Nonlinear Incentives, Plan Design, and Flood Mitigation: The Case of the Federal Emergency Management Agency's Community Rating System.

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Abstract

A basic proposition of *agency theory* is that output-based performance incentives encourage greater effort. However, studies find that incentive schemes can distort effort if rewards for performance are discrete or nonlinear. The Federal Emergency Management Agency's (FEMA) Community Rating System (CRS) is a flood mitigation program with a nonlinear incentive design. Under this program, localities are incentivized to implement a mix of 18 flood mitigation activities. Each activity is performance scored, with accumulated scores corresponding to a percent discount on flood insurance premiums for residents that hold National Flood Insurance policies. Discounts range from 0 to 45 percent and increase discretely in increments of 5 percent. With multivariate statistical and Geographic Information Systems analytic techniques, we test whether observed changes in annual CRS scores for participating localities in Florida are explained by nonlinear incentives, adjusting for hydrologic conditions, flood disaster histories, socioeconomic and human capital controls that can plausibly account for local mitigation activity scores over time. Results indicate that local jurisdictions are discount-seeking, with mitigation efforts partially driven by the nonlinear incentive design of CRS program. We end with recommendations to improve the operation FEMA's flood mitigation program.

Keywords

Florida, Flood Mitigation, Community Rating System, Nonlinear Incentives

Introduction

Floods are the most lethal natural disaster in the United States (U.S.). According to data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), 2,353 persons were killed and 17,129 people injured by flood events from 1960 to 2005. Over this time period, fewer people were killed by hurricanes, tropical storms, and tornados combined. The Centers for Disease Control mortality database corroborates SHELDUS estimates, showing 2,164 persons killed by floods and cataclysmic storms from 1979 to 1998. The Federal Emergency Management Agency (FEMA) estimates that flood events caused more than 10,000 deaths in the U.S. since 1900 (www.noaa.gov). The economic impact from flood events is substantial. From 1960 to 2005, SHELDUS data indicate that flood events caused, on average, $1.16 billion dollars of property damage, and $335 million dollars of crop loss every year (figures expressed in 2000 inflation adjusted dollars). The destruction of property and public infrastructure from flooding is unevenly distributed in the U.S., with states like Florida and Texas burdened more significantly. For example, SHELDUS data show that from 1960 to 2005 Florida alone suffered $2.03 billion dollars in property loss, and $962 million in crop damage. The damages incurred by Florida account for 3.8 percent of all property loss, and 6.2 percent of all crop damage endured by the country over this time period. Of course, such cold statistics do not fully capture the human suffering, the psychologies of dread and insecurity, the social disorder, or the indirect financial losses caused by flood events.

To limit the human, social and economic toll of flood events, localities enact various structural and non-structural mitigation plans. Structural efforts may involve the construction of dikes, dams, flood control reservoirs, diversions, floodways, and channel conveyances. Non-structural initiatives may include point source control and watershed management efforts, open space preservation, regulations and zoning, land acquisitions, economic incentive schemes, forecasting and warning systems, education campaigns, and maintenance of flood-related databases (Kundzewicz, 2002; Brody et al. 2007). The mix of planning instruments deployed by a local government may determine the variation in flood losses over time (Brody et al. 2007).

One way in which local communities implement structural and non-structural flood mitigation strategies is through the Federal Emergency Management Agency's (FEMA) Community Rating System (CRS). Under this program, localities adopt and implement a mix of 18 different activities to reduce the adverse impacts of floods. Each mitigation activity receives a score based on the degree to which it is implemented. A community's total score (derived from a federally constructed point system) corresponds to discounts on flood insurance premiums for individual residents. Currently, 1,206 municipalities participate in the CRS and initial research indicates that the program may reduce property damage and human casualties (Zahran et al. 2008; Brody et al., 2007). While these preliminary findings are promising, the effectiveness of this program in encouraging local jurisdiction to adopt flood mitigation activities has never been thoroughly investigated.

We address this issue by systematically evaluating the design and operation of the CRS program in Florida. Analytical procedures seek to answer the following research question: to what degree does the incentive design of the CRS program influence flood mitigation efforts over time? Specifically, we track mitigation activities for all participating local jurisdictions in Florida on a yearly time step from 1999 to 2005. Both descriptive statistics and multiple regression analyses isolate the effect of a nonlinear incentive design on the change in flood mitigation policies over time, adjusting for hydrology, disaster history, socioeconomic, and human capital variables that can plausibly explain local flood mitigation activities. Results provide insights on the way in which local policy responds to federal-level program design. These findings can help decision makers improve program performance, leading to more effective flood mitigation strategies and perhaps the reduction of property loss and injury resulting from chronic flooding.

Our investigation of the CRS incentive structure is organized into four sections. First, we describe the CRS program in greater detail, summarize theoretical literature on nonlinear incentives, and discuss empirical expectations that follow logically from literature. Second, we describe the elements of our research design, including logic of sample selection, variable operations and measurement, and analytical procedures. Third, we report both descriptive and multivariate regression results on the factors influencing local flood mitigation activities over time. Fourth, we discuss our results in relation to broader questions of planning design and flood mitigation.

Community Rating System and Nonlinear Incentive Design

The CRS program was created to reward localities for flood mitigation activities that exceed minimum standards of floodplain management set by the National Flood Insurance Program (NFIP). The CRS program incentivizes 18 flood mitigation activities organized into the following four categories of floodplain management: public information, mapping and regulation, flood damage reduction, and flood preparedness.[1] Up to 4,500 points are awarded for flood mitigation activities, with points earned by a locality corresponding to financial benefits in the form of flood insurance premium discounts.

The amount of points a locality can earn varies by mitigation activity. For example, activity *420 Open Space Preservation*, awards up to 900 points for restriction of development in flood prone areas. The CRS points earned by a locality (ranging from 0 to 4,500) correspond to a class rating that ranges from 10 to 1 (where 10 is the lowest class, and 1 is the highest class representing exemplary performance). According to conversion tables, a community with 1,005 CRS points earned is classified as an 8, while a community with 2,800 CRS points earns a classification of 5. Table 1 summarizes the scoring logic of the CRS program. The vast majority (89 percent) of CRS participating localities fall in the class range of 10 to 7. The same distribution obtains in Florida.

[1] Series 300 (public information) activities measure the extent to which a locality informs local populace about flood hazards, insurance, and protection measures. Series 400 activities (maps and regulation) measure regulatory enactment and enforcement activities that exceed the NFIP minimum standards. Series 500 activities (damage reduction) involve damage reduction measures like acquiring, relocating, or retrofitting existing buildings and maintaining drainage and retention basins. Series 600 activities (flood preparedness) coordinate local managerial efforts to minimize the effects of a flood on people, property, and building contents.

[Insert Table 1]

A CRS locality's class rating corresponds to a discount in flood insurance premiums. Premium rate discounts range from 0 to 45 percent and move in increments of 5 percent. For example, a locality with 1,600 CRS points is rated as a Class 7, with residents in this locality entitled to a 15 percent premium reduction in federal flood insurance. The discount incentive is designed to tighten the correlation between household purchase of flood insurance and flood mitigation activities of local governments. As local governments increase flood protection efforts, premium discounts increase, making household purchase of flood insurance more economical. In Florida, the observed correlation between CRS points earned and the number of NFIP policy holders is in fact significantly positive ($r = .2606$, $p = .000$). As of June, 2006 Florida had over 1.8 million NFIP policy holders that reside in 214 participating CRS communities. Property owners living within these communities saved approximately $98.5 million per year in insurance premiums from involvement in the CRS program (FEMA, 2006).

The conversion of points earned- to class rating-to premium discount in the CRS program is analogous to how university students are graded. In this case, numeric scores are translated into letter grades, with letter grades corresponding to grade points that figure into the calculation of a grade point average. As with the calculation of grade point averages, in the CRS program vital information (or measurement precision) is lost in the conversion of points to premium discounts. For example, a locality with 1,501 CRS points has the same class and discount benefits as a locality with 1,999 CRS points, even though the latter county has incurred greater cost (in time, money and effort) to mitigate negative flood outcomes. This imprecision in scoring and allocation of rewards may distort effort to mitigate flood risk.

Performance and Nonlinear Incentives

A basic proposition of *agency theory* is that policy instruments or contracts that bind rewards to performance encourage greater effort (Prendergast 1999). Many studies provide formal logical and empirical evidence that effort expenditures correspond to performance incentives (Williamson 1975, 1985; Holmstrom 1979; Holmstrom and Milgrom 1991; Lazear 2000). The overarching conclusion of this literature is that output-based incentives positively affect performance (Lazear 2000; Banker, Lee, and Potter 1996; Paarsch and Shearer 1999). However, theory also specifies that incentive schemes can distort effort if rewards are discrete or nonlinear, with agents modulating their effort to exploit the nonlinearity of a compensation schedule. Courty and Marshke (2004: 23-24) explain: "When performance awards depend nonlinearly on performance outcomes, agents have an incentive to manipulate the timing of their performance. Under bonus-based contracts, for example, agents may time their performance so that they just meet the numerical standard to receive their bonus."

Effort timing is not the only distortion that may arise from a nonlinear incentive scheme. Theory also suggests that effort expenditures decay once a performance quota is reached, and/or whether a performance quota is defined by an agent as unattainable (Oettinger 2002). In fact, when a performance target is defined as unreachable, a discrete incentive may do more harm than good, inducing a stall or even a *freeze of effort* (McEwan and Santibanez 2005; Oettinger 2002) . In such cases, the effort expended by an agent varies by their proximity to an award cutoff, not by some underlying demand for performance. Prendergast (1999: 26) writes: "an agent who is close to winning [a] prize will have greater incentive . . . than one who has either exceeded the quota or is unlikely to reach that quota."

By design, performance incentives in the CRS program are highly nonlinear because marginal improvements in flood mitigation go unrewarded, except when points gained from mitigation efforts eclipse a discount interval. This nonlinear incentive design may distort effort, and may even pervert the propensity to attenuate flood risks. That is, the expected gains from mitigation (in premium discounts terms) depend on where a locality is in relation to the next discount interval. An example from Florida will clarify what is meant by the distortion of effort by nonlinear incentive design.

In 2005, Osceola County had a population-weighted CRS point total of 1,483, and Leon County had a CRS point total of 1,068. Residents in both localities benefit from a 10 percent discount in flood insurance premiums, corresponding to the flood mitigation activities undertaken by their respective local governments. Let us assume that both local governments are thinking about a mail campaign to inform residents on the local risks of cataclysmic storms and floods. The CRS program awards 60 points for such an effort (as a fraction of the 380 points available within activity 330). The costs of such an information campaign are roughly equal for both localities - the population size in Osceola is 235,156, and 239,452 people reside in Leon.

Let us also assume that local officials in both localities are discount-seeking – that is, they hope to benefit residents by reducing flood insurance burdens. The marginal benefits (in dollars saved per NFIP policy holder) of the information campaign are decidedly different for both localities – 60 points earned from the information campaign push Osceola County into the next discount interval of 15 percent, and do nothing for Leon in terms of increased premium discount. By plan design, the flood mitigation efforts of both localities are incentivized differently on the basis of where they happen to be in the range of a discount interval. In nonlinear incentive schemes like the CRS where the minimum points required to achieve a premium discount are specified in advance, the flood mitigation efforts of a locality are likely to be strategic and possibly inefficient (unless the rating system is adjusted to more accurately capture the marginal benefit of effort).

Theory and intuition suggest that the CRS program incentivizes localities differently by their distance to the next discount threshold. Because premium discounts are realized sequentially, a locality's point distance to the next discount threshold ought to predict their future mitigation behaviors, with threshold proximate localities engaging in more flood mitigation than statistically similar localities positioned at the front end of a discount interval. This proposition is empirically testable:

First, if theory and intuition are correct, we ought to observe significantly higher CRS point growth rates between discount intervals as compared to growth rates within discount intervals. That is, because nonlinear incentives structure the return on effort differently by proximity to discount threshold, CRS point growth rates ought to spike noticeably as discount thresholds are eclipsed. If the CRS design awarded mitigation efforts linearly, we have no theoretical reason to presume such spikiness in year-to-year growth rates. Second, if localities are discount-seeking[2], we ought to observe clusters of CRS localities slightly above point totals that correspond with discount thresholds. Specifically, we ought to see excessive fractions of localities clustered around point totals of 500, 1000, 1500, 2000, 2500, and 3000 that correspond to discount boundaries. Third, if theory and intuition are correct, a locality's distance to the next discount threshold ought to predict conditions of "effort freeze," where CRS point growth rates grind to zero. Recall, agency theory claims that effort expenditures are likely to stall when agents define performance quotas as unachievable. Though one cannot directly observe an agent's definition of the attainability of a performance award, one can reasonably assume that calculations of attainability correlate highly with the point distances required to meet the next discount threshold. Finally, if localities are truly responsive to the nonlinear incentive design of the CRS program, threshold effects ought to predict CRS point totals

[2] It is important to note that official CRS literature deemphasizes the discount incentive. The benefits of participation in the CRS program emphasized include free technical assistance, access to Federal assistance programs, quality of life gains by protection of the environment, insulating residents from casualty risks, and protection of private property. Regarding discount incentives, the literature states: "Few, if any, of the CRS activities will produce premium reductions equal to or in excess of their implementation costs. In considering whether to undertake a new floodplain management activity, a community must consider all of the benefits the activity will provide, *not just insurance premium reductions* in order to determine whether it is worth implementing" (italics our emphasis, http://training.fema.gov/EMIWeb/CRS/m1s3main.htm).

earned, adjusting for hydrological, disaster history, and socioeconomic factors that can account for observed flood mitigation efforts.

Research Design

Study Area

We selected Florida as our study area for several reasons. First, Florida experiences significant annual economic losses from floods. Recent estimates indicate that from 1990 to 2003, Florida suffered almost $2.5 billion (in current US$) in property damage. The combination of rapid population growth, development, and high annual precipitation associated with a tropical and sub-tropical climate, make many local jurisdictions in Florida vulnerable to recurrent flooding. Flood damages in Florida are driven by both the cumulative effects of small flood events over time and large, widespread storms of short duration.[3] Second, 214 of Florida's local governments participate in FEMA's CRS program. This high level of community participation coupled with high flood risk make Florida an ideal laboratory for testing the correlates of flood mitigation behavior.

Dependent Variables

We measure and analyze three CRS outcome variables (variable operations are summarized in Table 2). First, we model CRS growth rate as the year-to-year change in CRS points earned for all local governments in Florida, including counties, cities, and townships with administrative authority. As of 2005, 214 localities in Florida participate

[3] For example, during a two day period in early October of 2000 Broward, Collier, Miami-Dade, and Monroe Counties collectively received over a foot of rain, causing over $450 million dollars of flood damage (NCDC, 2005) and prompting over 51,000 individuals to request financial assistance from the Federal Emergency Management Agency (FEMA, 2000).

in the CRS program. *CRS growth rate* is measured as CRS points earned in time 2 minus CRS points earned in time 1 divided by CRS points in time 1 multiplied by 100. Second, we model the likelihood of stalled growth in annual CRS points. *CRS stalled growth* is measured as a binary variable, where 1 = a less than 1 percent annual growth rate in CRS points earned, and 0 = a greater than 1 percent increase in year-to-year CRS points earned. Third, we model *CRS points earned* as a percentage of total points earnable. For this third variable, we aggregate CRS points to the county scale. The purpose of aggregation is to test the distortionary effects of nonlinear incentives, adjusting for hydrologic conditions, flood disaster histories, and socioeconomic variables that may account for observed variation in CRS point totals. This aggregation procedure requires some explanation.

[Insert Table 2]

Most counties in Florida earn their own CRS points. In many cases, independent municipalities nested in a county boundary earn separate points for mitigation efforts. In such cases, we population-adjust and summarize the mitigation activities of nested municipalities. Figure 1 illustrates the logic of measurement, showing Lee County and the nested municipalities of Bonita Springs, Cape Coral, Sanibel, and Fort Meyers Beach and City. As of 2000, each municipality has earned different point totals. First, we subtract population totals of nested municipalities from the total county population to derive the balance of residents in Lee County. Second, the population of each municipality is divided by the total county population to derive a weight. Third, we multiply this municipal weight by the observed CRS point total for each municipality. Fourth, we summarize population weighted CRS points to derive our county estimate. This procedure was performed for all participating counties (and nested entities for the period 1999-2005). As of 2005, residents in 52 Florida counties were eligible for flood insurance premium discounts.

[Insert Figure 1]

Incentive Design Variables

We measure two incentive design variables: *threshold distance* and *threshold eclipse*. *Threshold distance* is measured as CRS points in the next discount threshold minus the CRS points held by a locality. For example, as of 2003, Parker City had earned 843 CRS points. With the next discount threshold being 1,000 points, Parker City's distance to the next threshold is 167 points. From theory and intuition, we expect that both CRS growth rate and percentage of CRS points earned are negative functions of threshold distance. *Threshold eclipse* is measured as a binary variable, with 1 = a situation where change in locality's CRS point total eclipses the next discount interval, and 0 = a situation where change in a locality's CRS point total does not cross a discount boundary.

Control Variables

To test the extent to which local flood mitigation activities are responsive to nonlinear incentives, we analyze many control variables, organized into four categories: *flood history, natural hydrologic, economic, and measures of human and social capital.*

A critical factor influencing flood mitigation activities over time is the nature and severity of past events (Sabatier, 1995; Beem, 2006). The amount of damage or casualties incurred from previous flood events may influence a locality to undertake future flood mitigation activities (Folke et al., 2005). Hazard events can act as triggers to local policy change. Although natural disasters can be very damaging, they open windows of opportunity for policy change and action (Berkes, 2007). For example, as far back as the late 1970's researchers found that past flooding was a significant factor in the decision of local communities to participate in the National Flood Insurance Program, controlling for other community characteristics (Moore and Cantrell, 1976; Luloff and Wilkinson, 1979). More recently, Browne and Hoyt (2000) find that flood insurance purchases are highly correlated with the level of flood losses the previous year. Similarly, Burby (2003) demonstrates that chronic property loss from hazards (as measured by the number of NFIP repetitive loss properties) is a significant predictor of plan quality change for natural hazards, controlling for other factors. Also, in a recent study of policy change in England and Wales, Johnson et al. (2005) find that the magnitude of flood disasters act as a catalyst for local policy change with respect to flood mitigation. Therefore, to adequately test the extent to which localities mitigate flood outcomes as a function of nonlinear incentives, one must control for prior histories of flooding.

Two flood history variables are estimated. The intuition here is that localities are more likely to do flood mitigation if the flood risks faced are higher. Our flood history variables include: *flood frequency* and *flood property damage*. Both variables are measured at the county scale (the finest spatial resolution available). *Flood frequency* is measured as a ten-year rolling average of the annual number of flood events recorded in a county. To estimate the intensity of flood events experienced, we calculate a ten-year rolling average[4] of the annual property damage incurred from flood events. Property damage figures are adjusted for the time value of money fixed to the year 2000. Data on flood frequency and property damage are derived from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), 1990-2005[5].

Two hydrology variables are tested: *floodplain percentage*, and *stream length*. *Floodplain percentage* is measured as the total land area of a county (in square kilometers) located in the 100-year floodplain (delineated areas that have a one percent chance of flooding in any one year), divided by the total land area. Floodplain estimates were derived from the most recent FEMA Digital Q3 flood data. Theoretically, localities with high floodplain overlap face higher flood mitigation costs relative to expected gains. That is, more is required (in time, effort, and money) of such localities to stem the risks of repetitive flooding, and to acquire points and accompanying benefits in the CRS program. Insofar as localities are constrained by their hydrological conditions, we expect

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[4] A ten-year rolling average is both theoretically and practically reasonable. From theory and empirical evidence, we assume that flood mitigation planning is incremental. On the question of institutional change, Nobel laureate Douglass C. North (1995: 19-20) maintains that, "the overwhelming majority of change is simply incremental and gradual." A single flood event may not be enough to induce local institutional change - much depends on prior probability distributions. We presume that a locality is more likely to do costly mitigation if flood events are recurrent and cumulate in institutional memory. Practically, a ten-year rolling average sufficiently smoothes the noise in flood frequency and intensity measures.

[5] The SHELDUS consists of a county-level inventory of 18 natural hazard types, including hurricanes, floods, wildfires, and drought. Hazard event records include a start and end date, estimated property damage and crop loss, as well as the number of human injuries and deaths. SHELDUS data are derived from public sources like National Climatic Data Center monthly publications and NGDC's Tsunami Event Database. The data are limited to disaster events that cause more than $50,000 in crop loss or property damage.

counties with high floodplain overlap to possess lower CRS point totals. Our *stream length* variable was calculated in a GIS using the National Hydrography Dataset (NHD), and measured as the total length of all streams (in meters) in a county jurisdiction. Localities that are highly dissected by streams experience rapid hydrologic response to rainfall events (Horton, 1932). Both floodplain percentage and stream length are time invariant variables.

In addition to hydrologic conditions and flood histories, research shows that socioeconomic and human capital conditions may influence local flood mitigation activities (May 1992). Community-wide levels of income or wealth, education, and population composition may shape the type and speed of policy change in flood risk mitigation efforts. For example, wealthy communities may have higher valued property at risk from flooding and thus a greater stake in ensuring protective policy measures are taken. Also, high income jurisdictions will most likely have the financial resources to implement costly strategies, such as structural relocation, or drainage improvements. These and other characteristics related to the social and human capital of a locality determine the way rational planners calculate the expected costs and benefits of an intervention, shaping the willingness and capacity of a local jurisdiction to be responsive enough to alter their policies over time. Such socioeconomic and human capital variables are crucial to control for if one wishes to establish a credible link between change in local flood mitigation behavior and nonlinear incentives.

Two socioeconomic control variables are measured: *population density* and *reductions per policy holder*. *Population density* is measured as the total population in a county divided by the county area in square kilometers. Population values from the 1990 and 2000 U.S. Censuses are used to estimate missing years. A linear rate of population change is assumed between decadal censuses and for extrapolation beyond 2000. *Reductions per policy holder* is measured as the total monies saved by a county area from CRS discounts divided by the total number of NFIP policy holders residing in a county. Theoretically, this variable captures a couple of things. First, it estimates the benefits that flow to individual residents from local government efforts to attenuate flood outcomes. Insofar as local officials are economically rational, we assume that higher expected benefits per policy holder will induce more comprehensive flood management efforts.[6] Second, because the cost of policy instrument is equal to the value of property, this measure also captures the economic well-being of a locality. Annual data on monies saved per policy holder are collected from FEMA CRS files.

Finally, we measure three control variable of human and social capital: *median household income; percent college educated; and non-profit assets per capita. Household income* is measured as the sum of money received in a year by all household members 15 years old and over. *Percent college educated* is measured as the total number of persons age 25 and over with a bachelor's, master's, professional, or doctorate degree divided by the total population 25+ years of age. Income and education values from 1990 and 2000 Censuses

[6] It is important to note that local government participation in the CRS program is not synonymous with policy holder savings – in many localities we observe lower than expected counts of policy holders, and relatively low dollar savings. In fact, in an interview conducted by the lead author with members of the CRS Task Force, officials noted that in at least three CRS localities we observe zero NFIP policy holders.

are used to estimate intervening years, assuming equal intervals of change. Analyses show that the odds of purchasing an NFIP instrument increase with income and education. The estimated elasticity of income is .492 percent, adjusting for the price of insurance, mortgage size, and hurricane interval (Kriesal and Landry 2004). Assuming localities are discount-seeking, incentives to mitigate flood risks are higher in localities with residents that have higher propensities to purchase NFIP instruments. *Non-profit assets per capita* is measured as the total assets reported by all non-profit organizations of tax-exempt status with $25,000 dollars in gross receipts required to file Form 990 with the IRS in a county area, divided by the total population. Data are derived from the National Center for Charitable Statistics (NCCS), Core Files. All things held equal, we hypothesize that counties characterized by higher civic engagement will have higher CRS point totals.

Results

We begin our analysis by comparing CRS point growth rates *between* and *within* discount intervals. Results reported in Table 3 show that CRS growth rates are remarkably higher as localities eclipse discount thresholds (or between interval growth) as compared to within interval growth rates. Statistically significant differences obtain across all class ratings, where p = < .01. Substantively, mean differences in CRS growth rates between and within discount intervals range from 13.06 to 46.5 percent. Flood mitigation efforts appear to vary considerably by discount boundary effects. If not for the nonlinear incentives of the CRS program, we have no theoretical reason to presume that growth rates would behave so differently between and within discount intervals.

[Insert Table 3]

Next, we corroborate descriptive results by estimating the effects of incentive design on CRS growth rates, adjusting for class rating, by a panel corrected linear regression test with fixed effects. Regression results are reported in Table 4. In the fully saturated model, we observe that the CRS point growth rate increases by 40.37 percent as Florida localities hurdle discount thresholds, where p= <.01. Adjusting for class rating and between interval condition, a locality's distance to the next discount threshold negatively predicts CRS point growth rate (b= -.0473, p= <.01). On average, increasing a locality's distance to the next discount interval by 2 points, decreases the growth by roughly 1 percent. In terms of predictive power, without any reference to local political and socioeconomic conditions or the nature of flood risks faced by Florida localities, about 50 percent of the variance in CRS growth rates is covered by incentive design variables.

[Insert Table 4]

In Table 5, we test the hypothesis, based on agency theory described above, that flood mitigation efforts may actually *stall* when localities define the next discount interval as unattainable. More specifically, a locality's distance to the next discount threshold ought to predict the condition of a locality's CRS point growth rate slowing to less than 1 percent a year. Results show that threshold proximity explains the likelihood of stalled growth, adjusting for CRS class rating. A unit increase in point distance from the next discount threshold increases the odds of a binary condition of stalled growth by 1.2 percent (b= .0118, p = <.01). Results also show that the likelihood of stalled growth decreases as localities improve their class rating.[7] Overall, the proportion of variance explained by this simple model is roughly 55 percent (as indicated by Cragg and Uhler's R^2 statistic).

[Insert Table 5]

Next, to estimate the extent to which CRS localities in Florida *adjust their flood mitigation strategies in accordance with* the nonlinear incentive structure of CRS program, we visualize the distribution of CRS points earned by localities as a histogram with a kernel plot (or Epanechnikov kernel) estimating the underlying density function of the variable. The STATA default optimal width parameter is used, with optimal width achieved by minimizing the mean integrated squared error. Clustering in CRS points earned is indicated by bumps in the estimated density function. As expected, Figure 2 shows that Florida localities cluster in narrow point widths corresponding to discount intervals of 500, 1000, 1500, 2000, and 2500 CRS points. This visual evidence suggests that Florida localities are truly discount-seeking, performing flood mitigation work that maximizes the return on effort by accumulating just enough points to clear a discount interval.

[Insert Figure 2]

[7] Recall, the classification scheme moves in a counter-intuitive direction - a class rating of 9 in worst than a class rating 8, with a class rating of 1 constituting superior flood mitigation behavior. Therefore, to properly interpret the positive coefficient in the panel corrected binary logistic regression table, a numeric increase in CRS class rating means a worsening of mitigation efforts. Another way to understand this result is that the likelihood of stalled growth is higher as localities first enter the CRS program.

Finally, we model CRS points earned as a function of incentive design, adjusting for multiple biophysical and socioeconomic predictors that may also account for variation in the dependent variable. Controlling for various local contextual characteristics helps further isolate the relationship between incentive design and improvements in flood mitigation practices. Calculation of a modified Wald statistic revealed significant groupwise heteroskedasticity, requiring the use of a panel corrected feasible generalized least squares (FGLS) regression analysis. Table 6 reports results of five separate regression models. We load variables incrementally by conceptual domain to see if incentive design variables behave according to theory across different specifications. We begin with incentive design variables only, and end with a fully saturated model of incentive design variables including hydrology, flood history, economic, and human capital controls.

[Insert Table 6]

Because our dependent variable, *CRS points earned*, is measured as a percentage of total CRS points a locality can earn, coefficients in Table 6 represent the expected percent change in CRS points earned for a unit increase in an independent predictor. Beginning with control variables, results from our full model in column 5 show that an increase in the amount of county land area in the 100-year floodplain significantly deters local flood mitigation efforts. Moving from zero land area in the floodplain to 100 percent overlap decreases the percentage of CRS points earned by 3.21 percent, where $p = <.01$.

By contrast, both measures of flood history significantly increase the percentage of CRS points accumulated by participating local jurisdictions. A unit change in flood frequency increases the percentage of obtained points by roughly a half percentage point (b= .451, p=<.01). Similarly, a unit increase in annual flood related property damage increases flood mitigation activities (b= 7.82e-07, p = <.01). Together, these results suggest that Florida localities are more than rational discount-seeking entities. They also appear responsive to risk signals, undertaking more flood mitigation work as prior probabilities of flooding increase in both frequency and intensity. Results in Table 6 also indicate that the amount of monies saved per NFIP holder significantly increases the percentage of CRS points earned (b= .059, p= <.01). With respect to human and social capital controls, results indicate that mitigation efforts increase with levels of civic vitality as measured by the non-profit assets per capita observed in a locality and median household income.

As expected, incentive design variables strongly influence the percentage of CRS points earned by Florida counties. For every 100 points shy of the next discount threshold, we observe a reduction in the percentage of CRS points earned by a quarter percentage point (b= -.00248, p =<.01). Adjusting for hydrology, flood history, economic and human capital controls, we find that eclipsing a discount interval increases the percentage of CRS points earned by 1.36 percent, where p= <.01. Both incentive design variables are statistically robust predictors of local flood mitigation behavior across all specifications.

Discussion and Policy Implications

Overall, descriptive and explanatory statistical results strongly suggest that flood mitigation efforts are motivated by the nonlinear incentive structure of the CRS program. Not only do we find point totals and growth rates clustered around discount intervals, but our explanatory models provide evidence that proximity to these class thresholds are actually driving communities to adopt flood mitigation strategies. Even when controlling for multiple biophysical and socioeconomic variables depicting the local conditions of a jurisdiction, the distance to the next CRS discount interval and the prospect of reaching the next class rating motivates participating communities to take actions that reduce the adverse impacts of floods. Furthermore, localities appear to scale-back mitigation effort as the distance to the next discount threshold increases and expend their greatest effort as they hurdle discount intervals. Effort stalling is perhaps the most counterproductive outcome of the CRS incentive design because it acts as a deterrent for flood mitigation activities that may reduce property damage and possibly save lives over the long term.

We also find that localities are motivated by the easy gains embedded in the CRS program or the "low-hanging fruit" of point totals. For example, as shown in Table 3, growth rates are highest in the easier to reach classes (classes 7 and 8). Also, our results show that growth rates decrease as localities move into lower classes where activities are more costly, time-consuming, and difficult to achieve, evidenced by the negative coefficient for class rating in Table 4. [8]

The significantly negative impact of floodplain area on CRS points earned provides a final piece of supporting evidence that may help portray the strategic behavior of CRS

[8] In fact, a related analysis of the CRS program found that Florida localities disproportionately pursue class 300 (public information) and class 400 (mapping and regulation) activities while at the same time under-pursue class 500 and 600 activities. For example, in 2005, almost 74 percent of total points earned (on average) came from class 300 and 400 interventions, a figure 28 percent higher than the proportional weight assigned to these activities. Florida localities (on average and over the time period assessed) deviate below the proportional weight of class 500 scores by 23.49 percent (Brody et al., under review).

participating communities in Florida. One explanation for the negative coefficient shown in Table 6, model 5 is that increasing floodplain area within a locality makes it more difficult to sufficiently protect residents living within these areas. Mitigating the adverse impacts of floods in these cases requires more significant, expensive, and politically less desirable interventions. As a consequence, there is less available "low-hanging fruit" for jurisdictions wanting to maximize their CRS scores, making it difficult to accumulate points over time. In these instances, the economic benefit of reduced insurance premiums may not be equal to the cost of obtaining more CRS points. The fact that local jurisdictions appear to be rational actors when it comes to assessing the relative costs and benefits of accumulating CRS points is encouraging from a program design perspective.

Overall, our research shows that the CRS program not only reduces property damage incurred by floods, but may also save lives. For example, in Florida a real unit increase in CRS rating equates to a $303,525 reduction in average cost per flood from 1997 to 2005 (Brody et al., 2007). In Texas, we found that for every real unit increase in the CRS premium discount, the odds of death and injury decrease by 36.05 percent (Zahran et al., forthcoming). However, the policy implications stemming from our empirical results suggest that the CRS program can be improved to foster more efficient and extensive adoption of flood mitigation activities at the local level. Careful incentive design in the case is critical because the human stakes are too high to induce a stalling or freezing of mitigation effort.

FEMA officials should reform the CRS by setting discount rewards linearly. For example, 1,306 points accrued should be equal to a 13.06 percent reduction in premium discounts. As it stands now, insurance premium reductions are awarded only after a major point threshold is crossed. This program redesign would help limit interval gaming, strategic mitigation, and would help make the marginal benefits of mitigation equal to the effort expended. A more linear program design would also reduce any temptation to incorrectly score local jurisdictions based on their mitigation efforts. At present, the incentive to incorrectly score at discount cutoffs is higher because the marginal benefits are so large.

Conclusion

Our study provides initial empirical evidence on how the CRS program design impacts the degree to which local jurisdictions in Florida adopt flood mitigation activities over time. While our analysis provides some important insights into the relationship between incentive design and local performance, leading to suggestions for how to improve the efficiency of the CRS program, it should only be considered a first step in investigating the subject matter. Further research is needed on several fronts. First, we only consider a seven year time period when examining policy change. As the longitudinal record of data continues to expand, longer study periods should be analyzed to better gauge the policy learning time horizon. Second, we only examine one state, which limits the ability to externalize our results to other parts of the country. A multi-state study would help us better understand how jurisdictions learn via policy change, particularly from a comparative perspective. Third, we examine the entire state of Florida, but miss the possible influence of very local or difficult to measure characteristics. Case study analysis of both fast and slow learning communities would better contextualize our statistical findings. Fourth, our analysis is limited to the institutional level. Given that institutional CRS learning is partly a function of the number of policy holders, future research should investigate the factors motivating individuals and households to purchase flood insurance from the federal government. Finally, our study thus far has examined the policy behavior of localities already participating in the CRS program. Future analyses should seek to explain why localities engage in the System in the first place, since this decision point could be where the greatest reductions in property damage and human casualties from floods are made, particularly from a national perspective.

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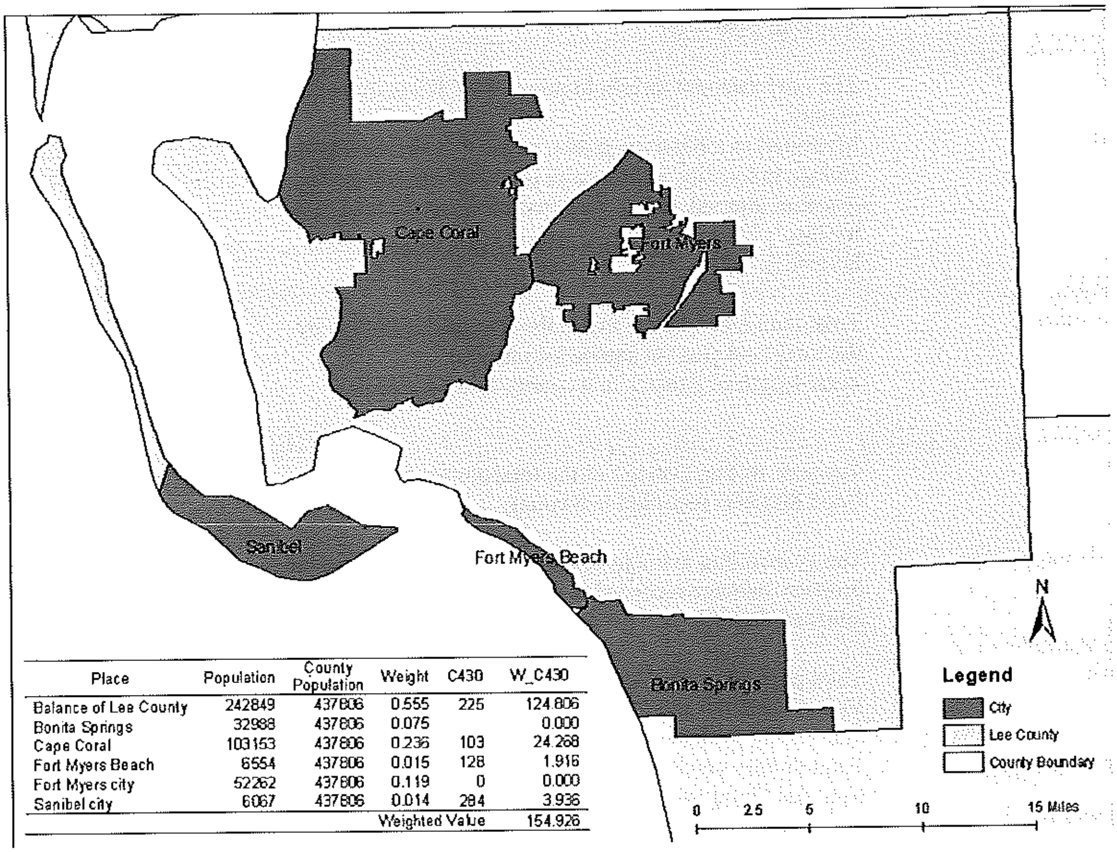
Table 1: Credit Points Earned, Classification Awarded, Premium Reductions, and Distribution of Florida Localities in the Community Rating System (as of 2005).

		Premium Reduction		Florida Localities	
Credit Points	Class	Special Flood Hazard Area (SFHA)	Non-SFHA	Number of Florida Localities	Percentage of Florida Localities
4,500+	1	45 %	10 %	0	0
4,000 – 4,499	2	40 %	10 %	0	0
3,500 – 3,999	3	35 %	10 %	0	0
3,000 – 3,499	4	30 %	10 %	0	0
2,500 – 2,999	5	25 %	10 %	6	2.9
2,000 – 2,499	6	20 %	10 %	13	6.2
1,500 – 1,999	7	15 %	5 %	60	28.6
1,000 – 1,499	8	10 %	5 %	97	46.2
500 – 999	9	5 %	5 %	34	16.2
0 – 499	10	0 %	0 %	0	0

Table 2: Variable Operations, Data Sources, and Expected Direction on CRS Mitigation Outcomes

Variable Name	Variable Operation	Sign	Data Source
Incentive Design Variables			
Threshold distance	The next discount threshold minus the CRS points held a county.	-	FEMA Community Rating System 1999-2005
Threshold Eclipse	Measured as a binary variable, with 1 = a situation where change in locality's CRS point total eclipses the next discount interval, and 0 = a situation where change in a locality's CRS point total does not cross a discount boundary.	+	FEMA Community Rating System 1999-2005
Hydrology Variables			
Floodplain percentage	Total land area of a county in the floodplain divided by the total land area (in square kilometers).	-	FEMA Digital Q3 flood data
Stream length	Total length of streams in a county area (in meters).	+/-	National Hydrography Dataset
Flood Disaster Variables			
Flood frequency	Ten year rolling average of the total annual number of flood disasters recorded in a county.	+	Spatial Hazard Events and Losses Database for the U.S., 1990-2005
Flood property damage	Ten year rolling average of the total annual flood caused property damage recorded in a county (in 2000 inflation adjusted dollars).	+	Spatial Hazard Events and Losses Database for the U.S., 1990-2005
Socioeconomic Variables			
Population density	Total population divided by country area (in square km). Values for 1990 and 2000 Censuses are used to estimate intervening years, assuming equal interval of change.	+	US Census Bureau, 1990, 2000
Reduction per policy holder	Total dollars saved divided by the total number of FEMA National Flood Insurance Program policy holders.	+	FEMA Community Rating System 1999-2005
Human Capital Variables			
Nonprofit assets per capita	The total assets reported by all number non-profit organizations of tax-exempt status with $25,000 dollars in gross receipts required to file Form 990 with the IRS in a county divided by the total population.	+	National Center for Charitable Statistics, Core Files, 1991-2004
Median household income	The sum of money received in a year by all household members 15 years old and over. Values for 1990 and 2000 Censuses are used to estimate intervening years.	+	US Census Bureau, 1990, 2000
Percent college educated	Number of persons age 25 and over with a bachelor's, master's, professional, or doctorate degree divided by the total population 25+ years of age. Values for the 1990 and 2000 Censuses are used to estimate intervening years..	+	US Census Bureau, 1990, 2000
Dependent Variables			
CRS points growth rate	CRS points in time 2 minus CRS points in time 1 divided by CRS points in time 1, multiplied by 100.		FEMA Community Rating System 1999-2005
Stalled CRS growth	Measured as a binary variable, where 1 = a less than 1 percent annual growth rate in CRS points earned, and 0 = a greater than 1 percent increase in year-to-year CRS points earned.		FEMA Community Rating System 1999-2005
CRS overall points	Population weighted sum of CRS points earned by a county divided by the maximum points earnable, multiplied by 100.		FEMA Community Rating System 1999-2005

Figure 1: The Logic of Population Weighted Measurement of CRS Points for Each County



Place	Population	County Population	Weight	C430	W_C430
Balance of Lee County	242849	437806	0.555	225	124.806
Bonita Springs	32988	437806	0.075		0.000
Cape Coral	103153	437806	0.236	103	24.268
Fort Myers Beach	6554	437806	0.015	128	1.916
Fort Myers city	52262	437806	0.119	0	0.000
Sanibel city	6067	437806	0.014	284	3.936
			Weighted Value		154.926

Table 3: Summary Statistics of CRS Growth Rates within and Between Discount Intervals

	Within Interval Growth Rate			Between Interval Growth Rate			Mean Comparison	
Class	N	Growth Rate	Std. Dev.	N	Growth Rate	Std. Dev.	Mean Difference	t-test
10	-	-	-	-	-	-	-	-
9	261	1.1982238	10.07675	-	-	-	-	-
8	589	1.053209	5.752776	29	47.551272	26.3698	46.49852	9.485**
7	222	.7302252	3.144332	54	40.44389	27.6668	39.71366	10.532**
6	26	-.2407692	.8514877	17	32.71765	19.87089	32.95842	6.835**
5	18	.72444	2.46943	5	13.782	5.220333	13.05756	5.427**
Overall	1116	.9874	6.57732	105	39.8865	26.39701	38.89905	15.056**

Note: Unequal variances assumed, with null hypothesis test of mean difference equal zero, ** $p<0.01$

Table 4: Panel Corrected Linear Regression Models with Fixed Effects Predicting Annual Growth Rate in CRS Flood Mitigation Points, 1999-2005

Variable	Coefficient	95% Confidence Interval		Coefficient	95% Confidence Interval	
Incentive Design Variables						
Threshold distance	-.0434398*** (.0038499)	-.0554591	-.0391344	-.0472968*** (.0041595)	-.0554591	-.0391344
Threshold eclipse	41.42562*** (1.155125)	38.10696	42.64042	40.37369*** (1.155125)	38.10696	42.64042
Control Variable						
CRS class				-2.686132** (1.112318)	-4.868858	-.5034055
Constant	15.03757*** (1.282669)			37.50986*** (9.393263)	19.07724	55.94247
N	1221			1221		
N Groups	211			211		
F	760.07			511.09		
R^2 within	.6013			.6036		
R^2 between	.2389			.2475		
R^2 overall	.5154			.5031		

Standard errors are in parentheses. Null hypothesis test of coefficient equal zero, *** $p<0.01$, ** $p<0.05$

Table 5: Panel Corrected Logistic Regression Model with Fixed Effects Predicting Stalled or Negative Growth Rates in CRS Flood Mitigation Points, 1999-2005

Variable	Coefficient	Odds Ratio	Unit Δ	95% Confidence Interval Odds Ratio	
Incentive Design Variable					
Threshold distance	.0118281*** (.0017064)	1.011898	1.2	1.00852	1.015288
Control Variable					
CRS class	4.04039*** (.5529143)	56.8485	5584.9	19.23435	168.0198
Log-Likelihood Intercept Only	-342.059				
Log-Likelihood Full Model	-277.545				
D	555.091				
LR	129.026				
Prob > LR	.000				
Maximum Likelihood R^2	.542				
Cragg & Uhler's R^2	.551				
AIC	3.388				
AIC*n	559.091				
BIC	-277.178				
BIC'	-118.814				
N	985				

Standard errors are in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01

Figure 2: Histogram with Kernel Density Plot of CRS Points Earned by Florida Localities, 1999-2005

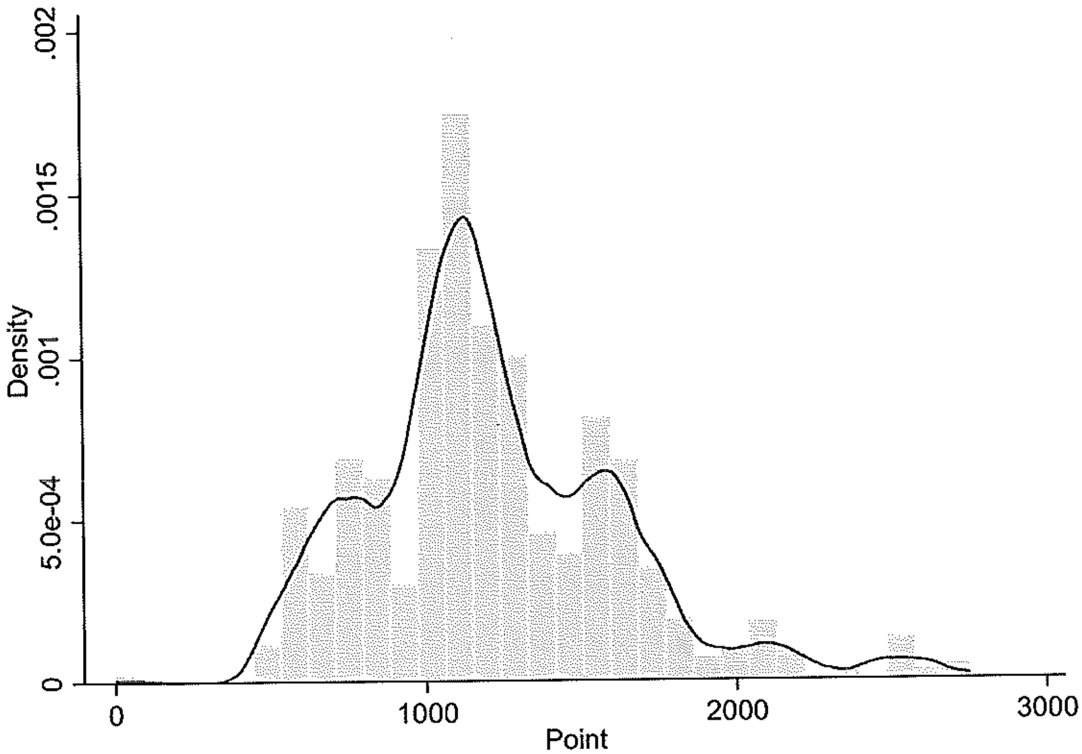


Table 6: Panel Corrected Linear Regression Models using Feasible Generalized Least Squares† Predicting CRS Overall Flood Mitigation Activities, 1999-2005

	(1)	(2)	(3)	(4)	(5)
Incentive Design Variables					
Threshold distance	-.0031111***	-.0030102***	-.0034306***	-.0022913***	-.0024809***
	(.0003632)	(.000344)	(.0003406)	(.0002963)	(.0003118)
Threshold eclipse	1.903485***	1.855218***	1.820473***	1.400319***	1.360148***
	(.1239919)	(.1191484)	(.1165316)	(.0844113)	(.100051)
Hydrology Variables					
Floodplain percentage		-6.300002***	-2.956925***	-5.97075***	-3.213659***
		(.7158587)	(1.00667)	(.817025)	(.8830281)
Stream length		-2.05e-07	-2.99e-06***	1.50e-08	-6.65e-07
		(9.52e-07)	(9.76e-07)	(5.39e-07)	(7.82e-07)
Flood History Variables					
Flood frequency			1.205285***	.2911401**	.4506553***
			(.1210661)	(.1176705)	(.1394196)
Flood property damage			7.01e-08***	5.26e-08***	7.89e-08***
			(1.75e-08)	(1.94e-08)	(2.19e-08)
Socioeconomic Variables					
Population density				.0066982***	.0016651
				(.0013324)	(.0017056)
Reduction per policy holder				.0678904***	.059193***
				(.0045243)	(.0051322)
Human Capital Variables					
Nonprofit assets per capita					.0001681***
					(.0000405)
Median household income					.0000405***
					(.0000183)
Percent college educated					.0152986
					(.0143976)
Constant	7.573504***	9.530944***	7.705781***	6.084303***	2.430427***
	(.1899224)	(.2505686)	(.4316253)	(.290974)	(.7628815)
Observations	354	354	354	354	354
Number of FIPS	52	52	52	52	52
Log likelihood	-358.517	-356.9197	-377.2255	-351.34	-355.4943
Wald χ^2	236.86	295.78	467.06	1035.08	1025.30

Standard errors are in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01, ** p<0.05, * p<0.1 † Models corrected for heteroskedastic error structure and panel-specific AR (1) serial autocorrelation