Farmland Rental Rates and Commodity Support Programs

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I. Introduction

Commodity support programs play a large role in many US agricultural markets. Accordingly, much research has been devoted to analyzing how these programs influence the markets they target, with the literature showing significant impacts of the payments on rental rates for farm land (Kirwan, 2007; Kirwan and Roberts, 2016; Goodwin and Mishra, 2005; Goodwin and Mishra, 2006; Hendricks, Janzen, and Dhuyvetter, 2012; Weber and Key, 2012). Tied to the Ricardian theory of rent, the hypothesis goes, that each dollar of subsidy translates into a dollar-for-dollar higher rent obtainable by the land-lord. Thus while the programs are designed to give income to farmers, this is at least partially transferred to land-lords as well. Given that a significant proportion of farmers rent land, rather than solely benefiting farmers, a portion of these payments represent wealth transfers from tax-payers to rural landowners, even if the farmer recieves the payment.

While previous research has analyzed the role of guaranteed subsidies on rental markets, recent changes in commodity support programs make revisiting the question worthwhile. From 1996 until the Farm Act of 2014, the most prominent commodity support program in the US was the Direct and Counter Cyclical (DCCP) Payments Program, and most notably the Direct Payments sub-program itself. Averaging $4.3 billion annually (from 2010 through 2014), Direct Payments received a great-deal of research into estimating the impacts of the subsidies (sources above). The key feature of the program was the fact payments were guaranteed and fixed for farmers, independent of production or market outcomes. Markedly making it a guarantee of income for farmers each year, and thus potentially making payments more readily transferable from farmer to rents. While there were other programs in the DCCP that were conditional in nature, others paled in magnitude, and accordingly, all of previously cited literature analyzed the Direct Payments portion of the program.[1]

With the 2014 Farm Act, this guaranteed subsidy was switched with conditional programs now taking the lead in size. The entire DCCP was replaced with two new conditional programs: the Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC). While these new programs continued the approach of decoupled payments tied to land, the timing of payments were made

[1] The other conditional programs were called Average Crop Revenue Election (ACRE) program and Counter-Cyclical Payments (CCP). In the years leading up to the Farm Act of 2014, Direct payments were 88% and 90% of expenditures in the DCP in 2013 and 2014.

entirely conditional on market outcomes, triggering when either revenue or price were below policy prescribed levels. The change in subsidy programs switched the certainty of how and when farmers would receive payments, moving from fixed to conditional ones. Averaging $6.6 billion annually in payments in the three years since inception, the creation of these conditional payment programs were not only notable due to size, but a change in the certainty of how and when the farmers would receive support. And importantly for this study, the subsidy pass-through with conditional payments on market outcomes has not yet been explored.

Featherstone and Baker (1988) estimated that cash rental values would fall by 13% over a four year period if all forms of subsidies were eliminated. Kirwan (2009), using a "quasi-experimental" approach that exploits changes in payment policies across years to identify the effect of subsidies on rental rates found a subsidy pass-through of 25%. However, not all previous work have shown this impact, in fact Lence and Mishra (2003) find a negative impact on rental rates from higher deficiency payments on land which is opposite of what theory would predict. Alston and James (2002) show that theoretical considerations, when taking into account supply elasticities of farmland, output elasticities, and other restrictions, predict that for every dollar of subsidy $0.40 to $0.60 passes through to the landowner. Hendricks et al. (2012) argue that discrepancies between theory and empirical estimation may be caused by inertia and tenancy arrangements, which would indicate studying the impacts of payments beyond a single year. Indeed, once corrected for these issues, they found the pass through to be smaller than previous papers.

While the incidence of subsidy pass-through from the farmer to the landlord has been documented, given that a portion of payments are no longer guaranteed, this incidence is expected to change. Weersink et al. (1999) find that the pass through of subsidies to agricultural land values was actually higher than the pass through rate of increases in net income generated from the land. This was attributed to differing discount rates due to differences in risk between income and government subsidies. Government payments have been historically viewed as more certain than the income from the farmland. This leads to the conclusion that when farmers view government subsidies as certain, they are willing to pay more for a parcel of land. The question then becomes, given that payments are now uncertain, how do these subsidies pass through to rental rates?

To shed further light on this topic of government payments and agricultural land rental rates, this paper analyzes the effect of the conditional government payments on rental rates of land. Using a repeated-cross section of annual farm level data, the paper highlights while the pass-through effect of payments on rental rates has diminished from the prior Direct Payments programs it remains both economically and statistically significant; roughly every dollar of payment increases rent by $0.50 to $0.70. With annual payments averaging over $6 billion dollars since program inception, this indicates a large transfer of wealth from tax-payers to rural land owners each year.

The rest of the article is organized as follows. Section II discusses in more detail the specifics of the relevant US farm policy and how it has changed over time. Section III provides a brief theory setting linking rental rates and farm land values. This important for recognizing the unmeasurable component and challenge with estimating effects related to expectations and land values. The fourth section discusses the empirical approach to measuring the policy incidence, and how the approach presented is able to disentangle the effect of payments and farming incomes. We present our results in section V. Section VI concludes.

II. Commodity Support Programs Background

Citing a number of motives, such as national security, or concern for farmer livelihoods, governments are often inclined, at some level, to provide monetary transfers to agricultural producers. One of the most studied government payment programs in agriculture is what has most recently been called the Direct Payments[2] program (Kirwan, 2007; Goodwin and Mishra, 2005; Goodwin and Mishra, 2006; Hendricks, Janzen, and Dhuyvetter, 2012; Weber and Key, 2012, Roberts, Kirwan, and Hopkins, 2003). This program came into inception (under a different name) with the Farm Act of 1996, and was administered by the USDA. The program provided cash payments to farmers, untethered to farming decisions. More specifically, the Direct Payment system paid farmers based on the crop historically planted on each piece of land, instead of what crop they planted that year and what production was realized. Effectively tying payments to prior decisions, as opposed to current planting decisions. Justifying this type of payment scheme-- was the idea that tying payments to farmers' plating decisions (e.g., subsidizing specific crops) or other market outcome would distort agricultural markets leading to overproduction and efficiency losses.

[2] While most recently the program associated with uncoupled payments was called Direct Payments, in its' earlier years it took on a different name, called Production Flexibility Contracts (PFCs). While the names were different, the programs behaved similarly, as one replaced the other.

The guaranteed payment system eventually came under scrutiny when commodity prices rose in the late 2000's and early 2010's. Stirring negative public perceptions regarding farm subsidies was the fact that, at the time, farmers were earning record-high incomes, while still receiving another $4.5 billion annually[3] in government assistance (Kilman, 2011). Consequently, in the 2014 Farm Act, Congress decided to remove the Direct Payments program and replace it with a system of conditional payments, the Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) programs. While conditional payment programs had existed before this Act, with programs such as the Average Crop Revenue Election (ACRE) Payments and the Counter-Cyclical Payments (CCP), these programs were significantly smaller in size than the Direct Payments or the newly created conditional ones.

The new programs, ARC and PLC, changed the way in which farmers received subsidies. For ARC, for a given crop, farmers only receive payments if county revenues fall below a formally derived average of previous outcomes. For PLC, payments are triggered only if average national prices fall below certain levels. Farmers are restricted to enrolling in only one of the programs, and do so based on which of these new conditional programs best suit their interests.[4] The main similarity between the programs is that payments are tied to the land (referred to as *base acres* in the language of the legislation) and not to production decisions. As well, an important distinction, is that payments are made based on county level outcomes for ARC, and on national outcomes for PLC, but not outcomes of the farm. While payments are intended to be related to the outcomes of specific crops, farmers are not restricted to grow the crop that is formally enrolled with either ARC or PLC.

For farmer's that planted the same crop as the base acre crop for which they have enrolled, these new programs provide payments and risk mitigation strategies in the event of less advantageous crop years, so long as the individual farmer's yield closely match that of the county average. Because payments are triggered based on the county average, farmers could still receive payment even when their fields performed well, so long as the county average is low. Conversely,

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[3] Calculated as the average annual cost of the Direct Payments program from 2011 to 2014.

[4] If a farmer did not make a choice, they defaulted to PLC. There was an additional choice within the ARC program, either ARC- County (ARC-CO) or ARC- individual (ARC-IC). The basic difference in the two programs related to whether revenue was calculated at the farmer level or the county average. Though the selection of ARC-IC additionally imposed other program restrictions. O'Donoghue et al. 2016 provides greater detail to the nuances of the programs. Given the size difference of the two programs 185 million versus 2 million acres, the generalized discussion refers to the ARC-CO program.

a farmer can have a disastrous year, but if the county average revenue is high enough, they receive no payments. Thus, while the programs behave similarly to crop insurance as a risk mitigation strategy in that they provide payments during less profitable years, there remains a risk for the farmer when (1) their yields differ from their neighbors, and (2) they choose to plant a different crop than that for which they are enrolled. Another important distinction from crop insurance, is that farmers simply have to sign up to receive payments but do not have to pay an insurance premium.

Consider the following simplified scenario to explain the programs and farmer's decisions. A farmer has 500 acres of land that has historically been allocated to both corn and soybeans. The distinction of land ownership is irrelevant for who receives the payments, only the farm operator receives the payments. Accordingly, the land has been classified as 200 base acres of soybeans and 300 base acres of corn. As previously mentioned, this can be unrelated to what the farm actually plants on those base acres. The farmer then makes their planting decision each year, and for simplicity, assume they continually rotate their crops each year; thus the farmer grows half soybeans and half corn (250 acres of each). Which crop is planted on which base acre is not important.

If the county level revenue falls below the county level average determined by the policy, as has been the case for many corn base acres from 2015 to 2018, the farmer receives payment on all 300 acres of corn base acres. Even though they only planted 250 acres of corn. The converse could be true for soybeans as well. The key distinction is that the individual's farming choices are unrelated to program payments. The only way the farmer's outcomes may influence the payments is in how the county average yield is measured. Thus with a large enough county, which is the case of many Midwestern counties, the farmer's individual outcomes are only loosely related to county average outcomes.

ARC and PLC programs are a significant expenditure for the government each year. Figure 1 presents the total cost of these Title 1 programs from 2011 to 2017, including the Direct Payments that were phased-out in 2014. From the figure, we observe two noticeable features; the program lapse in the 2014 fiscal year and the size of the new conditional programs. While Direct Payments were replaced with the conditional programs in the 2014 Act, this was not without a lapse in programs, causing a significant reduction in payments for 2015 (effectively the 2013 crop year[5]). Secondly, while the conditional programs were intended to reduce the burden on taxpayers relative to Direct Payments (Congressional Budget Office, 2014), the resulting decline in commodity prices from whence the program prices were set, has, in reality, caused an increase in the total program expenditures (Farm Service Agency, 2018).

III. Empirical Strategy

While the theory linking land values and rental rates is fairly straight-forward, and thus left elsewhere for the reader, implementing in the data is the most relevant exercise here because much of what determines rental rates is unobservable. Notably, expected profit of the farmer. Complicating matters even more, because of how the programs were designed, farming revenues and government payments are expected to be highly correlated posing problems for identification, as explained in more detail below.

Naively, we could try to estimate the effect of government payments on rental rates by regressing farm-level payments ($payment_i$) on farm-level rent, ($rent_i$):

$$rent_i = \beta_0 + \beta_1 payment_i + \varepsilon_i \qquad (1)$$

The β_1 coefficient in this regression would provide us with an estimate of the effect of the incidence of subsidy pass through to the landlord. As just stated, however, this estimate is unlikely to capture the causal effect of interest due to the standard issue of omitted variable bias. Its omission leads to biased OLS estimates of the causal effect β_1.

Survey Data

In this paper, we use farm-level data from the USDA's Agricultural and Resource Management Survey (ARMS). [6]The ARMS is conducted in three phases. The first phase is concerned with screening. The second phase is concerned with crop-specific costs and practices and is conducted on a rotating basis. In this paper, we use data from the third phase, called the Costs and Returns Report (CRR). The CRR is an annual nationally representative survey that collects farm business and farm household information from 30,000 farms in 48 contiguous states. Fifteen agriculturally important states are oversampled in order to provide a reliable national level

[5] The timing of payments and outcomes are not straight-forward due to the lag from when payments are determined and when payments are made, as well as the differences in fiscal and marketing years. For example, a payment for the 2013/14 crop year is made to farmers by the FSA in the 2015 fiscal year.
[6] Survey questionnaires are available online at https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/questionnaires-and-manuals/

sample of farms.[7] The ARMS sample is stratified on the basis of region, farm sales, and commodity specialization. Population weights are provided to account for differences in the probability of being sampled. A farm in this dataset is defined as any operation that produced and sold or normally would have produced and sold more $1,000 of agricultural products in the previous year.

We use the sample years of 2012 through 2016 to answer our question. Because the survey is a repeated cross-section, as opposed to a panel, we analyze the impact of payments each year and make inferences about how and why responses may differ across years. While the CRR is intended to provide a nationally representative sample of farms, we restrict our analysis to farms in thirteen Midwestern states that produced corn, sorghum, soybeans, barley, oats, or wheat.[8] This restriction is similar to Goodwin and Mishra (2006), which analyzed the farmers in the "Corn Belt."[9] Farmers that additionally produced other crops, such as rice, cotton, or peanuts, were omitted from this study.

Heterogeneity of program payments and crop types make a national comparison of crops problematic, and thus by limiting the sample to typical Midwestern growers, we improve the comparability of the farm units in our empirical model. By narrowing the sample to similarly substitutable crops, with similar production scheduling and equipment, the sample is expected to be more homogenous and representative of those farms.

While restricting the sample may limit the external validity of our results, our sample consists of roughly 3,000 farmers annually, which represent 54% of total payments, consisting of $3.6 billion annually.[10] Thus even if our results are solely internally valid, they are of interest given the sheer size and importance of the crops and growing region we have selected. Table 1 presents summary statistics for each year of the ARMS sample used. We computed sample averages using survey weights. As the table shows, while it is possible that the ARMS samples a different set of farms in each year, the average attributes of the samples are similar across sample years. This is comforting for comparison of results across sample years, since the sample appears to follow its directive in being representative of farms across years. Most acreage in this sample is devoted to

[7] These states are: Arkansas, California, Florida, Georgia, Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Carolina, Texas, Washington, and Wisconsin

[8] Farmers from the following states were used in this analysis: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin, and Wyoming

[9] Comparatively Goodwin and Mishra (2006) additionally sampled Kentucky, but left North Dakota, Wyoming, Kansas, Michigan, and Wisconsin.

[10] This is the average annual payments from the 2014 to 2016 crops years from states and crops included in this study (FSA, 2018).

either corn or soybeans, and in total averaging just over 800 acres each year. This table also shows that almost twice as much land in operation is rented, as opposed to owned by farmers, with over $50,000 in rental payments made annually. These statistics highlight the importance of rental markets in agricultural production. Also included in this table are the average per acre rental rates, as well as the relevant government payments.

Kirwan and Roberts (2016) present a discussion and results pointing to potential issues with using farm versus field-level data for analyzing the subsidy incidence on rental rates, though the argument is somewhat unclear. While it is accurate that farmer level data is unable to differentiate between the incidences of subsidies on either the owned or rented land, it is unclear why one would expect different subsidy rates across ownership structure. In their comparison of results between farm and field level econometric equations, they highlight the importance for controlling for the unmeasured land productivity, and the inclusion of this variable significantly reduced the estimated subsidy incidence in their field level analysis. However, when they analyzed the farm level data, they do not include a similar land productivity measure, yet compare the results. As expected when comparing one sample with one that did not control for productivity, the one without the control will have higher estimated coefficients, because it is positively biased from the omitted variable, and thus makes the comparison questionable.

An advantage of the data we use in this paper is that it captures a repetitive nationally representative sample of farms each year. While prior studies often have used either the Census or the Phase II portion of ARMS for analysis, (Kirwan, 2009; Kirwan and Roberts, 2016), these types of studies rely on a "quasi-experimental" approach where the main identification tool is a policy change between years. One assumption of this type of approach relates to no confounding variables that might influence the differences in outcomes across the repeated panel, beyond those of the policy changes. For agricultural commodity markets and prices that are continually evolving and related to the subsidy itself, the confounding assumption can be a strong one.

Accordingly, the results here present another approach to this subsidy pass-through question from a new perspective and data series. While the results show the estimates are reasonably consistent across years, the differences in coefficients across cross-section years further indicate the importance of sampling more data and years to corroborate the validity of estimates.

Estimation Strategy

To estimate how much of the government payments are passed through to rental values, we fit a series of linear models with various controls meant to address the endogeneity concerns briefly mentioned before and explained in more detail below. We divided government payments into two different categories based on the programs existence. For the 2011 to 2014 survey years, per acre government payments are measured by the sum of Direct, CCP, and ACRE payments divided by planted acres at the farm level. During the conditional payment regime, 2015 and 2016, per acre government payments are the sum of ARC and PLC payments divided planted acres.

The most meaningful source of omitted variable bias in the model above arises from the unobserved productivity of the land. Because commodity support programs have been conditional on the historical productivity of land through crop yields, it is correlated with both rental rates and payments. Land that produces more bushels receives higher payments, while at the same time is more valuable for farmers holding payments constant. The key with identification is that land productivity causes rental rates and not the other way around.

Ideally, our main strategy would be to control for farm productivity directly. However, this variable is unobserved, and because we have only repeated cross-sections of farms, we cannot control for it using such things like farmer fixed-effects. One positive attribute of the data for controlling for productivity is that farm revenue is observed. However, we are argue one issue with strictly using observed revenue to control for productivity relates to the uncertainty of yields and also about the timing of rental agreements. Crop yields are unknown when rental contracts are made, and without explicit documentation to these expectations, it is unclear realized yields would be the best determinant for rental rates. Thus to identify the effects of payments on rent, we need to exploit the variation in farming revenues and government payments across farms in each cross-section. Something just observed revnues is unable to do.

Subsequently to capture the productivity of the land, county-level average expected revenues are calculated and used. Notably, the expected revenue variables are calculated similarly to how program payments are determined. The ARC program uses a five-year Olympic average of national prices and county yields to determine the county-crop specific *expected revenue*, which is used to determine both payment triggers and program payment limitations.[11] The actual

[11] The exact calculation of this value is slight more complicated due to various program rules, including ones that set lower bounds on the historical prices and yields used for the calculation, as well as how yields are measured when

payments then are determined by the realized product of the actual national average marketing year price and the county yield. If this realized value is below 86% of the *expected revenue*, payment occurs. Additionally, per acre payments are capped at 10% of *expected revenue*.

While the ARC program calculates the expected revenue by crop, this study is at the farm level, thus requires aggregate productivity of land across crops within a county. To proxy this land productivity, we used county-level yield and national prices from NASS to calculate crop specific expected revenues (NASS, 2018). The values were calculated similar to the ARC program formulas, using a five-year Olympic average to proxy projected revenues. If the most recent five-years of yields were not reported, a simple average of those available was used. To estimate an average expected revenue, the county-crop specific revenues were weighted based on NASS planted acres for each year (NASS, 2018). The survey-weighted average of this calculated value is included in table 1.

The key with this approach is how county level expected revenue and farm level revenue interact. The results show these values correlate highly and with similar magnitude with rental rates across all sample years. However, consider the conditional nature of government payments in 2015 and 2016. The expected revenue formula used here closely relates to how the government measures the productivity of land and thus payments, though which county that actually receives payments is randomized due to weather and yields. Thus by controlling for this county-level productivity for deriving government payments, as well as with the actual payments received, we believe the remaining component of actual government payments received to be as good as randomly assigned. While this is expectedly true for the last two years of the sample, the effects appear consistent in years when payments were not randomized as well. Showing our approach to controlling for land productivity and the relationship of payments versus farming revenues appears valid.

Consider as well, that with the ARC program, over 80% of county-crop combinations resulted in either zero payment or the per-acre program cap (FSA, 2018). Inferring if payments were received, the amount received is jointly determined by this expected revenue calculation. The natural variation in farms receiving payment, by controlling for land productivity, allows for a random sampling of farms who did and did not receive treatment. While we believe these features

data is insufficient to report. The above discussion generalizes some of these details for a simpler narrative. For the interested reader to the exact program features, they are discussed in O'Donoghue et al. (2016).

allow for the identification of payments in the sample years of 2015 and 2016, the results of the estimated effect of expected revenue on rent in the other years of the surveys are very similar in magnitude, indicating a close fit for proxying land productivity for the survey years without ARC and PLC as well.

While the expected revenues are calculated based on county-level statistics, as are the true program payments, there remains individual-level heterogeneity in the land quality that would be reflected in the rent. We additionally include per acre revenues from the survey as an additional control. This variable measured by the survey is expected to encapsulate both the difference in productivity from the farm and county, as well as the difference in revenue from expected and actual revenue caused by randomizations of weather within the year. By including the county-level expected revenues, and the observed farm-level revenues, we believe a causal relationship can be inferred. Controlling for productivity and unobservable state-level differences, dummies for each state are also included for additional stability tests.

IV. Results

The estimated effects of government payments on rental rates are presented in Table 2. We fit our model for each sample year separately, due to the cross-sectional nature of the survey. Four linear models were estimated for each sample year, each with an increasing number of controls to test the stability of results and how each control variable influenced the estimated subsidy effect. All of our models are weighted using survey weights.

The first set of results show the estimated effect of payments on rental rates without any controls. As expected, and consistent across groups, the estimated effects are largest when we do not control for any potentially confounding variables. Interestingly, we show that the effect declines as we switch from guaranteed to conditional payments, as predicted by the aforementioned theory.

The second estimation results show the importance of accounting for the productivity of land, as the coefficients and t-values for our control are large (t-values are above 10 for all survey years). The coefficient for revenue is consistent across years, roughly 0.3 for all sample years, indicating the approach to measuring expected revenues is similarly valued across the years. Notable since the approach used for approximating expected revenue was taken from the ARC program, which did not exist prior to 2015. Comparing (1) and (2), a significant decline in coefficients are shown, highlighting the bias in subsidy effect when ignoring land productivity.

Including farm-level average revenue better explains rental rates. Capturing the farm level heterogeneity through actual revenue, there is an expectedly positive effect of revenue on rental rates. Interestingly as well, the expected revenue variable which is the same for all farms at the county level, better explains rental rates than actual payments, underlying the importance for capturing expectations in farmland values, rather than merely ex-post revenues.

Further including state-level dummies reduced the estimated subsidy pass through but only by a limited amount. The largest difference in results from the dummies, was for the year 2014. It is likely this difference with and without dummies is spurious due to how government payments were received in that marketing year. As displayed in table 1, the average payment in 2014 was only $1 per acre, and above $12 for all other years. Since only a limited number of farmers received, an even smaller payment that year, that result and difference across estimation are less believable.

It is meaningful to compare the estimated effect of payments on rental rates during the time periods of Direct Payments and the conditional payments. Looking at the results with both revenue variables and no state dummies, the effect of direct payments translates into rental rates about or greater than $1 to $1 during the regime of Direct Payments. This direct translation of uncoupled payments to rental rates follows directly with theory, and is higher than many prior results (Kirwan, 2007; Kirwan and Roberts, 2016; Hendricks, Janzen, and Dhuyvetter, 2012;). In contrast, to compare theses coefficients with the results under the conditional programs, the coefficient magnitude is much smaller in size, ranging from 0.40 to 0.60. Indicating while the conditional government payments still translate into higher rental rates, the magnitude is significantly smaller. One possible explanation for this result is due to the uncertainty with how and when payments are received. With guaranteed payments, the farmer and the landlord know exactly how much is going to be received and can plan ahead. With the new ARC and PLC payment systems, payments are uncertain, and a risk-averse individual would thus value the new conditional payments less.

The relative difference in subsidy pass-through across the two regimes is a meaningful result. Even if one believes the approach did not fully identify the casual effect, which we believe it did, it is unlikely this effect would vary across the program regimes. Higher estimated effects were shown with direct payments than conditional ones. Thus importantly showing, while the subsidy pass-through prior research has shown remains meaningful, the conditional nature of the new programs have also significantly reduced this effect.

V. Conclusions

Farmland values are a large component of the balance sheet for most farms, as well as rental rates influence the profitability each year. With uncoupled government payments equal to roughly $6 billion annually, and roughly two-thirds of land rented (according to the results of the sample used here), any pass-through from subsidies to landlords influences the livelihoods of farms. This paper finds two important results from studying rental rates and government payments. The results confirm the effect of prior papers showing Direct Payments translated directly into higher rental rates for farms. The results here are on the high end of the subsidy pass-through literature, ranging from every $1 of subsidy to $0.55-1.40 higher rental rates. While a pass-through above $1 is unlikely, these results indicate a significant portion of income was passed through from the subsidy to the land-lord. Further robustness tests will be included in further drafts of this paper to assess this result.

Importantly though, the results show with the change in programs from guaranteed Direct Payments to conditional programs (ARC and PLC), the subsidy pass-through has been reduced significantly. Showing each $1 of subsidy results in higher rental rates of $0.40 to $0.60. While this result is still economically meaningful for highlighting the negative externality effects of subsidies, since the subsidy for farmers translates into higher rental rates, the effect of the pass-through has been diminished due to the uncertainty of the conditional program payments. This reduction in pass-through of subsidy is in line with the theory of risk aversion and valuing uncertain payments, since risk-averse individuals will pay less money for something that is not a guarantee.

While this paper highlights the effects of one government program on farming outcomes, it brings to light further important research questions. Subsidies are often discussed in a context of distorting the market incentives of farmers, and markets in general. They are often used to explain how the incentives created by the programs can lead to things such as an over-production of commodities. Effectively lowering prices and increasing the number of farmers that would be in an undistorted market. However, if the subsidy is passed through to the landlord, as shown here (and research elsewhere), it is clear the subsidy influences land markets, however, because that extra welfare from the subsidy is almost entirely captured by the landlord, the increased incentives from government payments to produce specific commodities are heavily mitigated. Meaning, although the subsidies influence this land market, they likely do little to provide incentives that would encourage over-production of commodities, a typical concern in agricultural markets.

Further research could examine the role of these programs and other policies, such as crop insurance, on farming decisions.

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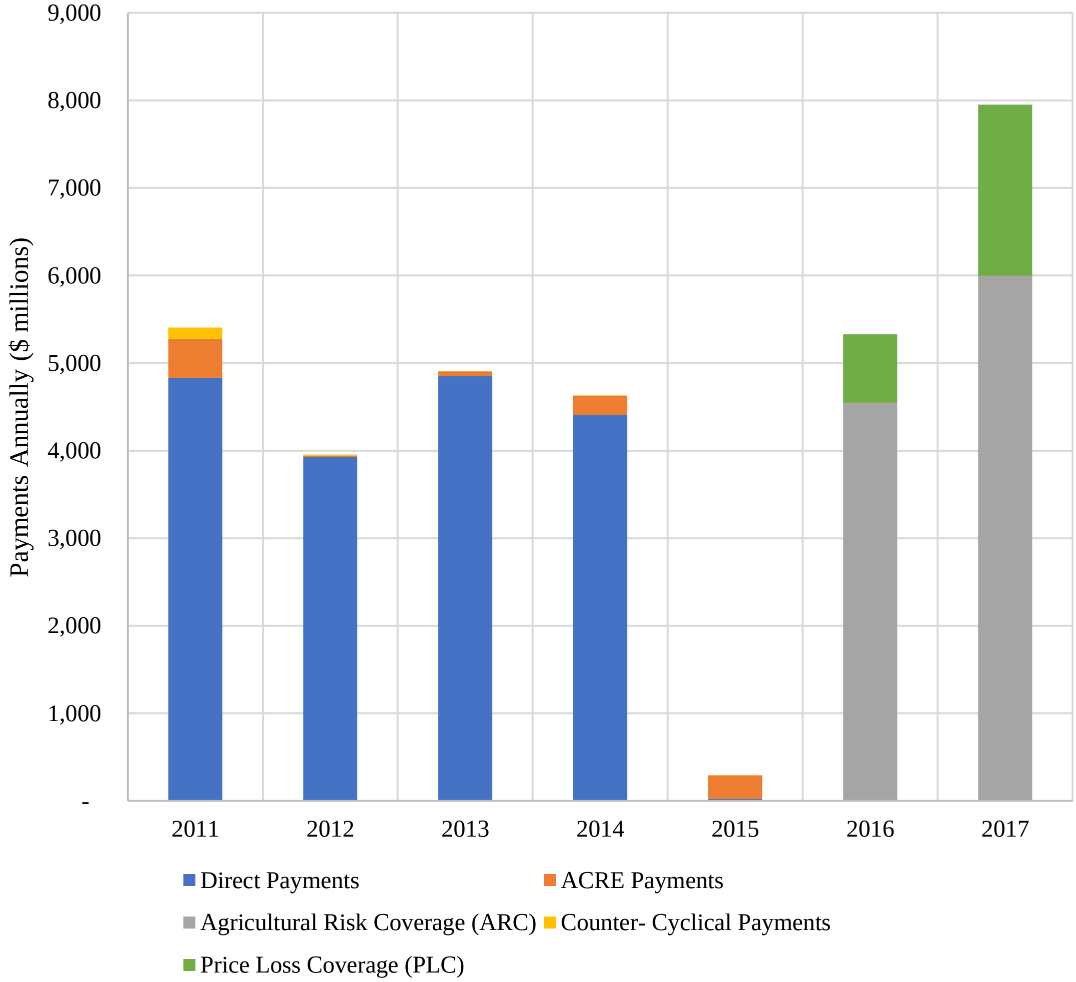

Source: Farm Service Agency

FIGURE 1. CHANGING OF THE COMMODITY SUPPORT PROGRAMS

TABLE 1. FARM SURVEY STATISTICS, MEAN VALUES

Variables	**2012**	**2013**	**2014**	**2015**	**2016**
Farm Characteristics					
Land Owned (acres)	309	303	292	289	291
Land Rented (acres)	533	563	543	545	536
Land Total (acres)	819	844	805	801	801
Total Costs of Renting ($)	53,590	72,897	69,800	70,492	66,917
Corn (acres planted)	297	342	318	317	326
Soybeans (acres planted)	248	283	299	285	291
Sorghum (acres planted)	7	9	10	16	13
Wheat (acres planted)	61	69	65	57	65
Per Acre					
Rental Rate, ($ acre)	104	128	122	126	123
Expected Revenue ($ acre)	573	646	678	683	640
Actual Revenue ($ acre)	428	499	445	407	423
Direct, CCP, and ACRE ($ acre)	12	13	1	Na.	Na.
ARC and PLC ($ acre)	Na.	Na.	Na.	11	17
Observations	4,338	1,832	3,368	2,395	2,634

Note: Farms sampled from the following states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin, and Wyoming.

TABLE 2. ECONOMETRIC RESULTS

Year	Variable	(1)	(2)	(3)	(3- FE)
2012	Direct, CCP, and ACRE	2.655***	1.654***	1.589***	1.403***
		(0.510)	(0.259)	(0.260)	(0.235)
	Expected Revenues		0.325***	0.312***	0.295***
			(0.016)	(0.019)	(0.028)
	Actual Revenues			0.0199**	0.0159*
				(0.009)	(0.008)
	Observations	4,338	4,322	4,322	4,322
	R-squared	0.064	0.187	0.19	0.236
2013	Direct, CCP, and ACRE	1.852***	1.133***	1.079***	0.996***
		(0.246)	(0.193)	(0.198)	(0.175)
	Expected Revenues		0.329***	0.289***	0.194***
			(0.016)	(0.017)	(0.023)
	Actual Revenues			0.0516***	0.0456***
				(0.009)	(0.009)
	Observations	1,854	1,832	1,832	1,832
	R-squared	0.069	0.25	0.268	0.346
2014	Direct, CCP, and ACRE	1.654***	1.271***	1.259***	0.545*
		(0.365)	(0.338)	(0.337)	(0.319)
	Expected Revenues		0.302***	0.285***	0.232***
			(0.012)	(0.014)	(0.020)
	Actual Revenues			0.0293**	0.0305***
				(0.012)	(0.012)
	Observations	3,398	3,368	3,368	3,368
	R-squared	0.009	0.193	0.199	0.283
2015	ARC and PLC Payments	1.243***	0.750***	0.705***	0.401
		(0.305)	(0.264)	(0.264)	(0.277)
	Expected Revenues		0.263***	0.239***	0.198***
			(0.016)	(0.019)	(0.028)
	Actual Revenues			0.0446***	0.0345**
				(0.015)	(0.015)
	Observations	2,441	2,395	2,395	2,395
	R-squared	0.06	0.199	0.207	0.268
2016	ARC and PLC Payments	1.100***	0.554***	0.553***	0.598***
		(0.159)	(0.134)	(0.136)	(0.136)
	Expected Revenues		0.310***	0.295***	0.230***
			(0.019)	(0.020)	(0.027)
	Actual Revenues			0.0258	0.0309**
				(0.018)	(0.015)
	Observations	2,653	2,634	2,634	2,634
	R-squared	0.072	0.252	0.255	0.339

Notes: Data is from econometric results with per acre rental rate as the dependent variable. Results included sample weighting. Equation intercepts and state dummies have been omitted for clarity. Model (1) included only government payments. (2) adds expected revenue to (1). (3) adds actual per acre revenue to (2). (3-FE) adds state level dummies to (3). Robust standard errors in parentheses Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1