2015-02
January 2015

The Charles H. Dyson School of Applied Economics and Management
Cornell University, Ithaca, New York 14853-7801 USA

Does Federal Crop Insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey

Authors: Jennifer Ifft, Todd Kuethe, Mitch Morehart

Acknowledgments:

The views expressed are those of the authors and should not be attributed to ERS or USDA. The authors wish to thank Joseph Glauber and Robert Johansson, from the USDA Office of Chief Economist, for helpful discussion of this research.

Structured Abstract

Purpose – The paper considers how the Federal crop insurance program influences farm debt use, one of the key financial decisions made by farm operators.

Design/methodology/approach – Using data from the nationally-representative Agricultural Resource Management Survey, the paper implements a propensity score matching model of the impact of Federal crop insurance participation on various measures of farm business debt use. To account for the simultaneity of financial decisions, the paper further tests this relationship using a seemingly unrelated regression model.

Findings – Federal crop insurance participation is associated with an increase in use of short term farm debt, but not long term debt, consistent with risk balancing behavior and current trends in the farm sector.

Research limitations/implications –In addition to risk balancing, the results are also consistent with credit constraints or lender preferences. The paper cannot fully establish causality between crop insurance participation and short term debt levels. Future research should address these limitations.

Practical implications – Agricultural lending standards are generally conservative and the farm sector as a whole currently has historically low leverage, which implies that an increase in debt use may not be a threat to the financial health of the farm sector.

Social implications – The results indicate that the reduction in total risk facing the farm sector is significantly less than the decline in risk provided by Federal crop insurance, which is an important consideration for policymakers.

Originality/value – This is the first paper to use an econometric model to analyse the relationship between federal crop insurance and farm debt use decisions. This paper can inform future research on the Federal crop insurance program and farm financial decisions.

Keywords: Agricultural finance, Crop insurance, Farm debt, Agricultural Resource Management Survey

Does Federal Crop Insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS)

Federal crop insurance (FCI) has become a key component of US farm policy. In farm bill negotiations in 2012 and 2013, crop insurance emerged as the preferred form of farm financial support for many farm sector participants. The Agricultural Act of 2014 ("new farm bill") cemented FCI as a pillar of US farm policy. Like other farm programs, FCI carries the potential to influence the behavior of market participants in various ways, and the change in behavior has important implications for the ability of farm policy to meet its stated goals, as well as potential adverse impacts. A vast literature has considered market responses to FCI and related programs, including adverse selection and moral hazard (Just et al., 1999), land uses decisions (Claassen et al., 2011; Turvey, 2012), farm structure (O'Donoghue, Roberts, and Key, 2009) and land values (Ifft, Wu, and Kuethe, 2014). FCI participation could also affect financial decisions, as it impacts both total farm income and income variability. Theoretical and empirical research on risk balancing has shown that farm operations might increase financial risk in response to a decline in business risk, but there is limited empirical research on the relationship between current government programs that decrease business risk and farm financial risk levels. In this article we consider how the FCI program might be influencing farm debt use, one of the key financial decisions made by farm operators.

Farm Policy and Federal Crop Insurance

FCI is administered as a "public-private partnership", where private companies offer a variety of insurance policies. Indemnity risk is shared by the government and insurance companies, and subsides are provided for administration of the program and a share of the premium based on total coverage. A total of almost 296 million acres were enrolled in a FCI program in 2013, with well over half of all acreage of most major agricultural commodities being enrolled. Premium subsides were $7.3 billion in 2013, about 62% of the total premium. This share has been relatively constant over the past decade (Risk Management Agency, 2014). One of the roles of the subsidies is to ensure sufficient enrollment, which can serve to lower total costs if risk can be spread across a large insurance pool. Total (net) government costs for the program have been estimated to approximately $4 billion per year from 2001 to 2012, and in addition the premium subsidies and other costs, the government can incur underwriting loss or gains (Barnaby, 2013). For a more detailed review of the FCI program, see Glauber (2013).

The growth of crop insurance has coincided with a decline in the importance of other farm programs. Over the past decade, payments linked to market prices averaged about 22% of total farm program payments, and countercyclical payments and loan deficiency payments were less than one percent of farm program payments in 2012 and 2013 (Economic Research Service, 2014). In the Agricultural Act of 2014, FCI was strengthened and direct payments were eliminated for almost all commodities. The Price Loss Coverage (PLC), Agricultural Risk Coverage, and Supplemental Loss Coverage (SLC) programs were all authorized and will be paid out based on market prices and/or yields.

Direct payments, as well as other programs, have been theorized to facilitate access to credit (Westcott and Young, 2004). One study found empirical evidence for this claim, in that that farms with a larger share of base acre faced slightly smaller interest rates for short term loans (Kropp and Whitaker, 2011). Direct payments in particular may have been considered a reliable source of income that could be used to service debt. Direct payments are paid based on historic acreage of eligible commodities or a farm’s base acres and remained relatively steady and were much smaller relative to revenues and expenses for most field crops in recent years compared to a decade ago. A study by Ifft et al. (2012) found that elimination of direct payments would *not* lead to a substantial decline in the financial position of the majority of farms receiving direct payments. Given the declining importance of direct payments and other farm programs over the last decade, crop insurance and related programs may have an even larger role in farm financial decisions than prior research would suggest.

Crop insurance and risk balancing

Crop insurance has been shown to potentially improve the financial health of agricultural lenders and farm operations. A study by Lee and Djogo (1984) found that crop insurance could reduce loan losses for agricultural lenders. Pfleuger and Barry (1986) found that crop insurance participation could improve liquidity and farm survival for a representative highly leveraged farm. However, Skees and Nutt (1988) found purchasing crop insurance could be detrimental to highly leveraged farms once lower levels of loss ratios are taken into account. These findings, which are largely based on simulations, might be less relevant under current FCI program parameters but point to important financial implication of the current FCI program. For lenders or producers concerned with reducing loan default risk, FCI can be an important risk management tool.

Risk balancing theory, however, predicts an increase in financial risk or debt use in response to both the income and risk reduction aspects of the FCI program. Gabriel and Baker (1980) first demonstrated that government policies that decrease business risk for a farm operation could induce the operation to take on additional financial risk, limiting the effectiveness of the original policy to decrease the total risk faced by the farm sector. Business risks are defined as risks that are independent of financing decisions. Farms might also take private actions, such as technology adoption, that decrease business risk but allow for additional financial risk. For the agricultural sector, most business risks would be related to various sources of price and yield risk.

Use of FCI, by design, can decrease both price and yield risk. Financial risks for the farm sector largely stem from risks related to debt financing and are formally defined as the change in the variability of cash flows due to debt financing and cash leasing. Collins (1985) further formalized this concept and also considered the introduction of policies that increase income levels. Featherstone et al (1988) use a mean variance model to determine the leverage response to risk reducing or income augmenting polices. Using a theoretical model, they found that farm policies can cause a large enough increase in leverage that the probability of negative returns to equity also increases.

Several studies have since extended these theoretical papers, but here we will briefly summarize a few key empirical findings. Various studies have shown evidence of risk balancing in the farm sector, although few if any have considered the impact of government programs, which can lower business risk, on financial risk. Moss (1990) found that an increase in expected farm sector returns or a decrease in expected variance of returns could lead to an increase aggregate debt, which indicates that the farm sector debt use responds to business risk in a manner consistent risk balancing. Jensen and Langemeier (1996) found that the variance in real operating profit, a key measure of business risk, can affect leverage. Escalante and Barry (2003) found evidence of risk balancing in over half of 80 Illinois farms, using longitudinal data from 1982 to 1998. Turvey and Kong (2009) found that Chinese farm households exhibited behavior consistent with risk balancing. de Mey et al (2014) recently found evidence of farm-level risk balancing in the EU using farm survey panel data for 15 countries from 1995-2008. Ifft et al. (2013) suggested that federal crop insurance now plays an increasingly important role in the farm safety net and found that farms that participate in federal crop insurance have a higher credit default risk. However, this result is only suggestive as farm characteristics that could impact both debt use decisions and FCI participation are not controlled for.

Methodology

Ideally, from the researcher's perspective, farm operations could be randomly assigned crop insurance coverage as a part of a controlled experiment. Treatment effects, or the impact of crop insurance on debt use, could then be identified by observing differences in an outcome variable between identical pairs of subjects assigned to "treatment" and "control" groups. Outside of a controlled experiment, however, treatment effects are difficult to observe because treatment and control groups are not independently assigned. Further, the same factors that determine whether a subject receives treatment or not may impact differences in the outcome variable. Like many farm programs, FCI has been implemented at the national level and participation is available to virtually all farms and is voluntary.

In our case, a farmer likely decides whether to purchase crop insurance based on the same factors that determine the farm's debt level. To take into account the simultaneity of these decisions, we use two approaches to test the relationship between debt use and FCI participation. We first use propensity score matching to estimate the difference in debt use between farm operations with and without FCI coverage. We then use a seemingly unrelated regression to explicitly model joint determination of farm debt structure, or different measures of financial risk, and crop insurance participation.

Propensity Score Matching

Propensity score matching (PSM) was developed by Rosenbaum and Rubin (1983) to simulate a controlled experiment framework for non-randomly assigned groups. PSM is derived from the equation

$$E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \quad (1)$$

where Y is the outcome variable and D is a binary variable that indicates whether the observation belongs to the treatment (D = 1) or control (D = 0) group. An observation can be in only one state, so the matching procedure attempts to estimate the unobservable counterfactual $E(Y_0 \mid D = 1)$. In our case, the unobserved counterfactual is the impact of not purchasing crop insurance on farm debt levels for farms that that actually purchase crop insurance.

The control group in our study is farms that did not purchase crop insurance. Rosenbaum and Rubin (1983) demonstrate that if treatment is determined by some set of covariates X, a control can be identified that is similar in X relative to the treatment group. Formally, this relationship is defined as:

$$E(Y_1 - Y_0|X, D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1) \quad (2)$$

The matching estimator pairs treated observations with one or more observationally similar non-treated observations, and pairings are based on the similarities of the covariates. The procedure yields accurate treatment effects when the outcomes are independent of the selection process after conditioning on the covariates. The conditional mean independence implies that:

$$E(Y_0|X, D = 1) = E(Y_0|X, D = 0) \quad (3)$$

The matching procedure, however, can be difficult to implement directly when a large number of covariates are required, and conditional mean independence typically requires a large set of covariates. Rosenbaum and Rubin (1983) suggest that, instead of conditioning on all the elements of X, one may condition on a one-dimensional function of the covariates. This one-dimensional function – the propensity score – can be estimated through discrete choice methods. The propensity score implies that if Y_0 is independent of selection when conditioned on X, then it is also independent of selection when conditioned on the probability of selection on X. This is formally defined as:

$$P(X) = P(D = 1|X) \quad (4)$$

While originally developed for the natural sciences, PSM methods have grown in popularity in agricultural and applied economics. Recent examples include the treatment effect of risk management tool adoption on farm-level profit (Kuethe and Morehart, 2012a), contracting on prices received (Katchova, 2010), credit constraints on productivity (Briggeman, et al., 2009), farmland preservation on farmland conversion (Lynch and Liu, 2007), and food aid programs on food consumption (Gilligan and Hoddinott, 2007).

PSM requires that no single covariate or combination of covariates can guarantee treatment. More formally, for a set of covariates X, the probability of treatment is strictly greater than 0 and strictly less than 1 ($\genfrac{}{}{0pt}{}{D = 1|X = x < 1 \forall x \in X}{0 < P}$). This condition must hold for each treated observation to have the potential of an analogue among the untreated observations. The impact of being treated is only valid for observations within the common support. Alternatively, the propensity scores for treated and untreated observations are positive and the distributions of propensity scores intersect. Propensity score matching also relies on the "selection on the observables" assumption, or the assumption that farm operations that have been matched based on observable characteristics are the same in relation to all relevant factors that influence both debt use and federal crop insurance participation. While this assumption has been shown to hold in some studies (Dehejia and Wahba, 2002), in others it does not, and ultimately causality cannot always be definitely established (Smith and Todd, 2005). While we cannot implement a controlled experiment to validate our results, we are able to match farm operations on a large set of characteristics. One major factor for PSM to be consistent with the results of a controlled experiment is the size and detail of the dataset being used. In this study will take advantage of a large, nationally-representative farm survey.

The first step of PSM is to estimate each producer's propensity for purchasing Federal crop insurance. The purchase decision, as it relates to farm characteristics, can be expressed:

$$Prob(Y = 1) = X\beta + \varepsilon \tag{5}$$

where Prob(Y = 1) is the probability that the operation receives treatment, X a set of observable farm and operator characteristics, β a set of unknown parameters relating the observable characteristics to the probability of treatment, and ε the residual. Equation (5) is estimated through a logit model using the delete-a-group jackknife (Kott, 1998).

Seemingly Unrelated Regression

Seemingly unrelated regression (SUR) allows us to jointly estimate a more comprehensive set of measures of financial risk and crop insurance participation. This approach was used by Escalante et al (2009) in an analysis of the sustainable growth challenge model that jointly estimated several financial determinants of growth. While SUR admits a less flexible functional form than PSM, it allows for joint modeling of crop insurance and multiple debt use decisions that are closer to actual farm-level debt structure decisions. Given that farms make multiple decisions about debt structure, it is likely that joint estimation will account for the relationship between these decisions better than PSM. To implement the SUR model, we assume that each measure of financial risk or debt use decision D, denoted by subscript j, is a linear function of the insurance participation decision by farm i, (Y_{ij}), as well as the same explanatory variables (X_{ij}) used to measure insurance participation as in the PSM model:

$$D_{ij} = \gamma_j Y_{ij} + X_{ij}\beta_j + \varepsilon_{ij} \tag{6}$$

The SUR model assumes non-zero covariance for the errors terms ε_{ij} across all j, k equations, or debt use decisions, for farm observation i, or $v(\varepsilon_{ij}, \varepsilon_{ik}) = \sigma_{ij}$. The model also assumes $Cov(\varepsilon_{ij}, \varepsilon_{ik}^{'}) = 0$ if $i \neq i'$ for all j, k debt use decisions. The feasible generalized least-squares algorithm that addresses heteroscedastic disturbances described in Greene (2003) is used to estimate the model. We estimate one SUR model with three measures of absolute debt levels: real estate debt, non-real estate long term debt, and short term debt. The other model estimates three ratios or measures of relative of debt use, specifically debt-to-asset ratio, current ratio, and the ratio of total operating debt to total operating expenses. Standard errors are calculated using a cluster bootstrap, with clusters drawn at the strata level, following the recommendations of Weber and Clay (2013). This approach allows us to estimate the standard errors implied by SUR while still accounting for ARMS survey design.

Data

We examine the relationship between federal crop insurance and farm debt use using recent data from the 2011 Agricultural Resource Management Survey (ARMS). ARMS is an annual survey of farm and ranch operators conducted by the USDA to obtain information about the status of farmer’s finances and resource use (Kuethe and Morehart, 2012b). Our analysis is limited to farm businesses, defined in this study using the same official USDA definition used by Ifft, Kuethe and Morehart (2013), which includes (1) farms where the principal operator’s primary occupation is farming (removing all “limited-resource,” “retirement,” and “residential/lifestyle” farms), (2) farms with sales over $250,000 and/or (3) non-family farms. ARMS stratified sample design requires weighted estimation of sample statistics, and we use the standard delete-a-group jackknife procedure of Kott (1998) for our PSM model.

We define treatment as the purchase of at least some amount of federal crop insurance, and our analysis suggests that approximately 30% of farm businesses meet this definition (Table 1). It is important to note, however, that over half of farm businesses (51%) derive the majority of their revenue from livestock production (beef cattle, hog, poultry, dairy, and general livestock) and an additional 10% derive the majority of their revenue from specialty crops, such as tobacco, fruits and tree nuts, vegetables, and nursery and greenhouse (Table 1).

There is a well-established literature that examines farm and farm operator characteristics that influence federal crop insurance purchase decisions. For PSM models, it is recommended that covariates are based on economic theory and previous research and also should not be influenced by the insurance participation decision (Caliendo and Kopeinig, 2008), and this approach was followed in our selection of covariates. Matching quality or "balancing" of covariates across the treatment and control groups is also important for PSM estimation. One approach recommended by Caliendo and Kopeinig (2008) is to use t-tests determine if means of covariates are not statistically different after the propensity score is calculated. For our selected covariates, nearly half are not statistically different after matching. While ideally all covariates should be balanced, in practice there are tradeoffs between balancing covariates and omitting variables that are important determinants of the key decision variable (Caliendo and Kopeinig, 2008). For comparability across our PSM results and SUR results, we elected to use the same set of covariates for each modeling approach based on the literature. While the level of balancing in our PSM analysis may be less than ideal, covariates are substantially more balanced after the matching procedure and results can be interpreted in a more relevant economic framework. The summary statistics for the covariates for estimating the logit model for the propensity to purchase federal crop insurance and the explanatory variables for the SUR Model (X_{ij}) are provided in Table 1.

Previous empirical studies demonstrate a statistically significant relationship between crop insurance purchasing decisions and farm acreage (Sherrick, et al., 2004), percent of acreage dedicated to cropland production (Coble, et al., 1996), the ratio of owned to total operated acres (Valendia, et al., 2009; Mishra and El-Osta, 2002; Sherrick, et al., 2004), off farm income (Velandia, et al., 2009), operator age (Sherrick, et al., 2004), and operator education (Sherrick, et al., 2004). In addition, Velandia, et al. (2009) and Mishra and El-Osta (2002) show regional variation in insurance adoption rates, and as a result, we account for regional differences using Economic Research Service (ERS) defined Farm Resource Regions (Heimlich, 2000). In addition, we control for differences in farm production specialty (Farm type) and scale (Sales class).

[TABLE 1 ABOUT HERE]

Figure 1 shows that farms that purchase at least some level of Federal crop insurance coverage are associated with higher debt levels. The average level of debt for farms with Federal crop insurance is roughly 225% higher than for farms without and approximately 93% than the average for all farms (with and without debt). This pattern is also consistent when observing either long-term– non-real estate and real estate debt – and short-term loan debt. Short-term debt – debt associated with production loans – can be further divided into debt that remains at the end of 2011 (outstanding) and short-term debt that includes all debt paid before the end of the calendar year (all). Debt relative to assets is 50% higher for farms that purchase Federal crop insurance compared to those that do not. In 2011 farms that purchased Federal crop insurance had a debt-to-asset ratio of 0.12, while those that did not had a debt-to-asset ratio of 0.08.

[FIGURE 1 ABOUT HERE]

However, it is important to note that the simple summary statistics can be deceiving. Farms with certain characteristics, including financial position, may be more likely to purchase crop insurance, and these same characteristics may also drive decisions related to debt. This endogeneity may bias the simple summary statistics and provides motivation for using both PSM and SUR approaches to estimate the effect of crop insurance on farm debt levels.

Results

The logit estimates suggest that Federal crop insurance purchases are associated with a number of farm and farm operator characteristics (Table 2). Farms with a larger share of cropland acres to total acres operated are more likely to purchase Federal crop insurance. In addition, farmers with higher levels of education, compared to the base category of "some high school," are more likely to purchase Federal crop insurance. The sales class categorical variables indicate that the probability of purchasing Federal crop insurance decreases as the volume of farm sales decreases. The categorical variables for farm type also show a significant effect relative to the omitted category "general cash grain." A number of farm types are associated with a lower chance of adoption: soybean, general crop, vegetables, nursery and greenhouse, beef cattle, hogs, poultry, dairy, and general livestock. Similarly, the regional indicator variables demonstrate regional variability in Federal crop insurance uptake relative to the omitted "Heartland" region. Farms in the Northern Great Plains were more likely to purchase crop insurance, yet a negative effect was found for farms located in the Northern Crescent, Eastern Uplands, Southern Seaboard, Fruitful Rim, and Basin and Range regions. The reported residual deviance, an approximation of goodness of fit, suggests that the model provides a reasonable fit to the data and, therefore, is a good predictor of Federal crop insurance participation (Greene, 2003 Appendix B, Manning, 2007).

[TABLE 2 ABOUT HERE]

The treated observations, those who purchase at least some level of Federal crop insurance coverage, are then matched to the control group based on the weighted logit propensity scores. The impact of crop insurance on farm debt at the operation level is estimated as the average treatment effect on the treated (ATT). Following Equation (2), ATT is expressed:

$$ATT = E(Y_1 - Y_0|P(X), D = 1) = E(Y_1|P(X), D = 1) - E(Y_0 \vee P(X), D = 1) \qquad (7)$$

ATT was calculated using an R program that employs nearest neighbor matching, with replacement. The estimated ATT for various definitions of farm business debt are reported in Table 3. The table reports the estimated level of farm debt, its standard error, and a *t*-test for the difference between treatment and control groups.

[TABLE 3 ABOUT HERE]

The ATT estimates suggest a statistically significant increase in short term debt. The results suggest a nearly $64,000 increase in short-term debt outstanding at the end of 2011, but when the short term debt paid throughout the calendar year is also included (all), the ATT increases by more than $214,000. This is an increase by about 2.6 to 3 times the average farm-level short term debt in 2011, respectively. The ATT for the level of total debt relative to total assets (farm debt to asset ratio) also suggests a statistically significant increase at 0.03. This effect may be driven by short term debt use, as the ATT for the level of total short term debt relative to total operating expenses also suggests a strongly statistically significant increase of 0.14. In contrast to the simple summary statistics reported in Figure 1, the ATT for total and long-term – real estate and non-real estate – farm business debt, as well as the current ratio, are not statistically significant. After farm characteristics are taken into account, total long term debt use is not related to crop insurance participation. In sum, the relationship between leverage and crop insurance may largely be driven by differences in short term debt use.

While the SUR results (Table 4) in some cases have a slightly lower level of statistical significance than the PSM, they are largely consistent. The differences between our SUR and PSM may be due to different functional forms being used. SUR imposes a linear relationship, which may be more restrictive, especially when lending behaviors affected by risk preferences are being analyzed. The differences may also be due to SUR being able to take into account the simultaneity associated with different debt use decisions. The Breusch-Pagan test statistics reported in Table 4 indicate that the error terms across the different equations are indeed not independent. Depending on actual behavior, taking into account broader measures of debt use may show more or less of a relationship with FCI participation.

The results suggest that FCI participation is associated with an almost $22,000 increase in short-term debt outstanding at the end of 2011, and an almost $16,000 increase in non-real estate long term debt. These measures are only statistically significant at the 10 percent level, and similar to the PSM results, FCI participation does not have a statistically significant impact on real estate debt. While FCI participation does not have a statistically significant impact on the current ratio and leverage in the SUR model of financial ratios, the impact on the ratio of short term debt to operating expenses is remarkably similar to that of the PSM model. FCI participation is associated with a 0.13 increase in short term debt relative to operating expenses, and this result is statistically significant at the five-percent level.

Overall, our results are consistent with risk balancing behavior, but not across all types of debt use. Crop insurance covers business risks within a single growing season, and risk balancing appears to be occurring for financial risk within the same period as opposed to longer term financial risks. One possible explanation for our finding of a nonexistent or weak relationship of FCI participation and long-term debt use is our reliance on cross sectional data available through the ARMS survey. ARMS is not a longitudinal study, and hence we do not examine the dynamic relationship between insurance adoption and long-term debt use, which is an important topic for future research.

However, the observed relationship between production loans and FCI participation is consistent with current trends in the farm sector. Access to short term debt or production loans may have been especially important for farm operations over the past decade, as farm expenses have increased substantially. In real terms, US farm sector cash expenses increased 127 percent from 2002 to 2011 (Economic Research Service, 2014). Production loans have short maturities and are typically paid out of current-year revenues, so loan terms at least loosely match the revenue (or yield) protection provided by FCI. For producers as well as lenders, FCI would substantially lower the default risk for production credit. Further, as expenses have increased over the past decade, crop insurance has become an increasingly important relative to other farm programs. Together, these trends are consistent with FCI playing a key role in facilitating access to production credit in recent years.

Our results are also consistent with bankers who allow producers to use crop insurance policies as collateral for operating loans. Bankers may even require crop insurance for access to a line of credit. If this is a key factor in the relationship between debt use and FCI participation, then producers may be exhibiting less risk balancing behavior than implied by our results. Alternatively, FCI could potentially bring credit use to socially optimal levels if credit constraints are present in the farm sector. Credit constraints are associated with an estimated 3 percent decline in value of farm production (Briggeman et al., 2009), yet commercial banks have recently reported relatively weak loan demand (Henderson and Akers, 2012). These are important topics for future research, as they may be a complimentary or competing explanations for risk balancing as a cause of the strong relationship between short term debt use and federal crop insurance participation.

Conclusion

US farms that use federal crop insurance use more short term debt than farms without insurance. This behavior is consistent with risk balancing and also is robust to controlling for multiple farm characteristics. Propensity score matching and SUR models allows us to consider debt levels between similar farms with and without federal crop insurance coverage. Short term debt as a share of operating expenses is 0.13-0.14 higher for these farms and use of short term loans is also higher. However, higher levels of long term debt are generally not associated with FCI participation. These findings may be related to growing use of short term debt to cover increasing farm production expenses.

Different methodologies can be used to characterize the relationship between debt use and farm policy, and approaches that further address the simultaneity of crop insurance and debt decisions should be considered. Although our paper does not fully establish causality or that debt levels are higher than they would have been without FCI, policy shocks or instrumental variable approaches could be used in future research. Use of panel data in particular would allow for changes in behavior over time to be analyzed, and could elucidate whether or not debt use has been increasing in response to availability of FCI or if FCI is being adopted to accommodate increasing debt use. The presence of credit constraints and the potential role of crop insurance in alleviating credit constraints should be further explored. The role of lender versus farmer preference in the relationship between debt use and crop insurance also merits further research. If lenders are driving FCI participation, farm operators may not be exhibiting as much risk balancing behavior as implied by our results.

Agricultural lending standards are generally conservative and the farm sector as a whole currently has historically low leverage (Ifft et al, 2014). In addition to our result that FCI participation is not related to long term debt use, this implies that the increase in average debt use in response to FCI may not be a threat to the financial health of the farm sector. However, if one of the goals of the FCI program is to lower the risk that is faced by farm operations, our results indicate that the reduction in total risk facing the farm sector is significantly less than the decline in risk provided by FCI. The impacts of the FCI program on farm financial decisions are an important consideration for policymakers as the debate on US farm policy continues.

References

Barnaby, A. (2013). "In Most Years, Farmers Write "Big" Crop Insurance Checks". Ag Manager. Available online at http://www.agmanager.info/crops/insurance/risk_mgt/rm_pdf13/AB_CropIns_TaxpayerCosts.pdf (Accessed October 21, 2013).

Briggeman, B. C., Towe, C. A., & Morehart, M. J. (2009). "Credit constraints: their existence, determinants, and implications for US farm and nonfarm sole proprietorships." *American Journal of Agricultural Economics*, 91(1), 275-289.

Caliendo, M., & Kopeinig, S. (2008). "Some practical guidance for the implementation of propensity score matching." *Journal of Economic Surveys*, 22(1), 31-72.

Coble, K.H., T.O. Knight, R.D. Pope, and J.R. Williams (1996) "Modeling farm-level crop insurance demand with panel data" *American Journal of Agricultural Economics* 78 (2): 439-447.

Claassen, R., F. Carriazo, J.C. Cooper, D. Hellerstein, and K. Ueda. 2011. "Grassland to Cropland Conversion in the Northern Plains." Economic Research Report 120, Economic Research Service, U.S Department of Agriculture, Washington D.C.

Collins, R. A. (1985). "Expected utility, debt-equity structure, and risk balancing." *American Journal of Agricultural Economics*, 67(3), 627-629.

de Mey, Y., et al. (2014). "Farm level evidence on risk balancing behavior in the EU-15." *Agricultural Finance Review*, 74(1), 17-37.

Dehejia, R. H., & Wahba, S. (2002). "Propensity score-matching methods for nonexperimental causal studies." *Review of Economics and Statistics*, 84(1), 151-161.

Economic Research Service. (2014) "Historical U.S. and State-Level Farm Income and Wealth Statistics." Available online at http://ers.usda.gov/data-products/farm-income-and-wealth-statistics/historical-us-and-state-level-farm-income-and-wealth-statistics.aspx (accessed May 22 2014).

Escalante, C. L. and Barry, P. J. (2003), "Determinants of the strength of strategic adjustments in farm capital structure." *Journal of Agricultural and Applied Economics*, 35(1): 67-78.

Escalante, C.L., C.G. Turvey, and P.J. Barry, (2009) "Farm business decisions and the sustainable growth challenge paradigm", Agricultural Finance Review, 69(2), 228 – 247.

Featherstone, A.M., Moss, C.B., Baker, T.G., & Preckel, P.V. (1988). "The theoretical effects of farm policies on optimal leverage and the probability of equity losses." *American Journal of Agricultural Economics*, 70(3), 572-579.

Gabriel, S.C., & Baker, C.B. (1980). "Concepts of business and financial risk." *American Journal of Agricultural Economics*, 62(3), 560-564.

Glauber, J. W. (2013). "The Growth of The Federal Crop Insurance Program, 1990–2011." *American Journal of Agricultural Economics*, 95(2), 482-488.

Gilligan, D. and J. Hoddinott (2007) “Is There Persistence in the Impact of Emergency Food Aid? Evidence on Consumption, Food Security, and Assets in Rural Ethiopia” *American Journal of Agricultural Economics* 89: 225-242.

Greene, W.H. (2003) Econometric Analysis, 5th Edition, Prentice-Hall, Upper Saddle River, NJ.

Heimlich, R. (2000) “Farm Resource Regions” Agricultural Information Bulletin Number 760. USDA Economic Research Service, Washington DC, Available at: www.ers.usda.gov/publications/aib760 (Accessed 1 July, 2013).

Henderson, J. & Akers, M. (2012). “Farmland values rise with crop prices.” Survey of 10th District Agricultural Credit Conditions, 1st Quarter, Federal Reserve Bank of Kansas City.

Ifft, J., Nickerson, C., Kuethe, T., & You, C. (2012). “Potential Farm-Level Effects of Eliminating Direct Payments.” USDA-ERS Economic Information Bulletin, (103). USDA-ERS Economic Information Bulletin, (103).

Ifft, J., Novini, A., & Patrick, K. (2014). “Debt Use By US Farm Businesses.” USDA-ERS Economic Information Bulletin, (103). USDA-ERS Economic Information Bulletin, (122).

Ifft, J., Kuethe, T. & Morehart, M. (2013). “Farm Debt Use by Farms with Crop Insurance.” Choices, 3rd Quarter.

Ifft, J., Wu, S. & Kuethe, T. (2014). “The Impact of Pasture Insurance on Farmland Values.” Agricultural and Resource Economics Review, forthcoming.

Katchova, A. (2010) “Agricultural Contracts and Alternative Marketing Options: A Matching Analysis” *Journal of Agricultural and Applied Economics* 42: 261-276.

Kropp, J. D., & Whitaker, J. B. (2011). “The impact of decoupled payments on the cost of operating capital.” *Agricultural Finance Review*, 71(1), 25-40.

Kuethe, T. H., & Morehart, M. (2012). “The profit impacts of risk management tool adoption.” *Agricultural Finance Review*, 72(1), 104-116.

Kuethe, T. and M. Morehart (2012b) “The Agricultural Resource Management Survey: An Information System for Production Agriculture” *Agricultural Finance Review* 72 (2): 191-200.

Jensen, F. E. and Langemeier, L. N. (1996), "Optimal leverage with risk aversion: empirical evidence", *Agricultural Finance Review*, Vol. 56 No. 1, pp. 85-97.

Just, R.E., L. Calvin, and J. Quiggin. 1999. “Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives.” *American Journal of Agricultural Economics* 81: 834–49.

Lynch, L. and X. Liu (2007) “Impact of Designated Preservation Areas on Rate of Preservation and Rate of Conversion: Preliminary Evidence” *American Journal of Agricultural Economics* 89: 1205-1210.

Manning, C. (2007) “Logistic Regression (with R).” Available at: http://nlp.stanford.edu/manning/courses/ling289/logistic.pdf (Accessed 22 Sept., 2014).

Mishra, A.K. and H.S. El-Osta (2002) “Managing Risk in Agriculture Through Hedging and Crop Insurance: What Does a National Survey Reveal?” *Agricultural Finance Review* 62 (2): 135-148.

Moss, C. B., J.S. Shonkwiler, and S.A. Ford. (1990) "A risk endogenous model of aggregate agricultural debt." *Agricultural Finance Review* 50(1): 73-79.

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

Pederson, G. (1990). “Determinants of crop insurance protection at agricultural banks.” *Agricultural Finance Review*, 50, 16-25.

Risk Management Agency (2014) “Summary of Business Reports and Data.” Available online at http://www.rma.usda.gov/data/sob.html (Accessed May 24, 2014).

Rosenbaum, P. and D. Rubin (1983) “The Central Role of the Propensity Score in Observational Studies of Causal Effects” *Biometrika* 701: 41-55.

Sherrick, B.J., P.J. Barry, P.N. Ellinger, and G.D Schnitkey. 2004. “Factors Influencing Farmers’ Crop Insurance Decisions”, *American Journal of Agricultural Economics* 86(1) :103-14

Skees, J. R., & Nutt, P. J. (1988). “The Cost of Purchasing Crop Insurance: Examining the Sensitivity of Farm Financial Risk.” *Agricultural Finance Review*, 48, 37-48.

Smith, A.J., & Todd, E.P. (2005). “Does matching overcome LaLonde's critique of nonexperimental estimators?” *Journal of Econometrics*, 125(1), 305-353.

Smith, V.H. and A.E. Baquet (1996) “The Demand for Multiple Peril Crop Insurance: Evidence from Montana Wheat Farms” *American Journal of Agricultural Economics* 78: 189-201.

Turvey, C.G. (2012) “Whole Farm Income Insurance” *The Journal of Risk and Insurance* 79 (2): 515-540.

Turvey, C. G. and Kong, R. (2009), "Business and financial risks of small farm households in China", *China Agricultural Economic Review*, Vol. 1 No. 2, pp. 155-172.

Velandia, M., R.M. Rejesus, T.O. Knight, and B.J. Sherrick (2009) “Factors Affecting Farmers’ Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales.” *Journal of Agricultural and Applied Economics* 41 (1): 107-123.

Weber, J.G., & Clay, D.M. (2013). Who Does Not Respond to the Agricultural Resource Management Survey and Does It Matter?. *American Journal of Agricultural Economics*, 95(3), 755-771.

Westcott, P. C., & Young, C. E. (2004). “Farm program effects on agricultural production: coupled and decoupled programs.” Decoupled Payments in a Changing Policy Setting. United States Department of Agriculture—Economic Research Service, Agricultural Economic Report, (838), 7-17.

Tables and Figures

Figure 1: Mean farm debt by FCI participation ($Thousands), 2011

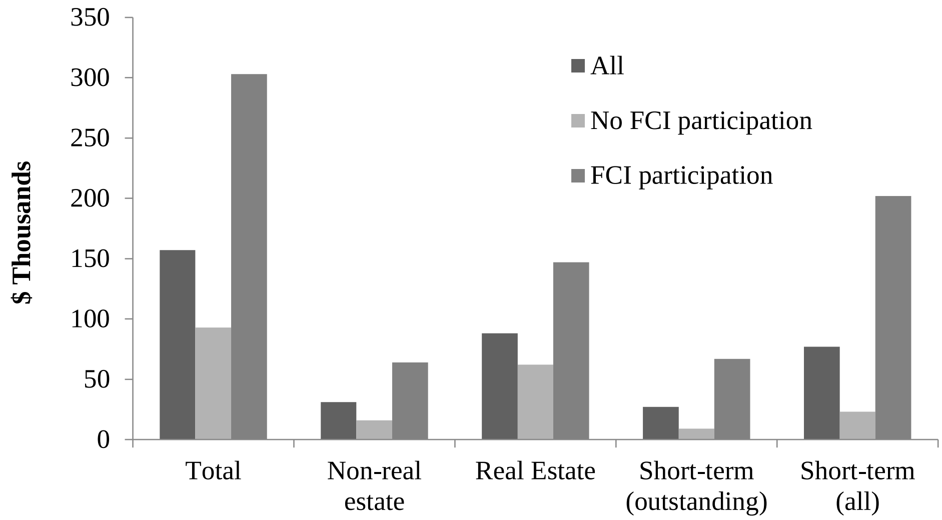

Table 1: Summary Statistics

	Mean/Share of Farms	Std. Err.		Mean/Share of Farms	Std. Err.
Total farm financial debt	152,716.40	6,673.84	Southern Seaboard	0.11	*
Non-real estate financial debt	29,399.86	4,861.87	Fruitful Rim	0.13	*
Real estate financial debt	84,657.19	1,984.09	Basin and Range	0.04	*
Short term financial debt (outstanding)	27,905.41	2,081.92	Mississippi Portal	0.03	*
Short term financial debt (all)	79,236.08	4,337.97			
Farm business debt to asset ratio	0.09	0.01	*Operator education*		
Share of short term financial debt (all) to total operating expenses	0.20	0.01	Some high school or less	0.09	*
Current ratio	1.21	0.21	Completed high school	0.48	*
FCI	0.28	0.01	Some college	0.24	*
Acres	729.59	22.30	Completed college	0.19	*
Percent cropland	0.54	0.01			
Ratio of owned to operated acres	0.92	0.03	*Farm type*		
Total off farm income	49,208.10	1,296.39	General cash grain	0.04	*
Operator age	58.24	0.31	Wheat	0.02	*
			Corn	0.12	*
Sales class			Soybean	0.04	*
$500,000 or more	0.14	*	Grain sorghum	0.00	*
$250,000 - $499,999	0.10	*	Rice	0.00	*
$100,000 - $249,999	0.13	*	Tobacco	0.01	*
$40,000 - $99,999	0.13	*	Cotton	0.01	*
$20,000 - $39,999	0.07	*	Peanut	0.00	*
$10,000 - $19,999	0.08	*	Fruits and tree nuts	0.12	*
$9,999 or less	0.35	*	Vegetables	0.05	*
			Nursery and greenhouse	0.02	*
ERS Farm Resource Region			General crop	0.03	*
Heartland	0.24	*	Beef cattle	0.31	*

Northern Crescent	0.15	*	Hogs	0.01	*
Northern Great Plains	0.05	*	Poultry	0.04	*
Prairie Gateway	0.13	*	Dairy	0.06	*
Eastern Uplands	0.11	*	General livestock	0.12	*

*****Standard errors not reported for share-of-farms measures; 13,629 observations; standard errors are calculated using the delete-a-group jackknife

Table 2: Logit Results: Impact of Farm Characteristics on Federal Crop Insurance Participation

	Coeff.	Std. Error	
Constant	0.387	0.677	
Acres (thousands)	0.010	0.020	
Percent cropland	1.532	0.362	***
Ratio of owned to operated acres	-0.006	0.260	
Total off farm income (thousands)	0.000	0.001	
Operator age	-0.005	0.007	
Operator education			
Completed high school	1.070	0.509	*
Some college	1.254	0.563	*
Completed college	0.903	0.570	
Sales class			
$250,000 - $499,999	-0.330	0.257	
$100,000 - $249,999	-1.170	0.192	***
$40,000 - $99,999	-1.382	0.248	***
$20,000 - $39,999	-2.577	0.414	***
$10,000 - $19,999	-2.835	0.368	***
$9,999 or less	-3.481	0.709	***
Farm type			
Wheat	1.210	0.489	*
Corn	0.176	0.273	
Soybeans	-0.227	0.469	
Grain sorghum	-0.712	11.825	
Rice	-0.040	0.760	
Tobacco	-0.848	1.462	
Cotton	0.275	0.799	
Peanut	1.652	0.809	*
General crop	-1.241	0.410	**
Fruits and tree nuts	0.189	0.524	
Vegetables	-1.841	0.554	***
Nursery and greenhouse	-3.467	0.709	***
Beef cattle	-1.538	0.323	***
Hogs	-1.546	0.560	**
Poultry	-2.572	0.462	***

Dairy	-1.832	0.3359	***
General livestock	-2.946	0.440	***
ERS Farm Resource Region			
Northern Crescent	-1.130	0.309	***
Northern Great Plains	0.819	0.438	
Prairie Gateway	0.213	0.410	
Eastern Uplands	-1.257	0.500	*
Southern Seaboard	-1.036	0.322	**
Fruitful Rim	-1.884	0.404	***
Basin and Range	-2.092	0.361	***
Mississippi Portal	-0.978	0.634	
Residual deviance	0.515		
Observations	13,347		

Significant at *$\alpha \leq 0.10$, **$\alpha \leq 0.05$, ***$\alpha \leq 0.01$; standard errors are calculated using the delete-a-group jackknife

Table 3: Average Treatment Effects: Impact of Federal Crop Insurance Participation on Debt Use

	Estimate	Std. Error	
Total farm financial debt	114,697	81,826	
Non-real estate financial debt	30,726	21,498	
Real estate financial debt	6,423	63,785	
Short term financial debt (outstanding)	63,964	23,883	**
Short term financial debt (all)	214,314	61,112	***
Farm business debt to asset ratio	0.03	0.01	**
Share of short term financial debt (all) to total operating expenses	0.14	0.00	***
Current ratio	0.41	0.59	

Significant at *$\alpha \leq 0.10$, **$\alpha \leq 0.05$, ***$\alpha \leq 0.01$

Table 4: Seemingly Unrelated Regression Results

	Absolute debt usage			Relative debt usage		
	Real estate debt	**Non-real estate debt**	**Short term debt**	**Debt-to-asset ratio**	**Current ratio**	**Short term debt to operating expenses**
FCI participation	-1,381	15,668*	21,887*	0.011	0.736	0.132**
	(16,953)	(8,936)	(12,177)	(0.010)	(0.482)	(0.062)
Constant	335,675***	117,059***	120,958***	0.349***	0.734	0.611
	(75,991)	(42,170)	(45,254)	(0.037)	(1.900)	(0.126)
Acres (thousands)	4,625	2,257	5,563	-0.002	0.013	0.005
	(7,684)	(3,243)	(10,460)	(.002)	(0.091)	(0.012)
Percent cropland	10,610	6,685***	7,911***	0.007**	0.072	-0.001
	(17,645)	(6,085)	(6,033)	(0.014)	(1.604)	(0.037)
Ratio of owned to operated acres	7,214***	1,798***	-414.6***	0.001***	0.337	0.000
	(2,072)	(1,237)	(472.0)	(0.003)	(0.866)	(0.003)
Total off farm income (thousands)	158.80*	35.54	39.10	0.000	0.000	-0.004***
	(93.10)	(66.60)	(59.84)	(0.000)	(0.002)	(0.000)
Operator age	-1,363***	-215.9	-321.6	-0.004	-0.037**	0.024***
	(433.84)	(200.8)	(184.5)	(0.001)	(0.019)	(0.001)
Did not complete high school	-8,064	-16,166**	-10,166**	0.003	1.199	-0.042
	(21,832)	(10,302)	(6,003)	(0.018)	(0.842)	(0.030)
Completed high school	-14,154	-10,040	-7,997	-0.002	0.755*	-0.015
	(8,834)	(7,677)	(4,807)	(0.019)	(0.454)	(0.024)
Some college	-1,151	-1,644	-9,927	0.007	0.036	-0.050**
	(14,032)	(7,126)	(5,689)	(0.012)	(0.319)	(0.021)
Sales Class						
$500,000 or greater	-199,100**	-84,052	-94,289*	-0.056**	-0.018	-0.072*
	(91,766)	(47,460)	(45,855)	(0.017)	(0.324)	(0.042)
$250,000 - $499,999	-218,220**	-107,612**	-116,606**	-0.058***	0.029	-0.171***
	(104,388)	(52,786)	(48,274)	(0.022)	(0.406)	(0.053)
$100,000 - $249,999	-264,850***	-111,126**	-120,332**	-0.085***	2.034	-0.229***
	(100,761)	(52,297)	(48,613)	(0.021)	(1.421)	(0.056)
$40,000 - $99,999	-249,335**	-115,148**	-123,218**	-0.083***	0.676	-0.229***
	(100,469)	(51,602)	(49,854)	(0.023)	(0.902)	(0.069)
$20,000 - $39,999	-277,171***	-114,078**	-121,600**	-0.107***	2.335*	-0.266**
	(96,384)	(50,164)	(49,190)	(0.027)	(1.319)	(0.107)

$10,000 - $19,999	-277,573***	-114,639***	-117,158***	-0.078***	1.873	-0.071
	(96,359)	(50,628)	(47,757)	(0.027)	(1.410)	(0.063)
Farm Type						
General cash grain	-12,468	-1,831	-4,950	-0.000	-1.308	0.035
	(31,140)	(10,441)	(15,127)	(0.019)	(0.841)	(0.080)
Wheat	17,035	-4,920	13,887	0.020	1.045	-0.024
	(34,837)	(10,890)	(20,737)	(0.019)	(0.957)	(0.038)
Corn	42,604	-2,536	4,808	0.034	-0.398	0.105**
	(55,885)	(11,608)	(15,987)	(0.026)	(0.428)	(0.048)
Soybeans	-55,445	-7,582	-7,379	0.047	0.788	0.182
	(38,689)	(17,372)	(18,867)	(0.080)	(2.965)	(0.206)
Grain sorghum	-82,146*	10,926	12,142	0.054	-0.752	-0.061
	(42,560)	(26,404)	(28,751)	(0.030)	(1.084)	(0.106)
Rice	-21,806	-378.3	19,325	-0.076	-0.652	0.062
	(33,409)	(18,781)	(22,094)	(0.036)	(0.781)	(0.061)
Tobacco	-80,711***	-9,645	-5,855	0.032	-0.449	0.081*
	(23,284)	(10,073)	(17,881)	(0.046)	(0.983)	(0.046)
Cotton	-34,120	29,096***	-14,520	-0.018	4.152	0.008
	(35,783)	(22,478)	(15,465)	(0.030)	(2.926)	(0.116)
Peanut	9,655	11,442	17,687	-0.003	-0.859	0.038
	(24,663)	(8,745)	(19,427)	(0.027)	(1.066)	(0.042)
General crop	68,892	343.5	13,623	0.033	-0.387	-0.008
	(46,277)	(9,919)	(15,418)	(0.033)	(1.640)	(0.108)
Fruits and tree nuts	9,755	35,182***	52,905***	0.093**	4.071	-0.062
	(27,789)	(28,926)	(46,298)	(0.051)	(3.675)	(0.067)
Vegetables	-7,123	-991.6	12,665	0.032	3.992	0.078
	(30,074)	(11,913)	(20,208)	(0.038)	(5.321)	(0.052)
Nursery and greenhouse	17,993	16,573	29,171	0.034	-0.621	-0.109**
	(24,197)	(11,302)	(24,599)	(0.025)	(0.769)	(0.052)
Beef cattle	32,051	14,344	-7,062	0.037	0.244	-0.080
	(90044)	(31,256)	(30,335)	(0.032)	(0.760)	(0.067)
Hogs	58,658**	-22,573	-22,911	0.064***	0.427	-0.180***
	(25633)	(19,428)	(25,652)	(0.035)	(0.855)	(0.060)
Poultry	92,097	56,938***	8,137	0.043*	0.194	-0.014
	(100897)	(46,835)	(29,963)	(0.023)	(0.504)	(0.068)
Dairy	18,838	15,921**	20,217***	-0.000	-1.138	-0.037
	(27540)	(12,881)	(21,656)	(0.024)	(0.990)	(0.049)
ERS Region						
Northern Crescent	7,760	-1,165	-4,825	0.002	-0.237	0.118***
	(11373)	(6,609)	(5,073)	(0.009)	(0.574)	(0.029)
Northern Great Plains	-8,809	3,833	13,535*	0.033**	0.864	0.019
	(21796)	(11,380)	(17,137)	(0.029)	(0.870)	(0.053)
Prairie Gateway	29,873	764.9	7,117	0.0307	1.976	-0.077**
	(22570)	(9,758)	(8,496)	(0.013)	(1.657)	(0.032)

Eastern	17,314	-4,953	-7,378	0.077***	0.438	-0.091**
Uplands	(12078)	(8,754)	(10,302)	(0.061)	(0.991)	(0.039)
Southern	-5,564	218.4	-10,871	-0.004	0.084	-0.108***
Seaboard	(14128)	(6,666)	(13,173)	(0.013)	(0896)	(0.032)
	20,455	4,994	3,485	0.007	1.683	-0.008
Fruitful Rim	(23134)	(12,748)	(11,467)	(0.017)	(1.712)	(0.042)
Basin and	-5,475	-6,266	-7,144	0.006	0.686	-0.064*
Range	(15484)	(10,376)	(7,534)	(0.016)	(1.269)	(0.036)
Mississippi	-37,230	-5,388	-16,095	0.008	0.287	-0.611***
Portal	(27358)	(11,312)	(16,504)	(0.021)	(1.112)	(0.033)
Observations	13,629	13,629	13,629	13,176	13,176	13,176
Breusch-Pagan Test Statistic	48,700	48,700	48,700	16,971	16,971	16,971

Note: Significant at *$\alpha \leq 0.10$, **$\alpha \leq 0.05$, ***$\alpha \leq 0.01$; Standard errors are calculated using 1000 cluster bootstrap iterations and are robust to correlation in standard errors at the strata level.

OTHER A.E.M. WORKING PAPERS

WP No	Title	Fee (if applicable)	Author(s)
2015-01	Rice Sector Policy Options in Guinea Bissau		Kyle, S.
2014-22	Impact of CO2 emission policies on food supply chains: An application to the US apple sector		Lee, J., Gómez, M., and H. Gao
2014-21	Informality among multi-product firms		Becker, D.
2014-20	Social Protection, Vulnerability and Poverty		Kanbur, R.
2014-19	What is a "Meal"? Comparative Methods of Auditing Carbon Offset Compliance for Fuel Efficient Cookstoves		Harrell, S., Beltramo, T., Levine, D., Blalock, G. and A. Simons
2014-18	Informality: Causes, Consequences and Policy Responses		Kanbur, R.
2014-17	How Useful is Inequality of Opportunity as a Policy-Construct?		Kanbur, R. and A. Wagstaff
2014-16	The Salience of Excise vs. Sales Taxes on Healthy Eating: An Experimental Study		Chen, X., Kaiser, H. and B. Rickard
2014-15	'Local' producer's production functions and their importance in estimating economic impacts		Jablonski, B.B.R. and T.M. Schmit
2014-14	Rising Inequality in Asia and Policy Implications		Zhuang, J., Kanbur, R. and C. Rhee
2014-13	Heterogeneous firms and informality: the effects of trade liberalization on labor markets		Becker, D.
2014-12	Minimum Wage Effects at Different Enforcement Levels: Evidence from Employment Surveys in India		Soundararajan.V.
2014-11	Thresholds, Informality, and Partitions of Compliance		Kanbur, R. and M. Keen
2014-10	On the Political Economy of Guest Workers Programs in Agriculture		Richard, B.
2014-09	Groupings and the Gains from Tagging		Kanbur, R. and M. Tuomala

Paper copies are being replaced by electronic Portable Document Files (PDFs). To request PDFs of AEM publications, write to (be sure to include your e-mail address): Publications, Department of Applied Economics and Management, Warren Hall, Cornell University, Ithaca, NY 14853-7801. If a fee is indicated, please include a check or money order made payable to Cornell University for the amount of your purchase. Visit our Web site (*http://dyson.cornell.edu/research/wp.php)* for a more complete list of recent bulletins.