Determinants of Agricultural Disaster Payments in the Southeastern U.S.: County Level Analysis

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Introduction

Direct disaster payments are considered the least efficient form of agricultural disaster relief (Goodwin and Smith, 1995). Several pieces of legislation were passed in the early 1990s in an attempt to make the process more market oriented, in particular by tying the payments to crop insurance. However, disaster relief is determined on an ad hoc basis by the legislators after a disaster occurs. Consequently, the disaster payments have often been a substitute for insurance (Gardner, 1994), and the disaster payment allocation has been described as a result of rent seeking by interest groups (Schmitz, Furtan, and Baylis, 2002). This process is more transparent at the higher levels of fund allocation (Brooks, Cameron, and Carter, 1998). It has been suggested that, on the congressional level, legislators are pressed by organized agriculture interest groups to subsidize farmers who experienced a disaster. As a result, the disaster payment allocation was found to be less dependent on the weather and more on those socio-economic and political variables that proxy the lobbying power of interest groups (Garrett, Marsh, and Marshall, 2006).

In this paper, we test a similar hypothesis on the county level. The area chosen for this analysis consists of crop producing counties in Alabama, Georgia, and Florida. The time period covers 11 years (1995-2005). In comparison to the more aggregate analysis, our local weather data is more representative of the unfavorable conditions causing agricultural disasters. However, as the process of disaster aid allocation at the county level is less transparent and, therefore good data are hard to obtain, the proxies for political forces that may be behind the process are less precise.

An agricultural disaster occurs when damages and losses due to a natural disaster amount to at least a 30-percent production loss of at least one crop in a county. The amount of money distributed as disaster payments is substantial: $25.8 billion has been distributed to 2 million recipients nationwide during 1985-2005. In 2006, USDA provided $250 million for crop disaster, livestock, tree, and aquaculture assistance through five new programs. In the Southeastern U.S., the aid for agricultural producers affected by hurricanes in 2005 was $2.8 billion, and disaster payments to farmers, ranchers and others through eight separate programs to producers in Alabama, Florida, Louisiana, Mississippi, North Carolina, and Texas was $1.2 billion.

Under perfect information, agricultural disaster payments should be affected only by the incidence of catastrophic climate events and the losses they cause. Since it is not always possible to measure the exact amount of the losses that a catastrophic event creates, in the absence of perfect information, actual payments may be affected by non-climate factors. To address the criticisms that payments are biased/inequitable (e.g. Environmental Working Group reports), this study tests the hypothesis that both climate related and non-climate variables such as economic, political, and community characteristics affect distributions of disaster payments.

The rest of the paper is structured as follows. Section 2 describes the methodology used in the analysis. Section 3 contains description of the data, Section 4 discusses the results, and Section 5 concludes.

2. Methodology

Following Garret et al. (2006), annual disaster payments (by county) are modeled as a function of climate data such as the minimum and maximum temperature during growing season, precipitation, and ENSO variables as well as socio-economic variables to proxy for producers' lobbying potential to receive disaster-related payments. Specifically, the model is

$$Payacres_{it} = f\,(X1_{it}, X2_{it}, a_{i},) + u_{it} \quad (1)$$

where *Payacres* is the crop disaster payments per acre, *X1* contains the weather variables, and *X2* contains the socio-economic variables expected to affect county-level crop disaster payments. a_i is the latent time-invariant variable and u_{it} is the idiosyncratic random error.

The methodology is dictated by the nature of the cross-sectional time series (panel) data. Panel data methods accommodate an unobserved (latent) time invariant variable in the fixed/random effect regression framework. Since Garret *et al.* found that disaster payments on the state level was affected by weather independent, and likely time invariant variables applying these methods using county level panel data permits estimating correctly the impact of climate variables even if weather independent factors are non-observable.

The fixed effects (FE) estimation is simply a pooled OLS on data transformed using time averages to eliminate the unobserved time-invariant variable assumed to be correlated with the regressors (such as socio-economic characteristics or lobby power). This assumption is necessary for efficient estimation with the FE technique. It is also plausible in the context of the problem addressed because possible lobby power (or other variables affecting distribution of disaster pay) are likely to be correlated with the climate related variables and socioeconomic variables. For example, farmers living in areas more prone to disasters will be more likely to organize to seek such payments.

The alternative random effects (RE) estimation allows for time-invariant regressors, such as some socioeconomic variables available from one census data during the study period, but it is based on the assumption that the unobserved variable is uncorrelated with the other regressors. The

FE is preferred to RE approach because RE assumes that the county-level observations are random draws from a large population. In addition, while it may be possible that the unobserved variables are uncorrelated with the weather variables, they are likely to be correlated with the census variables, such as farm concentration or production volumes. Empirical test of this assumption is done with a Hausman test (Wooldridge, 2002, Ch. 10).

The estimation choice, however, needs to account for the fact that disaster payment data used in the analysis are censored – some counties receive zero payments in some years (zero payments comprise only 12% of the data). To accommodate this, a Tobit estimation is used. While the FE model is in general preferred when counties are used because it is hard to make the argument that the counties are drawn from a random distribution, panel data Tobit models with fixed effects are inconsistent. These challenges are addressed by estimating fixed effects, random effects and Tobit random effect and comparing the robustness of the results. Given the small fraction of the censored observations linear FE and RE estimation provide good approximations for conditional distributions of the disaster payments (model coefficients) near the mean values.

3. Data Description

Variable definitions are described in Table 1 and summary statistics are in Table 2. The data for the analysis come from several sources. Data on disaster payments were collected from the Environmental Working Group's Farm Subsidy Database that lists county level payments for the period from 1995 to 2005. The payments only include crop related programs and not livestock related payments because the focus of the study is on the effects of weather and climate and livestock program payments are likely to be affected by different variables. In addition, metro counties and counties in the mountainous regions of Georgia and Alabama without significant crop production were excluded. The counties in the analysis produce mostly cotton, peanuts, corn, and soybeans. The panel dataset is comprised of 65 counties in Alabama, 15 counties in Florida, and 91 counties in Georgia, or a total of about 1,800 annual observations for the sample.

The payments used in the analysis include Crop Disaster Program Payments, Non-Insured Assistance Payments, Natural Disaster Payments, Disaster Reserve Assistance Payments, Quality Losses Program Payments, Disaster - Quality Adjustment Payments, Disaster Supplemental Payments, and Disaster Assistance Payments. All the payments were adjusted for inflation using data from the BLS.

In the context of this paper, the term "disaster payments" pools all of the above components. Some of the original annual payments (*paydis*) were negative (although small in absolute value), which was a result of excessive payments made in the previous year. The data were adjusted accordingly by applying the negative payments to the previous year.[1] Zero disaster payments constitute 12% of the data, most of which belong to 1996 and 1998 years. The per county crop disaster payments were divided by the total harvested crop acres in a county. The resulting per acre payment data (*payacre*) is more suitable for the analysis of the payment distribution. As Table 2 shows, the average annual per acre disaster payment was in Florida ($25), followed by Alabama ($14), and Georgia ($12) with all data presented in 2005 dollar equivalent.

The weather data were collected from the Florida State University's Center for Oceanic-Atmospheric Prediction Studies (COAPS) database provided by the South Eastern Climate Consortium (SECC). The database includes daily observations on minimum and maximum daily temperature and (cumulative) precipitation from all weather stations in Alabama, Florida, and Georgia. As there are fewer stations than counties and the stations' location is not always

[1] Estimation results are not changed by this adjustment.

representative of a county, a list of weather station – county correspondence compiled by the SECC meteorologists was used to assign the weather observations to counties.

As the analysis is done on relatively aggregate data (not "bottom-up" construction), the temperature data is used to approximate the probabilities (or incidences) of freezes and draught and the precipitation data are used to approximate the positive (watering) and negative (flooding) effects of rain. Rather than using an absolute minimum temperature, which is not representative of the damage caused by freezes, we constructed panel variable (per county and per year) consisting of the first percentile of the minimum daily temperatures for the growing and harvesting seasons defined as mid-March to mid-November (*min1pcgs*), corresponding to the major crops grown in the state. Table 2 contains the average temperature and for each state shows values roughly correspond to the below freezing points (slightly below 32F ensures frost damage). Similarly, the 95^{th} percentiles of the maximum annual growing season daily temperatures (*max95pc*) were constructed to reflect possible damages from heat as well as benefits from solar radiation, necessary for plant growth and are shown as state averages in Table 2.

Cumulative precipitation is calculated for the growing season and for the year in '000 per inch (*rain* and *raings*) and is also contained in Table 2. Squared cumulative precipitation is included to reflect the negative effect of excessive rain on crop yields (possibility of flooding).

The ElNino Southern Oscillation (ENSO) data used for grouping the yield series was constructed by the SECC climatologists from FSU and UFL specifically for the purpose by adjusting the *monthly* ENSO indices to reflect the ENSO conditions prevailing during the crops' growth season, not calendar time. The importance of the ENSO phases comes from the meteorological research findings that, in general, the weather is more variable during non-neutral ENSO years (LaNina and ElNino) and, in the Southeast, LaNina years are usually relatively dryer and hotter. The expectation is thus that the ENSO dummies (*el, la,* with neutral year as basis) should matter for disaster payments. The 1995-2005 time period contains only 2 El Nino and 2 La Nina years. Apart from the ENSO dummies, we also use annual dummies.

We did not include data on official disaster (area) declarations, number of payment applications, etc for two reasons. One is simultaneity: such data are likely to be endogenous (i.e., determined by the same variables as the payments). The other is that, even if it were not, disaster declaration data would be just a more precise substitute for the weather/climate data.

Data that serve as proxies for possible lobbying or local political power of farm groups on the county level were collected from the disaster payment census of agriculture. The last two censuses were conducted only in 2002 and 1997, but that does not preclude using them in the analysis as the data are largely time invariant (2002 census is more complete and time relevant). The data can be used in the random effects panel data regressions, fixed effects panel data regressions when interacted with annual dummies, and in the tobit models.

Understandably, there are no perfect indicators of the ambiguous (often alleged to be significant) lobbying power of various farm groups that may lead to inequitable and distorted distribution of agricultural payments. One of the best candidates is perhaps the disaster payment concentration (collected from the EWG's Farm Subsidy Database). This variable represents the percentage of the total disaster payments for a county in a given year distributed to the top one percent of the recipients (*pmt1pc*), and can proxy for political (redistributive) power of the farm lobby (or influential/connected producers) if we assume that such power is associated with small groups *and* that these groups, apart from getting a disproportionately bigger share of the available disaster payments, are also capable of increasing a county payments' total. Table 2 shows that the payment concentration is highest in Alabama (25 percent), followed by Florida (18 percent), and Georgia (15 percent).

County level agricultural census data include a number of socio-economic indicators that may approximate the "payment extracting" power of agricultural producers only to a certain extent. However, better data (such as perhaps data on the matching between the actual loss and the payment received and on the composition of the county Farm Service Agencies) are not available, and the span of the payment data is not long enough to use time-series analysis. Several variables from the 1997 and 2002 agricultural census were used. These are *bigfarmshare* (the share of farms with more than 1,000 acres, used to proxy the lobbying power and farm concentration in a county; *harvshare* (share of harvested cropland), *operatorfarm* (share of operators whose primary occupation is farming) and *govpayments* consisting of all government payments net of disaster payments per acre of harvested cropland in $1,000.

4. Discussion of the results

Tables 3 to 5 have two panels each and present the results from several regression specifications with weather-related and socio-economic variables as the dependent variables. In each table Panel A shows the results from a tobit model and Panel B shows the results from a FE and RE regressions. Due to possible high correlation of some of the socio-economic explanatory variables, to avoid multicolinearity, they are included in a step-wide fashion.

Since some of the census variables were not available for every county, some observations were lost in those regressions. Both FE and Tobit models show similar results. While the FE model is in general preferred when counties are used because it is hard to make the argument that the counties are drawn from a random distribution, panel data Tobit models with fixed effects are inconsistent. Thus, random effects (GLS) transformation, is used results whenever the time invariant census data are included. The unobserved variable is absorbed in the error term and the estimation involves a GLS transformation of the data followed by OLS estimation. In all our regressions, the random effects estimator (lambda) ranges from 0.06 to 0.20 showing that a large fraction of the unobserved effect is left in the error term. The residuals were also tested for serial correlation (possible due to weather data).[2]

There is consistency in the effects of weather and climate variables on the disaster payments in all three states. The minimum temperatures during the growing season reflect the incidence/frequency of freezes and are inversely related to the per acre disaster payments. For example in the state of Georgia, a one percent drop of the 5th percentile of the minimum temperature is associated with about 1-1.5 dollars per acre increase in the disaster payment (replacing the percentile with the number of days with min temperatures below the freezing point produces a comparable estimate).

Increase in the maximum temperatures is associated with larger payments. For Georgia a one degree increase in the 95th percentile of the highest temperature increases the disaster payment by 1 to 1.5 dollars per acre, perhaps due to drought.Cumulative precipitation reduces the disaster payments (more rain is better, especially for rainfed crops) but the relationship is non-linear and concave, as evidenced by the negative squared precipitation term. The non-linearity captures probably of flooding brought about by too much rain. We can see that in Georgia rain improves yields but precipitation beyond (37.8”) is associated with higher disaster payments. Comparing this to the average precipitation of 47.4” suggests that, on average, the area gets more than enough precipitation (also, the average share or irrigated harvested cropland is 24%).

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[2] The coefficient at the AR(1) parameter was very small and negative. Fitting cross-sectional time series linear models using feasible GLS did not change the results.

However, the weather variables explain the variance in the disaster payments better in Georgia than in Alabama, and better in Alabama than in Florida. Table 4 shows that high temperature (proxy for drought) is significant in only one of the regressions for Florida. This could be attributed to the greater incidence of hurricane related damage (most of the counties analyzed are in the Florida Panhandle), whereas we did not use hurricane data.

Among the most interesting results are those on the impact of ENSO phases. We find that in Georgia a La Nina year is associated with about 9 to 11 more dollars per acre compared to a neutral year and in Alabama with 10 to 15 more dollars. The results suggest that drier weather during the La Nina years affects disaster payment. We find that El Nino years are associated with decreased payments in Alabama (from 6 to 14 dollars per year based on several models various models) but no difference compared to neutral years in Georgia and Florida. In some of the regressions with data from Georgia, El Nino is weakly significant but it is not significant in the fixed effects regression. In Florida, however, ENSO phases do not seem to matter for the disaster payments, which is strange as the state's weather is more affected by the ENSO due to its geographic location. We can only suggest that the drier La Nino years, the higher frequency of hurricanes during Neutral, and more floods in the El Nino years may create the ambiguity. These results should be interpreted with caution because of the short span of the data that covers only two El Nino and two La Nina years, which is compensated in part by the larger cross-sectional variation.

The implication of these findings are that, since it has been argued that global warming will increase the incidence of El Nino and La Nina, one could expect that, at least in the Southeast, agricultural disaster payments will be affected. Given the increasing predictive power of climate forecasts, the results from such estimations can be used to better plan for such occurrences.

The disaster payment concentration data are used as a proxy for equity in payment distribution (EWG). We suggest two possible reasons for high payment concentration. One is the local character of crop failures and disastrous conditions affecting only a small number of producers. In this case, higher per acre payments could be associated with higher payment concentration. Another is the ability of a few to extract the payments. In this case, higher per acre payments are associated with higher concentration only if the ability to extract them also implies the ability to bias their allocation on the county level.

Alternatively, disaster payment concentration could be inversely related to the disaster payments if an agricultural disaster, when it occurs, affects a large number of producers leading to a more even payment distribution but, when the disaster incidence is small, only a few producers get the payments (for one reason or another), hence the higher payment concentration. In light of this, even the data on chronic disaster aid recipients cited by the EWG is not a strong indicator of unfair play. Our results show that the indicator of payment concentration used in the analysis (the % of total received by the top 1 percent of the recipients), not significant in Georgia and Florida negative and significant in Alabama. This suggest that the observed high payment concentration is not associated with the total amount of payments received by a county, i.e., the "appropriative" power of the top payment recipients does not affect apportioning of disaster assistance to the counties.

The indicators of farm concentration, the share of big farms and the average farm size (a proxy for the power of farm groups) matter for the disaster payments only in Alabama. Only the share of harvested land in the total cropland, a proxy for the intensity of the cropland usage, is marginally significant in Florida.

These results suggest that the weather and climate related factors alone explain most of the crop disaster payments at the county level while socioeconomic variables do not. Therefore, while there might be discrepancies in disaster fund allocations at state level, at the county level, it is distributed according to actual damage.

In summary, the results indicate that, in Alabama and Georgia but not in Florida, weather and climate variables explain a relatively large portion of the variation in the disaster payments. The significance ENSO phases may be important for disaster budget planning, as the phases are predictable with high confidence levels. Contrary to the countrywide study which found that non-weather related factors also affected distribution of agricultural disaster payments and that lobbying power and congressional committee representation mattered, we found only a limited impact of non-weather related factors on the county level in the analysis of the three Southeastern states. Many of the census variables described in the data section were experimented with but only a few were found significant. Considering this, and the state level differences in the estimation results, it is premature to conclude at this point whether there is any effect of lobbying and political preferences on the disaster payments at county level.

One of the reasons for lack of significance in socioeconomic variables is a possible selection bias: the counties were selected for analysis on the basis of their agricultural production volume (i.e., main crop producers in the state) because of insufficiency and sketchy character of the data on small producers. However, crop disaster payments are non-negative in counties with even little agricultural production. It is more likely that payments to counties with little production are more dependent on farm size distribution, payment concentration, and other socioeconomic variables. Exclusion of these small producers may have downplayed the importance of payment structure and farm concentration. We plan to extend the analysis by including more counties.

5. Conclusions

Using county level data we study if weather and climate variables or variables used as proxies for rent-seeking behavior determine disaster payment in the Southeast. The most important observation is that the weather variables (temperature and precipitation) are highly significant. Moreover, the ElNino Southern Oscillation phase dummies explain a large portion of the variation in the crop disaster payments. The socio-economic variables originally hypothesized to serve as proxies for lobbying power of farm groups and other rent-seeking behavior are significant only in Alabama bu have opposite to the expected sign. However, the variances of the time-invariant error components suggest that county effects not described by the census of agriculture variables are also significant in Georgia: both fixed and random effects models show greater relative significance of the latent time-invariant variable suggesting that the "behind the scenes" forces affecting disaster payment distribution on the county level may be present. However, the results neither support nor negate the existing criticisms of inequitable distribution of agricultural disaster payments but they suggest that future exploration of this topic with better data is warranted.

Table 1 Variables Definition

Weather and climate variables:		
Min1pc	1th percentile of min annual temperature, F	
max5pc	5th percentile of max annual temperature, F	
rain	cumulative annual precipitation, HI	
rain2	cumulative annual precipitation squared	
El	Dummy for ElNino years	
La	Dummy for LaNina years	
d95 … d05	Dummies for years	
Dependent variables:		
payacres	crop disaster payments/total harvested cropland acres, pure $	
Socio-Economic variables:		
pmnt1pc	% of disaster payments received by the top 1% of recipients	proxies the "equity" of payment distribution
bigfarmshare	# of farms with >1,000 acres/# of farms in county	proxies the lobbying power and farm concentration in a county
govpmts	all government payments per farm, $1,000	
Operatorfarm	share of farm operators with principal occupation "farming"	

Table 2 Summary Statistics

Variable	State	Obs	Mean	Std. Dev.	Min	Max
payacres (2005$)	AL	726	13.81	19.75	0	111.74
	FL	180	24.98	32.89	0	176.28
	GA	1001	12.36	15.36	0	109.24
min1pcgs	AL	698	25.94	4.31	11	38
	FL	177	32.29	4.28	0	41
	GA	994	29.25	3.77	16	39
max95pcgs	AL	698	94.22	2.83	82	103
	FL	177	94.48	2.36	84	101
	GA	994	93.36	4.32	80	99
rain	AL	698	5.59	1.14	1.24	10.22
	FL	177	5.38	1.43	1.70	8.98
	GA	994	0.05	0.01	0.01	0.08
raings	AL	698	4.16	1.02	0.94	8.77
	FL	177	4.31	1.23	1.02	7.55
	GA	994	3.64	0.88	0.77	6.21
El	AL	726	0.18	0.39	0	1
	FL	180	0.18	0.39	0	1
	GA	994	0.18	0.39	0	1
La	AL	726	0.18	0.39	0	1
	FL	180	0.18	0.38	0	1
	GA	1001	0.18	0.39	0	1
pmt1pc	AL	108	20.46	7.67	6	40
	FL	45	18.42	5.68	9	31
	GA	152	15.01	6.42	0	36
bigfarmshare	AL	726	0.04	0.04	0.0031	0.1471
	FL	180	0.03	0.02	0.0077	0.0728
	GA	1001	0.07	0.06	0.0024	0.2653
harvshare	AL	726	0.49	0.12	0.2771	0.7834
	FL	180	0.54	0.11	0.3607	0.7947
	GA	1001	0.69	0.15	0.3570	0.9111
govpmts	AL	726	1.87	1.60	0.1053	7.6012
	FL	180	1.63	1.72	0.2442	6.9272
	GA	990	3.93	3.38	0.0424	14.5092

Table 3. Panel A: Results from a tobit regressions for Alabama
The dependent variable is payment per acre

	(1)	(2)	(4)	(3)
min1pcgs	-0.713	-0.476	-0.451	-0.856
	(2.88)***	(2.23)**	(2.21)**	(3.98)***
max95pc	0.464	2.249	2.095	0.218
	(5.31)***	(6.23)***	(5.98)***	(1.50)
rain	-6.381	-10.400	-10.177	-9.923
	(4.00)***	(5.54)***	(5.52)***	(5.26)***
raings2	1.359	1.573	1.540	1.585
	(6.62)***	(6.51)***	(6.51)***	(6.58)***
el		-14.872	-14.785	-14.565
		(6.29)***	(6.30)***	(6.18)***
la		15.351	14.885	8.471
		(5.77)***	(5.76)***	(3.42)***
pmt1pc	-0.314			
	(2.68)***			
bigfarmshare		72.282		79.513
		(2.39)**		(2.95)***
govpmts		1.530	3.571	
		(2.21)**	(6.26)***	
harvshare			-35.086	
			(4.91)***	
operatorfarm				62.470
				(3.02)***
County dummies	yes			yes
Year dummies	yes	yes	yes	yes
Constant		232.117	234.286	
		(6.73)***	(6.99)***	
Observations	106	698	698	698
Number of countyn	54	65	65	65
sigma_u	2.53	3.37	.51	4.15
	1.51	2.37	0.07	3.07
sigma_e	7.35	19.98	19.95	20.32
	10.25	32.14	32.21	32.03
rho	0.10	.027	.0007	.04

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. Panel B: Results from FE and RE regressions for Alabama
The dependent variable is payment per acre

	FE	MLE (RE)	RE	RE
min1pcgs	-0.522	-0.705	-0.308	-0.333
	(2.45)**	(2.86)***	(1.75)*	(1.81)*
max95pc	1.577	0.459	1.338	1.446
	(4.40)***	(5.28)***	(4.49)***	(4.70)***
rain	-7.264	-6.297	-6.074	-6.061
	(4.23)***	(3.97)***	(3.86)***	(3.78)***
raings2	0.932	1.350	0.939	0.936
	(4.33)***	(6.62)***	(4.69)***	(4.58)***
el	-5.615		-6.229	-6.154
	(3.01)***		(3.36)***	(3.30)***
la	9.771		10.990	11.284
	(3.87)***		(4.78)***	(4.79)***
pmt1pc		-0.316		
		(2.72)***		
harvshare			-31.979	
			(5.13)***	
govpmts			3.259	1.527
			(6.53)***	(2.58)***
bigfarmshare				55.260
				(2.13)**
County dummies		Yes		
Year dummies	Yes	yes	Yes	yes
Constant	170.928		156.588	151.176
	(4.90)***		(5.53)***	(5.17)***
sigma_u	7.49	2.31	0	2.51
sigma_e	18.09	7.37	18.09	18.09
rho	0.15	0.09	0	0.02
Observations	698	106	698	698
R-squared	0.14			

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Panel A: Results from tobit regressions for Florida

The dependent variable is payment per acre

	FE	MLE (RE)	RE	RE
min1pcgs	0.969	-0.014	1.229	1.197
	(1.71)*	(0.01)	(2.31)**	(2.21)**
max95pc	-0.091	0.713	-0.468	-0.353
	(0.08)	(1.23)	(0.45)	(0.33)
rain	-0.026	-0.011	-0.024	-0.024
	(5.53)***	(1.46)	(5.26)***	(5.25)***
raings2	0.000	0.000	0.000	0.000
	(5.15)***	(1.63)	(4.97)***	(4.95)***
el	-6.418		-6.762	-6.674
	(1.10)		(1.16)	(1.15)
la	-4.879		-5.514	-5.462
	(0.84)		(0.95)	(0.94)
pmt1pc		-0.874		
		(1.39)		
harvshare			-101.637	
			(1.85)*	
govpmts			3.537	-1.918
			(0.99)	(0.79)
bigfarmshare				-40.973
				(0.19)
County dummies		yes		
Year dummies	yes	yes	yes	Yes
Constant	79.762		149.475	95.242
	(0.80)		(1.48)	(0.97)
sigma_u	13.1	0	7.79	9.67
sigma_e	28.44	21.88445	28.44	28.44
rho	.17	0	.069	.10
Observations	177	43	177	177
Number of county	15	15	15	15
R-squared	0.23			

Absolute value of z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Panel B: Results from FE and RE regressions for Florida
The dependent variable is payment per acre

	(1)	(2)	(3)	(4)
min1pcgs	-0.014	-1.805	-1.803	-1.711
	(0.01)	(2.52)**	(2.56)**	(2.50)**
max95pc	0.713	0.030	0.184	0.680
	(1.23)	(0.02)	(0.15)	(2.20)**
rain	-0.011	-0.035	-0.035	-0.036
	(1.46)	(6.13)***	(6.11)***	(6.59)***
raings2	0.000	0.000	0.000	0.000
	(1.63)	(5.73)***	(5.74)***	(6.12)***
el		-5.004	-5.060	-4.988
		(0.75)	(0.76)	(0.75)
la		-6.668	-6.420	-6.218
		(0.97)	(0.94)	(0.91)
pmt1pc	-0.874			
	(1.39)			
bigfarmshare		-110.636		-147.774
		(0.47)		(0.86)
govpmts		-1.370	3.832	
		(0.52)	(0.99)	
harvshare			-105.481	
			(1.77)*	
principaloperatorbyprimaryoccupa				0.036
				(2.01)**
County dummies	yes			Yes
Year dummies	Yes	yes	yes	Yes
Constant		73.652	132.245	
		(0.65)	(1.14)	
sigma_u	0.00	9.61	7.78	7.77
	(0.00)	(2.61)	(2.04)	(2.09)
sigma_e	21.88	31.95	31.90	31.97
	(9.27)	(15.82)	(15.85)	(15.84)
rho	0	.08	.05	.055
Observations	43	177	177	177

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Panel A: Results from tobit regressions for Georgia.
The dependent variable is payment per acre

	(1)	(2)	(3)	(4)
min1pcgs	-3.194	-1.274	-1.203	-1.305
	(4.42)***	(7.48)***	(7.22)***	(7.59)***
max5pc	3.425	0.314	0.099	0.401
	(6.04)***	(1.95)*	(0.76)	(2.37)**
rain	-2.359	-0.534	-0.886	-0.529
	(2.71)***	(1.93)*	(3.87)***	(1.92)*
rain2	0.023	0.005	0.008	0.005
	(2.61)***	(1.45)	(2.98)***	(1.43)
el		0.447	0.665	0.411
		(0.29)	(0.43)	(0.27)
la		11.196	10.975	11.125
		(7.41)***	(7.27)***	(7.37)***
pmt1pc	-0.007			
	(0.03)			
bigfarmshare		10.581	-4.703	
		(0.53)	(0.43)	
govpmts		-0.422		-0.038
		(1.25)		(0.14)
harvshare				-8.680
				(1.35)
operatorfarm			-17.091	
			(1.87)*	
County dummies	Yes		Yes	
Year dummies	Yes	Yes	Yes	Yes
Constant		-29.443		-29.618
		(2.92)***		(2.96)***
sigma_u	8.74	3.21	3.12	3.24
	3.76	3.66	3.58	3.74
sigma_e	13.41	16.03	16.08	16.01
	10.13	36.63	36.85	36.65
rho	.29	.03	.03	0.04
Observations	152	983	994	983
Number of counties	78	90	91	90

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Panel B: Results from FE and RE regressions for Georgia
The dependent variable is payment per acre

	FE	MLE (RE)	RE	RE	RE
min1pcgs	-0.947	-3.305	-0.863	-0.873	-0.900
	(6.09)***	(4.67)***	(6.17)***	(6.17)***	(6.34)***
max5pc	0.938	3.466	0.448	0.457	0.507
	(4.98)***	(6.23)***	(3.35)***	(3.43)***	(3.61)***
rain	-0.444	-2.258	-0.478	-0.487	-0.481
	(1.81)*	(2.65)***	(2.04)**	(2.07)**	(2.06)**
rain2	0.005	0.022	0.004	0.004	0.004
	(1.63)	(2.55)**	(1.51)	(1.56)	(1.51)
el	1.587		2.522	2.363	2.505
	(1.26)		(2.03)**	(1.89)*	(2.02)**
la	9.905		9.502	9.664	9.416
	(7.65)***		(7.43)***	(7.50)***	(7.36)***
pmt1pc		-0.051			
		(0.23)			
harvshare					-8.531
					(2.03)**
govpmts				-0.292	
				(1.66)*	
bigfarmshare			-15.081		
			(1.53)		
County Dummies		Yes			
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	-54.531		-23.308	-23.996	-22.559
	(4.37)***		(2.76)***	(2.84)***	(2.72)***
sigma_u	6.37	8.94	3.19	3.17	3.18
sigma_e	13.64	12.89	13.64	13.67	13.64
rho	.17	.32	.05	.05	.05
Observations	994	152	994	983	994
Number of counties	91	78	91	90	91
R-squared	0.17				

Robust t statistics in parentheses
*significant at 10%; ** significant at 5%; *** significant at 1%

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