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 91 crop producing counties in Georgia. 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, 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 (Environmental Working Group reportss), this study tests the hypothesis that both climate related and non-climate variables such as local/regional 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 some of which serve as proxies for producers lobbying potential to receive disaster-related payments. Specifically, the model is

$$Payacres_{it} = f\,(\alpha,\ \beta_1 X1_{it},\ \beta_2 X2_{it},\ a_i,\ u_{it}) \tag{1}$$

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 crucial for the estimation technique because, if it does not hold, the fixed effects estimation produces inefficient estimators. In the context that the FE is applied here, this assumption is also plausible 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 the census data, but it is based on the assumption that the unobserved variable is uncorrelated with the other regressors. In this case, it is difficult to assume that the county-level observations are random draws from a large population, so the fixed effects is a preferred approach. 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 assumptions are 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 results to show how robust the results are. 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. These are complemented juxtaposed to the marginal effects at the mean values from the Tobit estimation.[1]

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[1] Finally, although tests do not confirm endogeneity of the regressors, the crop insurance indemnity payments are supposed to be determined simultaneously with the disaster payments.
Future work, therefore, could include estimating a system of equations with 3SLS where, in one equation the disaster payments are regressed on the exogenous variables and the indemnities, and in the other the indemnities are regressed on the exogenous variables only. This satisfies the requirement to have M-1 (zero/exclusion) restrictions in M=2 equations which enables us to derive the structural parameter estimates provided that the system of relations and the restrictions are consistent and linearly independent (Judge et al, p616):

$$\begin{cases} Payacres = \beta_1 X1 + \beta_2 X2 + e_1 \\ Indemacres = \alpha X1 + e_2 \end{cases} \tag{2}$$

where *Indemacres* is crop insurance indemnity payments per acre and the rest of the variables are as defined above.

3. Data Description

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 socio-economic variables. Accordingly, we metro counties and the counties in the mountainous regions of Georgia without significant crop production were excluded. Out of the total of 159 Georgia counties, 91 counties located mostly in the southern and central parts of the state and producing mostly cotton, peanuts, corn, and soybeans are included. Figure 1 presents the area covered in the analysis. The panel dataset is comprised of 1001 observations.

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.[2] Zero disaster payments constitute 12% of the data, most of which belong to 1996 and 1998 years. The time distribution of the payments for the whole state is shown in Figure 2. Figure 3 shows the total annual disaster payments for the sample used in the analysis. Payment distribution is close to the

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

state total, which supports the selection of counties for the analysis and also shows the small magnitude of the livestock-related disaster payments.

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. Figure 4 shows the average per acre crop disaster payments for the sample used in the analysis 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 Georgia. As there are fewer stations than counties and the stations' location is not always 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 the precipitation data to approximate the positive (watering) and negative (flooding) effects of rain. Rather than using absolute minimum temperature, which is not representative of the damage caused by freezes, we constructed a panel data set of the first and fifth percentile of the minimum daily temperatures for the whole year (*min1pc* and *min5pc*) and for the growing and harvesting season defined as mid-March to mid-November (*min1pcgs* and *min5pcgs*), corresponding to the major crops grown in the state. Table 1 describes the temperature variables showing that the percentages roughly correspond to the freezing points (slightly below 32F ensures frost damage).

The little variation in the variables over the 11 year period is natural and suggests that the payment data has to be very sensitive to minimum temperatures in order for this variable to be significant. Similarly, 99^{th} and 95^{th} percentiles of the maximum annual and growing season daily temperatures (*max99pc*, *max99pcgs*, *max95pc*, and *max95pcgs*) were constructed to reflect possible damages from heat as well as benefits from solar radiation (necessary for plant growth).

Cumulative precipitation is calculated for the whole year and the growing season (*rain* and *raings*). 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 and particularly in the Southcentral Georgia, LaNina years are usually relatively dryer and hotter. The expectation is thus that the ENSO dummies (*el, la*, and *ne*) 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 small 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). The variables represent the percentage of the total disaster payments for a county in a given year distributed to the top one or five percent of the recipients (*pmt1pc* and *pmt5pc* respectively). These can be the proxies for the political (redistributive) power of the farm lobby (or influential/connected producers) only 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. Figure 5 shows the distribution of the crop disaster payments in Georgia by the proportion of their recipients over 1995-2005. It is clearly not uniform, but neither are the disaster incidences.

Crop insurance indemnity payment data were collected from the USDA's FSA database. This variable is included because crop insurance is often the eligibility requirement for the disaster payments and also because the indemnities are more strictly dependent on the actual yield/crop losses. Negative correlation between agricultural disaster payments and crop insurance would suggest that the market-oriented policies are working, while positive correlation would suggest that disaster aid complements insurance. The evidence on this so far has been mixed. (Wright, B., & Hewitt, J. (1994) and Schmitz, A., Just, R., & Furtan, H. (1994).

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. Sevaral variables from the 2002 agricultural census were used. *Bigfarmshare* (the share of farms with more than 1,000 acres (about 7.5% on average) is used as a proxie for the lobbying power and farm concentration in a county; *farms__number*_(number of farms in a county),*land_in_farms* (average size of farm in acres), *harvshare* (share of harvested cropland), i*rrigatedacreshare* (share of irrigated cropland), *operatorfarm* (share of operators whose primary occupation is farming), *operatorother* (opposite of the above), *bigfarmsaleshare* (share of farms with sales of more than $100,000), e*stimated_ market_value_of_land* (estimated market value of land and buildings per acre in a county). Proxies for wealth are *estimated_market_value_of_all_ma* (estimated market value of all machinery and equipment per farm), *govpmtacre_net* (in $1,000's all government payments net of the disaster payments per acre of harvested cropland, with a positive coefficients showing ability of payment extraction), *market_value_of_agricultural_pro* (market value of agricultural production per farm with a negative coefficient indicating a large disaster magnitude; and a positive coefficient indicating that money goes to the rich), *net_cash_farm_income_of_operati1* per farm, *total_farm_production_expenses_1* (per farm): another proxy production intensity.

Again, these variables serve as only remote proxies for the factors that determine disaster payments apart from the elements (factors not represented by the elements). Significance of any (group) of the above variables would perhaps let us suggest an explanation.

4. Discussion of the results

Table 3 presents the results from several regression specifications that include weather-related as well as most relevant socio-economic variables. The first two columns present results from specification where only weather variables are included, with the first column containing results from a fixed effect model and the second column presenting results from a tobit regression model. Models 3 through 6 include proxies for non-weather related factors, most importantly the percentage of agricultural disaster payments going to the top one percent of the recipients for potential incumbency or political clout of individual counties and also indicators of farm concentration (average farm size). Model 4 also adds the share of the irrigated harvested cropland to control for soil productivity and Model 5 adds the share of big farms (over 1,000 acres) as a proportion of total farms. Models 5 and 6 are results from Tobit estimation, while 3 and 4 are fixed effects results.

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 models were also chosen to avoid multicolinearity among certain variables (for example average farm and number of farms). The models are corrected for heteroscedasticity by using robust standard errors. The residuals were also tested for serial correlation (possible due to weather data). 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.

Perhaps the most important and notable result is that weather variables explain best county level disaster payments in the state of Georgia. In particular, 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). Similarly, 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 has a non-linear impact on per acre crop disaster payments. More rain is beneficial as it 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%).

Among the most interesting results are those on the impact of ENSO phases. While we do not find that El Nino years are associated with increased disaster payment, we find that a La Nina year is associated with about 15.5 to 17 more dollars per acre in such a year compared to a neutral year. These results are consistent with meteorologists’ assertions that La Nina years are generally drier and hotter in the Southeast. 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 also increase. Given the increasing predictive power of such forecasts, the results may be used to better plan for such occurrences.[3]

The results also show that current disaster pay schemes are not substitutes but (weak) complements to insurance payments. This perhaps reflects the requirement to have insurance payment in order to qualify for disaster payment but it also shows that one dollar increase in indemnity payment is associated with seven more cents of disaster pay on per acre basis.

A note on possible simultaneity of the crop insurance indemnity payments is in order. Similar to disaster payments, the indemnities are triggered by low crop yields which, in turn are caused by adverse weather. Oftentimes, having crop insurance is a prerequisite for eligibility for disaster payments. However, unlike disaster payments, indemnities are strictly yield dependent, i.e., are not likely to be influenced by the lobbying power of farm groups or distributed on ad hoc basis. On the one hand, there is a strong reason to expect the indemnity variable to be endogenous (simultaneity between disaster and indemnity payments). On the other, regardless of the common disaster payment eligibility requirement of having crop insurance, indemnities may be treated as additional exogenous variable reflecting factors other than weather that affect crop yields. In order to find out whether either of the two relationships is dominant, a simple engdogeneity test was performed. It uses fitted residuals from regressing indemnity payments per acre on the weather variables as a variable in regressing the per acre disaster payments on the indemnities and the weather variables. The coefficient at the fitted residuals was insignificant suggesting that insurance payments are not endogenous, sparing the need to use an instrumental

[3] Replacing the ENSO dummies with the dummies for 1998 and 1999 – the years when legislation was passed that temporarily increased the amount of disaster payments (Garrett et al., 2006) – have significant coefficients but of opposite signs.

variable for indemnities, which would be hard to find.[4]

The disaster payment concentration data has been suggested as a good 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. 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 none of the three indicators of payment concentration used in the analysis (% of total received by the top 1%, 5%, and 10% of the recipients) are significant in any regressions, suggesting 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. Similarly, the indicators of farm concentration, the share of big farms and the average farm size (something that proxies the power of farm groups) do not matter in any of the models. The share of irrigated crop acreage is also insignificant, which at least agrees with the result suggesting that there is no lack of rainfall and therefore drought is a less likely reason for disaster.

Another important result is that the explanatory power of the latent time invariant variable in both FE and RE models is quite small. The "fraction of variance due to a_i" is

$$\frac{\sigma_a^2}{\sigma_u^2 + \sigma_a^2}$$

[4] Estimation of the system of equations in (2) produced results identical to the FE estimation.

where a and u are the panel level and random components of the error term. Table 3 shows that the fraction of variance due to the unobserved (allegedly political) factors is much smaller than 1. Larger values would indicate a presence of unobserved but important factor other than weather affecting the disaster payments. This, together with the insignificance of the non-weather related variables, suggests that the weather and climate related factors alone explain most of the crop disaster payments at the county level. Therefore, while there might be discrepancies in disaster fund allocations at state level, once the money is available at the county level, it is distributed according to actual damage.

In summary, 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 did not find any impact of non-weather related factors on the county level within the state of Georgia. All the variables described in the data section were experimented with but in no specification did we find that non-weather related factors affect performance. Thus it could be concluded that at least at county level there is no effect of lobbying and political preferences.

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., the top 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

Preliminary estimation results show consistency over the alternative models used in the analysis. The most important observation is that the weather variables (temperature and precipitation) are highly significant. Moreover, the ElNino Southern Oscillation phase dummies are the most significant variables and 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 abilities to draw crop disaster payments are not significant in the estimation. Moreover, both fixed and random effects models show relative insignificance of the latent time-invariant variable suggesting that the “behind the scenes” forces affecting disaster payment distribution on the county level are minimal. This does not negate the existing criticisms of inequitable distribution of the payments but supports the hypothesis that counties in the sample are not discriminated in the payment distribution process.

APPENDIX

Figure 1

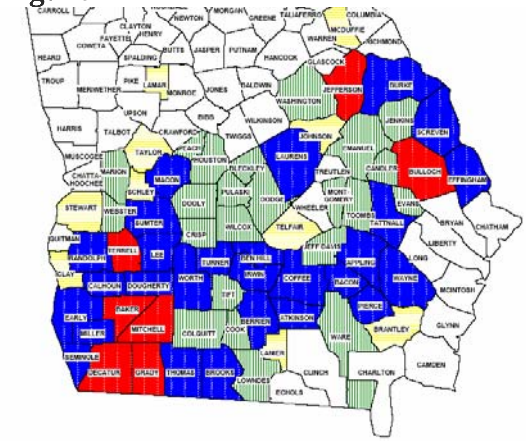

Figure 2

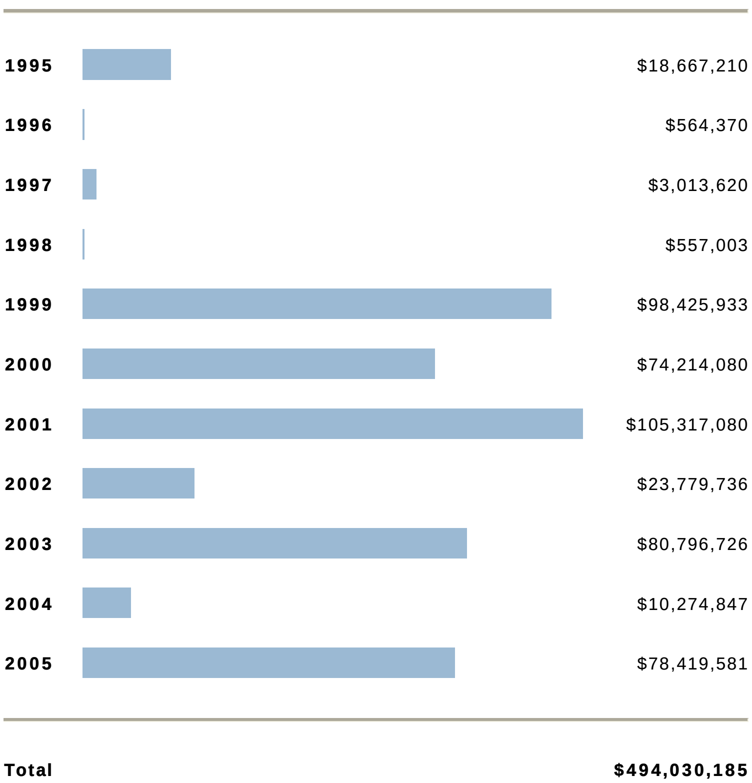

Figure 3

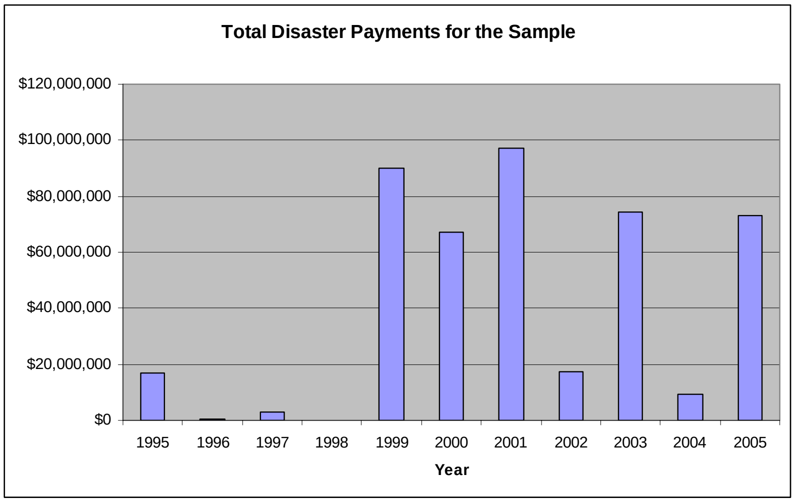

Figure 4

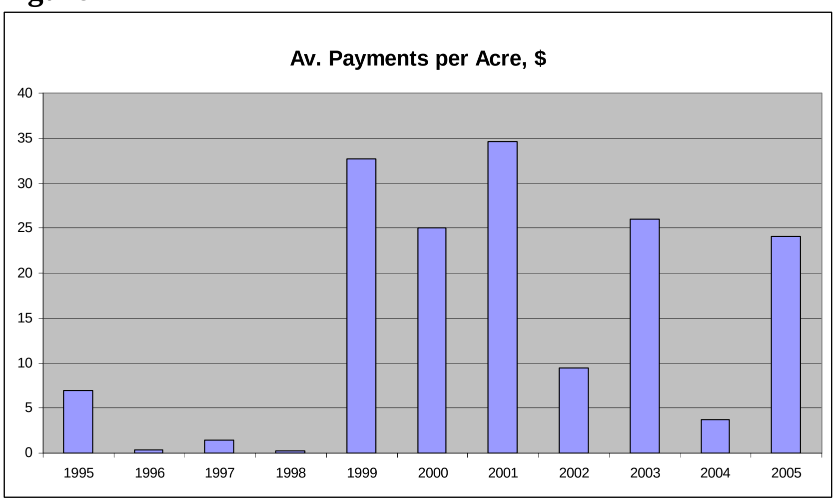

Figure 5

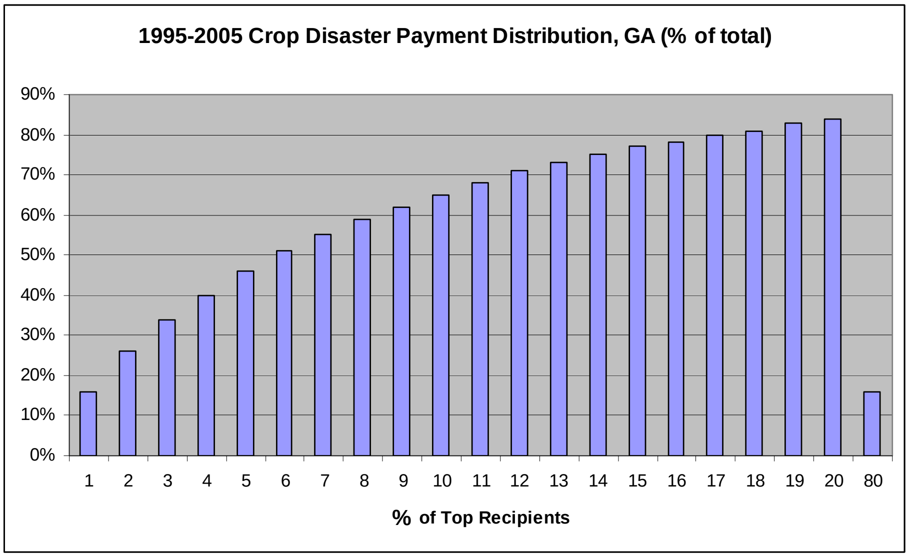

Table 1

Variable	Obs	Mean	Std. Dev.	Min	Max
min1pc	994	21.37	3.58	9	31
min1pcgs	994	29.25	3.77	16	39
min5pc	994	28.13	2.91	19	36
min5pcgs	994	36.00	3.67	26	47

Table 2

Variable	Obs	Mean	Std. Dev.	Min	Max
payacresALT	1001	14.94	18.41	0	118.70
indemacres	900	29.17	30.48	0.004	206.61
min5pc	994	28.12	2.90	19	36
max5pc	994	50.63	4.32	38	63
Rain	994	4739.63	1042.43	894	7708
rain2	994	2.35E+07	9338298	799236	5.94E+07
El	1001	0.18	0.39	0	1
La	1001	0.18	0.39	0	1
pmt1pc	847	10.51	4.59	4	30
irrigateda~e	979	0.24	0.16	0.003	0.64
land_in_fa~s	1001	315.78	182.25	74	992
bigfarmshare	1001	0.07	0.06	0.002	0.26

Table 3

	FE	Tobit, RE	RE	RE	Tobit, RE	Tobit, RE
Constant	-22.763	2.923	5.386	5.785	9.359	9.226
	(1.42)	(0.23)	(0.53)	(0.56)	(0.68)	(0.67)
indemacres	0.08	0.075	0.072	0.071	0.072	0.072
	(3.57)***	(2.96)***	(2.42)**	(2.39)**	(2.57)**	(2.57)**
min5pc	-2.619	-1.885	-1.155	-1.155	-1.859	-1.859
	(7.56)***	(4.61)***	(3.82)***	(3.81)***	(4.23)***	(4.23)***
max5pc	2.401	1.489	1.196	1.185	1.505	1.507
	(7.89)***	(5.45)***	(5.40)***	(5.09)***	(5.00)***	(5.02)***
rain	-0.7	-0.008	-0.008	-0.008	-0.010	-0.010
	(2.69)***	(2.26)**	(2.45)**	(2.43)**	(2.66)***	(2.66)***
rain2	0.008	0.000	0.000	0.000	0.000	0.000
	(2.75)***	(2.08)**	(2.13)**	(2.10)**	(2.55)**	(2.55)**
el	1.864	-0.091	2.594	2.613	-0.229	-0.232
	(1.20)	(0.05)	(1.47)	(1.48)	(0.11)	(0.12)
la	15.150	15.850	15.285	15.299	17.097	17.099
	(8.30)***	(8.08)***	(7.94)***	(7.95)***	(8.17)***	(8.17)***
pmt1pc			-0.244	-0.249	-0.288	-0.291
			(1.44)	(1.47)	(1.18)	(1.20)
Avg f Size			-0.005	-0.005	-0.005	-0.005
			(1.09)	(1.13)	(0.35)	(0.78)
Irrigated				1.492		
				(0.25)		
bigfarmshare					3.394	
					(0.07)	
Observations	897	897	771	771	771	771
Number of countyn	90	90	76	76	76	76
R-squared	0.25					
R2_O	0.1600		0.2124	0.2124		
R2_B	0.0012		0.0647	0.0676		
R2_W	0.2518		0.2401	0.2400		
fraction of variance due to a_i	0.236	0.265	0.013	0.013	0.274	0.274

Robust t statistics in parentheses

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

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