the environment? Revenue insurance and chemical input use. *Journal of Environmental Management*, 74(1), 11-20.

Mossin, J. (1968). Optimal Multiperiod Portfolio Policies. *Journal of Business*, 41, 215-229.

Sherrick, B. J., Barry, P. J., Ellinger, P. N., & Schnitkey, G. D. (2004). Factors influencing farmers' crop insurance decisions. *American Journal of Agricultural Economics*, 86(1), 103-114.

Sherrick, B. J., Zanini, F. C., Schnitkey, G. D., & Irwin, S. H. (2004). Crop insurance valuation under alternative yield distributions. *American Journal of Agricultural Economics*, 86(2), 406-419.

Smith, V. H., & Baquet, A. E. (1996). The demand for multiple peril crop insurance: evidence from Montana wheat farms. *American Journal of Agricultural Economics*, *78*(1), 189-201.

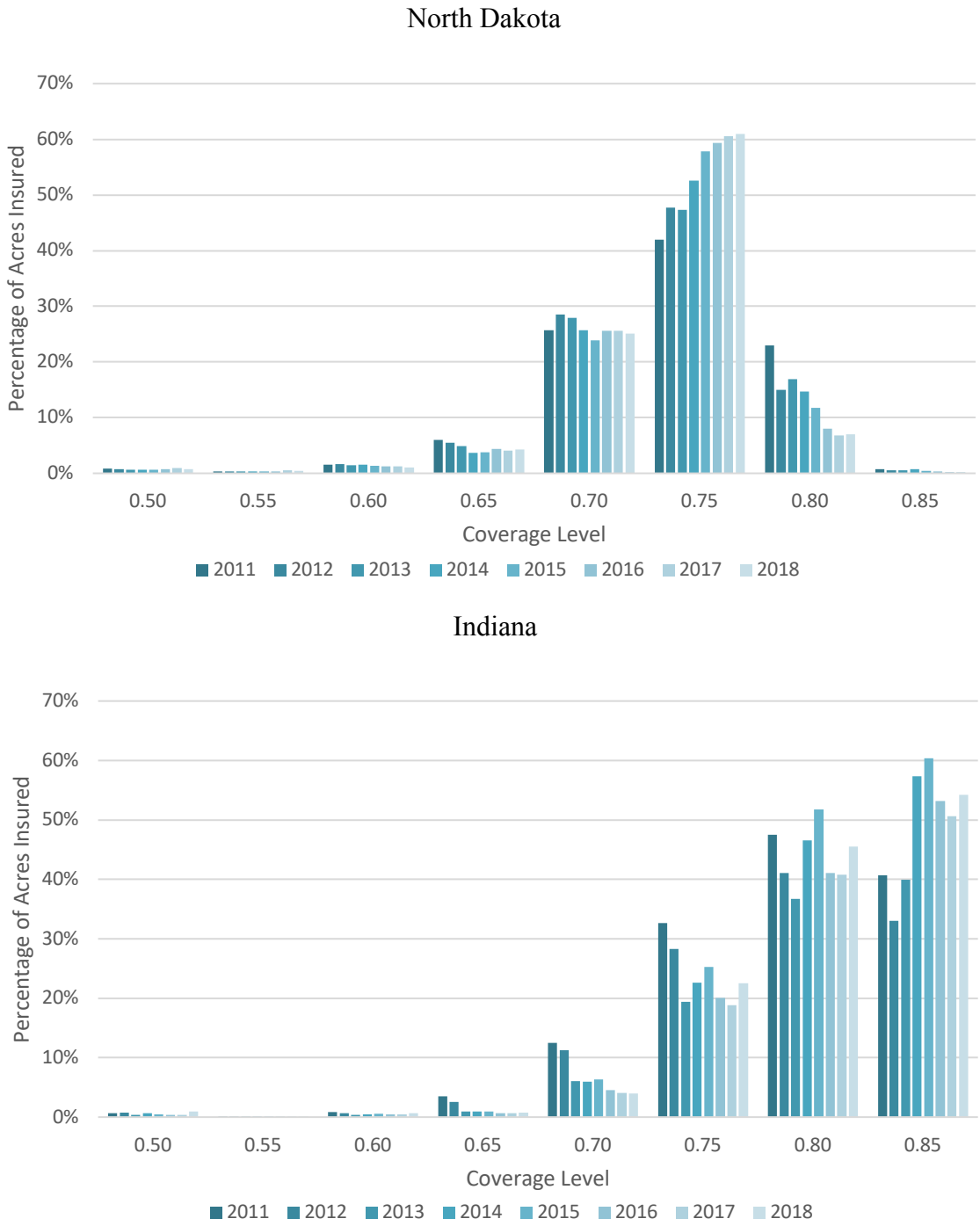
Smith, V.H. and B.K. Goodwin. (1996). Crop insurance, moral hazard, and agricultural chemical use. *American Journal of Agricultural Economics*, *78*(2), 428-438.

Walters, C. G., Shumway, C. R., Chouinard, H. H., & Wandschneider, P. R. (2012). Crop insurance, land allocation, and the environment. *Journal of Agricultural and Resource Economics*, 301-320.

Weber, J.G. and D.M. Clay (2013). What does dot respond to the Agricultural Resource Management Survey and does it matter? *American Journal of Agricultural Economics*, 95(3), 755-771.

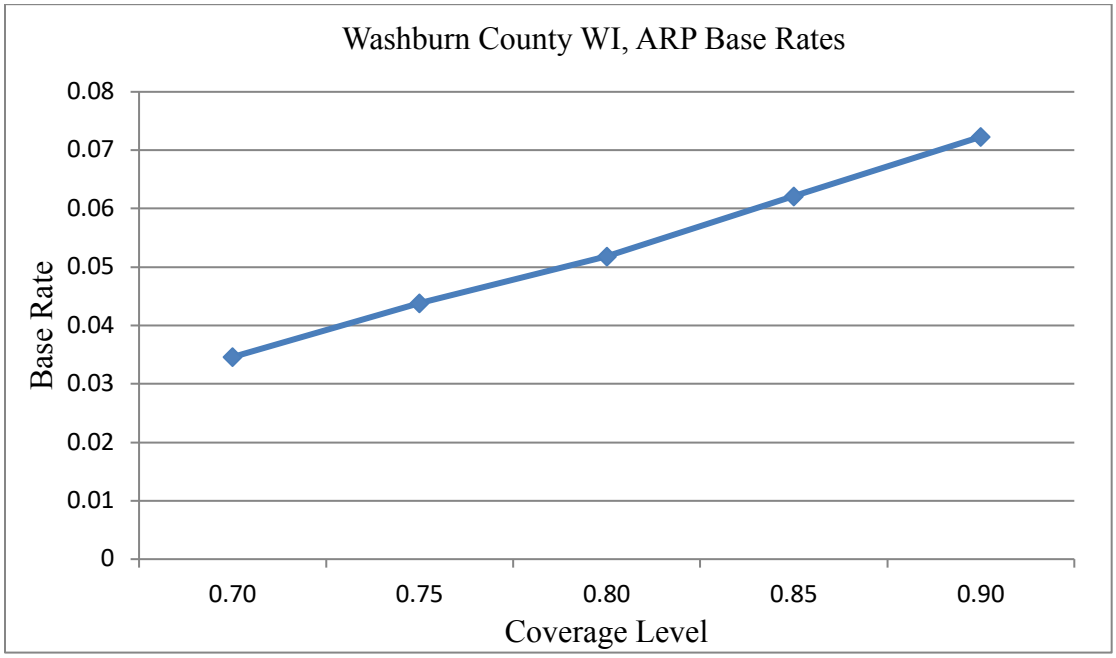
Woodard, J.D. and J. Yi. (2019) Estimation of insurance deductible demand under endogenous premium rates. *Journal of Risk and Insurance*, 87(2), 477-500.

Young, C. E., Vandeveer, M. L., & Schnepf, R. D. (2001). Production and price impacts of US crop insurance programs. *American Journal of Agricultural Economics*, 83(5), 1196-1203.



Source: USDA RMA Summary of Business

Figure 1: Coverage Level Selection for Corn Revenue Protection Policies by State, 2011-2018



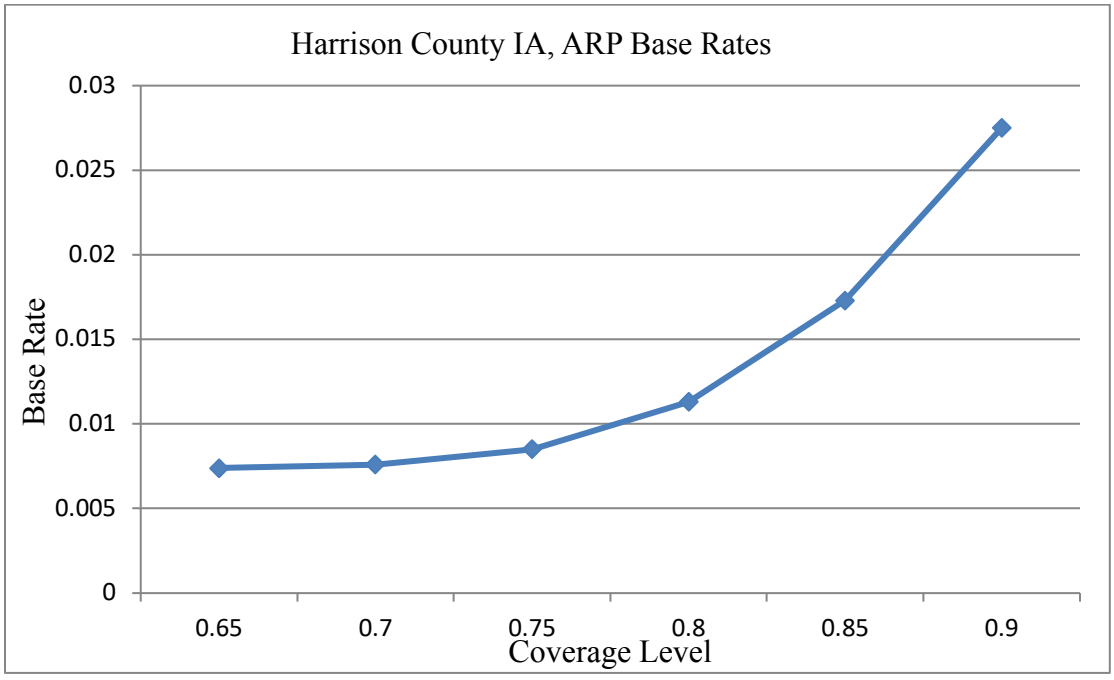


Figure 2: Relationship Between Base Rate and Coverage Level for Two Representative Counties

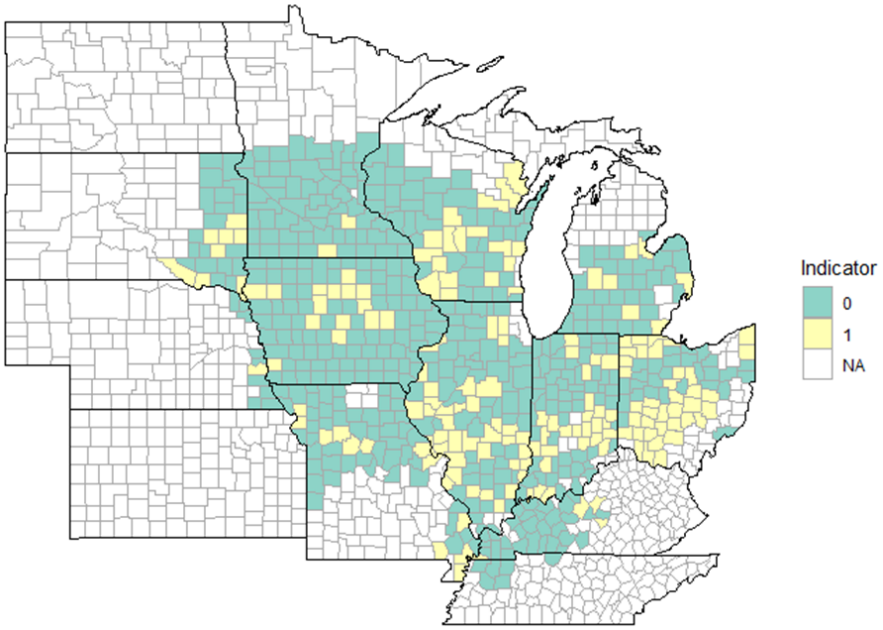


Figure 3: Map of Exponential (Indicator = 0) and Linear (Indicator = 1) Base Rate Increases Across Coverage Level.

Table 1. Summary of Variable Definitions from Agricultural Resource Management Survey

Variable Group	Variable Name	Units	Definition
Revenue	Off-farm income	$1,000s	Off-farm income earned by household
	Gross Farm Income/Acre	$100s	Gross farm income per acre
Expenses	Total VC/Acre	$100s	Total variable expenses per acre
	Total FC/Acre	$100s	Total fixed expenses per acre
Assets and Liabilities	Debt/Asset Ratio	Ratio	Farm business debt to asset ratio
	Net Worth/Acre	$1,000s	Net worth (equity)
	Total Debt/Acre	$100s	Total household and farm financial debt per acre
Acreage	Total Crop Acres	Acres in 100s	Total crop acres operated by farm
Household	Operator Age	Years	Age of Primary Operator
	Number of Owners	Number of Owners	Number of Owners
	Indicator of Operator Education	Four Classes	(1) Less than High School diploma, (2) a High School diploma, (3) some college including a n associate's degree, and (4) at least a four-year college degree.

Source: USDA ARMS data 12/11/2018.

Table 2. Summary of Agricultural Resource Management Survey Data, Explanatory and Control Variables

Statistic	N	Mean	25th Pctl.	50th Pctl.	75th Pctl.
Off-farm Income	9,262	48,062	0	27,500	56,525
Gross Farm Income	9,493	1,015,212	209,428	510,265	1,113,921
Total Variable Cost	9,493	549,503	109,057	258,454	561,342
Total Fixed Cost	9,493	177,925	31,700	83,200	197,870
Debt to Asset Ratio	9,493	0.24	0.02	0.11	0.28
Net Worth	9,493	3,343,535	823,703	1,938,174	3,940,786
Total Debt	9,262	664,473	99,364	303,732	807,057
Cropland Acres	9,493	1,320	340	800	1,648
Acres Owned	9,493	584	90	288	634
RP Corn Acres	9,493	341	0	100	425
Operator Age	9,493	53.8	47	57	64
Indicator of Operators Education	9,493	2.8	2	3	4
Number of Owners	9,493	1.73	1	1	2
Gross Income per Acre	9,493	983	441	656	946
Total Variable Cost per Acre	9,493	547	224	316	455
Total Fixed Cost per Acre	9,493	149	64	120	199
RE Debt and Interest per Acre	9,493	94	0	32	102.7
Net Worth per Acre	9,493	4,365	1,119	2,672	5,597
Total Debt per Acre	9,262	945	112	420	1,043

Source: USDA ARMS data 12/11/2018.

Table 3. Regression Results for Corn Insured under Revenue Protection

	Dependent Variable: Coverage Level						Std.
	(1)	(2)	(3)	(4)	(5)	(6)	Dev.
Off-farm Income	0.745***	0.579***	0.678***	0.544***	0.444***	0.816***	108,772
	(0.193)	(0.187)	(0.198)	(0.191)	(0.203)	(0.209)	
Gross Farm	1.319	-0.289	1.842*	0.562	5.384***	3.447***	2,441
Income /Acre	(0.974)	(0.951)	(0.999)	(0.973)	(1.051)	(1.009)	
Total VC/Acre	-1.720**	-0.619	-2.061**	-1.339*	-5.939***	-4.466***	1,520
	(0.795)	(0.779)	(0.816)	(0.796)	(0.847)	(0.818)	
Total FC/Acre	2.353***	2.437***	3.104***	3.069***	2.910***	2.565***	159
	(0.351)	(0.338)	(0.356)	(0.342)	(0.347)	(0.333)	
yr5LR	1.249***	1.604***	1.278***	1.723***	0.916***	1.121***	0.67
	(0.215)	(0.232)	(0.220)	(0.238)	(0.203)	(0.205)	
Yr5EPR	-4.249***	-4.353***			-3.941***	-3.764***	0.04
	(0.309)	(0.334)			(0.181)	(0.188)	
BaseRate70	-2.213***	-1.988***	-3.267***	-3.119***			0.04
	(0.190)	(0.207)	(0.178)	(0.192)			
BR Slope	0.204	0.018	0.126	-0.044			0.41
	(0.259)	(0.268)	(0.266)	(0.274)			
Debt/Asset Ratio	-1.844***	-1.659**	-2.341***	-1.987***	-0.986	-0.259	0.66
	(0.683)	(0.664)	(0.700)	(0.680)	(0.686)	(0.665)	
Net Worth/Acre	-3.371***	-1.774***	-3.152***	-1.712***	-1.783***	-0.807***	7,979
	(0.284)	(0.294)	(0.291)	(0.301)	(0.276)	(0.275)	
Cropland Acres	0.346**	0.568***	0.137	0.362**	-0.160	-0.045	1,743
	(0.175)	(0.179)	(0.179)	(0.183)	(0.110)	(0.119)	
Y2016	0.370*	0.392*	0.797***	0.743***	-0.319	-0.242	0.50
	(0.210)	(0.206)	(0.213)	(0.209)	(0.201)	(0.195)	
Number of Owners	-1.745***	-1.219***	-1.650***	-1.128***	-0.629***	-0.634***	1.13
	(0.187)	(0.186)	(0.192)	(0.190)	(0.160)	(0.163)	
Education	0.626***	0.704***	0.629***	0.764***	-0.027	-0.254	0.84
	(0.196)	(0.194)	(0.201)	(0.199)	(0.194)	(0.190)	
Operator Age	0.822***	0.511**	0.806***	0.531**	0.302	0.152	11.83
	(0.229)	(0.223)	(0.235)	(0.229)	(0.215)	(0.213)	
Fixed Effects		County		County		County	
Observations	3,866	3,866	3,866	3,866	5,075	5,075	
Adjusted R-squared	0.213	0.308	0.171	0.274	0.163	0.276	

Note: ***, **, and * indicates statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors are reported in parenthesis.

Appendix Table A1. Regression Results for Soybeans Insured under Revenue Protection

	Dependent Variable: Coverage Level						Std.
	(1)	(2)	(3)	(4)	(5)	(6)	Dev.
Off-farm Income	0.515***	0.261***	0.482***	0.271	0.911***	0.788***	113,356
	(0.238)	(0.234)	(0.243)	(0.239)	(0.207)	(0.203)	
Gross Farm	0.285	-0.979	0.692	-0.213	3.518***	1.873***	1,548
Income /Acre	(1.199)	(1.222)	(1.221)	(1.247)	(0.859)	(0.851)	
Total VC/Acre	-0.725	1.011	-0.903	0.424	-4.232***	-2.735***	1,259
	(1.080)	(1.105)	(1.101)	(1.129)	(0.810)	(0.804)	
Total FC/Acre	2.594***	2.093***	3.118***	2.586***	2.690***	2.266***	154
	(0.474)	(0.467)	(0.480)	(0.474)	(0.348)	(0.341)	
yr5LR	-0.345	-0.222	-0.954***	-0.727**	-0.631***	-0.599***	0.34
	(0.289)	(0.344)	(0.286)	(0.347)	(0.193)	(0.200)	
Yr5EPR	-4.032***	-4.680***			-3.767***	-4.018***	0.04
	(0.483)	(0.536)			(0.198)	(0.207)	
BaseRate70	-0.956***	-0.650*	-1.939***	-1.805***			0.01
	(0.290)	(0.338)	(0.270)	(0.318)			
BR Slope	0.629*	0.765*	0.778**	0.935**			0.41
	(0.354)	(0.393)	(0.361)	(0.402)			
Debt/Asset Ratio	-0.381	-0.470	-0.578	-0.587	-0.719	-0.365	0.65
	(1.104)	(1.095)	(1.126)	(1.120)	(0.672)	(0.659)	
Net Worth/Acre	-0.757	-0.367	-0.445	-0.212	-2.839***	-1.512***	7,576
	(0.522)	(0.513)	(0.531)	(0.524)	(0.293)	(0.304)	
Cropland Acres	-0.433*	-0.077	-0.349	-0.073	-0.150	-0.177	1,562
	(0.235)	(0.262)	(0.239)	(0.268)	(0.118)	(0.123)	
Y2016	0.730**	0.781**	0.924***	0.942***	0.200	0.250	0.49
	(0.297)	(0.307)	(0.302)	(0.313)	(0.201)	(0.200)	
Number of Owners	-1.043***	-0.846***	-1.078***	-0.880***	-0.903***	-0.550***	1.15
	(0.286)	(0.290)	(0.292)	(0.297)	(0.168)	(0.170)	
Education	0.976***	0.559*	1.047***	0.659**	0.518***	0.435**	0.84
	(0.278)	(0.292)	(0.284)	(0.298)	(0.191)	(0.190)	
Operator Age	0.198	-0.133	0.421	0.125	0.861***	0.340	11.83
	(0.342)	(0.344)	(0.348)	(0.350)	(0.215)	(0.215)	
Fixed Effects		County		County	County		
Observations	1,924	1,924	1,924	1,924	4,644	4,644	
Adjusted R-squared	0.125	0.232	0.090	0.196	0.161	0.243	

Note: ***, **, and * indicates statistical significance at 1, 5, and 10 percent levels, respectively.

Appendix Table A2. Regression Results for Wheat Insured under Revenue Protection

	Dependent Variable: Coverage Level		Std.
	(1)	(2)	Dev.
Off-farm Income	0.456	0.803*	50,119
	(0.438)	(0.436)	
Gross Farm	3.353	-0.013	2,864
Income /Acre	(4.884)	(4.864)	
Total VC/Acre	-16.560**	-10.954*	2,623
	(6.067)	(6.144)	
Total FC/Acre	-1.198	0.324	100
	(0.798)	(0.803)	
yr5LR	1.806***	0.455	0.41
	(0.416)	(0.474)	
Yr5EPR	-4.820***	-4.754***	0.06
	(0.348)	(0.427)	
Debt/Asset Ratio	1.216	-0.038	0.52
	(1.249)	(1.259)	
Net Worth/Acre	-0.464	-0.228	2,517
	(0.541)	(0.562)	
Cropland Acres	-0.208	-0.581**	2,529
	(0.187)	(0.242)	
Y2016	-0.295	-0.132	0.47
	(0.459)	(0.472)	
Number of Owners	-1.260***	-0.534	1.20
	(0.427)	(0.456)	
Education	-1.339***	0.759*	0.84
	(0.429)	(0.451)	
Operator Age	0.375	0.546	11.70
	(0.460)	(0.464)	
Fixed Effects		County	
Observations	1,786	1,786	
Adjusted R-squared	0.154	0.291	

Note: ***, **, and * indicates statistical significance at 1, 5, and 10 percent levels, respectively.